The Information Content of Decomposed Implied Volatility and Skewness Measures

Mattia Bevilacqua

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Kent Business School

University of Kent, UK

Supervisory Team: Prof. Radu Tunaru and Dr. David Morelli

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"Divide each difficulty into as many parts as is feasible and necessary to resolve it."

Descartes

Table of Content

Acknowledgement VI

List of Tables X

List of Figures XII

Summary XIII

Research Statement and Disclosure XV

1 Introduction **1**

2 Literature Review **15**

2.1 On the Volatility Measures 15

2.1.1 Realized (Historical) Volatility 16

2.1.2 Implied Volatility and Volatility Indexes 17

2.1.3 Volatility Risk Premium 23

2.2 Volatility Measures Decomposition 24

2.3 On the Stock Market and Volatility Determinants 27

2.4 Higher Risk Neutral Moments 31

2.5 Tail Risk Measures 34

2.6 Market Sentiment 38

2.7 Volatility Spillovers Literature 40

2.7.1 Volatility Spillovers Methodology: GARCH Models vs. Diebold and Yilmaz (2009) 40

2.7.2 Currencies Volatility Spillovers 43

2.7.3 Credit Volatility Spillovers 44

2.7.4 Volatility Asymmetry and Response to Good or Bad News 45

3 The Determinants of the Model-Free Upside and Downside Volatilities **47**

3.1 Introduction 47

3.2 Computation and Decomposition of Volatility Measures 52

3.2.1 Decomposition of Implied Volatility 52

3.2.2 Decomposition of Realized Volatility . . . 54
3.2.3 Decomposition of Volatility Risk Premium . . . 55
3.3 Data: Volatility Series and Selected Variables . . . 56
3.3.1 Volatility Series and Descriptive Statistics . . . 56
3.3.2 Macroeconomic and Financial Variables . . . 60
3.4 Identifying Determinants of Volatilities . . . 61
3.4.1 Relationship between Volatilities and Selected Variables . . . 62
3.4.2 Low Frequency and High Frequency Granger Causality Test . . . 62
3.4.3 Mixed Frequency Granger Causality Test . . . 63
3.5 Relationship between Volatilities and Selected Variables: Empirical Results . . . 66
3.5.1 Implied Volatility Stepwise Regression Analysis . . . 66
3.5.2 Volatility Risk Premia Stepwise Regression Analysis . . . 70
3.5.3 Implied Volatilities and Risk Premia Rolling Regressions . . . 73
3.6 Granger Causality at Different Frequencies: Empirical Results . . . 76
3.6.1 Granger Causality at Different Frequencies: Implied Volatilities . . . 76
3.6.2 Granger Causality at Different Frequencies: Volatility Risk Premia . . . 80
3.7 The Link Between Decomposed Volatilities and Economic, Political and Geopolitical Uncertainty . . . 84
3.8 Conclusion . . . 88

4 The SKEW Index: Extracting What Has Been Left **90**
4.1 Introduction . . . 90
4.2 Extracting the Positive and Negative Skewness . . . 94
4.2.1 The BKM Methodology . . . 94
4.2.2 SKEW Index and its Decomposition . . . 95
4.2.3 Data and Time Series Preliminary Findings . . . 97
4.3 Positioning the SKEW Indexes in Relation to Other Risk Measures . . . 100
4.3.1 Comparison with Volatility and Risk Premium Measures . . . 100
4.3.2 Comparison with Other Tail Risk Measures . . . 103
4.4 SKEW Indexes and Market Sentiment . . . 105
4.5 Decomposed SKEW Indexes and Equity Risk Premium Predictability . . . 109
4.5.1 Selected Predictors and Descriptive Statistics . . . 110
4.5.2 In-Sample Stock Market Predictive Exercise . . . 112
4.5.3 SKEW Indexes Relation to Other Predictors . . . 117
4.5.4 Out-of-sample Predictive Analysis . . . 120
4.5.5 The SKEW Indexes Predictability of International Markets . . . 124

4.6 Individual Stocks Analysis . . . 129
4.6.1 Largest and Smallest Stocks In-Sample Predictive Exercise . . . 129
4.6.2 Largest and Smallest Stocks Out-of-Sample Predictive Exercise . . . 135
4.7 SKEW Indexes and Asset Pricing . . . 135
4.8 Trading the Implied Skewness: General Considerations . . . 142
4.8.1 Trading Skew Based on Distributions Discrepancies . . . 142
4.8.2 Trading Skew Swaps . . . 143
4.9 The Link with Uncertainty and Macroeconomic Indicators . . . 144
4.10 Conclusion . . . 150

5 Asymmetric Connectedness of Fears in the U.S. Financial Sector 152

5.1 Introduction . . . 152
5.2 Data and Implied Volatility Decomposition . . . 155
5.2.1 Data on U.S. Financial Institutions . . . 155
5.2.2 Individual Upside and Downside Implied Volatilities of U.S. Financial Institutions 156
5.3 Asymmetric Fear Connectedness . . . 160
5.4 Fear Connectedness in the Financial Sector . . . 164
5.4.1 Fear Connectedness: Static Analysis . . . 164
5.4.2 Fear Connectedness: Time Dynamics . . . 165
5.4.3 Net Fear Receivers and Transmitters . . . 167
5.5 Asymmetric Fear Connectedness in the Financial Sector . . . 170
5.5.1 Asymmetric Fear Connectedness: Static Analysis . . . 170
5.5.2 Asymmetric Fear Connectedness: Time Dynamics . . . 173
5.5.3 Asymmetric Net Fear Receivers and Transmitters . . . 175
5.5.4 Additional Analysis of Individual Financial Firm Net Fear Connectedness . . . 180
5.6 Predictive Power of Fear Connectedness Indexes . . . 188
5.6.1 Predicting Macroeconomic Conditions and Uncertainty . . . 190
5.7 Asymmetric Connectedness of Implied Skewness . . . 195
5.7.1 Implied Skewness Connectedness: Methodological Framework . . . 195
5.7.2 Aggregate Skewness Connectedness: Static and Dynamic Analysis . . . 196
5.7.3 Asymmetric Implied Skewness Connectedness: Static and Dynamic Analysis . 198
5.8 Conclusion . . . 201

6 Conclusion 202

Bibliography 208

Appendices **230**

Appendix A Additional Material for Chapter 3 **230**

A.1 Volatility Modelling: GARCH Comparison 230

A.2 Realized Volatility: Empirical Results 232

A.2.1 Realized Volatility Stepwise Regression Analysis 232

A.2.2 Realized Volatility Granger Causality at Different Frequencies 236

Appendix B Additional Material for Chapter 4 **240**

B.1 Equity, Implied Volatility and Implied Skewness Indexes 240

B.1.1 Granger Causality Results 242

B.1.2 Zoom in Volatile and Turbulent Times 244

B.2 SKEW Indexes and Asset Pricing: Robustness 249

Appendix C Additional Material for Chapter 5 **254**

C.1 Main Ten U.S. Financial Institutions Ranking over Time 254

C.2 Post Financial Crisis and the Role of Berkshire Hathaway 254

C.3 U.S. Financial Sector Implied Skewness Measures 260

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List of Tables

2.1 **Relationships from the Literature between Stock Market and Macroeconomics** . 28

2.2 **Relationships from the Literature between Volatility and Macroeconomics** 29

2.3 **Skewness Measures Proposed in the Literature** 33

3.1 **Volatility Series Descriptive Statistics** 58

3.2 **Volatility Series Correlation Analysis** 59

3.3 **Stepwise Backward Regression between Implied Volatilities, Risk Premia and Selected Variables** 68

3.4 **Pairwise Granger Causality Test for Mixed Frequencies: From Implied Volatilities to Selected Variables ($\triangle$ VIX $\nRightarrow$ $\triangle$ X)** 78

3.5 **Pairwise Granger Causality Test for Mixed Frequencies: From Selected Variables to Implied Volatilities ($\triangle$ X $\nRightarrow$ $\triangle$ VIX)** 79

3.6 **Pairwise Granger Causality Test for Mixed Frequencies: From Volatility Risk Premia to Selected Variables ($\triangle$ VRP $\nRightarrow$ $\triangle$ X)** 82

3.7 **Pairwise Granger Causality Test for Mixed Frequencies: From Selected Variables to Volatility Risk Premia ($\triangle$ X $\nRightarrow$ $\triangle$ VRP)** 83

4.1 **Decomposed SKEW and Other Risk Measures: Correlation Analysis** 102

4.2 SKEW **Indexes and Other Tail Measures: Correlation Analysis** 104

4.3 **Regression Analysis Skewness Indexes on Investor Sentiment Indexes** 107

4.4 **Market Sentiment and** SKEW **Indexes: Predictive Regression** 108

4.5 **Equity Risk Premium and Predictors Summary Statistics** 112

4.6 **In-Sample Predictive Regression Results** 114

4.7 SKEW **Indexes and Dividend Variables Predictive Regression** 116

4.8 **Decomposed** SKEW **and** VIX **Indexes Predictive Regression** 117

4.9 **Decomposed** SKEW **and VRP Indexes Predictive Regression** 118

4.10 **SKEW Indexes and CRP Predictive Regression** 119

4.11 **Out-of-Sample Predictive Regression Results** 122

4.12 **In-Sample Predictive Regression Results Other U.S. Stock Indexes** 126
4.13 **In-Sample Predictive Regression Results International Stock Indexes** 127
4.14 **In-Sample Multivariate Predictive Regression International Markets** 128
4.15 **30 Largest S&P 500 Stocks: Multivariate Predictability** 130
4.16 **30 Smallest S&P 500 Stocks: Multivariate Predictability** 131
4.17 **30 Largest S&P 500 Stocks: Out-of-Sample Predicting Regression** 133
4.18 **30 Smallest S&P 500 Stocks: Out-of-Sample Predicting Regression** 134
4.19 **Fama-MacBeth Results: 25-Size/Book-to-Market Portfolios** 139
4.20 **Fama-MacBeth Results: 100-Size/Book-to-Market Portfolios** 140
4.21 SKEW Indexes Uncertainty Indicators Prediction (1) 146
4.22 SKEW Indexes Uncertainty Indicators Prediction (2) 148
4.23 SKEW Indexes Macroeconomic Activity Prediction 149

5.1 **U.S. Financial Companies Description** 156
5.2 **Aggregate and Decomposed Implied Volatility Indexes - Descriptive Statistics** . . . 158
5.3 **Static Fear Connectedness in the Financial Sector** 165
5.4 **Cumulative Net Fear Receivers and Transmitters** 169
5.5 **Asymmetric Fear Connectedness in the Financial Sector** 171
5.6 **Cumulative Net Upside Fear Connectedness Receivers and Transmitters** 178
5.7 **Cumulative Net Downside Fear Connectedness Receivers and Transmitters** 179
5.8 $\mathcal{C}_t$, $\mathcal{C}_t^-$ **and** $\mathcal{C}_t^+$ **Macroeconomic Activity Prediction** 192
5.9 $\mathcal{C}_t$, $\mathcal{C}_t^-$ **and** $\mathcal{C}_t^+$ **Uncertainty Indexes Prediction** 193
5.10 $\mathcal{C}_t^-/\mathcal{C}_t^+$ **Ratio, Macroeconomic Activity Prediction and Uncertainty Index Prediction** 194
5.11 **Static Skewness Connectedness in the Financial Sector** 196
5.12 **Asymmetric Implied Skewness Connectedness in the Financial Sector** 199

A1 **Stock Market and Selected Variables Conditional Variances** 230
A2 **Selected Macro and Financial Variables** 231
A3 **Stepwise Backward Regression between the U.S. Realized Volatilities and Selected Variables** 233
A4 **Pairwise Granger Causality Test for Mixed Frequencies: From Realized Volatilities to Selected Variables (**$\triangle$ **RV** $\not\Rightarrow$ $\triangle$ **X)** 238
A5 **Pairwise Granger Causality Test for Mixed Frequencies: From Selected Variables to Realized Volatility (**$\triangle$ **X** $\not\Rightarrow$ $\triangle$ **RV)** 239

B1 **Series Descriptive Statistics and Correlation Analysis** 241
B2 **Pairwise Cross-Moments VAR Granger Causality Test** 243

B3 **Pairwise Cross-Moments VAR Granger Causality Test in Turbulent Times** 245
B4 **Predictors Correlation Analysis** 246
B5 **U.S. S&P 500 30 Largest and 30 Smallest Stocks: Descriptive Statistics** 248
B6 **Sub-Samples Fama-MacBeth Results: 25-Size/Book-to-Market Portfolios** 250
B7 **Fama-MacBeth Results: 100-Size/Profitability Portfolios** 251
B8 **Fama-MacBeth Results: 100-Size-Profitability Portfolios Turbulent Events** 252
B9 **Fama-MacBeth Results: 12 Industries Portfolios** 253

C1 **Aggregate Financial Sector Aggregate Fear Connectedness: Post Crisis** 257
C2 **Financial Sector Upside and Downside Fear Connectedness: Post Crisis** 258
C3 **Aggregate and Decomposed Implied Skewness Indexes - Descriptive Statistics** . . 262

List of Figures

2.1 **CBOE VIX** . . . 20

2.2 **VIX vs. SKEW Scatter Plot** . . . 36

2.3 **VIX VERSUS SKEW Scatter Plot in Turbulent Times** . . . 37

3.1 **Decomposed Volatility Series** . . . 57

3.2 **Rolling P-Values for the Implied Volatility Regression** . . . 74

3.3 **Rolling P-Values for the Volatility Risk Premia Regression** . . . 75

3.4 **EPU, GPR and PCI Series** . . . 87

4.1 Skew, Skew^{-} and Skew^{+} Relationship . . . 98

4.2 **Decomposed SKEW Indexes** . . . 99

4.3 **Risk Measures Plots** . . . 102

5.1 **Upside and Downside Implied Volatilities of the U.S. Financial Sector** . . . 159

5.2 **The U.S. Financial Sector** VIX **Indexes** . . . 160

5.3 **Total Fear Connectedness Network** . . . 166

5.4 **Total Fear Connectedness Index** . . . 166

5.5 **Net Fear Connectedness** . . . 168

5.6 **Positive Fear Connectedness Network** . . . 172

5.7 **Negative Fear Connectedness Network** . . . 173

5.8 **Fear Connectedness Indexes and AFC** . . . 174

5.9 **Asymmetric Fear Connectedness Ratio:** $\mathcal{C}^{-}/\mathcal{C}^{+}$ . . . 175

5.10 **Upside Net Fear Connectedness** . . . 176

5.11 **Downside Net Fear Connectedness** . . . 177

5.12 **Net Fear Connectedness and Net AFC - Goldman Sachs** . . . 181

5.13 **Net Fear Connectedness and AFC - J.P. Morgan Chase** . . . 182

5.14 **Net Fear Connectedness and AFC - Citigroup** . . . 184

5.15 **Net Fear Connectedness and AFC - Bank of America** . . . 185

5.16 **Net Fear Connectedness and AFC - Bank of New York Mellon** . . . 186

5.17 **Total Implied Skewness Connectedness Index** 197
5.18 **Implied Skewness Connectedness Indexes and AFC** 200

A1 **Rolling P Values for the Realized Volatility Regression** 235

B1 **Decomposed SKEW and VIX Scatter Plot** 240
B2 **First Four Principal Components from Goyal and Welch (2008) 14 Predictors** . . 247

C1 **Net Aggregate Fear: 1 Year Ranking** 254
C2 **Net Positive Fear: 1 Year Ranking** 255
C3 **Net Negative Fear: 1 Year Ranking** 255
C4 **Total Implied Volatility Spillovers Indexes and AFC: 15 Banks** 259
C5 **Net Fear Connectedness and Net BRK - Berkshire Hataway** 260
C6 **Implied Skewness Measures in the U.S. Financial Sector** 261

Summary

This research investigates how decomposed forward looking measures extracted from equity options in the U.S. contribute to a more directional understanding of the financial market volatility characteristics and their connectedness. It shows how different components of implied volatility and skewness, namely, upside or *positive* and downside or *negative*, extracted only from call options and put options, respectively, might contain a more refined set of information compared to the aggregate measures. The information enclosed in the decomposed components of risk measures is able to enrich the set of financial tools which market participants and investors have at their disposal. The new set of directional information can be most certainly used to improve financial stability and predict future economic activity or future levels of uncertainty indicators. Overall, our empirical findings suggest that uncertainties related to upside or downside measures, proxies for good or bad market events and news, can be used to achieve better asset pricing and equity market premium predictability as well as a better understanding of the volatility connectedness in the financial markets.

When decomposed, implied volatility measures contain different information able to provide new insights of the separate determinants of volatilities among the macroeconomic and financial variables. The same is found to be true when risk neutral and physical measures are joined together to compute the volatility risk premia. By decomposing implied volatility measures, this study also shows that by doing this enables new light to be shed in the financial connectedness area through examining asymmetric volatility characteristics. Lastly, implied volatility measures extracted from single stocks in the U.S. financial sector further confirm the asymmetry characteristics in connectedness. This enhances the understanding of the financial institutions network and how this can be used for future economic activity and future levels of uncertainty predictability. Lastly, we show that different components of the implied skewness can be used to improve financial stability, provide a more prudent measure of tail risk, and contribute to asset pricing and uncertainty predictability.

The first chapter focuses only on the volatility series which is, however, considered both in its implied measure, realized measure and, merging the two, in its risk premium. Thus, both implied and realized volatility are computed model-free and decomposed into upside and downside components, thereby allowing us to compute volatility risk premia accordingly. The chapter analyzes the role of macroeconomic and financial determinants in explaining stock market volatility in the U.S. market. We distinguish the behaviour of each component of the implied volatility and risk premium in relation to their different determinants. The downside implied volatility appears to be linked more towards uncertainty and geopolitical risk indexes, whereas upside implied volatility is driven more by consumption and GDP. The role of put options, underlying downside implied volatility, has emerged more strongly in the post global financial crisis. A mixed frequency Granger causality approach uncovers causality relationships between volatilities and risk premia and macro variables and vice versa, a finding which

is not detected with a conventional low frequency VAR model.

In the second chapter, we disentangle implied skewness related to downward movements from the implied skewness associated with upward movements of the U.S. equity index. We decompose the implied skewness measure into its positive and negative components. The positive SKEW index is extracted from the S&P 500 call options, whereas the negative SKEW index is extracted from the S&P 500 put options. The information content of our measures is not captured by other risk and tail risk measures. They provide an additional powerful tool next to the second moment index and its components which might further improve asset pricing and economic predictability. The positive SKEW index is more connected with market sentiment indicators, whereas the negative SKEW index is proposed as a tail risk measure. We show that the decomposed SKEW measures are useful in predicting the S&P 500 as well as individual stocks future equity risk premium, mainly in the short-term. The positive SKEW also appears to be a robust predictor when we control for additional financial risk variables such as the decomposed implied volatility and the decomposed variance risk premia. The decomposed SKEW indexes are also informative when added to Fama-French asset pricing models. We show that the negative SKEW can play a significant role in predicting uncertainty indicators up to a one year horizon.

In the last chapter, single stocks implied volatilities are decomposed for the U.S. financial sector showing how they might be input, separately, into connectedness indexes with the aim of increasing their predictability power for macroeconomic and uncertainty indicators. Basically, we study how shocks to forward looking expectations of investors buying call and put options transmit across the financial system. We introduce a new contagion measure named asymmetric fear connectedness (AFC) that captures the information related to "fear" in the two sides of the options market, that can be used as a forward looking systemic risk monitoring tool. The decomposed connectedness measures provide timely predictive information for near future macroeconomic conditions and uncertainty indicators and they contain additional valuable information not enclosed in the aggregate connectedness measure. The role of upside/downside "fear" transmitter/receiver emerges clearly when we zoom into idiosyncratic financial institutions events. We identify banks that are predominantly upside/downside receivers of "fear", as well as banks positively/negatively transmitting "fear" in the financial system.

Research Statement and Disclosure

The research illustrated in Chapter 3 of this thesis has been accepted for publication in: Bevilacqua, M., Morelli, D. and Tunaru, R., 2019. The determinants of the model-free positive and negative volatilities. *Journal of International Money and Finance*, 92, pp.1-24. Available at: `https://doi.org/10.1016/j.jimonfin.2018.12.003`.

The research illustrated in Chapter 4 of this thesis has benefitted from comments from academics resulting from conferences presentations as well as journals' referees comments and suggestions which have been, certainly, improved the Chapter. The conferences in which I presented the Chapter are the following: *Socialising Business Research (SBR) 2017* - University of Kent – 5-7 June 2017 (Best Finance Paper), *The 15th INFINITI Conference on International Finance* – Universitat de Valencia, 13-16 June 2017, *World Finance Conference (WFC)* – University of Cagliari, Sardinia, 26-28 July 2017, *F.E.B.S. Conference*– University of RomaTre, Rome, 4-6 June 2018.

The research presented in Chapter 5 has been benefitted from my PhD visiting programme at *MNB - The Central Bank of Hungary* in 2017. See the Acknowledgement section for further information. During my stay at the Central Bank I developed - independently - all the methodological part on which my fifth Chapter is based. During this time I also improved my knowledge of the literature regarding financial volatility contagion and spillovers. The main idea of the fifth Chapter has been developed thanks to my knowledge of the aforementioned literature as well as the literature on implied volatility from options and systemic risk which allowed me to identify this gap in the financial literature. The interaction with experts in this area has benefitted the Chapter even further. The following conferences, meetings and workshops have also contributed to the idea: Workshop at *MNB – The Central Bank of Hungary*, Budapest, 15 September 2017, *10th FIW - Research Conference "International Economics"* - University of Economics and Business, Vienna, 9-10 November 2017 (Session Chair), Research Seminar at *Institute of Economic Studies, Charles University, Department of Economics*, Prague, 17 October 2018 (invited speaker), *European Economic Association Job Market Meeting*, Naples, Italy, 6-7 December 2018, *Royal Economic Society PhD Meeting*, Westminster Business School, London, 18-19 December 2018 (Session Chair), 12th IAFDS, Politecnico di Milano, Milan, Italy, 9-11 June 2019. Preliminary results of the developed methodology with a different application and story-line can be found in the MNB working paper series: WP 2018/2- Mattia Bevilacqua: Asymmetric Volatility Spillovers Between Developed and Developing European Countries. Available at: `https://www.mnb.hu/en/publications/studies-publications-statistics/working-papers-1-1`.

Chapter 1

Introduction

The vastness of topics concerning risk and measures of risk is daunting. Risk touches subjects such as psychology, mathematics, statistics, economics as well as finance. The concept of risk takes several shapes according to the different areas and subjects. The literature surrounding the concept of risk is monumental, continuously changing and always on the news. Understanding risk, measuring it and evaluating its consequences has always been of interest for many years. This research focuses, in particular, on measures of risk concerning financial markets, financial economics and macro finance. More specifically, this research focuses on implied measures of volatility and skewness which may be used as a forward looking proxy of risk in both academia and financial industry.

The main aim of this research is to develop new tools to better understand and monitor risk according to investors beliefs, expectations and perceptions. The novel set of information to improve the measure of risk in this direction is extracted from the U.S. options market. Furthermore, this research contributes to the recent literature on implied risk measures by separating the information enclosed in calls and puts. This methodology not only provides forward looking insights about investors' perspective of future risk, but also more refined and directional measures which are linked to the different investors' future beliefs reflected in both calls and puts. As this research will show, the separate content of calls and puts implied measures generates a synergistic measure of *perceived* risk in the U.S: information extracted from calls and puts in a separate way is more informative than the aggregate options portfolios when it comes to asset pricing, volatility connectedness measures, equity risk premium predictability and macroeconomic or uncertainty indicators predictability. We confirm this intuition not only with regards to the implied volatility measures, but also with regards to implied skewness measures and, lastly, with regards to implied volatility connectedness indexes.

The way in which measures of risk are defined and commonly recognized by the academic community and by practitioners have evolved over time. In fact, defining risk is not straightforward, though many attempts have been made over the years. The book of Bernstein (1996) - Against the Gods - is

an enlightening masterpiece in this regard. Risk can be defined as the possibility of gaining or losing something of value or an unfavorable outcome associated with an action. The word risk might have its origin from the Italian word - *risicare* - which means - to dare. In financial terms, risk would be, in this sense, a choice that investors decide to take rather than a supernatural fatal concept. Characterizing risk has always been a challenge in the literature as well as in practice. Damodaran (2012) defined risk as the likelihood that in life's games of chance, we receive an outcome that we will not like. Risk is - almost entirely - perceived in negative terms. In finance risk is the likelihood that we receive a return on an investment that is different from the return we expected to make. Thus, risk includes, according to this definition, not only bad outcomes (returns lower than expected) – downside risk – but also good outcomes (returns higher than expected) – upside risk. This research shows how is crucial to consider both when measuring risk.

The interest in risk increased following the seminal paper by Markowitz - Portfolio Selection - in which he argued that investors and fund managers should, not only, judge the performance of the fund or portfolio, but also the risk taken. Risk is what makes it possible to make a profit and the return from an investment relates to its associated risk generating a risk-return trade-off. Markowitz affirmed that investors consider expected return as a desirable thing and variance of return as undesirable thing. Markowitz was among the first who attempted to measure this risk. It is not easy to define and measure risk, thus Markowitz was the first who used measures of volatility (he called it variance) as a proxy for risk which investors should minimize. Variance measures how much the returns fluctuate from their average, it is closely linked to standard deviation and - volatility - which is the square root of variance. Thus, financial risk can be defined as the unpredictable variability or – volatility – of returns; this would include both potentially higher than expected as well as lower than expected outcomes or returns.

Volatility (or variance) has begun to be used as a proxy for risk in academia as well as in the entire financial industry (e.g. risk management, value at risk (VaR), derivatives). In risk management, volatility became a crucial measure. As we will mention later, usually when asset prices decrease volatility increases, signaling bad news driving to asset declines and collapse. The concept of volatility became of importance also as an academic idea studied in areas such as economics, statistic, probability, econometrics and finance. Thus, this research directly links to the use of volatility measures as a proxy of risk as commonly recognized in the financial literature.

The importance of volatility in the financial literature has been advocated by several seminal studies (see Shiller, 1981; Poterba and Summers, 1984; Shiller, 1989; Schwert, 1989; Day and Lewis, 1992; Bollerslev et al., 1994; Engle, 1995; Bates, 1996). According to Andersen and Bollerslev (1998) volatility permeates finance since the variation in economy-wide risk factors is important for the pricing of financial securities, and return volatility is a key input to option pricing and portfolio allocation problems. Accurate measures and good forecast of volatility are critical for the implementation and

evaluation of asset (see Bollerslev et al., 1992, 1994). Financial market volatility is an important input for investment, option pricing, and financial market regulation (see Poon and Granger, 2003). Volatility is also a more informative measure compared to assets' returns when it comes to spillovers measure (see Diebold and Yilmaz, 2009). Thus, within finance, areas such as asset pricing, asset allocation and derivatives lay on the concept of volatility. By trading any derivatives implies an implicit expectations on the future levels of volatility.

Options trading started to increase in popularity since 1973 when Black and Scholes (1973) published the well known Black Scholes model which calculates the value of options, where a crucial parameter is volatility itself. Options trading is commonly used for hedging or speculation. In order to place a bet on market turbulence, an options strategy such as a straddle – buy both call and put – can be entered. When both are sold it can be seen as a bet on market tranquility. Options and swaps are among the main derivatives in which volatility plays a fundamental role. These instruments have been widely used mainly for hedging strategies to reduce or offset the risk in the financial markets as well as for speculation in which investors are looking to increase the risk exposure with the aim of achieving higher returns. Investors have always felt the need to hedge themselves against market drops by entering into short position in equity derivatives. Later on, investors realized that they can actually trade volatility and it becomes a tradable asset as well as a risk management tool. Entering into a long position on volatility derivatives would actually compensate the investors for market downturns.

In 1992, Robert Whaley at the Chicago Board Options Exchange proposed an options-based volatility index which by 1993 became well know as the CBOE Volatility Index – VIX . Despite many changes in its methodology, in general the VIX index measures the next month expected volatility of the U.S. stock market as extracted from the stock market index option prices. Volatility contracts and assets which could be traded started to be proposed and built. The first volatility derivative appears to have been a variance swap dealt in 1993 at UBS. This tool allowed investors not only to hedge against volatility, but it becomes also a strategy in order to grasp potential arbitrage between realized volatility and implied volatility. In other words it is a bet on the difference between how volatile markets are and how volatile markets will be in the near future. See also Demeterfi et al. (1999) for an exhaustive guide on variance and volatility swaps. Variance and volatility swaps were widely used by financial institutions, hedge funds and other institutional investors. However the VIX index was – and still is – the volatility proxy the whole financial world was following. Thus, in 2004 the CBOE launched VIX Futures and in 2006 introduced options on VIX . In this way investors could exactly trade the same benchmark they were following to monitor volatility levels. The volume of these contracts increased quickly in the next decade, especially in the aftermath of the global financial crisis (see Rhoads, 2011)[1]. See Carr and Lee (2009) for an excellent survey about volatility derivatives.

[1]The increase in popularity of the VIX based products turned into a quick raise of exchange traded product based on VIX . The first was the Barclays VIX linked ETP by using volatility futures in 2009.

Once academics and practitioners agreed on the definition of risk as well as of a common measure of it, namely, volatility (variance), the challenge became the development of strategies and techniques to manage it. A lot of progress has been made over the last decade, however there is still a long way to go before even the major banks and other large financial institutions will really know their risks. Uncertainty has always been a main adversary of risk management. Damodaran (2012) defined risk in terms of uncertainty about future returns. The greater this uncertainty, the more risky the investment. Secondly, risk can be decomposed into risk that can be diversified away by investors and risk that cannot. The most common model in order to link risk and expected returns is the capital asset pricing model (CAPM).

The urgency of a discipline in finance called risk management was without doubt. Plenty of models and measures aiming to better evaluate financial risk have started to be developed from financial institutions. The importance of forecasting what can happen in the future has become crucial. Fundamental contributions in areas of risk management have come from subjects such as mathematics, statistics and probability. Pascal, Fermat, de Moivre, Bernulli, Bayes are only a few among the names who contributed massively to the understanding of risk. Several ways in which risk could be measured or assessed include; probabilities of negative events, statistical methods, expected utility, loss function. How Bernstein affirmed in his book Against the Gods:

The essence of risk management lies in maximizing the areas where we have some control over the outcome while minimizing the areas where we have absolutely no control over the outcome and the linkage between effect and cause is hidden from us.

More recently, in 1952, Markowitz not only proposed a statistical measure for risk, but he also proposed a fundamental strategy for risk management, namely diversification. This contributed to modern portfolio theory in which risk is studied as a condition in order to have higher returns and some kind of risks can be diversified away. The importance of diversification and the modern portfolio theory are based on this idea:

Under certain given conditions, an investor's portfolio choice can be reduced to balancing two dimensions, i.e., the expected return on the portfolio and its variance. Due to the possibility of reducing risk through diversification, the risk of the portfolio, measured as its variance, will depend not only on the individual variances of the return on different assets, but also on the pairwise covariances of all assets.

Thus, risk could be divided into two categories, the first, systematic risk which affects all assets in the same class being linked to the overall asset class and capital-market system which, therefore, cannot

be diversified away. This is also called market risk. The second is the non-systematic risk (or specific risk) is any risk which is not related to the market itself, but only to a specific company or asset related news and events. Thus, this is the diversifiable risk.

Among the biggest challenges that central bankers, policy makers and investors are facing nowadays, there is, without doubts, an increase in financial and economic instability. This is driven by the situation of uncertainty surrounding global financial markets including, also, the most developed economies. Central banks are concerned that a sudden collapse in asset prices might happen and drag the entire financial sector down in a dangerous declining spiral and into another recession. In addition, whereas we are witnessing a long period of economic growth, low unemployment rates, inflated asset prices, underestimation of future credit risk on one side of the globe, we can observe the opposite scenario for other countries. While an increase in interest rates should be considered in order to help some economies to reach their inflation targets, it could be, on the other hand, generating a slowdown in economic growth. This makes many global central banks more hesitant about their future policies and decisions. The short-term financial instability might be even further triggered by increasing volatility and uncertainty due to trade wars, Brexit uncertainty, and political conflicts worldwide.

Risk is a concept commonly intertwined with uncertainty. The latter means that the status or outcome of any situations or actions is unpredictable and uncontrollable, thus taking risky actions and decisions implies taking actions and decisions in uncertainty. Knight (2012), in his seminal work Risk, Uncertainty, and Profit, established the distinction between risk and uncertainty:

Uncertainty must be taken in a sense radically distinct from the familiar notion of risk, from which it has never been properly separated. The term risk, as loosely used in everyday speech and in economic discussion, really covers two things which, functionally at least, in their causal relations to the phenomena of economic organization, are categorically different. The essential fact is that risk means in some cases a quantity susceptible of measurement, while at other times it is something distinctly not of this character.... We, accordingly restrict the term uncertainty to cases of the non-quantitative type.

According to Knight (2012), uncertainty is immeasurable, not possible to calculate, while risk is measurable. Uncertainty makes what will happen in the future more blurry and cloudy. The greater the uncertainty, the greater the risk. Nowadays, indicators which aim to track uncertainty have spread out. Many of them are linked to economic and macroeconomic conditions, some others to geopolitical conditions, some to political events. Overall, they do not quantify the uncertainty, but they are able to identify whether we are in a period of low or high uncertainty. In the latter, measuring risk becomes even harder. Volatility in the U.S. has also been politically-driven since the end of 2016. In this context of uncertainty, it becomes of interest to study the relationship between volatilities and macroeconomic, financial and uncertainty indicators. Chapter 3 will cover this topic of interest.

In parallel, a growing stand of research has started to study how investors appear to be driven by irrational choices, myopia or inconsistencies when it comes to investing decisions and portfolio choices. The rise of a new area in finance, namely, behavioral finance appeared to be in need. Often investors decision cannot be considered following the traditional model of rationality, but they appear to be driven by market sentiment, irrational decision, greed or other psychological elements. According to Shiller (1989) in his book - Market Volatility - prices movements may be due to changes in investors' opinion or psychology thus generating a change in confidence, speculative enthusiasm and shocks. Consequently, changes in prices and speculative activity guide many economic activities in our society. This intuition was the ground for Shiller's research on excess volatility - the variation of prices is too large to be justified only in terms of efficient markets models and fundamentals. This concept will be recalled in Chapter 3.

Investors are, also, different in front of their risk tolerance. Risk loving investors would react differently compared to risk averse investors. In other words there are no investors always rationally trading off risk and returns. Uncertainty cannot be neglected either when investors have to make their decision. The set of information they have is limited. Emotions, fear and greed can also impact on investors' decision. All these elements should be taken into account when measures of risk are developed. If investors tend to violate the rational model and if investors are driven by irrational behaviors, new measures of risk should be developed. We will also acknowledge how investors may react in different ways to uncertain future risks or events. Positive emotions or expectations drive towards a more optimistic risk assessments. Negative emotions and expectations drive towards a more pessimistic risk assessments. Optimistic or pessimistic risk judgements influence the way investors trade in the financial market. Investors' beliefs and emotions are reflected on the options market.

Existing measures of risk and volatility as well as existing and proposed risk management tools do not always appear to be efficient and valid. News and speeches from the U.S. at the time of writing this thesis have reinforced and called for the need of better measures of volatility as well as a more accurate and prudent means of monitoring it. According to the ex Federal Reserve Chair Janet Yellen, the U.S. economic outlook is subject to considerable uncertainty from multiple sources, and dealing with these uncertainties is an important feature of policymaking especially for understanding the forces driving inflation. And, again, at the beginning of 2016, she mentioned that concerns regarding the global economic prospects might increase financial market volatilities in the U.S.

Thus, motivated by this uncertain financial and geopolitical scenario, this research aims to extract new information from the financial options market. First of all, greater importance and attention should be given to the increase of risk perceived by investors and to their future expectations. Rather than relying on backward looking information, this thesis proposes to expand into a new avenue of research by looking at forward looking information. Information extracted from the options market will serve

this purpose. which can better track, first of all, investors' expectations and beliefs in a forward looking manner. These options-based measures of volatility track the future month investors perspective, thus allowing for improved predictability and monitoring. Second, by relying on the options market, allows us to differentiate by investors beliefs.

Indeed, proposing improved and refined measures of risk has become of interest in the financial literature. We mainly anchor this research to a specific growing trend in the financial literature which has begun to decompose risk management measures (see Barndorff-Nielsen et al., 2010; Segal et al., 2015; Feunou et al., 2017; Kilic and Shaliastovich, 2018). More specifically, volatility measures have been decomposed into *good* and *bad* volatilities or into *upside* and *downside* volatilities. Segal et al. (2015) defined as good volatility (or uncertainty) the one regarding positive news for asset prices, impacting underlying assets in a positive way, contributing to future growth, investments and increase in production and consumption. On the other hand, bad volatility (or uncertainty) includes all the news and events contributing to market tension, decrease in options' underlying value, decline in market productivity, unemployment, disinvestments and market depression. In other words, good volatility is associated with potential profits reflecting what investors like, whereas bad volatility is associated with potential losses reflecting what investors dislike.

As an example, assuming the similarity between the financial market and the human blood: news and market information could be seen as lipoproteins; bad lipoproteins carry and dissolve bad cholesterol in the blood, on the other hand, good lipoproteins carry good cholesterol. Moreover, from this analogy between cholesterol and market volatility, more can be said. Indeed, in the medical world bad cholesterol - LDL - tends to deposit itself along the arteries and clog them, make them less flexible (atherosclerosis) while the good cholesterol -HDL- is supposed to take the bad one away from the arteries. Translated in financial terms, bad volatility could scare the investors, making them less flexible and inclined to speculative or long equity strategies and, rather, promoting hedging and insurance strategies; good volatility, on the other hand, helps the market to attenuate the fear relative to equity shortfall and market losses.

Disentangling the information associated with the upside and downside measures has been done, mainly, with regards to realized risk measures. We go a step further, by following the seminal paper of Bakshi et al. (2003) (henceforth, BKM) as well as CBOE (2009) methodology in order to extract information from the options market to compute and decompose the U.S. implied volatility. We define the downside volatility as VIX^{-} , whereas the upside volatility as VIX^{+} . The first is extracted from S&P 500 puts only, whereas the latter from S&P 500 calls only. For the first time in the literature, this implied volatility decomposition is applied not only to the S&P 500 index, but also to single stocks' options. More specifically, we apply the aforementioned methodology and decomposition to U.S. financial sector stocks. For instance, we define $GS - VIX$ as Goldman Sachs implied volatility index

which is decomposed in upside and downside defined as GS - VIX^{+} and GS - VIX^{-} . Same definitions are applied for the other main stocks in the U.S. financial sector. Volatility measures extracted from calls will mostly signal optimistic investors' expectations, whereas volatility measures extracted from puts pessimistic investors' expectations. The aforementioned methodology and seminal papers we follow, position this research as a cutting-edge topic in the financial literature.

In addition, this research goes a step further from the recent literature proposing new tools in order to enhance the financial risk measures available to track volatility. By applying Bakshi et al. (2003) methodology we extend the discussion about additional sources of risk which are not captured by volatility, namely, tail risk. Tail risk measures have been proposed to help quantifying and predicting outliers or *black swans*, thus the two concepts can be associated. A black swan, according to Taleb (2007) is a highly improbable and unpredictable event. It carries massive impact though. After it happens we begin to explain and contextualize it making it appear less random in the future as well as more predictable. Yet, we still fail to acknowledge the frequency of these events since we focus on things that we already know, underestimating what we do not know. This explains why there has been a growing interest in tail risk measures.

We feel that the need for a more refined and timely tail risk index is imperative, especially given the current economic, macroeconomic and political environment. For the first time in the literature a directional tail risk measure extracted from the U.S. options market is proposed. Following the same methodology applied for the volatility measures, this research decomposes the U.S. SKEW index into positive SKEW^{+} and negative SKEW^{-} . The first is computed from S&P 500 call options and reflects extreme positive returns in the equity market or, in other words, extreme positive events; the second is computed from S&P 500 put options and is a measure of extreme negative events. Bearing in mind the importance of the downside risk, we propose a new tail risk measure which relies on the SKEW^{-} . It could give us a more prudent view of the market sentiment and expectation about negative risk events. It allows investors to be more conservative and hedge their portfolios more efficiently, compared with other tail risk measured in the literature.

Lastly, this is the first time that several areas of research, namely, financial market volatility, options market and forward looking investors' beliefs and volatility spillovers, are bridged together so as to better investigate and monitor the ex-ante volatility spillovers and propagation of risk, which itself could contribute to monitoring purposes. Indeed, in this global scenario, financial market deregulation and integration make, especially with respect to the biggest economies, a scenario where they are even more connected by creating a dangerous net in which unexpected positive and negative shocks, investors' fears and enthusiasm might propagate faster than in the past. Thus, investors, central bankers and regulators, not only need to monitor the local and regional economic and financial condition, but also, the ones which might be due to the intensification of unexpected negative or positive developments

and events in other (connected) economies. The need of a timely monitoring tool of financial volatility contagion appears to be of urgency. In Chapter 5 we propose a new implied volatility connectedness - or fear - monitoring tool.

We will talk about fear in this thesis as a response to perceived danger. Investors might perceive this danger in different ways and with different intensities. Risk could be said to be the way we collectively measure and share this fear. The latter might be due to uncertainty, rational doubt, irrational doubt or behaviour, risk aversion and a set of biases coming from investors own experience. This field is interconnected with behavioural finance. The focus on human risk-aversion, asymmetric regret and asymmetric behaviour varies from investor to investor. We will study how fears can be connected in the selected financial system and how they can spread among investors increasing the level of fear connectedness. Fear has long been associated with negative risk perceptions. In this thesis, this specific negative risk perception will be defined as negative fear. A positive risk perception, thus still a risk, will be defined as upside fear. When they are interconnected among investors generating a spread in fear connectedness in the system, we will refer to them as downside fear connectedness and upside fear connectedness. Different behaviours and beliefs of investors would generate an asymmetry in fear connectedness. See Chapter 5 about this topic being applied in the U.S. financial sector.

By using a metaphor, our system might be thought as a class of students. Some students are athletic, doing sport often as well as having a healthy diet. Other students live a more defective life characterized by parties, use of alcohol and being habitual smokers. Most of the time, the two groups - considered as upside and downside - are kept separated. The first group can be classified as a positive habits (which in financial terms would be upside volatility) transmitter to the class. On the other hand, the second group can be classified as a negative habits (which in financial terms would be downside volatility) transmitter to the class. Habits transmitters are, overall, the strongest members in a community or system. Habits receivers are, overall, the weakest members who, using this metaphor, are affected by the others' habits. When more class members start to go to the gym and live a more healthy lifestyle, we observe a spread in good habits (upside volatility). When more students are going to parties, consuming alcohol and smoking, we observe a spread in negative habits (downside volatility). The difference between these two creates an asymmetry in habits in the classroom (system).

In general, each of the following chapters, rotates around the idea of either decomposing implied volatility or implied skewness measures. All of them are anchored to the importance of forward looking information extracted from options when it comes to proposed new risk measures as well as predicting other indicators or variables. All of them are about the importance of information enclosed in calls and puts and how this is helpful when taken separately in asset pricing and in equity, macroeconomic or uncertainty predictability. The three main chapters of this thesis all confirm the main intuition which has

driven this research, namely, that by considering information enclosed in decomposed implied volatility and implied skewness, enriches the set of information practitioners as well as academics can access. The two separated information sets are more informative than the aggregate in many applications. The three main chapters of this thesis present three different applications based on this idea.

Parallel research, at the time of writing of this thesis, decomposing volatility measures both realized and implied volatility measures has subsequently been published (see Kilic and Shaliastovich, 2018). We have, not only, found our results to be in line with these studies, but we also go a step further by looking at the determinants of decomposed volatility measures as well as their information content in predicting, in turn, macroeconomic and financial variables. Imagining the financial market volatility as an electronic battery that can be positively or negatively charged, what this research aims to better understand in the next Chapter is which variables are contributing to the positive or negative battery charge.

We further extend the existing literature by conducting a directional study of implied skewness in the U.S. contributing to the higher risk neutral moments, tail risk and equity market premium predictability areas. There has been no literature so far decomposing the implied third risk neutral moment. We find that this intuition opens up to a more refined classification of implied skewness according to the portfolio of options we consider. We find that by decomposing the implied skewness measure makes possible a strong linkage with market sentiment, tail risk measures as well as enhancing equity risk premium predictability.

Lastly, we study, for the first time in the literature, how implied volatility connectedness in the U.S. financial sector spreads and behaves when information is extracted from individual stocks' options and separated into upside and downside implied volatilities. By applying this innovative methodology to the U.S financial sector we are able to propose a more timely ex-ante systemic risk monitoring tool which systemic risk literature has been pointing to in the recent years.

Overall, we contribute to the existing financial literature by answering the following main questions which were still open at the time being of this thesis:

- *Which are the main determinants of the decomposed implied volatility measures in the U.S.?*
- *Can we extract additional information from the options markets by computing and decomposing the implied skewness measure?*
- *Are the decomposed implied skewness indexes useful for asset pricing, equity market premium predictability and macroeconomic and uncertainty predictability?*
- *Can we better track systemic risk spread, increase in uncertainty and decrease in macroeconomic conditions by computing an asymmetric implied volatility connectedness index extracted from the individual stocks' options prices in the U.S. financial sector?*

Other sub-questions, of minor importance, but still necessary in order to understand the overall research picture will be discussed in each corresponding chapter.

An extensive overview of the literature to which this research is anchored and which helps to answer these research questions is provided in Chapter 2. More specifically, Section 2.1 spans volatility measures such as realized volatility, conditional volatility inferred from ARCH/GARCH models, implied volatility and volatility indexes (e.g. VIX) extracted from options as well as volatility risk premium. Section 2.5 describes the financial literature about tail risk measures which have been proposed. Section 2.4 spans the literature about higher risk neutral moments (e.g. skewness). Section 2.6 illustrates the literature on market sentiment. Section 2.2 contains the literature review one of the core parts of this thesis on volatility measure decomposition and the different information enclosed in good volatility and bad volatility measures. Section 2.3 discusses the topic of stock markets and volatility determinants. Section 2.7 illustrates the state of the art on volatility spillovers spanning different assets, countries and methodologies as well as intertwining it with the new trend of decomposing volatility measures. Every section will be extended and enriched with empirical results and confirmations in the corresponding Chapters. We mention the research gaps in the literature review sections that we aim to fill within the next three Chapters of this thesis. More specifically, the main research questions will be answered in Chapters 3 to 5.

We rely on the seminal Bakshi and Madan (2000) and Bakshi et al. (2003) model-free methodology in order to extract information from the U.S. stock options market. Econometric and statistical models are applied for the empirical exercises in this thesis; OLS regressions, vector autoregressive (VAR) models, Granger causality tests, mixed-frequency Granger causality tests (see Ghysels et al., 2016; Ghysels, 2016) (see Chapter 3). Predicting models in the spirit of Bakshi et al. (2011), Allen et al. (2012), Rapach and Zhou (2013), Neely et al. (2014) and Bollerslev et al. (2015) are performed in order to study the risk measures' predictability ability both in-sample and out-of-sample. Asset pricing models are run as well (see Fama and French, 1993, 2017) (See Chapter 4). Forecast error variance decomposition in order to compute spillovers indexes (see Diebold and Yilmaz, 2009, 2012; Diebold and Yılmaz, 2014) are applied in Chapter 5.

The research questions addressed in this thesis as well as a summary of the main findings for each Chapter is illustrated in the next paragraphs. In Chapter 3 we answer the first main question: *Which are the main determinants of the decomposed implied volatility measures in the U.S.?* and some related sub-questions – *Are upside and downside implied volatility and volatility risk premium components related to macro and financial variables in different ways? Are these relationship time-varying and financial crisis driven?* and, lastly, – *Can we detect, not only unilateral feedback from volatilities to the selected variables, but also vice versa or bilateral feedback, especially when a more refined mixed-frequency*

Granger causality test is applied?

The main findings in this Chapter show that different determinants are related to the implied volatilities and volatility risk premia according to the volatility components which are considered. For instance, macroeconomic variables are found to impact more on the upside implied volatility component, VIX^{+} , especially in the case of GDP and inflation. Conversely, the financial conditions variables such as credit, liquidity, economic policy uncertainty (EPU) index and geopolitical risk (GPR) index impact more on the downside implied volatility component, VIX^{-} . A similar pattern is shown for volatility risk premia and realized volatilities. There is a shift caused by the global financial crisis in the importance of variables influencing volatility measures. From a more relevant role of macroeconomic variables, after the financial crisis, a prevalent role of the financial conditions variables is detected. By applying a mixed-frequency Granger causality test, relationships from macro variables to volatility and vice versa are detected. These are, otherwise, hidden at lower frequency. We detect and confirm implied volatility as a good predictor of economic activity, whereas the volatility risk premium a good predictor of future stock returns. Overall, different components of volatility and risk premium are found to contain a separate set of information useful for future financial and economic activity predictability.

In Chapter 4 we answer the following two main questions: *Can we extract additional information from the options markets by computing and decomposing the implied skewness measure? Are the decomposed implied skewness indexes useful for asset pricing, equity market premium predictability and macroeconomic and uncertainty predictability?* Also we are asking whether or not decomposed implied skewness indexes provide additional information not enclosed in other financial risk measures such as implied volatilities, variance risk premia and other tail risk measures. In addition, we ask whether or not the predictability of the decomposed skewness indexes extend also to individual U.S. stocks and it is useful in a Fama-French asset pricing exercise.

The main findings show how the decomposed SKEW indexes, namely, SKEW^{+} and SKEW^{-} can predict future S&P 500 equity premium better than the aggregate SKEW . Their predictive ability is limited to a short horizon due to the fact they are computed from options. The decomposed SKEW indexes are useful predictors also for the majority of the 30 largest and 30 smallest stocks in the S&P 500 and they are informative in a Fama-French asset pricing exercise, especially in the post financial crisis. The predictability of the decomposed SKEW indexes is robust also when other variables such as principal components extracted from macroeconomic variables, financial market predictors (decomposed VIX and decomposed VRP) are taken into account. Their predictability power does not appear to diminish. Overall, the predictability ability of the decomposed SKEW indexes is higher than the aggregate SKEW . Last but not least, we propose SKEW^{-} as a tail risk proxy for the U.S. financial market and we find that it is a useful measure in order to predict uncertainty indicators and the NBER recession periods at different horizons of up to one year.

In Chapter 5, we provide new insights with regards to the implied volatility connectedness in the U.S. financial sector by answering the following questions: *Can we better track systemic risk spread, increase in uncertainty and decrease in macroeconomic conditions by computing an asymmetric implied volatility connectedness index extracted from the individual stocks' options prices in the U.S. financial sector?* and – *Are the decomposed implied volatility connectedness indexes providing additional information in predicting uncertainty and macroeconomic indicators compared to the aggregate connectedness index?* and – *Are the investors' expectations on future financial sector trend extracted from calls and puts separately improving the monitoring of the banks network in response to both macro events and idiosyncratic events?*

The chapter's findings show a different behavior of the connectedness of single equity VIX indexes when extracted from calls only or puts only. The upside connectedness index extracted from the ten main financial institutions prevails, most of the time, over the downside one. However, the downside implied volatility connectedness inflates mainly during turbulent periods, reflecting "fear" among investors. The newly proposed asymmetric fear connectedness (AFC) measure for the ten main U.S. financial institutions can serve as an additional monitoring tool next to the existing systemic risk measures. Given that it is computed from options prices it is forward looking, thus it is proposed as a potential more timely monitoring tool. When we examine the predictive power of our connectedness measures with respect to macroeconomic and uncertainty indicators we find that the decomposed fear connectedness measures perform better than the aggregate measure. They are able to predict well future levels of economic activity and decrease in macroeconomic conditions. Moreover, the downside connectedness measure extracted from puts can predict forthcoming recession perception as well as increase in VIX levels. A ranking of the top ten financial institutions in the U.S. is provided. They are classified into net upside or net downside transmitters or receivers. This can provide a more refined overview in the spread of uncertainty and systemic risk perception in the U.S. financial sector. In addition, we confirm the different roles played by VIX^{+} and VIX^{-} on the net fear connectedness indexes, especially when we focus on idiosyncratic company events.

The practical applicability of this research is threefold. First, it provides a new set of more reliable, timely and directional risk monitoring tools useful for risk management purposes. These decomposed implied moment indexes improve the predictability ability with regards to future equity risk premium, macroeconomic indicators and uncertainty indicators. Second, this research contributes to the developing of a new tail risk index - SKEW^{-} - extracted from puts and being forward looking. It could be useful to monitor future investors' *perception* of tail risk given it is computed from the options market. It is found to be a useful proxy in order to track and predict future macroeconomic and economic downturn as well as of increasing uncertainty and possible recessions. Lastly, important applications for improving financial stability can be drawn from this thesis. We show that the forward looking con-

nectedness of volatility is a highly valuable tool for monitoring uncertainty and systemic risk spread in the U.S. as well as recessions and downturns. Overall, by developing forward looking and pessimistic-side related monitoring tools and risk measures could be helpful in preparing the markets and investors to a sudden increase in volatilities and risk, an increase in tail risk and spread of volatility within the considered system of study, crucial for policymakers, investors and regulators.

To recap, the remainder of the thesis is organized as follows. Chapter 2 illustrates a detailed literature review encompassing the main strands of literature in which the thesis and the following Chapters are anchored. As mentioned, Chapters 3, Chapter 4 and Chapter 5 embrace the main topics and ideas of the thesis. Each of them presents an introduction, a brief literature review, the corresponding methodology applied in order to answer the therein research questions and, lastly, the findings of the empirical analysis before concluding. Chapter 6 provides final discussions, concluding the thesis and points towards new directions in which this research might go in order to fill the gaps still open in the financial and volatility literature. The Appendix at the end of the thesis includes further analysis and material we felt should be separated from the main text.

Chapter 2

Literature Review

This chapter presents a detailed and extensive literature review on which this thesis is based. Many areas and strands of literature are encompassed in this chapter, whereas the corresponding literature for every chapter will be recalled more in brief therein. Specifically, section 2.1 includes general literature on different volatility measures, most common volatility models used in the literature and the volatility modelling issue. Subsection 2.1.1 is about realized volatility measures, subsection 2.1.2 discusses some of the recent developments in the financial volatility literature and the shift to a model-free volatility measure approach and subsection 2.1.3 illustrates the literature on volatility risk premium. Section 2.2 is the core section in this literature review describing recent avenues in the financial literature examining the different sides and components of volatility measures. Section 2.3 discusses the studies that have covered the relationship between volatility measures and macroeconomic and financial determinants. Section 2.4 presents the literature in relation to higher risk neutral moments (e.g. skewness and kurtosis). Section 2.5 encompasses the literature surrounding the topic of tail risk and some of the well known tail risk measures in the financial literature. Section 2.6 relates to the description of the role of market sentiment and its link with the stock market literature and asset pricing. Section 2.7 includes subsections regarding the volatility connectedness topic with several applications sub-categorized based on the volatility model applied, the asset of interest (e.g. equity, currencies and credit) and, lastly, a subsection with relation to the connectedness literature extension towards decomposed volatility spillovers measures.

2.1 On the Volatility Measures

The concept of volatility is something that has always generated interest and curiosity among academics and practitioners due to its importance and the information it contains. Its fundamental role in the financial market, trading and options strategy, derivatives, asset allocation, risk management and forecasting

is beyond doubt (see Shiller, 1981; Poterba and Summers, 1984; Shiller, 1989; Schwert, 1989; Day and Lewis, 1992; Bollerslev et al., 1994; Engle, 1995; Bates, 1996; Bollerslev and Mikkelsen, 1996; Andersen et al., 2003; Poon, 2005) to cite a few seminal papers on the aforementioned topics on volatility.

Financial market volatility can be defined as the measure of changes in asset prices or returns over time. The inter-temporal relation between risk and return has been examined by several seminal studies (see Fama and Schwert, 1977; French et al., 1987; Harvey, 1989; Campbell and Hentschel, 1992; Nelson, 1991; Chan et al., 1992) to name a few. There is a general agreement in the literature that investors require a larger expected return from riskier securities, however there is not such agreement about the relationship between risk and return across time (see Glosten et al., 1993).

There are several volatility measures computed in theory and practice. The methodology through which volatility is computed depends on the selected asset, context, purpose, market and available dataset. This explains the huge number of papers and studies examining financial market volatility which will be covered in this Section. In general volatility measures can be classified as realized (historical) volatility and implied volatility. The first is computed through observed assets' prices in the market over a specific time period or inferred from volatility models, while the latter is extracted from the option prices and it is a forward looking measure. The next two subsections describe in more depth these two different volatility computational approaches.

2.1.1 Realized (Historical) Volatility

Among this category we can find two approaches. One is considered a direct and immediate measure for computing volatility – the realized volatility – based on historical prices. It is considered a model-free approach and it consists of computing the volatility from the standard deviation of the actual assets' past returns over a specific time period, being this intra-daily, daily, monthly, quarterly and so on. This is why this measure is defined as realized or historical and it is backward looking. Several realized volatility measures have been developed and they can be computed at any frequency over a given sample period. Among them, we find high to low version by Parkinson (1980), the Garman-Klass formula of Garman and Klass (1980) and its improvement by Yang and Zhang (2000) taking into account the opening price jumps and zero drifts. Further exhaustive studies and literature reviews on realized volatility measures include Andersen et al. (2001), Barndorff-Nielsen (2002), Andersen et al. (2007) and McAleer and Medeiros (2008). More recently. realized volatility measures computed from assets' prices at higher-frequencies have been proposed (e.g. Liu et al., 2015)[1].

The second method can be defined as a model-based approach and includes ARCH (autoregressive conditional heteroscedasticity) or GARCH (generalized autoregressive conditional heteroscedasticity) models. ARCH/GARCH models assume that the returns' variance or volatility varies in the considered

[1] Further details on the high-frequency realized volatility measures can be found at `https://realized.oxford-man.ox.ac.uk/`

time period according to a time series model. The volatility extracted from this class of models is called conditional volatility. Unfortunately, this method is not able to reflect market future expectations and market sentiment representing a natural limit in term of forecasting ability. Thus, a vast number of models have been developed and continuously improved from these basic ARCH and GARCH family. We do not provide extensive details on these models in this thesis since it is beyond the scope of this research. The most common application of the GARCH models is their usage for forecasting (see Franses and Van Dijk, 1996). Poon and Granger (2003) provide an extensive literature review on volatility models and their application in forecasting. Bollerslev (2009) provides an extensive description of ARCH and GARCH models.

It has been assessed from the literature that volatility models may present some limitations. One may be due to the so called volatility modelling issue (see Beltratti and Morana, 2006; Engle and Rangel, 2008; Daníelsson et al., 2016; Jokivuolle and Tunaru, 2017). For instance Daníelsson et al. (2016) defined model risk as the potential risk for different models to provide inconsistent outcomes. Model risk may increase with market uncertainty. During calm periods market risk is negligible while disagreement between candidate models increases with market distress. The second limitation of volatility models is the fact that they rely on historical data and prices. Thus, in this thesis and starting from the next section, the focus will be on the forward looking implied volatility measures extracted from the options market in a model-free manner.

It has been suggested that the simple historical volatility model (Figlewski, 1997) and standard historical volatility model (Andersen and Bollerslev, 1998) generally predict future volatility more accurately than the more complicated volatility models. The model-free methodology proposed by Barndorff-Nielsen (2002) is one of the most popular to compute realized measures of volatility:

$$RVOL_t = \sqrt{\frac{252}{n}\sum_{i=1}^{n} r_{t,i}^2} \tag{2.1}$$

where $r_i = ln(\frac{P_t}{P_{t-1}})$ represents daily log returns computed from the price difference, with P_i representing the daily asset levels with $i \in \{1, \ldots, n\}$.

2.1.2 Implied Volatility and Volatility Indexes

In this Section implied volatility measures and indexes are illustrated in detail. Implied volatility measures provide forward looking information containers reflecting investors future expectations exploiting current market information enclosed in options prices. The information content of implied volatility as well as the superiority of the implied volatility measures over the historical volatility models has been examined in many studies in the financial literature, volatility forecasting literature and spanning several asset classes (see Day and Lewis, 1992; Christensen and Prabhala, 1998; Fleming, 1998; Blair

et al., 2001; Giot, 2005; Corrado and Miller, 2005; Giot and Laurent, 2007; Wayne et al., 2010; Taylor et al., 2010; Bams et al., 2017). Implied volatility is well known for being extracted from the Black and Scholes (1973) (BS) formula based on option market and prices. The advantage of this measure is that it is oriented towards the future investor expectations and sentiment (assuming market efficiency) and is more useful for trading strategies and forecasting (see Giot and Laurent, 2007). However, the disadvantage is that this measure is not model-free since it is based on the assumptions behind the BS model including and carrying some biases and limitations (see Black and Scholes, 1973; Hull, 2003).

The general trend in recent decades has been to develop and rely on model-free methodologies to eliminate these biases. The necessity of increasing the volatility measure efficiency, eliminating biases, assumptions and modelling risk had led to model-free volatility measure. This allows us to have a common measure and proxy of volatility, useful and crucial especially in negative and turbulent times. This measure is still based on the options market and, thus, based on forward looking information and prices which can be extrapolated from it. Moreover, this measure is also free from every kind of model constraints and assumptions (see Carr and Wu, 2006; Jiang and Tian, 2005)

Nowadays, the most important financial market volatility indicator is the VIX index. It was introduced by the CBOE in 1993, in response to the 1987' Black Monday, as a barometer of equity market risk, well-known also as *fear gauge* and it is computed in a model-free manner from a bunch of S&P 500 options prices over a broad range of strike prices and by interpolating the two closest maturities in order to reflect a maturity of 30-days (see Whaley, 2000). It is not only a measure of investor sentiment, but its importance for volatility forecasting, risk management, hedging strategies, measuring uncertainty and financial stability is commonly recognized among academics and practitioners.

In the recent year, using this kind of approach for studying the implied volatility characteristics and trends has become more common also in the financial literature. VIX is not only a measure of perceived future volatility in the U.S., but also worldwide. Indeed, even though many other countries started to follow the CBOE methodology to compute their own country/region volatility index[2], the CBOE VIX it still the most successful. The CBOE VIX is the most studied and used not only for being the leading proponent of this kind of volatility benchmark, but also for the negotiations' volume and amount it represents. The CBOE working paper illustrate the VIX computational methodology in details (see CBOE, 2009). The following formula is used to calculate the implied variance:

$$\sigma^2_{VIX_j} = \frac{2}{T}\sum_{i=1}^{n}\frac{\Delta K_i}{K_i^2}e^{rT}Q_t(K_i) - \frac{1}{T}\left[\frac{F_t}{K_0} - 1\right]^2 \tag{2.2}$$

where $i = 1, \ldots, n$ marks the options strike price available on that specific date, T is the expiration date, j is either (1) or (2), representing the near or far term, respectively, and F_t is the forward price of

[2]The same methodology, after the success of CBOE VIX index, is used in order to compute other volatility indexes around the world: NASDAQ 100 volatility index (VXN) and DJIA volatility index (VXD), but also in Europe as, for instance, VSTOXX for the EUREX Group, FTSE 100 IVI for the UK, among the others.

S&P 500 calculated from the Put-Call parity as $F_t = e^{rT}[c(K,T) - p(K,T)] + K$. K_0 (Reference Price) is the first exercise price less or equal to the forward level F_t ($K_0 \leq F_t$) and K_i is the strike price of *i* - OTM option, which would be a call option if $K_i > K_0$, a put option if $K_i < K_0$ and the average between call and put options if $K_i = K_0$. r is the risk free rate with expiration T, and $\Delta(K_i)$ is the sum divided by two of the two nearest strike prices to the exercise price K_0. Equation (3.1) is based on the variance swap approximation as shown by equation (3.2):

$$\sum_{i=1}^{n} \frac{\Delta K_i}{K_i^2} e^{rT} Q_t(K_i) \tag{2.3}$$

where $Q_t(K_i)$ is the price of a European call or put with a strike price respectively above or below K_0, the first strike price below F_0. In the case $K_i = K_0$, $Q_t(K_i)$ is equal to the average between an ATM call and an ATM put, relative to that strike price. To calculate the expected variance, an adjustment term is added to the expression in (3.2). This adjustment is required to convert in the money (ITM) calls to out of the money (OTM) puts: $\frac{1}{T}\left[\frac{F_0}{K_0} - 1\right]^2$. The VIX index is calculated by interpolating the near term variance and the far term variance, $\sigma^2_{VIX_1}(T_1)$ and $\sigma^2_{VIX_2}(T_2)$. These are the closest expirations to a 30 days average target in which monthly or weekly S&P 500 options are traded. The aim of the VIX calculation is to better track the 30-days implied volatility in the equity market, an aim easily achieved with the introduction of Weekly S&P 500 options since 2014. Weekly S&P 500 options selected must have an expiration of ≥ 23 days, ≤ 37 days. When monthly S&P 500 options are selected, the first 3-months expirations are considered. VIX is calculated through the interpolation of the first two months expirations, 1M and 2M. Where the first month is not available or less than 3 days are left for its expiration, the selected month is rolled onto the next expiration, taking the 3M, since if shorter the impact of volatility and volume can misdirect the computation. The VIX index always reflects an interpolation of two points along the S&P 500 volatility term structure. The VIX index is calculated as follows through equation (3.1):

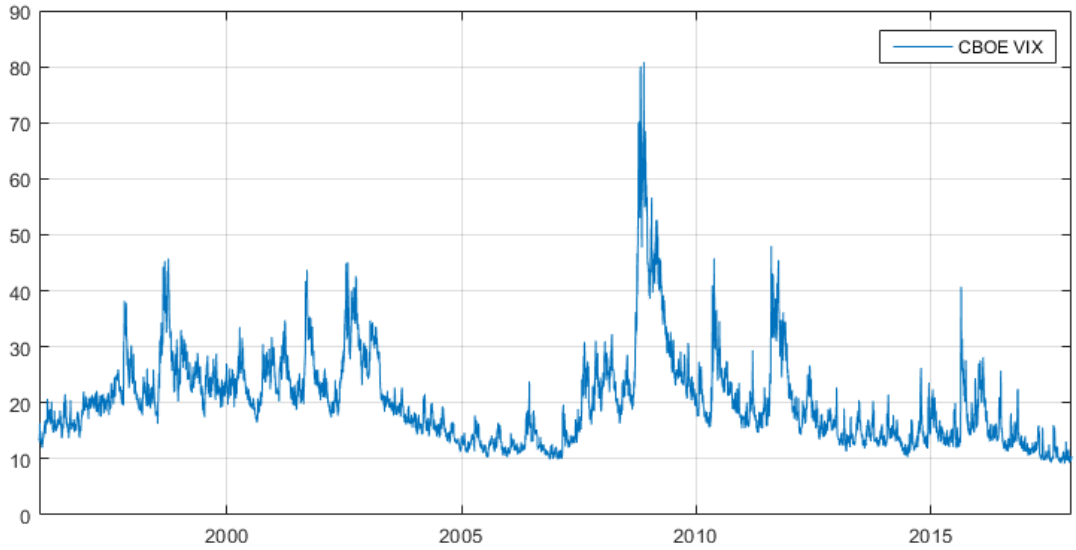
$$VIX_t = 100\sqrt{\frac{365}{30}\left[T_1\sigma^2_{VIX_1}\frac{N_2 - 30}{N_2 - N_1} + T_2\sigma^2_{VIX_2}\frac{30 - N_1}{N_2 - N_1}\right]} \tag{2.4}$$

The main motivation for the success of VIX appears to be, especially from the academic point of view, the way in which it is calculated. Indeed, it is a model-free computation (see Britten-Jones and Neuberger, 2000) that gives more flexibility and independence from the model approach so beloved to the financial literature, and it is well-known for being more informative in comparison to other historical or model-based approaches. Due to its innovation and success, extensive literature surrounding it has been developed along the years, leading to a combined interest from academia and industry merged together.

Figure 2.1 shows the CBOE VIX trend during the last 20 years. Noticeable is the sharp spike in

2008 corresponding to the global financial crisis. Other two spikes occurred in October 1997 and in October 1998. Evidence of volatility mean-reversion is found from the plot since in the aftermath of each spike, the VIX index returned to its average and to more normal levels. Two other spikes are found corresponding to the two stages of the Eurozone sovereign debt crisis in 2010 and 2012. More recently, the VIX index appeared to react to the Chinese Yuan collapse and to the U.K. Brexit vote in summer 2015 and summer 2016, respectively.

Figure 2.1: **CBOE VIX**



Notes: This plot illustrates the CBOE VIX index from 04-01-1996 to 29-12-2017, at daily frequency.

The clear negative relationship between VIX and S&P 500 has documented the literature (e.g. Whaley, 2009; Vodenska and Chambers, 2013). Even though the closing levels of the VIX index and S&P 500 index appear, most of the time, to spike in opposite directions, there are also times - being rare - when they move together. A run-up in stock prices may be accompanied by a run-up in volatility. This occurred for instance in January 1999 (i.e., investors were becoming more nervous) while the level of the S&P 500 index was rising. The same pattern appears in June and July of 1997, and December 1999 (see Whaley, 2009). Clearly, investors can become nervous even during market advances. This pattern will be further discussed in Chapter 3.

The seminal paper of Fleming et al. (1995) asserted that VIX represents a market-consensus estimate of future stock market volatility which offers to academics and practitioners an important new source of information. Another important study about the success of the VIX index is the survey paper from Gonzalez-Perez (2015). The study surveys all the research about VIX index and model-free up to that point, their applications, limitations and further extensions. It also summarizes the main motivation

for the success of the VIX index which appears to be, especially from the academic point of view, the way in which it is calculated. Indeed, it is a model-free computation that, provided that an exhaustive range of options prices is needed, gives more flexibility and independence from the model approach commonly used in the financial literature. The main results that have arisen from this survey are the three different categories in which the VIX literature can spread out:

- VIX as a market risk measure and benchmark.
- VIX as a financial product for hedging investors against market drops or volatility risk.
- VIX as an additional element and source of information in order to better estimate spot pricing path, forecasting volatility and volatility risk premium and jumps.

On the first point, several studies have been focused on the reliability of this index starting from the way in which it is computed. The VIX index, well known as the *fear gauge* represents the next 30-days future projection of the S&P 500 options prices implying that, when the investors feel market danger, their options demand and supply request change; usually turbulent and volatile periods mean enlargement of protective S&P 500 puts trading volume and price, increasing the index level (see Whaley, 2000). Bollen and Whaley (2004) showed that the demand to buy out-of-the-money and at-the-money S&P 500 puts is a key driver in the movement in S&P 500 implied volatility measures such as VIX (see Section 2.2). VIX is also found to be important because it can affect banks and hedge funds' value-at-risk (VaR). Low volatility leads to low VaR, and high volatility leads to high VaR. Brownlees and Gallo (2009) provides a detailed literature on the volatility measures comparison in order to measure VaR.

Regarding the second category, since its introduction the necessity of VIX trading for both speculative and hedging purpose has always been urgent and in force. Due to this, the CBOE introduced VIX Futures and VIX Options in 2004 and 2006, respectively. While before the benefits of using VIX in equity portfolios were only theoretical (see Daigler and Rossi, 2006), ever since its introduction concrete strategies using VIX derivatives can be implemented. The CBOE volatility index becomes, then, not only a proxy for the volatility level expected in the market but, also a useful asset that can be exploited in order to hedge equity portfolios against market drops and, furthermore, a source of additional information regarding stock expected future returns, volatility paths or jumps and market sentiment. Financial literature has been growing surrounding these new kinds of derivatives, especially focusing on the hedging benefits they can add in equity portfolios when financial crisis and market drops occur (see Rhoads, 2011; Szado, 2009; Stanescu and Tunaru, 2013).

Szado (2009) illustrated how having a position on VIX derivatives during the financial crisis could have helped investors reduce their losses considerably. Best performance during those specific troubled months would have been attributed to VIX options, due to their higher financial leverage compared

to VIX Futures. Following the same path, Stanescu and Tunaru (2013) described how the usage of VIX , but also VSTOXX Futures can be helpful for protecting investors' equity position against equity market drops, in a longer time frame extending and updating Szado (2009)'s time-frame, limited only to the 2008's crisis. Dawson and Staikouras (2009) studied how the trading of the newly set of volatility derivatives has impacted the volatility of the underlying S&P 500 index finding a lower cash market and cash market index volatility as well as a reduced impact of shocks to volatility.

The milestone behind the hedging properties of VIX derivatives is, clearly, due to the strong and negative relationship between volatility and the equity market (see Whaley, 2009; Vodenska and Chambers, 2013). This, indeed, holds on the well known negative relationship between volatility and current and past stock returns. In other words, volatility tends to be higher when equity prices drop than when equity prices increase. The traditional interpretation of this asymmetric relationship is the so-called leverage effect. According to this explanation, a fall in equity prices would generally imply a rise in firms' leverage, and in turn raise the riskiness of a given stock. An alternative explanation relates the negative correlation to changes in attitudes towards risk: since low volatility is associated with increased willingness to take on risk, a low-volatility environment is likely to be accompanied by rising asset valuations. While before the VIX derivatives introduction this negative correlation could have been exploited only with the use of instruments such as volatility swaps (see Demeterfi et al., 1999), now VIX derivatives give investors and portfolio managers an extra card to play.

A lot of studies have focused on the phenomenon of the negative asymmetric return volatility relationship, trying to find an explanation and a justification for it. Every innovation and positive change in the volatility market is followed by a negative change in returns. Black (1976) asserted that the main theory for explaining this asymmetric relation is due to the leverage effect: negative shocks in the market impact on the firms' leverage ratio, increasing it and, consequently, its risk and its volatility. Since his seminal work other theories have been developed. For instance, another well-known hypothesis behind the return-volatility relation is the volatility feedback theory (see Campbell and Hentschel, 1992): the negative return-volatility relation, especially in the short term, is explained by traders' expectation, news in the market and dividends. Hibbert et al. (2008) proposed a behavioral explanation for the asymmetry between return and volatility. They provide a study on the short-term relationship between market volatility and market returns, considering S&P 500 , Nasdaq and their respective volatility indexes, VIX and VXN. One interesting result that they found is that, by performing quantile analysis there is strong evidence of an asymmetric relation related to extreme returns and volatility changes. This stresses the point that tail events and implied volatility skewness are fundamental determinants of the return-volatility relation.

Another important finding is the one of Dennis et al. (2006): they study the implied volatility and return relationship considering both systematic and idiosyncratic volatility innovations. The asymmet-

ric volatility behavior is more driven by the systematic innovations in comparison with the idiosyncratic ones. The difference between relations in return -volatility at a single firm and index level has already been developed in the literature (Bakshi et al., 2003); the results they have obtained are the same. Moreover, they distinguish a strong form of asymmetric volatility when this relationship is driven by a strong negative correlation, negative or positive return shocks imply increase or decrease in implied volatility and a weak form where the strong negative correlation occurs only after having controlled for the absolute return shock and volatility innovation.

On the third point, several studies have used the VIX index as a proxy for implied volatility and, also, in order to better forecast future volatility (see Day and Lewis, 1992; Taylor et al., 2010; Wayne et al., 2010).

2.1.3 Volatility Risk Premium

By comparing measures of implied and realized volatility, measures of volatility risk premium (VRP) can be inferred. This premium can be thought of as the compensation demanded by investors for bearing risk related to sharp changes in market volatility. In the most recent years, VIX has been commonly used as a proxy for implied volatility in order to compute the risk premium. Thus, researchers have often compared implied volatility (e.g. VIX) with realised volatility over the same horizon. In the financial literature two definitions of volatility risk premium can be found.

First of all, several studies talk about variance risk premium which is the squared measure of volatility risk premium computed by comparing implied variance and realized variance. The first common definition of risk premium is as in Carr and Wu (2008), namely, as the difference between physical (realized) and the risk neutral expectation of return variation extracted from options (implied):

$$VRP_t = RVOL_t - VIX_t \tag{2.5}$$

By applying this, variance risk premium is the difference between realized variance and implied variance. Volatility risk premium is computed as the difference between realized volatility and implied volatility. The same definition is applied in the most recent study by Kilic and Shaliastovich (2018). Other studies have computed risk premia as a short position in a variance swap, namely, as the difference between risk neutral and physical expectations of returns (e.g. Bollerslev et al., 2009; Bekaert and Hoerova, 2014; Feunou et al., 2017). According to Bekaert et al. (2013) the difference between implied and projected realized volatility can be interpreted as a proxy for investors' attitude towards risk.

When volatility spikes during stress episodes, investors' attitude towards risk usually follows. Indeed, investors are less willing to hold positions in risky assets or to provide insurance against asset price changes. Papers, such as, Bollerslev et al. (2009), Bekaert and Hoerova (2014) and Feunou et al.

(2017) found a measure of variance or volatility risk premium which is, most of the time, positive. Implied variance of volatility measures are, overall, higher than the corresponding time-period realized variance or volatility measures. Opposite results are found in studies by Carr and Wu (2008) or Kilic and Shaliastovich (2018) in which the risk premium measures are computed as the difference between physical and risk neutral measures, thus obtaining risk premia, most of the time negative. Some of the aforementioned studies have also investigated the properties of risk premia to predict future stock market returns (see Bollerslev et al., 2009; Kelly and Jiang, 2014; Feunou et al., 2017; Kilic and Shaliastovich, 2018). According to Bollerslev et al. (2009), the variance risk premium has predictive powers for short-term stock returns, from three to six months, a finding also confirmed by Bekaert and Hoerova (2014). More details on volatility risk premia will be provided in Chapter 3 in which the determinants of risk premium measures will be investigated.

2.2 Volatility Measures Decomposition

This section illustrates a recent strand of literature with relation to the possibility of decomposing volatility measures in order to improve the information content they carry both in asset pricing terms, but also in financial stability terms. This represents the main motivation and core area of research to which this thesis is anchored.

The importance of downside risk in the financial literature has been highlighted by Ang et al. (2006). A growing area in the financial literature has begun to examine volatility in its different shapes and components. For instance Beltratti and Morana (2006) decomposed volatility into one part associated with structural break and one associated with long memory dynamics. Engle et al. (2013) decomposed volatility into short and secular run components and Bekaert and Hoerova (2014) decomposed VIX into a proxy for risk aversion and a proxy for uncertainty, suggesting that both components have a different relationship to macroeconomics. Several studies have continued this line of research considering the decomposition of volatility measures into upside and downside components.

The seminal paper, in this sense, is Barndorff-Nielsen et al. (2010) who decomposed realized volatility into good and bad realized volatilities. The decomposition into good and bad components for the realized volatility is achieved by taking only sums over positive returns or sums over negative returns, indicated as RVOL^{+} and RVOL^{-} , respectively:

$$RVOL_t^{+} = \sqrt{\frac{252}{n}\sum_{i=1}^{n} r_{t,i}^2 1_{(r_{t,i}>0)}} \quad and \quad RVOL_t^{-} = \sqrt{\frac{252}{n}\sum_{i=1}^{n} r_{t,i}^2 1_{(r_{t,i}\leq 0)}}, \tag{2.6}$$

where $r_i = ln(\frac{P_t}{P_{t-1}})$ represents daily log returns computed from the price difference, with P_i representing the daily asset levels with $i \in \{1, \ldots, n\}$. The upside semi-realized volatility considers only

positive returns while the downside semi-realized volatility only negative returns. The good uncertainty is associated with potential profits, representing what investors like, different from the bad uncertainty associated with potential losses, representing what investors dislike (see Segal et al., 2015).

After this seminal study, many other papers followed. Segal et al. (2015) affirmed that the bad volatility comprehends all the news can spread the market tension, decrease in the options' underlying value, decline in market productivity, unemployment, disinvestments and market depression. Conversely, good volatility regards news impacting underlying assets in a positive way, future growth, investments and increase in production and consumption.

Several studies have begun to apply this decomposition to implied volatility measures. DeLisle et al. (2014) introduced the possibility of VIX de-construction through a regression model. The regression is built testing the percentage of daily VIX change on some different regressors, as the nature of the options, call or put, the moneyness of the options, the expiration's date, front month and next month, and also the interaction between them. The result is that the total amount of VIX changes are driven more by the downside volatility component in comparison to the upside volatility part. This is due to the fact that because the S&P 500 puts are more expensive than the S&P 500 calls there is more demand for puts especially during negative times (see Bondarenko, 2014). The options trading is well known to be closely linked to investors' sentiment (e.g. Buraschi and Jiltsov, 2006; Mixon, 2009).

The same evidence is highlighted by Fu et al. (2016): they decomposed the VIX index into two parts affirming that information from OTM put options are more useful in order to predict future returns; indeed, they capture information regarding the possibilities of downward movements in the equity markets with the respective upward movements of volatility. The opposite is true for OTM call options. In term of hedging strategies this means that investors in order to earn higher premiums should rely on put options portfolios the most.

We anchor this thesis to this growing strand of research by decomposing the implied volatility index into its upside and downside components. In implied volatility terms, we recognize that investors are more willing to buy equity index put options for hedging purposes during negative times and crises (see Bakshi et al., 2003; Bollen and Whaley, 2004; Bondarenko, 2014). We have applied the same model-free decomposition separating information coming from S&P 500 puts and S&P 500 calls. We define the downside volatility component, extracted from S&P 500 puts only, as VIX^{-} , whereas the upside volatility component, extracted from S&P 500 calls only, as VIX^{+} .

In order to compute the upside and downside components of the VIX , an adjustment is made to equation (3.1), applying filters on the K_i term. For VIX^{+} only S&P 500 call options are considered when $K_i \geq K_0$, and for VIX^{-} only put options are considered when $K_i \leq K_0$. We define the first options sub-sample with strike prices above the reference price as K_i^{+} and the sub-sample below the reference price as K_i^{-}. Substituting K_i in equation (3.1) with both K_i^{+} and K_i^{-} provides the two

respective near and far term upside and downside variances:

$$\sigma^2_{VIX_t^j} = \frac{2}{T}\sum_{i=1}^{n}\frac{\Delta K_i^j}{(K_i^j)^2}e^{rT}Q_t(K_i^j) - \frac{1}{T}\left[\frac{F_t}{K_0} - 1\right]^2 \quad with \quad j = + \quad or \quad - . \tag{2.7}$$

Resultantly, the two implied volatility components VIX^+ and VIX^- are:

$$VIX_t^+ = 100\sqrt{\frac{365}{30}\left[T_1\sigma^2_{VIX_1^+}\frac{N_2 - 30}{N_2 - N_1} + T_2\sigma^2_{VIX_2^+}\frac{30 - N_1}{N_2 - N_1}\right]} \tag{2.8}$$

$$VIX_t^- = 100\sqrt{\frac{365}{30}\left[T_1\sigma^2_{VIX_1^-}\frac{N_2 - 30}{N_2 - N_1} + T_2\sigma^2_{VIX_2^-}\frac{30 - N_1}{N_2 - N_1}\right]} \tag{2.9}$$

Extracting volatility only from call options provides us with a proxy for upside implied volatility, whereas extracting volatility only from put options provides a proxy for the downside implied measure. While the downside VIX component is the one reflecting the real market fear from investors want to hedge their portfolios, the upside component is the one can be considered as a volatility premium which investors have to pay in order to enter in long VIX strategies but, basically, reflecting the part of volatility is not dangerous for the long equity investors.

By considering model-free calculations, important are the study of Feunou et al. (2017) and Kilic and Shaliastovich (2018), which in parallel to us, further extend this decomposition as to include volatility risk premium. By merging the two volatility measures, namely, realized and implied, these studies decomposed volatility risk premium measures in their upside and downside components.

By following the definition of variance risk premium as in Carr and Wu (2008), namely, as the difference between physical and risk neutral expectations of return variation, Kilic and Shaliastovich (2018) found that the downside VRP is the main component of the variance risk premium. It is found to be significant with a positive relationship with the equity premium, and showing superior ability in explaining future excess returns compared to the aggregate and upside VRP . We compute the volatility risk premium following their methodology by taking the difference between the upside and downside physical measure of volatility (realized) and the corresponding upside and downside risk neutral expectation of return variation extracted from options (implied):

$$VRP_t^+ = RVOL_t^+ - VIX_t^+ \tag{2.10}$$

$$VRP_t^- = RVOL_t^- - VIX_t^- \tag{2.11}$$

We find a measure of risk premium which is, most of the time, negative due to the way it is calcu-

lated. Other papers, such as, Bollerslev et al. (2009), Bekaert and Hoerova (2014) and Feunou et al. (2017) defined the variance risk premium as the difference between the risk neutral and physical expectations of return variation, finding a measure which is, most of the time, positive.

This volatility series decomposition methodology will be applied in Chapter 3 for the U.S. stock market index. The methodology will be illustrated more in details therein. For the first time in the literature we link the decomposed volatility measures together with macroeconomic and financial variables with the aim to find their main drivers. An extensive literature review on this topic and research gap is illustrated in the next Section.

Motivated by the same intuition, this thesis will bring the implied moments decomposition a step beyond by looking at the behaviour and characteristics of decomposed implied skewness (see Chapter 4), and lastly, for the first time in the literature, this methodology will be applied to U.S. individual stocks in the financial sector and for implied volatility spillovers (see Chapter 5). Extensive literature reviews about these topics are provided from Section 2.4 to 2.7 in this Chapter.

2.3 On the Stock Market and Volatility Determinants

This section encompasses the research that has been conducted on stock market returns and, especially, stock market volatility determinants. Various studies have examined the link between stock market returns and macroeconomic variables (see Miller et al., 1976; Fama and Schwert, 1977; Firth, 1979; Chen et al., 1986; Poon and Taylor, 1991; Humpe and Macmillan, 2009) to name but a few. Chen et al. (1986) recognized that macro variables had not been considered as a possible explanation of stock returns and, found evidence of the importance of such variables in asset pricing. Chen et al. (1986) investigated the reaction of stock market returns to economic state variables' innovation that were candidate to carry a reward for exposing investors to their risk. According to them, the co-movements of asset prices suggest the presence of underlying exogenous influences, but we have not yet determined which economic variables, if any, are responsible.

Poon and Taylor (1991) replicated the study of Chen et al. (1986) to the U.K. stock market. They affirmed that the results and the relation between macroeconomics and stock market are slightly different from the ones found for U.S. market, especially in terms of risk premium, term structure and inflation. Several countries and financial markets have been taken into account in this literature. Kumar (2011) applied a causal relationship between macroeconomic variables and stock prices to the India NSE Index, Nifty. Humpe and Macmillan (2009) detected a long-term positive relation between industrial production and stock market returns and a negative one between stock prices and both interest rate and consumer price index for U.S. Similar results are found for Japan in the same study. Masuduzzaman (2012) investigated the long run relation between macroeconomic factors and stock returns for

Table 2.1: **Relationships from the Literature between Stock Market and Macroeconomics**

Study	Country	Selected Macroeconomic Variables			
		IP	INF	UR	TS
Lintner (1973)	U.S.		(-)*		
Miller et al. (1976)	U.S.		(-)*		
Fama and Schwert (1977)	U.S.		(-)*		
Firth (1979)	U.K.		(+)*		
Chen et al. (1986)	U.S.	(+)*	(-)		(-)
Poon and Taylor (1991)	U.K.	(+)*	(-)*		(-)*
Humpe and Macmillan (2009)	U.S.	(+)*	(-)*		(-)*

Notes: This table sums up, in chronological order, all the relations between stock market returns and selected macroeconomic variables have been found in previous studies. The first column represents the authors and the year of the paper, the second column the country of application for the study. The other columns are the macro-variables selected for comparison. The table shows which was the sign of the relation between that specific macro variable and the stock market returns. When a variable is market with * is meaning that it was found significant in that study, the opposite when is not marked.

Germany and U.K.

Many studies have also investigated the movements in stock market volatility and their causes. Black and Scholes (1973) asserted that changes in volatility are partly explained by the financial leverage effect. Shiller (1981) argued that the level of stock market volatility is too high to be explained only by the variability of dividends. Officer (1973) and Schwert (1987) were among the seminal studies which started to relate changes in volatility with macroeconomic variables. Most of the time an end-of-the-month monthly volatility from daily log-returns is considered when studied in relation to macroeconomic variables (see Schwert, 1989).

Following these two seminal studies, macroeconomic variables began to be looked upon as possible determinants of volatility in many other empirical studies (see Cutler et al., 1989; Kandel and Stambaugh, 1990; Whitelaw, 1994; Lettau et al., 2007; Diebold and Yilmaz, 2008; Engle and Rangel, 2008)[3]. Schwert (1989) examined the relationship between macroeconomics and stock market volatility and found no significant evidence in the U.S. stock market. Cutler et al. (1989) argued that macroeconomics explains only a fraction of volatility movements. A similar conclusion was reached by Morelli (2002) for the U.K. financial market. These studies opened up a new strand of subsequent research on the relationship between macroeconomic and stock market volatility. Focusing on the role of macroeconomic variables, Engle and Rangel (2008) found inflation and industrial production impacting on the stock market volatility, while Diebold and Yilmaz (2008) provided evidence of a relationship between stock market volatility and gross domestic product (GDP). However, the overall conclusion reached on the relationship between stock market volatility and macroeconomic activity is by no means clear cut.

Table 2.1 shows a brief and concise survey about the relation between macroeconomics and stock market returns for some of the most relevant studies. Table 2.2 depicts a brief survey about some of

[3]Among the others, Tanha et al. (2014) analyzed the relationship between macroeconomics announcements and implied market volatility for the Australian stock index market. Khandaker and Islam (2015) investigated the impact of several macro independent variables on the stock market volatility for both developed and emerging countries. Errunza and Hogan (1998) for many countries in Europe.

the most relevant studies on the relation between macroeconomics and volatility measures. Having in mind the negative relationship between stock market returns and volatility can be useful to compare the results in Table 2.1 and Table 2.2. The negative correlation between stock market returns and stock market volatility is due to leverage effect (see Daigler and Rossi, 2006; Whaley, 2009; Vodenska and Chambers, 2013). Lintner (1973), Miller et al. (1976) and Fama and Schwert (1977) found evidence of a negative relation between stock market returns and inflation due to the positive relation between stock market and real variables, determinant of the equity prices. According to Fama (1981), the negative relation between inflation and real activity causes the negative relation between stock returns and inflation. Inflation has, instead, a positive link with volatility (see Schwert, 1989).

Table 2.2: **Relationships from the Literature between Volatility and Macroeconomics**

Study	Country	Model	Selected Macroeconomic Variables					
			GDP	IP	INF	UR	TS	ER
Schwert (1989)	U.S.	12th Autoregression		(+)	(+)			
Liljeblom and Stenius (1997)**	Finland	12th Autoregression GARCH(p,q)		(-) (-)	(+)* (+)*			
Errunza and Hogan (1998)	U.S. Europe**	GARCH(p,q) GARCH(p,q)		(+) (+)	(+) (-)			
Morelli (2002)	UK	GARCH(1,1), ARCH(1)		(-)	(+)			(-)
Engle and Rangel (2008)**	48 Countries	Spline-GARCH	(+)*		(+)*		(+)*	(-)
Diebold and Yilmaz (2008)**	40 Countries	Autoregression	(+)*		(+)			
Engle et al. (2013)**	50 Countries	GARCH-MIDAS		(-)*	(+)*			
Khandaker and Islam (2015)**	17 Countries	Historical Vol.	(-)		(-)	(+)		

Notes: This table sums up, in a chronological order, all the relations between volatility market and some macroeconomic variables found in previous studies. The first column lists the authors and the year of the paper, the second column the country considered in the study. The other columns are the macro-variables selected in the studies. Mostly used in this branch of literature are inflation, GDP, term structure, exchange rates, unemployment rate and industrial production. The table shows the sign of the relation between macro variables and volatility. (*) means that the variable was found significant in that study. When the study is looking to several different countries or sub-periods (indicated by **) the sign of the variable's coefficient reported in here represents the sign of the relation that has been found for the majority of countries or for the total period.

Schwert (1989) found very little and not significant results about the relation between stock market volatility and macroeconomics. With regards to other countries outside the U.S.; Liljeblom and Stenius (1997) for Finland and Morelli (2002) for U.K. concluded that macroeconomic volatility, for the variables they selected, failed to clearly explain the stock market volatility. While macroeconomics has emerged to play a quite established role in influencing stock market returns and business cycle, the same cannot be recorded, instead, for volatility market[4]. This trend is confirmed in Table 2.2.

Common finding in the literature, on the other hand, is the high dependence of stock market volatility to the business cycle or economic stage (see Koren and Tenreyro, 2007; Diebold and Yilmaz, 2008; Bloom, 2014). Close and positive relation has also been found between volatility and developing or emerging countries (see Engle and Rangel, 2008). Most of the time emerging countries exhibit higher financial market volatility compared to the developed ones. Stock market volatility and risk aversion increase with recession (see Officer, 1973; Schwert, 1989; Bloom, 2014).

The use of volatility measures such as ARCH and GARCH or implied market volatility through Black-Scholes-Merton formula seems to be the common denominator in these studies. Many of them

[4] An alternative approach examines the effects of news or announcements on returns. See Cutler et al. (1989), Ederington and Lee (1996) and Andersen et al. (2007) for some relevant studies.

have been analyzing the macro-volatility link, most of the time, trying to find the best model to measure volatility. Engle and Rangel (2008) studied the macro-volatility link using a Spline-GARCH model that is able to smooth the high data frequency of volatility to be better compared and linked with the low frequency macroeconomic data. In Spline-GARCH model (see Engle and Rangel, 2008) relaxed the assumption of low frequency volatility mean reversion. The advantage is that the non-parametric approach allows the data to provide the functional determinants of low frequency volatility. For a comparison between different volatility models having as inputs economics fundamentals, Engle et al. (2013) provided an exhaustive survey. They are using a mixed data sample approach (GARCH-MIDAS) for studying the same macro-volatility link.

Thus, linking this Section with Section 2.1.1, we briefly discuss a common problem in the literature when it comes to understanding the main drivers of volatility. The issue is the so called volatility modelling and it is well recognized in the model risk literature (see Engle and Rangel, 2008; Daníelsson et al., 2016; Jokivuolle and Tunaru, 2017). When we are interested in analyzing the main determinants of volatility and the latter is computed by financial models, the relationship appears to be, most of the time, unclear and not unique. The identification of the determinants of volatility is highly sensitive to the method used to measure volatility, often referred to as the volatility modelling problem.

The number of models that have been developed to predict volatility based on time series information is astronomical, but the models that incorporate economic variables are hard to find. (Engle and Rangel, 2008).

The econometric model choice, variables and market period selection increases the uncertainty and subjectivity of volatility determinant analysis (see Beltratti and Morana, 2006). In many of the studies highlighted in Table 2.2, macro-variables show no or low significance in explaining equity volatility. We could advocate two possible explanations. Firstly, model construction and choices behind the conditional variance computation might lead to approximations and errors, thereby making the overall relationship uncertain, and secondly, it may be that macroeconomics is not the correct place to look when attempting to explain the key determinants of volatility (Cutler et al., 1989). Beltratti and Morana (2006) affirmed that the picture around the stock return volatility' causes is cloudy. Financial market periods shifting between tranquil and turbulent periods and presence of structural breaks make the relation between volatility and macroeconomic variables even trickier.

In this thesis and especially in Chapter 3 we try to overcome this volatility modelling problem by working only with model-free volatility measures extracted by asset prices as well as from options. This thesis aims to shed new light on the identification of the potential determinants of asymmetric volatility and risk premium, and to contribute to different strands of literature by taking into account a new set of variables, which include both macroeconomic and financial variables (see Chapter 3).

2.4 Higher Risk Neutral Moments

In addition to volatility measures, we extend in this section the discussion about other implied moments, namely, skewness and kurtosis. In the last decades, an extensive amount of literature has been studying the importance of higher risk neutral moments, especially skewness, in order to better understand and predict future stock returns, options pricing, portfolio selections and hedging strategies implementation.

The seminal paper, of pivotal importance in this thesis and common to the majority of the studies on higher moments is Bakshi et al. (2003). They show how to link and extract information about volatility, skewness and kurtosis from the options market in a model-free manner. Like the physical density, the risk-neutral density has first, second, third, and fourth moments, respectively, mean, variance, skewness, and kurtosis. All densities can be extracted from options for a given horizon. To estimate the higher moments of the (risk-neutral) density function they rely on the results of Bakshi and Madan (2000) showing that any payoff to a security can be constructed and priced using a set of option prices with different strike prices on that security. More details on the Bakshi et al. (2003) (BKM) methodology will be provided in Chapter 4.

By using the same model-free methodology, Mitton and Vorkink (2007) linked the higher risk neutral moments literature to the asset prices and portfolio management areas. Hansis et al. (2010) stressed the fact that higher risk neutral moments of stocks return are important for investors, especially when calculated from options. In fact, options carry forward looking information, the most recent information about return distributions that are available in the market. Bali et al. (2019) showed that ex-ante measures of volatility, skewness, and kurtosis implied from stock option prices are positively related to the cross section of ex-ante expected stock returns.

Conrad et al. (2013) investigated the relations between risk-neutral higher moments and subsequent returns by focusing on the role of co-moments with the market portfolio. They measured co-moments using the approaches of Bakshi et al. (2003) and Harvey and Siddique (2000) and they subsequently decomposed total moments into co-moments, such as co-skewness, and idiosyncratic moments. For instance, Harvey and Siddique (2000) proposed an asset pricing model where skewness is priced. They included skewness measures in the asset pricing framework: if a systematic skew risk affects the asset returns, it should be incorporated as a compensation of accepting this risk in the CAPM. Basically, everything being equal, investors prefer portfolios that are more right skewed; assets more left skewed are less desirable and more risky; they, indeed, command higher expected return. On the other hand, assets making portfolio's return more right skewed command lower expected return. In order to find a measure of the relationship among the assets in the portfolio with each other and with the portfolio itself they introduced a measure of co-skewness. It measures how much two assets change together in response to extreme events. Co-skewness is related to skewness as covariance is related to variance. They define co-skewness as the component of an asset's skewness related to the market portfolio's

skewness. Adding an asset with negative co-skewness to a portfolio makes the resultant portfolio more negatively skewed.

A vast strand of literature started to consider implied model-free higher risk neutral moments since they can increase the accuracy of their estimation compared to the historical higher moments in reflecting future asset prices (see Han, 2008; Hansis et al., 2010; Rehman and Vilkov, 2012). The study of Liu (2016) is an exhaustive survey paper in this instance since it clearly explained two different ways in which skewness is calculated:

- Raw Approach: Applied by Dennis and Mayhew (2002), Conrad et al. (2013) and Bali and Murray (2013). They basically used the data as they are, without filtering or modification. The aim of the first work was to better understand the relationship between skew and other various factors in the stock prices, such as leverage, β, size, trading volume and put-call volume ratio. They found that skew is more negative in periods of high market volatility. Size and trading volume are significant factors in explaining skew changes, the opposite is true for leverage and put-call ratio. They also confirmed that skew for index options tends to be more negative than skew for individual stock options.

- Smooth Approach: On the other hand two different kinds of smooth approaches are highlighted: data interpolation, where an interpolation between OTM puts with lowest strike and OTM calls with highest strike is applied. This method is followed, among others, by Hansis et al. (2010). They used interpolation because they underlined the limit in Bakshi et al. (2003) about the continuum of available strike prices, limit range of option prices. The other technique is the data extrapolation between the highest and lowest strike prices.

Other methodology that could be applied in order to calculate the skew, different from BKM, is the non-parametric approach used for instance by Xing et al. (2010) and Mixon (2011). Xing et al. (2010) affirmed that option implied volatility smirk has a predictive power for future equity returns. In this thesis, we apply the first approach, following Dennis and Mayhew (2002). Once that the higher risk neutral moments are computed, precious information can be extracted from them in term of asset pricing, portfolio theory and predictability.

Interesting is also the relation between skewness and diversification. Related to the relationship between individual firm skewness and aggregate level skewness, Albuquerque (2012) provided an unified theory on the firm level positive skewness due to firm announcement events. He defined the skewness of a portfolio returns as the sum of firm level returns skewness and co-skewness terms[5]. Co-skewness can be, additionally, seen as the correspondent concept of portfolio covariance: how much the portfolio assets' returns are changing in relation of other tail events for the other assets in the portfolio

[5]Portfolio skewness is defined as: $PortfolioSkewness = \sum_{i=1}^{n} w_i Skew_i + \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j Co - Skewness_{i,j}$.

(see Harvey and Siddique, 2000). Co-skewness terms, according to Albuquerque (2012) captured the co-movements in one asset conditional to the other assets' reaction to extreme events. Co-skewness will be negative when, on average, a low return of one stock will coincide with high return volatility in the portfolio of remaining stocks. According to Mitton and Vorkink (2007), portfolio returns of under-diversified investors are more positively skewed than those of diversified investors. They affirm how diversification is a two-edged sword for investors: it eliminates undesired variance in return distribution, but also eliminates desired skewness. There is then a clear trade-off between skewness and diversification. Christoffersen et al. (2013) not only surveyed the available methods in order to extract forward looking information from option markets, but explain also how the extracted information can be used for forecasting purposes.

Table 2.3 reports a summary of the main skewness and skew measures proposed in the literature in a chronological order. Some of them will be described more in depth in Chapter 4.

Table 2.3: **Skewness Measures Proposed in the Literature**

Study	Measure	Model/Approach	Journal
Kraus and Litzenberger (1976)	Probability Distribution	Model-Based	JF
Harvey and Siddique (2000)	Conditional Skewness	Model-Based	JF
Dennis and Mayhew (2002)	Risk-Neutral Skewness	Model-free and Raw Approach	JFQA
Bakshi et al. (2003) (BKM)	Risk-Neutral Skewness	Model-free measure extracted from stock options	RFS
Jiang and Tian (2005)	Risk-Neutral Skewness	Smooth Approach, Cubic Spline Interpolation	JD
Mitton and Vorkink (2007)	Idiosyncratic Skew	Model-Based	RFS
Han (2008)	Risk-Neutral Skewness	Model-free and Raw Approach	RFS
Hansis et al. (2010)	Risk-Neutral Skewness	Smooth Approach, Cubic Spline Interpolation	WP
Xing et al. (2010)	Risk-Neutral Skewness	Non-Parametric Approach	JFQA
CBOE (2011)	The SKEW Index	Model-free Approach based on BKM	CBOE WP
Mixon (2011)	Risk-Neutral Skewness	Non-Parametric Approach	JD
Neuberger (2012)	Realized Skewness	Model-free from high-frequency returns	RFS
Rehman and Vilkov (2012)	Risk-Neutral Skewness	Model-free and BKM Smooth Approach	WP
Conrad et al. (2013)	Risk-Neutral Skewness	Model-free and BKM Raw Approach	JF
Bali and Murray (2013)	Risk-Neutral Skewness	Model-free and Raw Approach	JFQA
Chang et al. (2013)	Risk-Neutral Skewness	Model-Free from Options	JFE
Amaya et al. (2015)	Ex-Post Realized Skewness	Model-free from intra-daily stock returns	JFE

Notes: This table summarizes the main skewness measures proposed in the literature so far in a chronological order. We specify the authors, a brief description of the measure, the model or approach used, and the journals as follows: JF = Journal of Finance, RFS = Review of Financial Studies, JFE = Journal of Financial Economics, JFQA = Journal of Financial and Quantitative Analysis, JD = Journal of Derivatives, CBOE WP = CBOE Working Paper, WP = Working Paper.

Several papers also studied the options implied kurtosis next to the implied second and third moments; Bakshi et al. (2003); Xing et al. (2010); Conrad et al. (2013); Bali et al. (2019). Conrad et al. (2013) found that individual securities' risk-neutral volatility, skewness and kurtosis are related to future returns. Kurtosis is, most of the time, found to be positively related with future stock returns. However, when controlling for both volatility and skewness, the kurtosis effect does not appear to be stable. Bakshi et al. (2003) also found that the risk-neutral kurtosis is empirically not significant.

In this thesis we will focus only on the first two implied moments (volatility and skewness), since the role of kurtosis in asset pricing and portfolio allocation has been found to be less robust compared to the risk neutral skewness and it is beyond the scope of this research[6]. We mainly focus in this thesis on

[6]Preliminary exercises have tested the role of implied kurtosis into, first a Granger causality analysis and, second, into asset

the role of the implied skewness, well known in the financial literature to be a proxy for measuring tail risk. The tail risk literature and the higher risk neutral measure literature are getting closer, intertwining each other so as to better support the source of information contained in the implied volatility indexes, completing and better explaining the overall risk in the financial market. Further discussion and findings on the higher risk neutral moments will be provided in Chapter 4.

2.5 Tail Risk Measures

In light of the recent years' events and turbulent financial events a strand of the literature has begun to look for additional risk measures that can support the VIX index during these times. For instance, Du and Kapadia (2014) pointed out that the volatility indexes under-estimate the real stock market volatility when the period is bearish and jumpy and when outliers occur. After Black Monday, 1987, the fear of other crashes led to a higher weighting for events in the left side of equity return distributions. Furthermore, the 2008' financial crisis has accentuated even more the interest in tail events and outliers. Private and institutional investors' consideration about tail events has increased[7].

The general trend seems that the possibility of these *outliers* occurring is still under-estimated, (see Taleb, 2007). In addition, Barberis (2013) advocated that people over-estimate extreme events when they have a suitable set of information or the memory of some similar event is fresher in their mind. Recent financial crisis seem to be carved in the investors' memory. However, not all the crises are the same nor may they happen for the same reasons. When the information set is limited or when similar tail events have never taken place before, investors underestimate their likelihood. The same behaviour seems to be reflected in financial markets and in the volatility indexes supposed to capture the general market fear (see Whaley, 2000).

Thus, if the volatility indexes are not able to capture this additional sources of risk, a new benchmark ought to be developed. In brief, many new measures have been proposed that can be useful in order to extract some additional information about this potential missing risk extracted, mainly, from the equity market. Several other studies have proposed tail risk measures for capturing financial market risk, in addition to the source of information included in the VIX index. Noteworthy the studies of (Bollerslev and Todorov, 2011; Du and Kapadia, 2014; Kelly and Jiang, 2014; Zhen and Zhang, 2014; Bollerslev et al., 2015; Almeida et al., 2017).

Bollerslev and Todorov (2011) estimated the Investor Fears Index (FI). By using high-frequency

pricing framework. We confirmed the non-significance of the implied kurtosis, calculated following Bakshi et al. (2003) in predicting other implied moments as well as in predicting future stock market returns. This results are in line with Bakshi et al. (2003) and CBOE (2011).

[7]According to a SSgA survey together with EIU (Economist Intelligence Unit) a survey reveals that 71% of Institutional Investors believe that a significant tail risk event will occur in the next year. This survey shows how tail risk possibility is always underestimated, but, due to the growing occurrence of these kind of events recently, institutional investors are becoming more sensitive to this phenomenon. For further details: http://newsroom.statestreet.com/press-release/state-street-global-advisors/ssga-report-highlights-continued-concerns-about-tail-risk.

intra-day data, they estimate expected jump tails in the market and relate them to the corresponding variance jump risk premium. It is the premium the investors want to receive for bearing jump tail risk. Also, investors will require a time-varying compensation for bearing disaster risk and fear. They, additionally, decompose this variance jump risk premium into its positive and negative components. The magnitude of the latter is, as expected, bigger. From this decomposition they interpret the difference between the downside VRP and the upside VRP as a measure of investor fear (FI). Their findings are that large variance jump risk premium is translated in a compensation for jump tail risk, where the investor (FI) plays a crucial role in explaining the magnitude of the variance jump tail risk. Research surrounding risk neutral higher moments and tail risk is more than alive.

The study of the risk neutral third moment can enrich the set of information traders and investors can have in order to implement their investment decisions and strategies. Among the papers have been tried to propose a tail risk measure, Du and Kapadia (2014) provided the construction of a Jump and Tail Index (JTIX) based on the previous assumption of VIX inadequacy to model and capture information from the tails. This new index of extreme fear is capable of measuring time variations in jump intensity and it derives from high moments as skewness and kurtosis of returns and jumps distribution. This index can be replicated by a short position in an options portfolio of risk reversal – an option position of short OTM puts and long OTM calls. Bollerslev et al. (2015) separated components of the variance risk premium, namely price fluctuations and jump tail risk with the latter found to improve the return predictability.

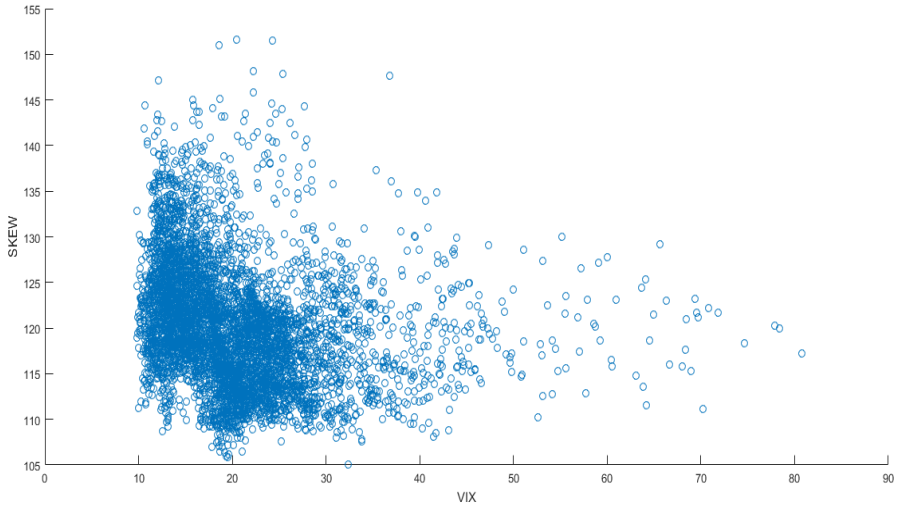
Taking a different approach by working with returns at the firm level Kelly and Jiang (2014) developed a measure of tail risk called TAIL Index. The measure they proposed is based on returns for individual stocks where the tail distribution is modelled with a time varying power law. Basically, each month they compute common time varying λ_t applying Hill's power law in order to set the daily data for all the considered stocks monthly. Higher the λ_t, fatter the tail of the distributions and higher the probabilities of extreme events. They base their dynamic index on the assumption that even if different firms are subjected to different risk, they can be aggregated in a single process, assuming similarity in risk dynamics. The relation between tail risk and individual stock returns is positive. This is coherent with the fact that the grater the tail risk the greater will be the investors' required returns. Investors are in this sense tail risk averse. The TAIL Index is found to also have a strong predictive power for future market returns. A similar approach in Almeida et al. (2017) considered a tail risk measure based on cross-sectional portfolio returns' expected shortfall (ES). Recently, Andersen et al. (2019) studied the pricing of tail risk in index options in international equity markets finding that the risk premium associated with negative tail events is unrelated to volatility, and that tail risk premium is a strong predictor of future returns.

In addition to these studies, the same CBOE introduced a SKEW index as a benchmark providing

additional market risk information (see CBOE, 2011). It is computed from S&P 500 options following the methodology outlined by Bakshi et al. (2003) (BKM). As discussed in 2.4, tail risk literature and higher risk neutral moments literature are getting closer. The importance of higher moments, especially skewness, has started to be drawn close to market tail risk measures. The SKEW index can be an additional source of information where the VIX cannot access. The SKEW index measures the slope of S&P 500 implied volatility options prices, that since 1987, seems to show this clear skew curve, as apposed to smiling as in the past[8]. The steeper this curve, the higher will be the SKEW index.

The skewness level has increased in recent years, after the financial crisis: options traders expect an higher tail risk. Remarkable the fact that, even if calculated from the same S&P 500 options, the two indexes have low, even if positive, correlation and often they carry different information and they perceive different market sentiments. When VIX spikes, SKEW remains on its average and vice-versa. They show an interesting relationship especially during outliers when they carry even more distinct information. Scatter plots between VIX and SKEW during a 20-years time period and during shorter turbulent times are shown in Figure 2.2 and 2.3, respectively. Thus, the SKEW index encapsulates different information than the corresponding VIX index. While the VIX is the market fear gauge, closer to the *likely*, it is the SKEW measure that is the extreme market fear gauge, closer to the *unlikely*.

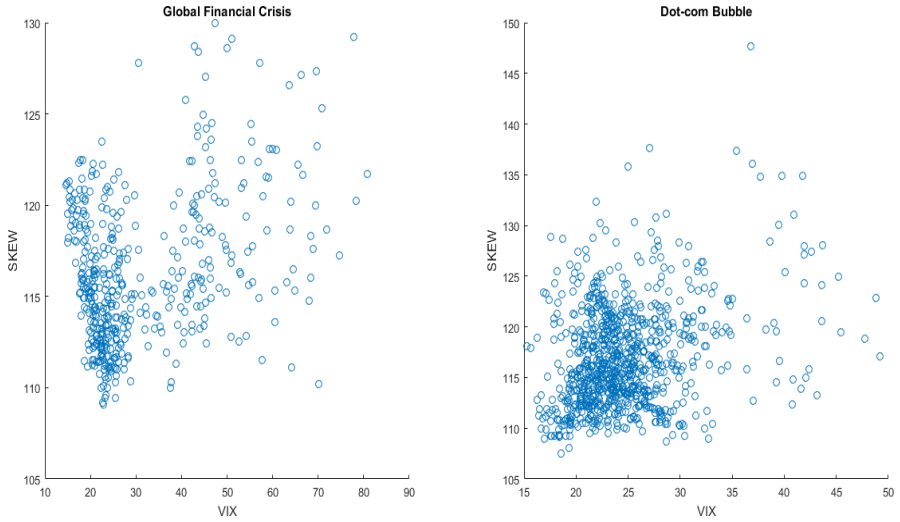
Figure 2.2: **VIX vs. SKEW Scatter Plot**



Notes: This scatter plot illustrates the relationship between VIX and SKEW . It shows that the information provided by the volatility and skew indexes are different, especially during outliers. The selected period goes from 04-01-1996 to 30-09-2016, at daily frequency.

[8]The implied volatility of OTM S&P 500 puts options is considerably higher than the implied volatility of the OTM S&P 500 calls options resulting in this skew.

Figure 2.3: **VIX VERSUS SKEW Scatter Plot in Turbulent Times**



Notes: This scatter plot illustrates the relationship between VIX and SKEW during the financial crisis (left figure) and dot-com bubble (right figure). It shows that the information provided by the volatility and skew indexes are different, especially during outliers and the relations between the two indexes weaker. The selected period goes from 02-07-2007 to 31-03-2009 for the financial crisis and from 01-07-1998 to 31-12-2001 for the dot-com bubble, at daily frequency.

Another measure from the CBOE that has been proposed close to the tail risk concept is the VVIX Index. It is the CBOE index of volatility of volatility, calculated applying the same VIX methodology to a wide range of OTM VIX options[9]. In fact, according to Park (2015), the volatility of the stochastic volatility could be a different way in order to measure the tail risk. The author affirms that this index is more reliable than VIX in order to explain and measure market extreme events risk because it is a mixture of volatility of volatility risk and also volatility jump risk.

More recently, Kaeck (2017) has studied the variance-of-variance risk premium (VVP) as the difference between the ex-ante risk-neutral variance extracted from options and the ex post realized variance of the VIX index. He provided evidence on the risk premia that investors require in relation to the changes in the VIX index over time. In other words the investors are exposed to the vol-of-vol (VVIX) risk, thus demanding a premium.

Among all the literature about tail risk and extreme events measures, another important study is Wang and Daigler (2012). In their work both the CBOE SKEW and also CBOE VVIX were considered and linked together. According to them the BKM measure of SKEW represents an estimation of Black Swan or tail risk in the market and VVIX represents a measure of volatility of volatility, or better fear of fear in the market. More details on these tail risk measures as well as additional commentary will be discussed in Chapter 4.

[9]For further information: http://www.cboe.com/micro/vvix/

2.6 Market Sentiment

We provide here, some background on the market sentiment literature with relation to higher risk neutral moments, volatility, skewness and market risk measures.

Shiller (1989) posed the following question: *Can we trace the source of movements back in a logical manner to fundamental shocks affecting the economy, the shocks to technology, to consumer preferences, to demographics, to natural resources, to monetary policy or other instruments of government control? Or are price movements due to changes in opinion or psychology, that is, changes in confidence, speculative enthusiasm or other aspects of the world-view of investors, shocks that are best thought of as coming ultimately from people's mind?* The answer is – still – not well established.

In his book Shiller (2000) argued that "the market is not well anchored by fundamentals". Most of the time, the exuberance that moves the traders' choices is seen as speculative activity. Baker and Wurgler (2000) asserted how the presence of investor sentiment is actually impacting on stock prices and suggested that market sentiment is close as a definition to the propensity of market speculation. It is not easy to define what speculation is (see Szado, 2011), although there is a lot of literature explaining anomalies, greed and overconfidence in the market. Han (2008) confirmed that there is a link between higher risk neutral moments and market sentiment. Exploring the relationship between market sentiment and S&P 500 options prices, his findings are the following: when the investor sentiment is bearish the index option volatility smile is steeper and the risk neutral skewness is more negative. On the other hand, when the investor sentiment is bullish the volatility smile will be flatter and the risk neutral skewness less negative. Thus, the market sentiment affects the price of the equity index options changing the price of market volatility and market skewness. This thesis aims to contribute to this area of research (see Chapter 4).

Starting from this assumption, the SKEW index proxy in the literature for tail risk might actually reflect different investors classes and expectations given the fact that it is computed from equity index calls and puts. This represents the main motivation behind Chapter 4 which we try to investigate further. The same relationship between skew and market sentiment is tested by Dennis and Mayhew (2002). The assumption they tested is that there should be a significant relationship between skew and put-call ratio due to the fact that, assuming it is a sentiment proxy, more puts volume indicates pessimism. Especially in pessimistic market times, skew should be more negative. Demand for OTM puts is higher and increases the price of low strike options, or deep OTM puts. According to Pan (2002), investors tend to choose OTM equity puts to express their concern about possible negative market trends. Thus, OTM puts become more expensive inflating the negative part of volatility and skewness indexes which may be influenced by pessimistic traders driving up prices for bad states. Dennis and Strickland (2002)

stated that when markets are volatile it is institutions not individuals who are selling when prices move lower and buying when prices move higher.

Seo and Kim (2015) stressed the importance of market sentiment in playing a role for a better forecasting activity regarding option market, stock market, their distributions and moments. In fact, they affirmed that market sentiment can help to better predict implied market volatility and skew. More specifically, risk neutral skewness has better predictive power during high sentiment market periods. A large number of traders participate in the stock market impacting on the options and stock prices. Along this path, Andreou et al. (2016) explored the dynamic and cause of dispersion in options traders' expectations about future stock returns. In a nutshell, they link the dispersion measure to the different options volume in all the options range, across moneyness levels. A low dispersion index implies similar traders views on the future stocks return; conversely, high level of dispersion indicates different opinions and stock returns expectations. Their assumption is that the traders expectations about future stock returns are basically mirrored and reflected in the moneyness level at which they trade. According to them, an optimistic market view can be illustrated from long OTM Call and short ITM put trading. On the other hand, a pessimistic market view is given by long OTM puts and short ITM calls. A part from this assumption, then, in practice, the dispersion level is separated from the risk neutral distribution extracted from options prices as in our case. In their final section, as a robustness check, they compare the dispersion level with option implied measures, such as, slope from Xing et al. (2010), hedging pressure (HP) in the index options market, Put-Call Ratio and risk neutral moments (VIX , skewness and kurtosis). The evidence shows that these measures are quite different from the dispersion level is that they do not have significant impact on it, especially after a short period of time.

Lemmon and Ni (2008) found that investors' sentiment has a greater impact on the speculative demand in comparison to the hedging demand, that is, most of the time, invariant to market sentiment. According to them, market sentiment can be seen as the totality of investors' beliefs, unrelated to fundamentals. Indeed, they separated the Positive Exposure Demand, (PD) for S&P 500 puts, considering it a proxy for hedging market demand, and the PD for S&P 500 Calls and also single stocks Calls and puts as a proxy for speculative demand. The same intuition has been found in Andreou et al. (2016): optimistic traders' expectation can be revealed in OTM calls trading; vice-versa negative views about assets' future returns would be either revealed from OTM long puts or OTM short calls. The side concerning OTM calls seems to be the one related to market sentiment. It has little impact on equity index options price because it is carried only by the calls side. Less volume, trading activity and marginal contribution for the call side is found for equity index, the opposite is true when individual stocks are considered. Results from Chapter 4 and Chapter 5 will confirm these assumptions.

2.7 Volatility Spillovers Literature

In this section, we focus on the literature about volatility contagion in the financial markets. Diebold and Yılmaz (2014) coined the term connectedness which is nowadays commonly used in the literature to refer to how variables in a system are connected. They introduced the term connectedness in replacement of volatility spillovers or contagion. In this thesis we use the three concepts without difference in meaning and all will refer to measures of interdependence among variables in the system.

The methodological framework for measuring connectedness both in returns and also in volatility is anchored in the financial connectedness literature spanned by the seminal papers by Diebold and Yilmaz (2009, 2012); Diebold and Yılmaz (2014). Diebold and Yilmaz (2009) firstly provided a measure of interdependence of both asset returns and volatilities for 19 global equity markets. They found that while the returns spillovers plot is uneventful displaying gentle increases, the volatility spillovers plot ranges widely and it responds to economic events worldwide. Diebold and Yilmaz (2012) followed up on this topic focusing only on assets volatility spillovers. By using a forecast error variance decomposition framework invariant to variable ordering they were able to measure both total and also directional volatility spillovers of U.S. stocks, bonds, foreign exchange and commodities markets. Main findings showed how the volatility spillovers increased after the global financial crisis with spillovers going from the stock market to the other markets. Diebold and Yılmaz (2014) focused on the U.S. financial sector stocks volatilities. They provided measures of connectedness which they argued can be closely related to measures of systemic risk as well as network theory. We will expand these concepts more in details in Chapter 5.

The literature studying assets return contagion is vast (see Bae et al., 2003; Syriopoulos, 2004; Voronkova, 2004; Diebold and Yilmaz, 2009; Bekaert et al., 2014; Diebold and Yilmaz, 2015). However, according to Diebold and Yilmaz (2015), it is better to look at volatility spillovers, first, because they tracks investor fear which connectedness provides an idea about the fear connectedness by market participants and, second, because volatility connectedness is of interest when studying economic, financial and political events which might potentially increase the level of countries' uncertainty. Thus, in this thesis we focus mainly on volatility spillovers. See also Gagnon and Karolyi (2006) for an excellent survey of both return and volatility contagion.

2.7.1 Volatility Spillovers Methodology: GARCH Models vs. Diebold and Yilmaz (2009)

The methodology commonly used to assess the presence of volatility spillovers is based on multivariate GARCH models (see Pericoli and Sbracia, 2003). More specifically, among them the most common are the BEKK-GARCH by Engle (1995), the DCC-GARCH by Engle (2002) and the ADCC by Cappiello

et al. (2006) which looks at asymmetric effect in conditional correlation. However, these models do not provide the same set of dynamic and directional connectedness information and their specifications might suffer from the curse of dimensionality. Due to the reduced flexibility of these models limiting their scope for some specific application, many more recent studies opt for the application of the Diebold and Yilmaz (2009) and Diebold and Yilmaz (2012) methodology. The choice is dictated by the fact that a more appropriate and flexible modelling framework is needed when the research aim is to study asymmetric behaviours of volatility spillovers, directional volatility spillovers net receivers or transmitters and pairwise spillovers. This methodology is even more in need when different measures of volatility want to be tested in contagion framework (e.g. realized volatilities, implied volatilities). These are some of the main reasons why a forecast error variance decomposition (FEVD) framework by Diebold and Yilmaz (2012) will be considered also in this thesis instead of more structured volatility models (see Chapter 5).

Firstly, studies on volatility spillovers focused on the importance of the U.S. in influencing other markets (see Bae and Karolyi, 1994; Karolyi and Stulz, 1996). Subsequently, other studies have started to look at volatility spillovers not only from the U.S., but also regional markets and worldwide shocks. Liu and Pan (1997) studied the mean return and volatility spillovers from the U.S. and Japan to four Asian stock markets, namely, Hong Kong, Singapore, Taiwan, and Thailand finding that the U.S. market is more influential than the Japanese market in transmitting returns and volatilities to the four Asian markets. In a similar way, Ng (2000) examined the volatility spillovers from Japan and the U.S. to six Pacific–Basin equity markets finding significant spillovers from the region to many of the Pacific–Basin countries. Baele (2005) investigated volatility spillovers between the U.S. and Western Europe region, instead. By using a regime-switching model the main findings showed that both the EU and U.S. shock spillovers increased over the 1980s and 1990s. Trade integration, equity market development, and low inflation played an important role. Evidence for contagion from the U.S. market to local European equity markets was found. Engle et al. (2012) modelled the interdependence of equity market volatility in eight East Asian countries before, during, and after the Asian currency crisis.

With regards to the European countries selection, for instance, Savva and Aslanidis (2010) found that the integration between Eastern European countries and Eurozone has increased following the accession to the EU with stronger evidence for Czech and Polish markets which are more correlated to the Eurozone than to the U.S. Syllignakis and Kouretas (2011) found an increase in the conditional correlation coefficients among countries such as Germany, U.S. and Russia together with CEE countries due to and after the financial crisis. A reason why the study of these developing CEE countries next to the developed European countries deserves further analysis, especially when a more recent market time period is taken into account. By using conditional volatility measures, how the asymmetric behaviour of volatility is transmitted in its spillovers effect has been also studied under its volatility leverage

effect (see Gjika and Horvath, 2013; Clements et al., 2015). Gjika and Horvath (2013) applying an asymmetric DCC model, found that conditional variances and correlations increases during volatile periods and crisis in the central European stock market, decreasing diversification opportunities. This is also confirmed by Reboredo et al. (2015) examining more specifically the co-integration among the CEE stock markets themselves using dynamic copulas. Overall, an increase in dynamic correlations is commonly found during crisis period (see Bekaert et al., 2014; Horváth et al., 2017).

Another general trend in the volatility spillovers literature is that, most of the time, an unilateral volatility spillovers effect from mature financial markets to the emerging markets is found, while small markets do not affect bigger markets significantly. Scheicher (2001) found that the emerging CEE stock markets are influenced by Central European and developed financial markets, but there is also a regional and local integration among the CEE countries. Bhar and Nikolova (2009) found, using a bivariate EGARCH model, that India has the highest level of integration within the BRIC countries with a negative relation with Asia-Pacific region countries opening up to portfolio diversification opportunities. Beirne and Fratzscher (2013) measured volatility spillovers from mature to emerging stock markets by applying a tri-variate GARCH-BEKK model which takes into account conditional correlations between mature and emerging market returns. Most of the time, mature market volatility affects conditional variances in many emerging markets with conditional correlations between local and mature markets increasing during turbulent episodes. Using a two stages GARCH-M models, Moon and Yu (2010) detected volatility spillovers from the U.S. S&P 500 to the Chinese Shanghai Stock Exchange index. On the same line, Le et al. (2010) found volatility spillovers effects from the U.S. and China to emerging markets as Indonesia and Malaysia. Using VARGARCH(1,1)-in-mean model, Caporale and Spagnolo (2011) found that volatility spillovers from Russia and UK impact on CEE countries stock market volatilities, but there is no linkage in the opposite way. The same leading role of the U.S. is found by Elyasiani et al. (2015) who applied a VAR-BEKK model in order to study the volatility (and return) connectedness among U.S., U.K., EU and Japanese banks and insures during the pre-crisis and crisis period. They found that the spillovers effect strengthened during the crisis.

Rather than multivariate GARCH models, recently, the main methodology in order to study volatility spillovers or connectedness relies on Diebold and Yilmaz (2009, 2012). They proposed a spillovers index based on forecast error variance decomposition. The second version of the index manages to capture also the volatility spillovers directions since the variables are ordering invariant. By applying this methodology, for instance, Zhou et al. (2012) measured the directional volatility spillovers between the Chinese and world equity markets, finding that the U.S. market shows a prevalent volatility impact on other markets during the sub-prime crisis, while the Chinese stock market volatility had an impact on other Asian markets since 2005. Tsai (2014) investigated volatility spillovers in five developed stock markets, namely, the U.S., the U.K., Germany, Japan, and France finding that Germany and the U.S. are

the main stock markets transmitting information to other international markets. More recently, Gamba-Santamaria et al. (2017) improved the Diebold and Yilmaz (2012) spillovers index in the volatility factor measured through a DCC-GARCH model in order to allow for a time-varying asset pricing correlations and volatility clustering. By applying this methodology to the Latin American stock market they found Brazil as a net volatility transmitter, while Chile, Colombia and Mexico as net receivers.

2.7.2 Currencies Volatility Spillovers

Many studies on volatility spillovers have focused only on the equity market without considering other important financial markets such as the foreign exchange (e.g. Soriano and Climent, 2006). The literature on currency market volatility integration has started from the seminal paper by Ito et al. (1992) finding how news from adjacent regions (meteor shower) is to be preferred to local influences from the previous day (heatwave) as an explanation of the transmission of volatility in the forex market.

Kočenda and Valachy (2006) studied the exchange rate volatility in the Visegrad countries (Poland, Hungary, Slovakia and Czech Republic) accounting for path dependency and asymmetric shocks. They found that the monetary framework of these countries played an important role for volatility spillovers. According to Kočenda and Valachy (2006), foreign exchange risk has been pronounced for the new EU members, thus impacting on currency volatility spillovers, the latter intensified even more by the increasing integration between developing and developed countries in the Eurozone. The volatility and its contagion among developed and developing countries in the EU represent a key factor for international investors and opens up to possible portfolio diversification strategies (e.g. De Zwart et al., 2009; Jotikasthira et al., 2012).

More recent studies such as Pérez-Rodríguez (2006) adopting a DCC-GARCH model found a strong presence of volatility spillovers between Euro and Pound against U.S. dollar after the Euro introduction. Using a GARCH-BEKK model, Fedorova and Saleem (2010) focused on the volatility interdependence between emerging CEE countries and Russian stock market and currencies finding the presence of unilateral volatility spillovers from the latter to the stock market for Poland, Hungary and Russia. Kitamura (2010), applying a varying-coefficient MGARCH model, examined the intraday volatility spillovers among the euro, the British pound and the Swiss franc, finding that there is a volatility spillover transmitted from the euro to the other two currencies. McMillan and Speight (2010), using a realized variance method, found that the dollar rate dominates the Japanese Yen and the British pound in terms of volatility spillovers. Bubák et al. (2011) found presence of volatility spillovers among central European exchange rates increasing with market uncertainty in the central European currency market using model-free volatility measures. Antonakakis (2012) found that the U.S. dollar's appreciation plays a crucial role for volatility spillovers.

2.7.3 Credit Volatility Spillovers

In the recent years and, especially, in response to the sovereign debt crisis in Europe, the studies surrounding volatility propagation among countries have rapidly moved towards the study of credit volatility spillovers. Hunter and Simon (2005) affirmed how the correlations between bond market returns are driven by macroeconomic and financial market events and Ehrmann et al. (2011) showed how the European Monetary Union has led to substantial convergence in the Eurozone sovereign bond markets. These studies use, mainly, CDS spread market in order to tackle this analysis. According to Calani et al. (2012), using CDS spread allows us to direct interpret it as a default probability measure or premia impacting on the fixed income credit spread in relation to a sovereign risk-free asset mirroring the selected country counter-party risk. The advantage of using CDS spread data over bond spread is assessed also by Caporin et al. (2013). It is directly observable in the market while computing the bond spread might be subjective to the researcher. CDS capture the sovereign risk and therefore enable a more straightforward analysis while bond spreads might be conditioned to other factors as monetary policy and central bank and policymakers decisions. For instance, Caporin et al. (2013) measured the sovereign risk contagion through CDS and bond spreads of selected countries in Europe. CDS contagion has been quite constant for the 2008-2011 period while bond spreads contagion increase in intensity from the pre and post crisis periods.

More recently, many studies have looked at volatility contagion by relying on the Diebold and Yilmaz (2009, 2012) spillovers index methodology. More specifically, Calani et al. (2012) investigated the relation between credit spread in sovereign debt and CDS spread concluding that there is no evidence of contagion during the first and second quarter of 2012 with a clear separation between two groups of countries: the first in which CDS spreads affect bond yield in a positive way, and the second in which the bond yields are independent to variation in CDS spreads (safe-havens). Evidence of a CDS volatility contagion from troubled countries on CDS on sovereign debt to not-troubled countries is also found. Alter and Beyer (2014) by extending the Diebold and Yilmaz (2012) methodology, measured spillovers between sovereign credit markets during the sovereign debt crisis between October 2009 and July 2012 in the euro area, finding systemic effect among sovereigns and banks due to an unexpected shock to the creditworthiness of one of the two. Claeys and Vašíček (2014) found significant spillovers between EMU countries during the financial crisis by using a factor-augmented version of the Diebold and Yilmaz (2009) VAR model (FAVAR). Antonakakis (2012) related the sovereign bond yield spread spillovers with the presence of news announcement and policy changes, finding strong spillovers effect from the periphery to the core of the Euro area especially during turbulent periods. Louzis (2012) studied the volatility spillovers among the money, stock, foreign exchange and bond markets in Euro-area between 2000 and 2012 finding that, on average, more than 50% of the forecast-error variance is explained by spillover effects with the stock market being the main volatility spillovers transmitter.

2.7.4 Volatility Asymmetry and Response to Good or Bad News

Recently, a recent stand of literature has seen some other extensions of the Diebold and Yilmaz (2009, 2012) spillovers index which have been proposed in the literature in order to take into account the volatility asymmetry. Until that moment the presence of asymmetric volatility in volatility spillovers has not received the same attention as in financial markets in which is well recognized (e.g. Black and Scholes, 1973; French et al., 1987; Campbell and Hentschel, 1992). The original rationale of volatility asymmetry in financial markets relies on the fact that past returns are negatively related with present volatility (e.g. Bekaert and Wu, 2000; **?**). Since volatility propagates across markets it can be assumed that also volatility spillovers may present asymmetries.

According to Clements et al. (2015), asymmetric transmission of volatility can be either established as a leverage effect, when there is an asymmetric impact on assets' volatility due to positive or negative shocks or news of identical size, or that can be established as asymmetric volatility spillovers caused by good or bad news separately (e.g. Segal et al., 2015).

There are two predominant theories on the first asymmetric volatility effect. The first one is the leverage effect by Black (1976) stating that after a decrease in an asset value, the leverage ratio of a firm holding that asset increases and so its volatility. Thus, negative news and shocks may have larger impacts on volatility compared to positive shocks of the same absolute value. An alternative theory, called volatility feedback (see Campbell and Hentschel, 1992), asserts that news that volatility will be higher in the future will induce risk-adverse investors to sell positions today until they are compensated for that increase. Financial markets decrease in advance in order to already discount future volatility increases. However, after a negative return shock and an increase in volatility the increase in expected return will generate even more volatility (feedback). This volatility feature might be studied and incorporated in spillovers measures by computing GARCH models' conditional volatilities.

The second volatility asymmetry is instead given from the fact that volatility responds in a different way to different events, thus, it can be classified, separately, as good or bad (e.g. Barndorff-Nielsen et al., 2010; Segal et al., 2015). For instance, according to Baruník et al. (2016), there are events which impact more on the upside volatility, while some others impact more on the downside side. The same asymmetry effect can be consequently transmitted on volatility spillovers measures. According to Diebold and Yilmaz (2015) the volatility spillovers coming from the good volatility should not be neglected since they can be a source of returns. This effect can be captured by inputting the decomposed realized volatilities into the spillovers indexes as in Baruník et al. (2015, 2016, 2017). The volatility asymmetric effect in spillovers has also been studied for the currency market (see Wang and Yang, 2009; Clements et al., 2015; Baruník et al., 2017).

For instance, Baruník et al. (2015, 2016, 2017) proposed an asymmetric version of the spillovers index computing the volatility series trough the decomposed realized measure relying on the new measure

of decomposed volatility proposed by Barndorff-Nielsen et al. (2010). Baruník et al. (2015) detected asymmetries in volatility spillovers for the petroleum commodities. Baruník et al. (2016) studied the volatility spillovers asymmetry for the U.S. financial market detecting ample asymmetric effect at sectoral level with negative asymmetries in spillovers more frequent than the positive. Baruník et al. (2017) found asymmetry in volatility spillovers for the most actively traded currencies by using high-frequency data. They detected monetary policy and real-economy events as main drivers of positive spillovers, whereas fiscal factors are found as the main drivers of negative spillovers.

Thus, we anchor our research to this new volatility spillovers branch of literature which takes into account the asymmetric volatility characteristics and the separate role of upside and downside volatilities. Other studies have started to look at the transmission of volatility spillovers among different assets and countries when news and macroeconomic announcements (e.g. Belgacem et al., 2015) or financial, economic and political events occur (e.g. Belke et al., 2016). In Chapter 5 more details on the connectedness methodology and on the asymmetric volatility connectedness literature and measures will be provided with an application to implied volatility from options as well as more insights on the linkage with the systemic risk literature.

Chapter 3

The Determinants of the Model-Free Upside and Downside Volatilities

3.1 Introduction

In recent years there has been much interest in the asymmetric behaviour of volatility and the different roles associated with its upside and downside components within different areas of finance (e.g. Ang et al., 2006; Barndorff-Nielsen et al., 2010; Segal et al., 2015; Baruník et al., 2016, 2017; Feunou et al., 2017; Kilic and Shaliastovich, 2018).

As already discussed in Chapter 2, the information content of the two realized volatility components reflect opposite economic state or different investors' expectations. According to Segal et al. (2015) and Feunou et al. (2017), good uncertainty is associated with potential profits, representing what investors like, different from the bad uncertainty associated with potential losses, representing what investors dislike. In addition, Segal et al. (2015) affirmed that the bad realized volatility comprehends all the news can spread the market tension, decrease in assets' value, decline in market productivity, unemployment, disinvestments and market depression. Conversely, good realized volatility regards news impacting underlying assets in a positive way, future growth, investments and increase in production and consumption.

In terms of implied volatility, by decomposing the VIX index into two components, separate information enclosed in OTM puts and OTM calls can also be accessed (see Kilic and Shaliastovich, 2018). Implied volatility extracted from OTM put options captures information regarding the possibilities of downward movements in the equity markets. Implied volatility extracted from OTM call options is linked to upward movements of volatility. While the decomposed realized volatilities depict different economic and financial states according to *realized* events, decomposing implied volatility allows us

to access separate investors' expectations on future financial markets trend and economic states. The upside implied volatility reflects the positive and optimistic investors' beliefs enclosed in calls, whereas the downside implied volatility captures the negative investors' perspective and pessimistic views concerning downwards markets. In terms of decomposed implied volatilities, investors' expectations and sentiment is closely linked to the call-put options trading (see Bollen and Whaley, 2004; Buraschi and Jiltsov, 2006; Mixon, 2009).

By decomposing each of the volatility measures (realized and implied) we are, not only, able to access different type of information, but also to study the main drivers of each of the decomposed volatility measure. Furthermore, having separate measures of upside and downside volatility we are able to compute separate measures of volatility risk premia. We analyze which may be the main drivers of the upside and of the downside components of volatility, expecting these to be different due to the different events and beliefs the two components reflect.

Hence, the question arises as to what are the determinants of volatility and, more specifically, its upside and downside components. This study aims to contribute to the financial volatility literature and to the better understanding of its relationship with macroeconomics and financial conditions variables by answering the following questions - *Are the decomposed upside and downside components of volatility driven by the same variables? Are they, in turn, carrying similar information useful to predict the financial or macroeconomic activity?* This chapter applies a model-free approach to compute both implied and realized stock market volatility measures in the U.S. and to combine them into volatility risk premium measures, considering them in a comparative framework in which the determinants of their upside and downside components are investigated.

This chapter aims to shed new light on the identification of the potential determinants of asymmetric volatility and risk premium, and to contribute to different strands of literature by taking into account a new set of variables, which include both macroeconomic and financial conditions variables. Macroeconomic variables have often been looked upon as possible determinants of volatility in many empirical studies (see Schwert, 1989; Cutler et al., 1989; Kandel and Stambaugh, 1990; Whitelaw, 1994; Lettau et al., 2007; Diebold and Yilmaz, 2008; Engle and Rangel, 2008). These studies opened up a new strand of subsequent research on the relationship between macroeconomic and stock market volatility (see Chapter 2). However, as already mentioned, the overall conclusion reached on the relationship between stock market volatility and macroeconomic activity is by no means clear cut.

The opacity of this relationship between stock market volatility and macroeconomic activity might be due to at least two reasons. Firstly, it may simply be that macroeconomics is not central in explaining the key determinants of volatility (Cutler et al., 1989). Our chapter also considers other financial variables that appear to better detect and track the volatility trends and behaviour alongside the macrovariables in line with Paye (2012) and Christiansen et al. (2012). We expand our set of variables by

including market sentiment, credit and liquidity proxies, the political and economic uncertainty index by Baker et al. (2016) and the geopolitical risk index by Caldara and Iacoviello (2018), to test the role, if any, such variables play in driving volatility. Macroeconomic factors are able to capture the state of the economy, but less able to capture investors' expectations, whereas these financial conditions proxies may be better able to reflect such beliefs and also contribute to volatility over a shorter time frame. Shiller (1981) showed that the level of stock market volatility can be too high to be justified solely by dividends and fundamentals. In addition, market sentiment cannot be ignored for understanding investors' future beliefs and expectations. For model-free implied volatility, in particular, the main determinants are more likely to be placed mostly among the contemporaneous time variables related to investors' sentiment, such as exuberance and fear driving options trading.

Secondly, many different models have been applied in an attempt to best measure volatility when this is related to macro variables. Engle and Rangel (2008) employed a Spline-GARCH model which smooths out the high data frequency of volatility so as to allow a better comparison and linkage with low frequency macroeconomic data. The identification of the determinants of volatility is highly sensitive to the method used to measure volatility, often referred to as the volatility modelling problem. This is a problem that is well recognized in the model risk literature (see Engle and Rangel, 2008; Daníelsson et al., 2016; Jokivuolle and Tunaru, 2017). The model choice and market period selection increases the uncertainty and subjectivity of volatility determinant analysis (Beltratti and Morana, 2006). A simple exercise in Appendix A.1 highlights differences in terms of conditional volatility of dependent and independent variables, when they are inferred from different GARCH models. Model choices behind the conditional variance computation might lead to approximations and errors, thereby making the overall relationship uncertain.

In order to circumvent this volatility modelling problem, we consider in this chapter model-free volatility measures, namely, the implied volatility index, VIX , extracted from a bunch of S&P 500 options by following the CBOE methodology, and the realized volatility computed from stock market returns. Our chapter is also motivated by recent studies which have begun to examine volatility in its different shapes and components. For instance, Beltratti and Morana (2006) decomposed volatility into one part associated with structural break and one associated with long memory dynamics, Engle et al. (2013) decomposed volatility into short and secular run components and Bekaert and Hoerova (2014) decomposed VIX into a a proxy for risk aversion and a proxy for uncertainty, suggesting that both components have a different relationship to macroeconomics.

We continue this line of research through the decomposition of the volatility indexes into their upside and downside components, with upside volatility computed only from call options, referred to in this chapter as VIX^{+} and downside volatility computed only from put options, referred to as VIX^{-} . In implied volatility terms, we recognize that investors are more willing to buy equity index put options

for hedging purposes during negative times and crises (see Bakshi et al., 2003; Bollen and Whaley, 2004; Bondarenko, 2014). Following Barndorff-Nielsen et al. (2010), we decompose realized volatility into good and bad realized volatility, RVOL^{+} and RVOL^{-} . We disentangle the good uncertainty associated with potential profits, representing what investors like, from the bad uncertainty associated with potential losses, representing what investors dislike (see Segal et al., 2015; Feunou et al., 2017).

In addition, by considering model-free calculations we further extend our analysis to include volatility risk premium, VRP , and its components by following the definition as in Carr and Wu (2008), namely, as the difference between physical and risk neutral expectations of return variation. The same definition is applied in Kilic and Shaliastovich (2018), whereas other studies computed risk premia as a short position in a variance swap, namely, as the difference between risk neutral and physical expectations of returns (e.g. Bollerslev et al., 2009; Bekaert and Hoerova, 2014; Feunou et al., 2017).

This recent strand of literature has begun to investigate the explanatory ability of the risk premia and its components with relation to the stock market. For instance, according to Bollerslev et al. (2009), the variance risk premium has predictive power for short-term stock returns (from three to six months), a finding also confirmed by Bekaert and Hoerova (2014). However, according to Feunou et al. (2017), considering only the aggregate VRP measure is restrictive given that this imposes the same coefficient on both the asymmetric views of investors in relation to the two components of VRP related to good uncertainty (VRP^{+}) and bad uncertainty (VRP^{-}). Indeed, they found that the downside VRP (which would correspond to our VRP^{+}) is the main component of the variance risk premium, finding it to be significant with a positive relationship with the equity premium, and showing superior ability in explaining future variations in excess returns compared to the aggregate and upside VRP (which would correspond to our VRP^{-}). Amengual and Xiu (2017) linked upward and downward volatility jumps together with policy measures, finding that resolutions to policy uncertainty leads to a downward volatility movement. More recently, Kilic and Shaliastovich (2018) measured good and bad variance risk premia which help predict assets returns in the long term horizon. The good variance premium predicts future assets returns with a positive sign, whereas the bad variance risk premium with a negative sign, thus, both components of the variance premium should be considered in order to obtain a higher return predictability.

However, the literature on the determinants of implied volatility is quite sparse: Corradi et al. (2013) found that VIX and the business cycle are related to industrial production growth and Bekaert et al. (2013) assessed that VIX is also linked to monetary policy highlighting that lax monetary policy decreases risk aversion. Furthermore previous literature is silent on the potential information content of volatility risk premium and its components with relation to macro and financial variables. Thus, we aim in this chapter, not only to further investigate the linkage between decomposed volatilities and equity, but also to expand this linkage to other selected macro and financial variables in order to determine

which are the main variables driving their two components separately.

As far as we are aware, this is the first research looking at the impact of macro and financial factors on implied volatility within a framework separating information contained in call options from that contained in corresponding put options. In addition, we focus on risk premium, since it uses final market information which naturally cleanses option implied volatility from the effect of physical volatility (realized), resulting in a measure correlated with risk aversion (see Bekaert and Hoerova, 2014). Also, the predictability power of the variance risk premia is mainly driven by the implied volatility, which contributes more than realized volatility; reason why we believe that understanding the main determinants of the decomposed implied volatility and risk premium is paramount compared to the realized volatility measures.

Firstly we conduct an empirical analysis based upon a temporal aggregation in which all the macroeconomic and financial conditions variables are considered at their lowest common frequency, namely monthly, and are tested in an OLS stepwise framework and in a single LF-VAR model. Subsequently, the variables are divided according to their frequency, namely, low and high frequency, modelling the low frequency variables in a mixed frequency VAR model with respect to the daily volatility series, and the high frequency variables in a high frequency daily VAR model. This is undertaken with the objective of testing for Granger causality relationships at the most accurate frequency for our selected variables following the mixed frequency Granger causality methodology as in Ghysels et al. (2016) and Ghysels (2016). Diebold and Yilmaz (2008) advocated that one-way causality from macro-variable volatility and stock market volatility deserves further research, especially in the case of implied volatility. A lead-lag relationship is examined through different VAR models at different variable frequencies to capture, not only unilateral feedback from the variables to volatility, but also vice versa, with the aim of identifying any potential bilateral feedback (e.g. Jermann and Quadrini, 2006; Bansal et al., 2014)[1].

While some literature has investigated the role of macroeconomic and financial variables in driving the realized volatility measures (see Christiansen et al., 2012; Paye, 2012), this research further build up on this relationship mainly studying implied volatility and volatility risk premium measures. Although the literature about volatility drivers is vast, it has never explored the implied volatility drivers and especially the drivers of decomposed implied volatilities. We report in this chapter the analysis about decomposed VIX and volatility risk premia which deserve more attention in the financial literature. We report more details about the realized volatility measures in Appendix A.2.

We find evidence of different determinants dependent upon the volatility components considered, for both implied volatility and risk premium. There is evidence that the macro variables impact more on the upside implied volatility component, VIX^{+} , especially in the case of GDP and inflation, which are variables more attached to the investors' consumption sphere. On the other hand, the financial

[1] A recent study by Amengual and Xiu (2017) found that volatility is responsive to news not only upward in relation to bad news, but also downward in relation to good news.

conditions variables such as credit, liquidity, EPU and GPR indexes impact more on the downside implied volatility component, VIX^{-} . The global financial crisis has generated a shift in importance from macroeconomic to financial conditions variables, both for implied volatilities and also for risk premia. We uncover Granger causality relationships by applying a mixed frequency VAR model, especially from macro variables to volatility and vice versa. We detect and confirm implied volatility as a good predictor of economic activity, whereas the volatility risk premium a good predictor of future stock returns. We find that different components contain different information useful for future financial and economic activity predictability.

The remainder of this chapter is organized as follows. Section 3.2 summarizes the model-free approach to compute and decompose our volatility measures. Section 3.3 describes both the volatility series and also the selected macroeconomic and financial variables. Section 3.4 discusses the empirical methodology of the chapter, namely, stepwise backward regression, high frequency, low frequency and mixed frequency VAR models and Granger causality tests. Sections 3.5 and 3.6 report the empirical results for both the implied volatility and volatility risk premia with regards to the stepwise regression and Granger analysis, respectively. Section 3.7 discusses the linkage between volatility measures and economic, political and geopolitical indexes. Section 3.8 concludes the chapter. Robustness exercises and additional material can be found in Appendix A.

3.2 Computation and Decomposition of Volatility Measures

In this section, we describe the measures and the decomposition of implied volatility, realized volatility and volatility risk premia briefly relating it to previous literature. We rely entirely on a model-free approach to compute the implied and realized volatility measures and their upside and downside components in order to be able to compute the upside and downside volatility risk premia accordingly. Aiming to understand how macroeconomic and financial variables impact on the aggregate implied volatility along with its components, and likewise on the volatility risk premium and its components, the following hypothesis is considered: **Hypothesis 1**: *Implied volatility and risk premium components - upside and downside - are related to macroeconomic and financial variables in a different way.* We thus investigate whether or not macroeconomic and financial variables impact in the same way on both the downside and upside components of volatility and on the respective aggregate measures.

3.2.1 Decomposition of Implied Volatility

The implied volatility measure, VIX , is computed model-free from a set of out of the money (OTM) S&P 500 options, being an interpolation between the near term and far term option maturities for each day in which it is calculated. It is, therefore, a forward-looking volatility measure based on the changes

over the next 30 days in the S&P 500 options price (both calls and puts) (see CBOE, 2009). The following formula is used to calculate the implied variance:

$$\sigma^2_{VIX_j} = \frac{2}{T}\sum_{i=1}^{n}\frac{\Delta K_i}{K_i^2}e^{rT}Q_t(K_i) - \frac{1}{T}\left[\frac{F_t}{K_0} - 1\right]^2 \tag{3.1}$$

where $i = 1, \ldots, n$ marks the options strike price available on that specific date, T is the expiration date, j is either (1) or (2), representing the near or far term, respectively, and F_t is the forward price of S&P 500 calculated from the Put-Call parity as $F_t = e^{rT}[c(K,T) - p(K,T)] + K$. Moreover, K_0 (Reference Price) is the first exercise price less or equal to the forward level F_t ($K_0 \leq F_t$) and K_i is the strike price of *i* - OTM option, which would be a call option if $K_i > K_0$, a put option if $K_i < K_0$ and the average between call and put options if $K_i = K_0$. r is the risk free rate with expiration T, and $\Delta(K_i)$ is the sum divided by two of the two nearest strike prices to the exercise price K_0.

As volatility rises and falls the strike price range of options tends to expand and contract. As a result, the number of options used in the calculation may vary from month to month, but even from day to day. The moneyness $= S/K$of the selected options ranges between 135% to 75%, varying according to the market period. The number of S&P 500 options available every day provides adequate supply of observation as to obtain a good VIX estimate. The number of observation is sufficient from both sides of the options distributions (calls and puts), this varying according to the market period (bullish or bearish). Before the global financial crisis the number of S&P 500 options for every day ranges between 60 and 100, whereas after the financial crisis and, mostly, in the recent years, the number of options available on S&P 500 every day is way above 100. The number of observation is also reduced every day as to account for simple options literature filter and rules (see Dennis and Mayhew, 2002; CBOE, 2009). Despite that, the number of options available is still sufficient for an adequate VIX computation.

Equation (3.1) is based on the variance swap approximation as shown by equation (3.2):

$$\sum_{i=1}^{n}\frac{\Delta K_i}{K_i^2}e^{rT}Q_t(K_i) \tag{3.2}$$

where $Q_t(K_i)$ is the price of a European call or put with a strike price respectively above or below K_0, the first strike price below F_0. In the case $K_i = K_0$, $Q_t(K_i)$ is equal to the average between an ATM call and an ATM put, relative to that strike price. To calculate the expected variance, an adjustment term is added to the expression in (3.2). This adjustment is required to convert in the money (ITM) calls to out of the money (OTM) puts: $\frac{1}{T}\left[\frac{F_0}{K_0} - 1\right]^2$. The VIX index is calculated by interpolating the near term variance and the far term variance, $\sigma^2_{VIX_1}(T_1)$ and $\sigma^2_{VIX_2}(T_2)$. These are the closest expirations to a 30 days average target in which monthly or weekly S&P 500 options are traded. The aim of the VIX calculation is to better track the 30-days implied volatility in the equity market, an

aim easily achieved with the introduction of Weekly S&P 500 options since 2014. Weekly S&P 500 options selected must have an expiration of ≥ 23 days, ≤ 37 days. When monthly S&P 500 options are selected, the first 3-months expirations are considered. VIX is calculated through the interpolation of the first two months expirations, 1M and 2M. Where the first month is not available or less than 3 days are left for its expiration, the selected month is rolled onto the next expiration, taking the 3M, since if shorter the impact of volatility and volume can misdirect the computation. The VIX index always reflects an interpolation of two points along the S&P 500 volatility term structure. The VIX index is calculated as follows through equation (3.1):

$$VIX_t = 100\sqrt{\frac{365}{30}\left[T_1\sigma^2_{VIX_1}\frac{N_2-30}{N_2-N_1} + T_2\sigma^2_{VIX_2}\frac{30-N_1}{N_2-N_1}\right]} \tag{3.3}$$

In order to compute the upside and downside components of the VIX , an adjustment is made to equation (3.1), applying filters on the K_i term. For VIX$^+$ only S&P 500 call options are considered when $K_i \geq K_0$, and for VIX$^-$ only put options are considered when $K_i \leq K_0$. We define the first options sub-sample with strike prices above the reference price as K_i^+ and the sub-sample below the reference price as K_i^-. Substituting K_i in equation (3.1) with both K_i^+ and K_i^- provides the two respective near and far term upside and downside variances:

$$\sigma^2_{VIX_t^j} = \frac{2}{T}\sum_{i=1}^{n}\frac{\Delta K_i^j}{(K_i^j)^2}e^{rT}Q_t(K_i^j) - \frac{1}{T}\left[\frac{F_t}{K_0}-1\right]^2 \quad with \quad j = + \quad or \quad - . \tag{3.4}$$

Resultantly, the two implied volatility components VIX$^+$ and VIX$^-$ are:

$$VIX_t^+ = 100\sqrt{\frac{365}{30}\left[T_1\sigma^2_{VIX_1^+}\frac{N_2-30}{N_2-N_1} + T_2\sigma^2_{VIX_2^+}\frac{30-N_1}{N_2-N_1}\right]} \tag{3.5}$$

$$VIX_t^- = 100\sqrt{\frac{365}{30}\left[T_1\sigma^2_{VIX_1^-}\frac{N_2-30}{N_2-N_1} + T_2\sigma^2_{VIX_2^-}\frac{30-N_1}{N_2-N_1}\right]} \tag{3.6}$$

Extracting volatility only from call options provides us with a proxy for upside implied volatility, whereas extracting volatility only from put options provides a proxy for the downside implied measure.

3.2.2 Decomposition of Realized Volatility

The importance of identifying the downside risk in the volatility, as shown in Ang et al. (2006), brings a decomposition of the realized variance measures in an attempt to better understand the two different risk components separately (see Barndorff-Nielsen et al., 2010; Patton and Sheppard, 2015; Segal et al., 2015). In this chapter, the realized volatility (RVOL) is calculated starting from the historical S&P 500 index returns, thus, using close to close price realized volatility measures consistent with the model-

free approach[2]. We have decided to use monthly low frequency close to close price realized volatility measures consistent with the model-free approach in order to compare the realized volatility measures directly with the decomposed implied volatility series. This is an end-of-the-month monthly volatility, computed from daily log-returns (see Schwert, 1989). The formula used in this chapter for the annualized realized volatility is $RVOL_t = \sqrt{\frac{252}{n}\sum_{i=1}^{n} r_i^2}$, where $r_i = ln(\frac{P_t}{P_{t-1}})$ representing daily log returns computed from the price difference, with P_i representing the S&P 500 daily index levels with $i \in \{1, \ldots, n\}$. The decomposition into the upside and downside components for the realized volatility is achieved by taking only sums over positive returns or sums over negative returns, indicated as RVOL^+ and RVOL^- , respectively. We further follow the methodology in Barndorff-Nielsen et al. (2010) to get:

$$RVOL_t^+ = \sqrt{\frac{252}{n}\sum_{i=1}^{n} r_{t,i}^2 1_{(r_{t,i}>0)}} \quad and \quad RVOL_t^- = \sqrt{\frac{252}{n}\sum_{i=1}^{n} r_{t,i}^2 1_{(r_{t,i}\leq 0)}}, \tag{3.7}$$

where $r_i = ln(\frac{P_t}{P_{t-1}})$ represents daily log returns computed from the price difference, with P_i representing the S&P 500 daily index levels with $i \in \{1, \ldots, n\}$. The upside semi-realized volatility considers only positive returns while the downside semi-realized volatility only negative returns.

3.2.3 Decomposition of Volatility Risk Premium

We are, now, able to combine these different volatility measures and their components according to their respective upside and downside binaries in order to obtain the volatility risk premium series. The importance of the risk premium for explaining stock market expected returns has been well documented in the literature (see Bollerslev et al., 2009; Kelly and Jiang, 2014; Feunou et al., 2017; Kilic and Shaliastovich, 2018). In this section, following the definition in Carr and Wu (2008), we compute the volatility risk premium by taking the difference between the physical measure of volatility (realized) and the risk neutral expectation of return variation extracted from options (implied). It represents the return of buying volatility in a volatility swap contract (see Carr and Wu, 2008), where the VIX replaces the conditional return volatility using a risk neutral probability measure and the realized volatility is given by the actual physical probability measure (see Bekaert and Hoerova, 2014; Feunou et al., 2017). Thus, by following Kilic and Shaliastovich (2018), we decompose the volatility risk premium into its upside and downside components, the first as the difference between RVOL^+ and VIX^+ and the latter as the difference between RVOL^- and VIX^- as follows:

[2]We are aware of the different volatility measures that have been developed, and that they can be computed at any frequency over a given sample period. For instance, high to low version by Parkinson (1980), the Garman-Klass formula of Garman and Klass (1980) and its improvement by Yang and Zhang (2000) taking into account the opening price jumps and zero drifts. It has been suggested that the simple historical volatility model (Figlewski, 1997) and standard historical volatility model (Andersen and Bollerslev, 1998) generally predict future volatility more accurately than the more complicated volatility models (e.g., ARCH and GARCH). Further exhaustive studies on realized volatility measures include Andersen et al. (2007) and McAleer and Medeiros (2008).

$$VRP_t^q = RVOL_t^q - VIX_t^q \quad where \quad q = Tot, +, -. \tag{3.8}$$

Other papers, such as, Bollerslev et al. (2009), Bekaert and Hoerova (2014) and Feunou et al. (2017) defined the variance risk premium as the difference between the risk neutral and physical expectations of return variation, finding a measure which is, most of the time, positive. In our chapter, we find a measure of risk premium which is, most of the time, negative due to the way it is calculated. Feunou et al. (2017), because of the same reason, also obtained opposite signs compared to us when decomposing risk premium in its upside and downside components.

3.3 Data: Volatility Series and Selected Variables

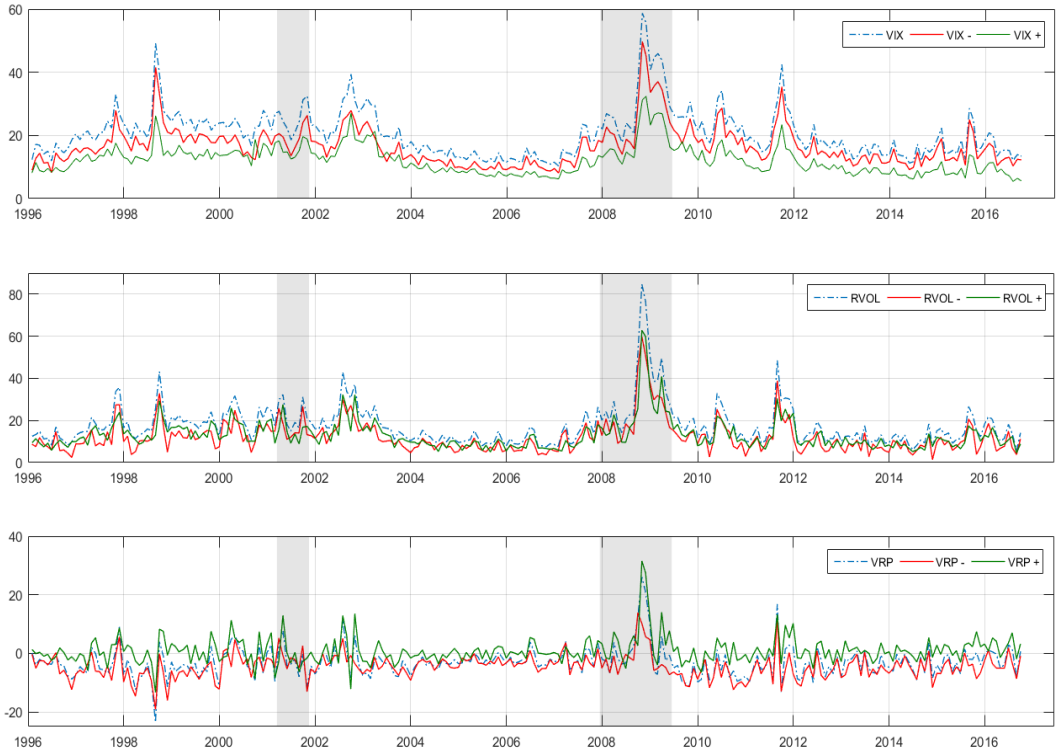
In this section, we illustrate the options data and stock market index (S&P 500) prices used to compute our volatility and risk premia series, and provide a discussion of our findings presenting plots and correlation analysis in relation to the volatility measures in subsection 3.3.1. Subsection 3.3.2 describes the macroeconomic and financial conditions variables which are used for the empirical analysis in order to test the hypotheses in this chapter.

3.3.1 Volatility Series and Descriptive Statistics

Daily S&P 500 options and index prices are collected from OptionMetrics and Bloomberg over a total time period ranging from 04-01-1996 to 29-09-2016. Daily observations total 5222, while when monthly observations are taken, end-of-the-month, they total 250 for each volatility and risk premium series in the study. The following Figure 3.1 illustrates the relationship between the decomposed model-free implied and realized volatilities as well as risk premia, at monthly frequency, during the total period. Events such as the Asian financial crisis, the dot-com bubble, the 9/11 terrorist attack, the Iraq invasion, the 2008 financial crisis and the Lehman Brother crash, the European sovereign debt crisis, the tension between Russia and Ukraine, the Chinese Yuan collapse and the Brexit vote, are only some of the various political, economic and financial events in the U.S. and worldwide which are included within our time period spanning from 1996 to 2016.

The upper panel in Figure 3.1 compares the VIX together with its upside and downside components. The spikes in the indexes correspond to all the main financial events during our time period. For instance, we notice a peak corresponding to the Asian financial crisis at the end of 1997, to the Russian Financial Crisis and to Long-Term Capital Management (LTCM) collapse in 1998, to the dot-com bubble period and the 2001-2002 NBER recession period (highlighted in gray). In response to the Russian financial crisis in August 1998, the VIX index reached its all time high before the global financial crisis. It then spiked massively during the 2008 financial crisis, especially in response to the

Figure 3.1: **Decomposed Volatility Series**



Notes: This figure shows a comparison between the VIX , VIX^- and VIX^+ indexes (upper panel), RVOL , RVOL^- and RVOL^+ (mid panel) and VRP , VRP^- and VRP^+ (bottom panel) during the period from 04-01-1996 to 29-09-2016, at monthly frequency. The NBER recession periods are highlighted in gray.

Lehman Brother collapse in September 2008. Subsequently, the implied volatility indexes reacted to the two stages of the European sovereign debt crisis, to Grexit and the Chinese Yuan crisis in mid 2015 and, finally, to Brexit in June 2016. The downside and upside implied volatilities closely track the aggregate measure VIX , especially during turbulent times and VIX^- is, most of the time, higher than VIX^+ (see DeLisle et al., 2014; Fu et al., 2016; Kilic and Shaliastovich, 2018). There are times, be it rare, when VIX^+ is higher than VIX^- , but only during calm and optimistic periods characterized by positive investors' expectations and a more active call options trading such as around the dot-com bubble. Post global financial crisis, VIX^- is always found to be higher than VIX^+ emphasizing the puts hedging role and investors' concerns regarding the possibility of another similar event occurring. We recognize that there exists an asymmetry in the volatility indexes possibly due to the fact that investors are more willing to buy put options for hedging purposes, especially during negative times, which, in turn, inflates the downside volatility component (Bollen and Whaley, 2004; Bondarenko, 2014).

The mid panel of Figure 3.1 depicts almost the same pattern for the realized volatilities which reacted and spiked to the same events. All the realized series move closely to each other. RVOL^- and RVOL^+ are more intertwined without a clear predominance of one over the other showing how both are equally important for the aggregate measure, RVOL . In turbulent market times and periods of

increased volatility, RVOL^- is found to be above RVOL^+ , having one of the highest spread around the 9/11 terrorist attack due to the stock exchanges closing, whereas during calmer periods and especially in bullish periods such as the dot-com bubble, RVOL^+ is found to be higher than RVOL^- (see Kilic and Shaliastovich, 2018).

The last panel of Figure 3.1 shows the trend for the volatility risk premia. We observe that the aggregate VRP oscillates between positive and negative values, being, on average, negative due to the fact that for most of the time VIX is higher than RVOL . VRP^- is also negative, whereas VRP^+ is positive for most of the time period. According to Feunou et al. (2017), VRP is the premium that a market participant is willing to pay to hedge against variation in future realized volatilities. This is expected to be positive, in their case, since they measure it as difference between implied and realized volatility which is, most of the time, positive. In their terms, the positive premium for VRP^- represents the amount financial agents should pay for protection against market downside risk entering into hedging strategies. However, VRP^+ is negative most of the time, indicating the amount agents would be willing to pay for investing in the volatility market specifically selling volatility. In this case the negative premium shows that, by contrast, the upside volatility could even increase the equity portfolios performance.

Table 3.1 reports the descriptive statistics for the volatility series. The maximum values for all the volatility series and premia are attained during the Lehman Brother collapse in September 2008. For realized volatility the minimum value is captured by the downside component, while for the implied by the upside component. The standard deviation of the downside implied and realized volatility, VIX^- and RVOL^- , is higher than the corresponding upside components, VIX^+ and RVOL^+ , while the opposite holds for premia. Skewness is found to be positive for all the volatility series and premia which are also leptokurtic. VRP^+ appears to be more right-skewed and leptokurtic compared with VRP and VRP^- .

Table 3.1: **Volatility Series Descriptive Statistics**

	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis
VIX	20.76	19.28	58.70	10.28	7.75	1.68	7.29
VIX^-	16.64	15.27	49.68	8.12	6.34	1.82	8.08
VIX^+	12.36	11.64	32.36	5.43	4.62	1.40	5.78
RVOL	17.73	15.23	84.75	5.73	10.04	2.82	15.56
RVOL^-	12.20	10.45	59.85	1.39	7.82	2.37	11.66
RVOL^+	12.86	10.79	62.79	4.51	7.28	3.04	18.02
VRP	-3.02	-3.51	26.04	-23.57	5.18	1.32	9.47
VRP^-	-4.43	-4.62	13.85	-19.11	4.19	0.50	5.72
VRP^+	0.85	0.29	31.53	-13.30	4.77	2.01	13.23

Notes: This table reports the main descriptive statistics and correlation analysis for the implied volatilities, realized volatility and volatility risk premia series during the period from 04-01-1996 to 29-09-2016, at monthly frequency.

The correlation analysis in Table 3.2 shows that upside and downside implied volatility are highly

correlated in levels, while less correlated in first differences. The same is also found for the realized volatility measures. These results are in line with many studies which have decomposed variance measures (see Barndorff-Nielsen et al., 2010; Fu et al., 2016; Feunou et al., 2017; Kilic and Shaliastovich, 2018). There is a high positive correlation between the implied and realized series decreasing from the aggregate to the upside. Positive, but smaller is the correlation between VRP^- and VRP^+ . Correlations among our volatility series decrease when first differences are taken and we observe that the correlations between upside and downside VRP are smaller than those for upside or downside volatilities (see Kilic and Shaliastovich, 2018). For this reason, in this chapter, we aim to show, first of all, how different options portfolios, namely, calls and puts, might contain different information compared to the VIX alone and, then, how the smaller correlation found between risk premia might suggest that these measures contain separate information and may be driven by different variables[3].

Table 3.2: **Volatility Series Correlation Analysis**

	Volatility Series: Levels								
	VIX	VIX^-	VIX^+	RVOL	RVOL^-	RVOL^+	VRP	VRP^-	VRP^+
VIX	1.00								
VIX^-	0.98	1.00							
VIX^+	0.96	0.92	1.00						
RVOL	0.86	0.85	0.82	1.00					
RVOL^-	0.84	0.84	0.80	0.95	1.00				
RVOL^+	0.79	0.79	0.76	0.95	0.82	1.00			
VRP	0.17	0.18	0.14	0.64	0.59	0.65	1.00		
VRP^-	0.08	0.06	0.10	0.49	0.58	0.34	0.82	1.00	
VRP^+	0.27	0.31	0.20	0.65	0.48	0.78	0.85	0.42	1.00
	Volatility Series: First Differences								
	VIX	VIX^-	VIX^+	RVOL	RVOL^-	RVOL^+	VRP	VRP^-	VRP^+
VIX	1.00								
VIX^-	0.92	1.00							
VIX^+	0.89	0.79	1.00						
RVOL	0.40	0.42	0.32	1.00					
RVOL^-	0.48	0.49	0.40	0.81	1.00				
RVOL^+	0.08	0.12	0.02	0.77	0.32	1.00			
VRP	-0.20	-0.15	-0.26	0.71	0.44	0.73	1.00		
VRP^-	-0.04	-0.05	-0.03	0.67	0.70	0.35	0.78	1.00	
VRP^+	-0.23	-0.14	-0.34	0.51	0.11	0.82	0.83	0.32	1.00

Notes: This table reports the correlation analysis for the implied volatility, realized volatility and volatility risk premium series during the period from 04-01-1996 to 29-09-2016, at monthly frequency.

However highly correlated implied and realized volatilities show different behaviours as it is shown in the existing literature with relation to many areas (see Segal et al., 2015; Patton and Sheppard, 2015; Baruník et al., 2016; Fu et al., 2016; Kilic and Shaliastovich, 2018). Despite similarity in correlation and in descriptive statistics, we check how these quantities will differ when added in dynamics and taken in first difference. Especially when considered at their first difference they show different behaviour and lower correlation. The first difference of these measures are the variables we use in the rest of the

[3]For a better insight into the correlation analysis, we have also computed correlations leaving out the months during the great financial crisis period. The correlations are:$Corr(VIX; VIX^-) = 0.97$, and $Corr(VIX; VIX^+) = 0.95$, $Corr(VIX^-; VIX^+) = 0.89$ $Corr(RV; RV^-) = 0.93$, $Corr(RV; RV^+) = 0.91$, $Corr(RV^+; RV^-) = 0.73$ in levels, and they are equal to $Corr(VIX; VIX^-) = 0.90$, $Corr(VIX; VIX^+) = 0.88$, $Corr(VIX^-; VIX^+) = 0.77$, $Corr(RV; RV^-) = 0.80$, $Corr(RV; RV^+) = 0.76$, $Corr(RV^+; RV^-) = 0.30$ at first difference.

chapter, in the OLS regression analysis as well as in the VAR model.

Our analysis is undertaken considering, not only the total time period spanning from January 1996 to September 2016, but also the pre-crisis and post-crisis periods. This is done with the aim of checking for potential differences in our dependent variables and covariates' behaviour. Upon applying a Bai and Perron (2003) break-point test on the daily S&P 500 and VIX series, August 2007 is selected as the pre-crisis ending month, having then a January 1996 - August 2007 pre-crisis sub-period with April 2009 as the month in which the global financial crisis turbulence vanished. Thus the post-crisis sub-period spans from April 2009 to September 2016.

3.3.2 Macroeconomic and Financial Variables

The variables in this study are divided into two main groups, namely, the macroeconomic variables and the financial conditions variables. The following macroeconomic variables are collected from FRED (Federal Reserve Economic Data) for the U.S.: the consumer price index (CPI) as a proxy for inflation, the industrial production (IP) as a proxy for the real activity, the unemployment rate (UR), the money supply (M1) and the real gross domestic product (GDP) as a variable accounting for changes in real economic activity. The quarterly GDP series is interpolated into a monthly series. The term structure component (TS) is computed as the difference between long term government bond rates (10 years) and short term government bond rates (2 years). The difference in interest rates should be considered at differences without logs (see Engle and Rangel, 2008). Among the macroeconomic variables we also include crude oil price (OIL), gold price (GOLD) and the JPY-USD exchange rate (ER), however these variables are extremely close to the financial market activity and can be considered a hybrid group. We adopted the JPY-USD exchange rate because the introduction of the EURO occurred after the beginning of our time period and we decided to select a exchange rate that was available for the entire time period. In addition, U.S. and Japan are two of the largest global economies and they are heavily linked through both imports and exports and are both mixed economies resulting in common news which might drive both the economies impacting on both stock markets (e.g. Karolyi and Stulz, 1996; Ng, 2000).

Among the financial conditions variables, we select those that better track the markets' reaction to financial, economic and political events, investors' sentiment and future expectations. However, they are included in the financial conditions category for simplicity. From FRED we collect the S&P 500 (SPX) as the stock market index proxy, the credit spread (CRE) computed as the difference between Moody's BAA and AAA corporate bonds yields (see Christiansen et al., 2012), the market sentiment (SENT) identified by the Consumer Sentiment Index from the University of Michigan which tracks consumers' attitudes and market expectations, and the TED spread (TED), computed as the spread between the 3-Month USD LIBOR and the 3-Month Treasury Bill. The TED spread has commonly been recognized in the financial literature as a liquidity proxy (Brunnermeier et al., 2008; Christiansen

et al., 2012). We also select variables that mostly track economic, political and geopolitical uncertainty, namely the U.S. Economic Policy Uncertainty (EPU) index by Baker et al. (2016) and the Geopolitical Risk (GPR) index by Caldara and Iacoviello (2018). These two variables are collected from the following web-sites, `http://www.policyuncertainty.com/` and `https://www2.bc.edu/matteo-iacoviello/gpr.htm`, respectively, at daily frequency and matched with the other daily variables by excluding weekend data.

The variables are collected at their highest available frequency which is monthly for CPI, IP, UR, M1, GDP (interpolated) and SENT, while all the other variables used in the main empirical analysis (TS, OIL, GOLD, ER, SPX, CRE, TED, EPU, GPR) are collected at daily frequency. As in Schwert (1987), all the variables are expressed in log-differences except those which are already expressed in percentage rates.[4] Following the augmented Dickey Fuller (ADF) unit root test, all the selected variables are first difference stationary I(1).

3.4 Identifying Determinants of Volatilities

The first part of our empirical section consists of a regression analysis, stepwise backward approach, in order to detect the main variables driving the aggregate and decomposed implied volatilities and the risk premia with the aim of testing **Hypothesis 1**, as mentioned in Section 3.2[5]. This empirical analysis is conducted over the total time period as well as over the two sub-periods, pre and post global financial crisis, in order to further test the following - **Hypothesis 2**: *A difference in significance among the selected variables in explaining the volatility series might be found between the total time period (1996-2016) and the two pre-crisis and post-crisis sub-periods.* Static results together with rolling p-values for those variables found to be significant in explaining the volatility series are reported in Section 3.5 for both the implied volatility and volatility risk premium. In addition, Granger causality tests are performed through Vector Autoregressive (VAR) models in order to test whether or not the macro and financial variables have informative power in explaining the implied volatility and risk premium measures and vice versa. In other words, we examine the presence of unilateral or bilateral relationships between the volatility series and their components and the independent variables by testing the following hypothesis - **Hypothesis 3**: *There are unilateral (or bilateral) interactions at different frequencies depending on the two volatility components and characteristics.* Results of the Granger analysis are reported in Section 3.6.

[4] We also undertake a correlation analysis between all the differences or log-differences of our determinants, finding that there is no evidence of multi-collinearity between the selected variables. We expected multi-collinearity between EPU and GPR though we found no evidence and, consequently, we can consider the two together in the same regression model.

[5] Other potential approaches have been considered for this empirical analysis, however the main drivers are found to be robust to the regression model chosen. More details are discussed in Section 3.5.

3.4.1 Relationship between Volatilities and Selected Variables

Because of stationarity issues, the first difference of the volatility series is taken to avoid problems of spurious regressions. The covariates we consider in the analysis are the macroeconomic and financial conditions variables discussed in Section 3.3.2. The regression analysis is conducted through the following equation:

$$\triangle VOL_t^q = \alpha + \sum_{j=1}^{n} \beta_j (\triangle X_{Macro,Fin})_{t,j} + \sum_{j=1}^{n-1} \gamma_j (\triangle X_{Macro,Fin})_{t-1,j} + \epsilon_t^q. \tag{3.9}$$

where VOL is either the VIX variable or the VRP variable with $q = Tot, +, -$ and X being the matrix containing the macroeconomic and financial variables with j varying from 1 to $n = 15$.

3.4.2 Low Frequency and High Frequency Granger Causality Test

The Granger causality approach conducted through different frequency VAR models is undertaken so as to obtain an improved understanding of the lead-lag relationships between the volatility measures and the financial conditions and macroeconomic determinants. We assess the significance of the impact of the determinants on the various implied volatility and risk premium measures, and furthermore, we also investigate whether these volatility measures or their upside or downside components contain useful information in predicting the economic and financial activity. More so the implied volatilities which are well recognized in the literature to anticipate the financial and economic conditions through investors' expectations and options trading. The information they carry is already projected ahead since they are 30-days forward looking information containers. Thus, from the Granger causality test it should emerge whether or not a set of variables contains useful information in predicting another set of variables, especially when the implied volatility indexes are considered (e.g. Diebold and Yilmaz, 2008). The results for each pair of variables considering differences or log-differences of the series is tested through the following VAR models for the low frequency (LF) and high frequency (HF) variables. The LF-VAR is expressed as follows:

$$\triangle Y_j^L = \omega^L + \sum_{i=1}^{\tau_L - l_L} \alpha_i \triangle Y_i^L + \sum_{i=1}^{\tau_L - l_L} \beta_i \triangle \chi_i^L + \epsilon_j^L \tag{3.10}$$

where L denotes the low frequency domain, $j = 1, ...6$ is an indicator for the variables available only at monthly frequency and included in χ^L, l_L is the lag indicator, in this case monthly with τ_L the number of observations in the sample, at monthly frequency. In the case of high frequency, we keep the implied volatility and risk premium measures as daily and model them in relation to the other variables available

at daily frequency. The HF-VAR model is expressed as follow:

$$\triangle Y_k^H = \omega^H + \sum_{i=1}^{\tau_H - l_H} a_i \triangle Y_i^H + \sum_{i=1}^{\tau_H - l_H} b_i \triangle \chi_i^H + \epsilon_k^H \tag{3.11}$$

where H denotes the high frequency domain, $k = 1, ...9$ is an indicator for the variables available at daily frequency, l_H is the daily lag indicator, τ_H is the number of observations of the daily sample. The regressors are the lagged Y dependent variables and the lagged χ^H independent variables and ϵ is distributed as $N(0, \sigma^2)$. The null hypothesis we test is H_0*: X does not Granger cause (GC) Y*, abbreviated to H_0*:* $X \nRightarrow_{LF} Y$ for the low frequency case, and to H_0*:* $X \nRightarrow_{HF} Y$ for the high frequency case and vice versa from Y to X.

3.4.3 Mixed Frequency Granger Causality Test

We check, in addition, whether or not temporal aggregation, in our case from high daily frequency to lower monthly frequency, end-of-the-month, may hide causality links among our covariates. According to Ghysels et al. (2016), a mixed frequency (MF) approach is able to recover more casual relationships compared to the standard LF approach which, in turn, might not capture causality even in simple cases. Given that our dependent variables are available daily and temporal aggregation would result in a loss of information, we test whether or not in our framework MF approach recovers underlying patterns better than the traditional LF approach.

We compare the analysis we have undertaken through a LF-VAR model considering the temporal aggregated volatility series, end-of-the-month, and common frequency with our macroeconomic variables, with the MF-VAR model which is run taking the volatility series at the highest frequency at which they are available. We then compare the interaction between our daily dependent variables (VIX , VIX^- , VIX^+ and VRP , VRP^- and VRP^+) and the six explanatory variables that are available only at monthly frequency.[6] The following hypothesis is tested - **Hypothesis 4**: *Mixed frequency (MF) analysis should uncover additional causality relationships among our covariates compared to the conventional low frequency (LF) approach.*

The following simplifying assumptions are applied for estimating the MF model: m is implicitly fixed equal to 20 and the total time period re-scaled accordingly[7] and only two frequencies are selected, namely, daily and monthly.

We discuss in details, the mixed-frequency VAR model together with the mixed frequency Granger

[6]The macroeconomic variables include CPI, IP, UR, M1, GDP plus market sentiment, SENT. We consider the interpolated GDP growth rate at monthly frequency so as not to complicate the analysis even further by having only a single variable at a different lower frequency.

[7]More specifically, since not every month contains 20 daily observations, but can vary from 19 to 23, we consider a common and fixed number of observations equal to 20. When more than 20 observations are observed the days exceeding 20 are averaged with the 20th observation, while when only less than 20 observations are available the interpolation between end-of-the month and beginning of the next month is considered. This allows us to still have a large sample totalling 4980 and 259 observations for HF and LF, respectively.

causality definition. According to Ghysels et al. (2016), the latter relies on and is an extension of Dufour and Renault (1998) definition. We follow the notation in Ghysels et al. (2016) and Ghysels (2016). The high frequency (HF) process includes $\{\{\chi_H(\tau_L,\kappa)\}_{k=1}^{m}\}_{\tau_L}$ and $\{\{\chi_L(\tau_L,\kappa)\}_{k=1}^{m}\}_{\tau_L}$, where $\tau_L \in \{0,....,T_L\}$ is the LF indicator (monthly), $k \in \{1,....,m\}$ is the HF indicator (daily) with m denoting the number of HF periods within the LF time. The HF variables are $\chi_H(\tau_L,\kappa) \in \mathbb{R}^{K_H \times 1}, \quad K_H \geq 1$ observations, whereas $\chi_L(\tau_L,\kappa) \in \mathbb{R}^{K_L \times 1}, \quad K_L \geq 1$ are latent LF variables since they are not observed at HF (daily). The MF process is given by all the HF variables $\{\{\chi_H(\tau_L,j)\}_{j=1}^{m}\}_{\tau_L}$ and only aggregate LF variables $\{\chi_L(\tau_L\}\}_{\tau_L}$ and the MF-VAR model contains all the observable variables in a mixed frequency vector:

$$\chi(\tau_L) = [\chi_H(\tau_L,1)',....,\chi_H(\tau_L,m)',\chi_L(\tau_L)']'. \tag{3.12}$$

where the dimension of the MF-vector is $K = K_L + mK_H$ and the LF block, $\chi_L(\tau_L)$, is conventionally observed after the HF block of variables, $\chi_H(\tau_L,m)$. $X(\tau_L)$ follows a VAR(p) model for some $p \geq 1$ as follows:

$$\chi(\tau_L) = \sum_{p}^{k=1} A_k \chi(\tau_L - k) + \epsilon(\tau_L) \tag{3.13}$$

where A_k are the $K \times K$ matrices for $k = 1,...,p$ and the error vector $\epsilon(\tau_L)$ is a strictly stationary martingale difference. The condition for stationarity applies here as in the LF-VAR case, and variables log-differences and first differences are taken. After having estimated the MF-VAR model illustrated in Formula 3.13, we test for Granger causality in mixed frequency case defined as in Ghysels et al. (2016) who relies, in turn, on Dufour and Renault (1998) definition of:

Definition 3.4.1. Granger (Non)-Causality at Different Horizons. **y** does not cause **x** at horizon h given l (we denote it as $\mathbf{y}NGC_h\mathbf{x} \mid l$) if: $P[\mathbf{x}(\tau_L + h) \mid \mathbf{x}(-\infty,\tau_L] + \mathbf{z}(-\infty,\tau_L]] = P[\mathbf{x}(\tau_L + h) \mid l(\tau_L)] \forall_{\tau_L} \in \mathbb{Z}$ and **y** does not cause **x** up to horizon h given l ($\mathbf{y}NGC_h\mathbf{x} \mid l$ if $\mathbf{y}NGC_k\mathbf{x} \mid l$ for all $k \in 1,....,h$.

Considering $\mathbf{W}(\tau_L) = [\mathbf{x}(\tau_L)',\mathbf{y}(\tau_L)',\mathbf{z}(\tau_L)']'$ as a vector of random variables, $l(\tau_L) = \mathbf{W}(-\infty,\tau_L)$ is the Hilbert space spanned by the vector $\mathbf{W}(\tau) \mid \tau \leq \tau_L$. In other words $l(\tau_L) = \mathbf{x}(-\infty,\tau_L) + \mathbf{y}(-\infty,\tau_L) + \mathbf{z}(-\infty,\tau_L)$. $P[\mathbf{x}(\tau_L + h) \mid l(\tau_L)]$ is the best linear prediction of $\mathbf{x}(\tau_L + h)$ based on $l(\tau_L)$ which, according to definition A.1 is unchanged whether the past and present values of **y** are available or not. Further details on the notation and specification of the Granger causality at different horizon in Dufour and Renault (1998).

In our case, the MF-VAR model is constructed by including one dependent HF variable, χ_H, which can be, in turn, VIX or VRP (or their sub-components) and six LF explanatory variables $\chi_{L,1...6}$ with $m = 20$ being the frequencies ratio. Expanding equation (3.12), we obtain, in this case, a 26×1 vector

as follow:

$$\chi_{\tau_L} = [\chi_{H,j}(\tau_L, j, 1), \chi_{H,j}(\tau_L, j, 2), ..., \chi_{H,j}(\tau_L, j, 20), \chi_{L,1}(\tau_L), \chi_{L,2}(\tau_L), ...\chi_{L,6}(\tau_L)] \quad (3.14)$$

where the two concatenated mixed frequency sub-vectors are $[\chi_{H,j}(\tau_L, j, 1), \chi_H(\tau_L, j, 2), ..., \chi_H(\tau_L, j, 20)]'$ at HF and $\chi_L(\tau_L)$ at LF with $j = 1...6$ indexed for the two set of model-free volatility measures considered in the chapter, namely, VIX , VIX^- , VIX^+ , VRP , VRP^- and VRP^+ . As an example, for the first variable, aggregate VIX and the six LF variables, the concatenated vector would be as follow:

$$\chi_{\tau_L} = [VIX_H(\tau_L, 1), VIX_H(\tau_L, 2), ..., VIX_H(\tau_L, 20), CPI(\tau_L), GDP(\tau_L), UR(\tau_L), IP(\tau_L), M1(\tau_L), SENT(\tau_L)] \quad (3.15)$$

Following Ghysels et al. (2016) and by applying definition 3.4.1, χ_H does not Granger cause χ_L at horizon h given l ($\chi_H \nRightarrow \chi_L \mid l$) if $P[\chi_L(\tau_L + h) \mid \mathbf{x}_{H,2}(-\infty, \tau_L] + \chi_L(-\infty, \tau_L]] = P[\chi_L(\tau_L + h) \mid l(\tau_L)] \forall_{\tau_L} \in \mathbb{Z}$. The same definition applies for the reverse, χ_L does not Granger cause χ_H at horizon h given l ($\chi_L \nRightarrow \chi_H | l$).

To sum up, we test all three possible Granger causality cases according to the frequency of our variables:

- **I Case: LF to LF** - Granger causality from the χ_{L,i_1} to the χ_{L,i_2} low frequency variable at horizon h through model (3.10) considering all the variables at monthly frequency. $H_0^1 : \chi_{L,i_1} \nRightarrow_{LF} \chi_{L,i_2} \mid l$.
- **II Case: HF to HF** - Granger causality from the χ_{H,i_1} to the χ_{H,i_2} high frequency variable at horizon h through model (3.11) considering only the variables available at daily frequency. $H_0^2 : \chi_{H,i_1} \nRightarrow_{HF} \chi_{H,i_2} \mid l$.
- **III Case: Mixed Frequency (MF)** - Granger causality from the χ_{L,i_1} low frequency to the χ_{H,i_1} high frequency variable at horizon h (and vice versa from the χ_{H,i_1} to the χ_{L,i_1}) through model 3.15 considering our set of variables at the available frequency $H_0^3 : \chi_{L,i_1} \nRightarrow_{MF} \chi_{H,i_1} \mid l(\chi_{H,i_1} \nRightarrow_{MF} \chi_{L,i_1} \mid l)$.

Lags are selected in accordance with the minimum value between Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) for the LF-VAR and HF-VAR, while the MF-VAR lag is chosen equal to one, $l = 1$. The prediction horizon h is set between one and four, $h \in \{1, \ldots, 4\}$. As discussed in Ghysels et al. (2016) redundant lags might have an adverse impact on power especially when h, the prediction horizon, increases. The groups of variables in the MF-VAR are the LF-monthly variables (CPI, GDP, IP, UR, M1, SENT) and the HF-daily dependent implied volatility and risk premium series. The frequency ratio is set to $m = 20$ such that the LF observations in our MF-VAR model are equal to $T_L = 249$ ($T_H = 4980$ HF observations divided by 20). $K_H = 1$, is the dependent

variable, whereas $K_L = 6$, are the low frequency variables having a total number of variables in the MF-VAR which is $K = 26$. The analysis is run following Ghysels et al. (2016), considering Newey (1987) HAC covariance estimator and Newey and West (1994) automatic lag selection.

3.5 Relationship between Volatilities and Selected Variables: Empirical Results

In this section we report the results of the stepwise regression analysis of the aggregate and decomposed model-free implied volatility indexes, VIX , VIX^- and VIX^+ , and of the aggregate and decomposed volatility risk premia, VRP , VRP^- and VRP^+ , onto the macroeconomic and financial variables performed by running equation (3.9). Due to the large number of covariates, a stepwise backward regression approach with stopping threshold equal to 0.1% is undertaken. One period lagged variables are also included in the analysis to check for any possible interactions of the lagged variables. The results of the stepwise backward regression are presented in Table 3.3 for the implied volatilities and risk premia in the first panel and second panel, respectively.

3.5.1 Implied Volatility Stepwise Regression Analysis

We observe, in general, that the stock market proxy, S&P 500 , impacts significantly on the implied volatility indexes, with a negative sign in the contemporaneous relationship, whereas positive and decreasing in the first lag. The S&P 500 index appears to be impacting more on the VIX^- during the post financial crisis, showing investors' concerns about market downturns and the possibility of another crisis which is reflected in the puts hedging strategies. The S&P 500 has a sizeable contribution to the adjusted R^2, explaining on its own about half of this goodness-of-fit statistic. This variable plays an important role in our analysis and controlling for it, allows us to compare our results with previous studies in this area (see Paye, 2012; Christiansen et al., 2012). Furthermore, retaining the S&P 500 variable also permits us to investigate volatility properties in relation to the equity variable such as leverage effect as well as to study its asymmetric impact on decomposed volatility series. Considering the equity levels in the Granger analysis allows us to anchor our chapter to previous literature that has studied the predictability power of volatility and risk premia towards equity and vice versa (see Feunou et al., 2017; Kilic and Shaliastovich, 2018).

Some of the pure macroeconomic variables, namely inflation (CPI), industrial production (IP), gross domestic product (GDP), money supply (M1) and term structure (TS) are weakly significant in explaining the VIX indexes, with significance levels, where significant, never exceeding 5%. No relevance at all is found for unemployment rate (UR). Macroeconomic variables, such as CPI, IP and GDP appear to be also more significant in explaining the VIX^+ component, the agents consumption willingness or

a country's production ability being linked to the good volatility proxy. Inflation shows a weak effect with regards to volatility in line with previous studies, and the sign of this relationship in contemporaneous time is found to be negative, the opposite to previous studies looking at realized volatility (e.g. Schwert, 1989; Paye, 2012; Engle et al., 2013). This interesting negative relationship between changes in implied volatilities and changes in inflation might be justified by the fact that the time period of this study has been characterized by a relatively low level of inflation in the U.S., thus, investors react in a positive way when, starting from a very low level, inflation increases, since this is considered good news for the stability of the financial system and leads to a decrease in volatility (see Coibion et al., 2012). An increase in inflation might be seen as an economic stimulus and stabilization implying less uncertainty on the investors' consumptions and trades, thus, decrease of VIX^{+} . On the other hand, when inflation moves towards disinflation or, eventually, deflation, this is actually bad news for the economy and the volatility may suddenly increase.

During the total and pre-crisis periods, we find that the impact of the macroeconomic variables is skewed towards the upside implied volatility, VIX^{+} , with their role appearing to be placed mostly in the call options, whereas financial variables appear to impact more on VIX and VIX^{-} , the aggregate and downside implied volatilities. It is found that an increase in the credit spread drives an increase in the implied volatility. This is due to the variation in the credit default conditions underlying the bonds which reflects the credit risk perception and changes in the financial market, thereby being related to financial volatility in a positive way, and this link appears to pass, mainly, through the puts channel.

The JPY-USD exchange rate is found to be a significant driver of the implied volatility indexes impacting with a negative sign in contemporaneous time. One must recognize that the exchange rate is quoted as number of yens per one dollar and the U.S. is a net importer. Hence, when JPY-USD drops, the dollar depreciates against the yen, resulting in U.S. companies experiencing more expensive imports which will increase their costs and impact negatively on their revenues and on their stock prices, thus, resulting in an increase in stock market volatility. The opposite chain applies when JPY-USD rises and dollar appreciates against the yen. This relationship might also be discussed with a more market sentiment explanation, such as, when the dollar appreciates against a foreign currency this is seen as a stabilization and strengthen signal for the U.S. economy, thus, it might reflect in a drop in the U.S. uncertainty level and so in a drop in the "fear" index, VIX , and vice versa when dollar depreciates. While the first more market driven explanation might apply with relation to the VIX^{+} , more related to investments and consumptions, the second market sentiment explanation might be more related to the VIX^{-} , more related to investors fear and uncertainty. Overall, both volatility components are negatively related to the exchange rate, thus, resulting in an overall negative relationship between JPY-USD and volatility.

Table 3.3: **Stepwise Backward Regression between Implied Volatilities, Risk Premia and Selected Variables**

PANEL 1: Stepwise Backward Regression between Implied Volatilities and Selected Variables

	Total Period						Pre-Crisis Period						Post-Crisis Period					
	VIX		VIX^-		VIX^+		VIX		VIX^-		VIX^+		VIX		VIX^-		VIX^+	
	t	t-1	t	t-1	t	t-1	t	t-1	t	t-1	t	t-1	t	t-1	t	t-1	t	t-1
CPI	-0.064*		-0.080*		-0.114**	0.081*					-0.863*						-0.278**	
IP			0.277*			0.295*	0.421**		0.539**			0.593**						
GDP	0.112*				0.125*	-0.127*	0.168*				0.234**	-0.178*	0.274**		0.313**			
UR																		
M1								-0.328**				-0.402**						
TS	0.101*				0.150**	-0.142**				0.176*	0.219**							
OIL																		
ER	-0.068**		-0.078*		-0.062*								-0.129*	0.136**				0.147**
GOLD																		
SPX	-0.260***	0.090***	-0.256***	0.082***	-0.269***	0.091***	-0.216***	0.089***	-0.226***	0.059***	-0.206***	0.121***	-0.403***	0.180***	-0.465***	0.210***	-0.401***	0.133***
CRE	0.149*		0.209**											0.314**		0.432***		0.331**
SENT					-0.403*			-0.665***		-0.606*		-0.627**						-0.044*
TED							0.058*		0.100**					-0.104*		-0.116*		-0.103*
EPU	0.127**	0.107**	0.184***	0.145**			0.196***	0.132*	0.268***	0.157*					0.217*			
GPR	-0.040*		-0.055**						-0.067**									
Adj R^2	0.558		0.466		0.550		0.525		0.415		0.517		0.663		0.638		0.660	

PANEL 2: Stepwise Backward Regression between Risk Premia and Selected Variables

	Total Period						Pre-Crisis Period						Post-Crisis Period					
	VRP		VRP^-		VRP^+		VRP		VRP^-		VRP^+		VRP		VRP^-		VRP^+	
	t	t-1	t	t-1	t	t-1	t	t-1	t	t-1	t	t-1	t	t-1	t	t-1	t	t-1
CPI						0.277**						0.376*						
IP																		
GDP																		
UR				-0.386*				-0.684*		-0.803**								
M1	0.707*	-0.643*	0.739**	-0.916***			1.493**	-1.764***		-1.563***	1.035**	-1.125**						
TS					0.710***	-0.380*			0.733**									
OIL							1.579**		1.396**		0.843*			-2.875***		-2.019*		-2.422***
ER		0.423***		0.328**		0.308**								0.676**		0.700**		
GOLD													0.249*			-0.283**	0.198**	
SPX	0.294***	-0.511***	-0.126*		0.529***	-0.646***	0.278**	-0.796***	-0.242**	-0.226**	0.549***	-0.953***	0.828***	-0.505**	-0.420*		0.761***	-0.498***
CRE	0.684*	-0.890**			1.242***	-1.027***		1.107*	1.613***			1.608***	2.292**	-2.192***		-2.392***	2.068***	-1.060*
SENT	-0.176**	0.144*	-0.142**		-0.150**										0.217*	-0.227*		
TED													0.727**		0.729**		0.407*	
EPU	0.459**		0.252*	0.414*	0.205**								0.827**	1.042**	0.813**	0.778**		
GPR					-0.125*			-0.279**		-0.198*		-0.225**						
Adj R^2	0.268		0.234		0.508		0.348		0.180		0.650		0.363		0.309		0.432	

Notes: This table presents the output of the stepwise backward regression analysis between our dependent variables, both implied volatilities (VIX , VIX^- and VIX^+) and also the volatility risk premia (VRP , VRP^- and VRP^+) and the 15 selected macroeconomic and financial variables, namely, Inflation (CPI), Industrial Production (IP), Gross Domestic Product (GDP), Unemployment Rate (UR), Money Supply (M1), Term Structure (TS), Oil Price (OIL), JPY-USD Exchange Rate (ER), Gold Price (GOLD), S&P 500 Index (SPX), Credit Spread (CRE), Market Sentiment (SENT), TED Spread (TED), Economic and Policy Uncertainty (EPU) Index and GeoPolitical Risk (GPR) Index in the first and second panel, respectively. The regressions as shown in equation (3.9), for implied volatility: $\triangle IV_t^q = \alpha + \sum_{j=1}^{n} \beta_j (\triangle X_{Macro,Fin})_{t,j} + \sum_{j=1}^{n-1} \gamma_j (\triangle X_{Macro,Fin})_{t-1,j} + \epsilon_t^q$ and for risk premium, $\triangle VRP_t^q = \alpha + \sum_{j=1}^{n} \beta_j (\triangle X_{Macro,Fin})_{t,j} + \sum_{j=1}^{n-1} \gamma_j (\triangle X_{Macro,Fin})_{t-1,j} + \epsilon_t^q$ are run for contemporaneous variables (t) and one period lag (t-1) variables. The table reports the regression coefficients only for the variables that passed the stepwise regression test. Selection method is stepwise backwards with stopping threshold p-values higher than 10%. All the variables are taken with difference or log-difference and re-scaled accordingly. Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01. The regression is run over the total period, from 04-1996 to 09-2016, over the Pre-Crisis period from 01-1996 to 08-2007 and over the Post-Crisis period from 04-2009 to 09-2016, at monthly frequency.

The variables EPU and GPR present higher coefficients and stronger significance with respect to VIX^- impacting more on the put options side, whereas they appear to never impact on the VIX^+ . This reflects the investors' fear regarding economic, political and geopolitical uncertainty, and consequently the investors' willingness to hedge themselves against it. The positive relationship between the EPU index and the implied market volatility is in line with Pastor and Veronesi (2012, 2013).

The geopolitical risk index by Caldara and Iacoviello (2018) is found to show a negative relationship mainly with VIX^- which is justified by the composition of the index which does not appear to respond to financial events in the same way of VIX and EPU. The relationship between GRP and implied volatility is found to emerge mainly in the period before the crisis due to the presence of events such as 9/11 and Iraq invasion as confirmed also from Figure 3.2. The relationship between implied volatilities and EPU and GPR will be analysed more in-depth in Section 3.7.

Interestingly, in the pre-crisis period, we find no role for commodities, exchange rate and credit in driving the implied volatilities. We find, instead that the implied volatilities are driven by variables, such as, market sentiment, liquidity, EPU and GPR indexes as well as the stock market, finding that might be justified by the events which occurred during this time period. This time period includes events such as the Asian financial crisis, the Russian financial crisis and the LTCM collapse in 1998, the 9/11 terrorist attack and the recession period between 2001-2002, all events which spread uncertainty for the U.S. economic stability. We find that the liquidity proxy, TED, is positively related, in contemporaneous time, to stock markets falls, and, consequently, to an increase in financial market volatility in line with Christiansen et al. (2012). This is due to the fact that an increase in the TED spread is seen as a warning sign, namely that liquidity might be withdrawn due to the fact that lenders expect an increase in counterparty risk which in turn will increase the LIBOR component of the TED spread, a mechanism which reached its extreme during the global financial crisis (see Cornett et al., 2011).

The post financial crisis bullish period and the exuberance resulting from the dot-com bubble period might, instead, be identified as possible causes for the fact that market sentiment impacts mainly on the upside volatility proxy, VIX^+ . The sentiment index has a lagged and inverse relationship with implied volatilities. This relationship is interesting knowing that the sentiment index seems to reduce the level of the next period implied volatilities, which itself makes sense in that it reduces the investor's uncertainty about the future spending behaviour of consumers and general future states of the economy.

In the post-crisis period, we observe a weak and minimal effect of macro determinants on the implied volatilities. Table 3.3 shows a clear shift from a mixed macro-financial variables effect detected in the pre-crisis period towards a financial oriented determinants effect in the post-crisis period. Iconic is the role of industrial production, a variable which illustrates changes in the structure of the economy and may be an indicator of future inflation thereby possibly impacting on financial markets. While in the post-crisis period the level of IP was very low thus having no impact on financial market volatility,

during the pre-crisis period we observe how higher level of IP signals a stronger economy, future inflation outlook and, thus, it plays a role on the financial market. Basically, during the post-crisis period, the concerns of another event such as the global financial crisis had moved the attention of investors trading S&P 500 options underlying VIX towards other variables such as credit, TED spread, EPU index and market sentiment, more related to investors' expectations, financial risk and uncertainty.

In general, we can assess that the variables identified as playing a more important role in influencing both the aggregate VIX and VIX^{-} are more attached to the financial market conditions group of variables, namely credit spread, market sentiment and the EPU index. These variables are the ones found to be significant at the 1% level at least once either over the total time period or over the two sub-periods. On the other hand, macroeconomic variables play a smaller role showing significance at the 5% level and their effect is placed, most of the time, on the upside volatility component, VIX^{+} . We find no relevance at all for commodities in explaining the implied volatility indexes. For instance, gold which is mainly seen as a hedge against inflation, shows a negligible effect in relation to volatility due to the overall low period of inflation in the U.S. It is notable that the lag of the credit proxy appears to increase in importance in the post financial crisis, whereas the EPU effect is found to be, in general, stronger in a contemporaneous framework, with coefficients decreasing in significance when the first lag is considered. These two findings are in line with Amengual and Xiu (2017), confirming that policy news is more relevant in the short term while credit default spread is important in the long run.

3.5.2 Volatility Risk Premia Stepwise Regression Analysis

The second panel in Table 3.3 shows how the aggregate volatility risk premia are largely impacted by the S&P 500 , credit, market sentiment, and economic and policy uncertainty during the total period. Among the macroeconomic variables, money supply has the largest and most significant impact on the all the premium series before the crisis, but it becomes non-significant after the crisis, possibly due to important changes in monetary policies. In the pre-crisis period, we find that inflation is still driving the upside component, VRP^{+} , while over this period the term structure drives VRP^{-} . The unemployment rate shows its major impact on VRP^{-} . The post-crisis period shows a poor role for the macroeconomic variables in impacting the VRP series, instead finding that the VRP series are mostly impacted by commodities, such as, oil and gold, and the exchange rate (except for VRP^{+}) and also the financial conditions variables.

In the total period, the JPY-USD exchange rate is also found to be highly significant in influencing all the VRP series with its first lag. A similar predominant role is found for S&P 500 and credit, EPU index and market sentiment, Commodities such as, oil and gold are shown to be significant in explaining the volatility risk premia, in contrast to the implied volatility indexes where they were found to have difficulty showing significance. In particular, oil is significant during the two sub-periods, with

a positive sign on the risk premia coherent with the well established negative relationship between oil price and stock market confirmed. The pre-crisis period being stressed by turbulence due to the Iraq war and the post-crisis period by OPEC cutting oil production and the tension in the Middle East.

Regarding the equity market, we detect a stronger impact of S&P 500 on the VRP^+ in the total and pre-crisis periods, whereas a smaller impact on the VRP^+ in the post-crisis period compared to the aggregate. The predominant role of the VRP^+ as a volatility risk premium component confirms the results in Kilic and Shaliastovich (2018) who found that the VRP^+ is more related to the aggregate risk premium, and also in line with Feunou et al. (2017) who found that the VRP^+ is the main component of the aggregate VRP .[8] We find a positive and significant (1%) relationship between VRP^+ and the stock market, whereas a negative and barely significant (10%) between the VRP^- and the stock market during the total period. We observe that when S&P 500 increases, VRP^+ increases as well, VRP^- decreases, while VRP shares, most of the time, the same sign as for the VRP^+ implying it increases. However, while is evident that the VRP^- (VRP^+) shows a negative (positive) relationship with the equity market, the relationship sign between the aggregate VRP and equity can sometimes be masked since it is a mixture of information emanating from the two components, VRP^+ (positive sign) and VRP^- (negative sign) as pointed by Kilic and Shaliastovich (2018). In addition, we also notice that the VRP^+ is influenced by more variables compared to VRP and VRP^- , resulting in a higher adjusted R^2, in both the total sample and sub-samples.

We find a positive relationship between the EPU index and risk premia, regardless of their nature, implying that the higher the economic and policy uncertainty the higher the premia that the investors are willing to pay in order to be hedged against it, in line with Pastor and Veronesi (2012, 2013). The relationship between EPU and the negative component (VRP^-) is confirmed to be stronger when compared to the upside component (VRP^+) risk premia case. We detect no role for EPU in the pre-crisis period. Interestingly, we find, again, a shift in the role of the variables when moving from the pre-crisis to the post-crisis period during which we notice that there is no role left for the macroeconomic variables in explaining the volatility risk premia. On the other hand, financial variables, such as, equity, credit, liquidity and the EPU index, but also commodities, strengthen in their role in the post-crisis period, with increased β coefficients as compared to the pre-crisis or total period.

In Table 3.3 it can be seen that the signs of the coefficients for some variables change when lags are introduced. Thus, we examine the coefficients of the second difference, $\triangle X_{t-l} - \triangle X_{t-l-1}$ with $l = 0, 1$ over the total time period by running the following regression model for both the implied

[8] In Feunou et al. (2017) however, VRP^+ corresponds to the downside VRP since they compute the risk premia as a difference between implied volatilities and realized volatilities, opposite to us.

volatility and volatility risk premium:

$$\triangle VOL_t^q = \alpha + \sum_{j=1}^{n} \beta_j (\triangle^2 X_{Macro,Fin})_{t,j} + \sum_{j=1}^{n-1} \gamma_j (\triangle^2 X_{Macro,Fin})_{t-1,j} + \epsilon_t^q. \tag{3.16}$$

where $q = Tot, +, -$. In relation to the implied volatility, we find that despite the change in sign, the speed of the rate of change coefficient is found to be positive for inflation, credit, liquidity and term structure ($\triangle^2 CPI$, $\triangle^2 CRE$, $\triangle^2 TED$, $\triangle^2 TS$), whereas it is found to be negative for S&P 500 and GDP ($\triangle^2 S\&P500$, $\triangle^2 GDP$) confirming the leverage effect for S&P 500 and the GDP negative relationship with volatility as suggested in the literature (e.g. Engle and Rangel, 2008). Stock return volatility behaves counter-cyclically (e.g. Schwert, 1989; Paye, 2012) moving counter-cyclically with respect to GDP (see Campbell and Diebold, 2009). We also check the speed of the rate of change coefficient with respect to those variables where the sign of the coefficient changes between time periods t and $t-1$ in relation to the volatility risk premia ($\triangle^2 M1$, $\triangle^2 S\&P500$, $\triangle^2 CRE$, $\triangle^2 SENT$) finding that the coefficients sign detected at time 0 holds for all the variables.

In short, partial least squares regression is probably the least restrictive of the various multivariate extensions of the multiple linear regression model. This flexibility allows it to be used in situations where the use of traditional multivariate methods is severely limited, such as when there are fewer observations than predictor variables. Furthermore, partial least squares regression can be used as an exploratory analysis tool to select suitable predictor variables and to identify outliers before classical linear regression.

To conclude this Section, preliminary results of this chapter were obtained by using alternative regression analysis and methodologies. The robustness of the results has checked by, first, employing a stepwise forward regression with threshold 0.1% and, second, by implementing a partial least squares regression. The latter is also commonly used as an exploratory analysis tool in order to select the main predictor variables from a wide range before classical linear regression. The sensitivity of the results is found not to depend on the methodology chosen and the main variables emerged with the stepwise backward regression still hold when robustness checks are undertaken. We decided to report the results of the stepwise backward regression for easier comparison between the decomposed VIX and VRP analysis and in order to further highlight the difference in variables significance and coefficients' sizes when the dependent variable is changing (VIX , VIX^+ , VIX^- and VRP , VRP^+ and VRP^-). The covariates found to be significant in explaining one of the selected dependent variables lead to the same results and regression explanatory power when re-fitted in OLS regressions. As will be shown in Section 3.6, similar results and same set of drivers are also detected as main explanatory variables in the Granger causality analysis, further reinforcing the validity of the results of our stepwise regressions.

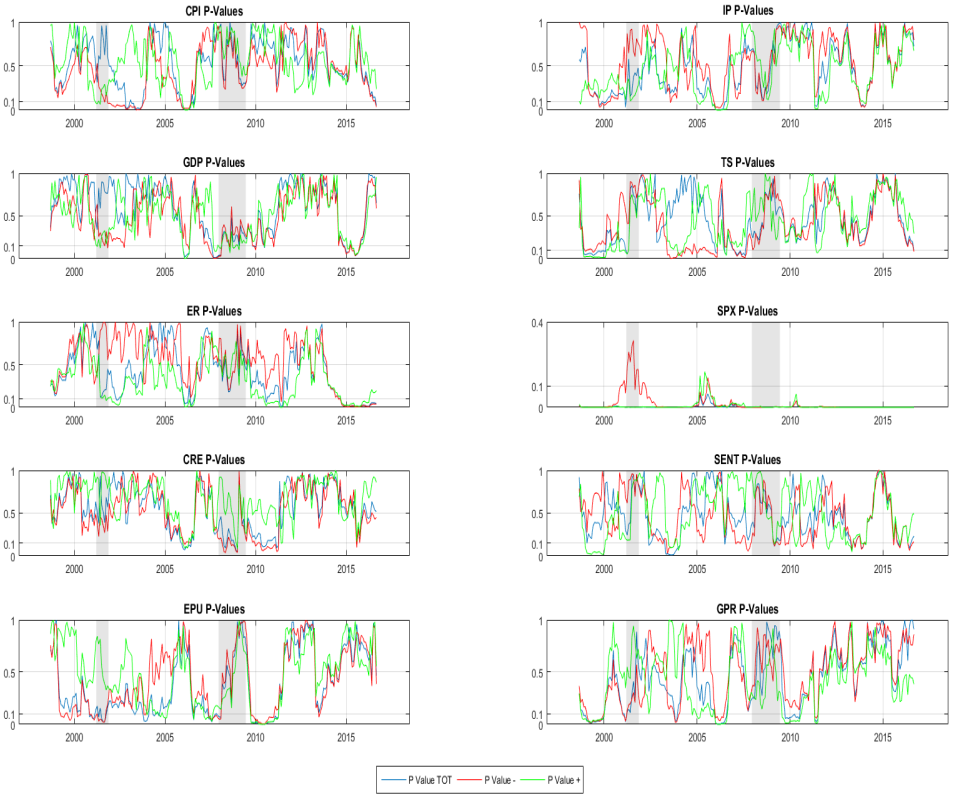
3.5.3 Implied Volatilities and Risk Premia Rolling Regressions

Overall, from Table 3.3, we detect an asymmetric impact of the selected variables according to the different volatility components studied. In order to further test both **Hypothesis 1** and **Hypothesis 2** in a dynamic framework, we conduct a rolling regression over the total time period. Figures 3.2 and 3.3 show the selected variables' rolling p-values for the VIX and VRP series, respectively. The rolling p-values are reported only for those variables found to be significant for at least one of the VIX series or VRP series from the stepwise backward regression in Equation 3.9 as reported in Table 3.3 over the total time period. Rolling window length is selected equal to 30 months and the regression is rolled every month.

For the implied volatility, interesting differences in behaviour of the selected variables emerge from the pre-crisis to the post-crisis periods and especially in the midst of the two recession periods. For instance, before the first 2001-2002 recession period, resulting from the dot-com bubble and optimistic investors' expectations, many of the variables (CPI, TS, S&P 500 , SENT) are shown to be impacting mainly on the VIX^{+} , a proxy for upside implied volatility, rather than on the negative component. Market sentiment actually only affects the VIX^{+} component during the dot-com bubble, reflecting the investors' exuberance at that time. Inflation is found to be significant mainly during the pre-crisis period, while during the post financial crisis inflation is hardly seen as a problem in the U.S. as also reflected in Table 3.3. Industrial production alternates, showing periods in which it impacts more on VIX^{-} , while others on VIX^{+} . GDP is found mainly to be significant in the period surrounding the financial crisis and the 2008-2009 recession, but also at the end of 2014 and beginning of 2015. After the dot-com bubble, term structure is found to be significant for VIX^{+} while relevant for VIX^{-} in the immediate pre-crisis period. The JPY-USD exchange rate is associated mainly with the VIX^{+} , especially in the post global financial crisis. For instance, in October 2010 the dollar value dropped below 84 yen for the first time in almost two decades. It was seen as negative news for U.S. companies facing more expensive imports and reflected on American consumers and, in turn, reflected on VIX^{+} , more associated to investors' consumption sphere. By the end of 2014, the dollar increased above 110 yens and JPY-USD is found, again, to mainly impact on VIX^{+} .

The credit measure, as shown also in Table 3.3, emerges as significant for VIX^{-} mainly in the post-crisis period. Market sentiment appears to drive the two implied volatility components according to the market period and investors' beliefs. It impacts on the VIX^{+} component during the dot-com bubble and it translates into carrying fear and concerns to the VIX^{-} in the immediate pre and post financial crisis periods. The EPU index impacts mainly on the VIX^{-} responding to concerns due to events such as; the Russian financial crisis, the 2001-2002 recession, the 9/11 terrorist attack, the Lehman Brother failure, the European sovereign debt crisis, the Russia-Ukraine conflict and the Brexit vote. The GPR index mainly spikes in relation to events which are not related to economic and financial activity as

Figure 3.2: **Rolling P-Values for the Implied Volatility Regression**

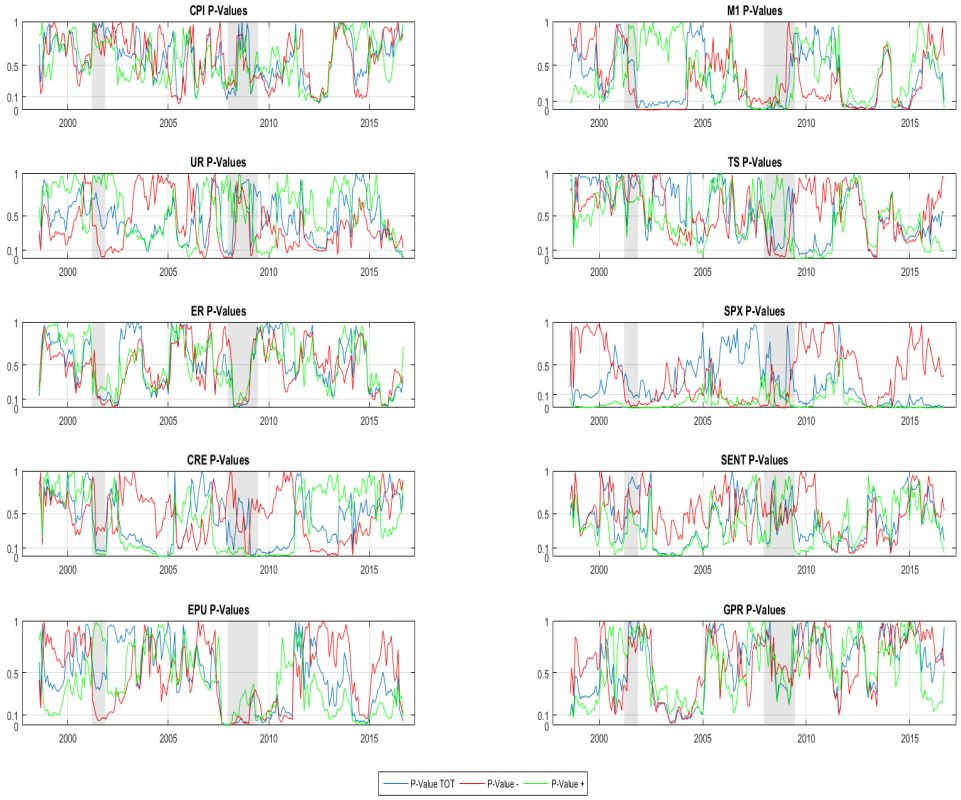


Notes: This figure shows the rolling p-values for the variables selected by the stepwise backward regression in equation (3.9) to explain at least one of the implied volatility components over the total time period (see Table 3.3): Inflation (CPI), Industrial Production (IP), Gross Domestic Product (GDP), Term Structure (TS), JPY-USD Exchange Rate (ER), S&P 500 Index (SPX), Credit Spread (CRE), Market Sentiment (SENT), Economic and Policy Uncertainty (EPU) Index and GeoPolitical Risk (GPR) Index. The reported rolling p-values are associated to the different volatility series, namely, VIX (blue line), VIX^- (red line) and VIX^+ (green line). 10% significance threshold is shown. Selected window size is 30 months and the regression is rolled every month. The NBER recession periods are highlighted in gray. The rolling regression analysis is run over the total time period from 01-1996 to 09-2016, at monthly frequency.

discussed in subsection 3.5.1 and how it will be further discussed in Section 3.7.

In relation to the volatility risk premia, we observe that money supply is found to explain the VRP series especially during the global financial crisis and more recent years, whereas it is found to impact, mainly, VRP^- in the post 2000-2001 recession period. A similar pattern appears to be confirmed for the unemployment rate, whereas term structure is found to affect the VRP series mainly during the global financial crisis and its aftermath. The JPY-USD exchange rate is found to be significant mainly during the 2000-2001 recession period, financial crisis and Brexit. We detect a major role for the S&P 500 in driving the upside volatility risk premium, VRP^+ , as also shown in Table 3.3, in line with Feunou et al. (2017) and Kilic and Shaliastovich (2018), while affecting the VRP^- only during the global financial crisis. Credit is found to impact on VRP^+ in the pre-financial crisis and during the crisis, while it is found to invert its role from 2012 onwards with a clear breakpoint, becoming significant in explaining VRP^- . Market sentiment is mainly detected as significantly driving the VRP^+ during the dot-com bubble and during the post global financial crisis, thereby reflecting periods

Figure 3.3: **Rolling P-Values for the Volatility Risk Premia Regression**



Notes: This figure shows the rolling p-values for the variables selected by the stepwise backward regression in equation (3.9) to explain at least one of the volatility risk premium components over the total time period (see Table 3.3): Inflation (CPI), Money Supply (M1), Unemployment Rate (UR), Term Structure (TS), JPY-USD Exchange Rate (ER), S&P 500 Index (SPX), Credit Spread (CRE), Market Sentiment (SENT), Economic and Policy Uncertainty (EPU) Index and GeoPolitical Risk (GPR) Index. The reported rolling p-values are associated to the different volatility series, namely, VRP (blue line), VRP^- (red line) and VRP^+ (green line). 10% significance threshold is shown. Selected window size is 30 months and the regression is rolled every month. The NBER recession periods are highlighted in gray. The rolling regression analysis is run over the total time period from 01-1996 to 09-2016, at monthly frequency.

of investors' optimism. Only for few years, between 2012 and 2014 does it significantly impact the VRP^-. The opposite trend is shown by the EPU index which is found to to be mainly related to VRP^-. Inflation and geopolitical risk index appear to be rarely significant in impacting on the VRP series as shown in Table 3.3.

Overall, from both Table 3.3 and Figures 3.2 and 3.3, we can confirm **Hypothesis 1** and **Hypothesis 2**: different selected variables appear to impact on the different implied volatility and volatility risk premium components, VIX , VIX^- , VIX^+ and VRP , VRP^- , VRP^+ and, in addition, variables' behaviour and effect vary, for the majority of them, according to the selected time period, namely, the pre and the post global financial crisis.

3.6 Granger Causality at Different Frequencies: Empirical Results

In this Section, we report the Granger causality (GC) analysis results from the different frequency VAR models as shown by equations (3.10), (3.11) and (3.15) with the aim of testing our **Hypothesis 3** and **Hypothesis 4**. In all the models we test for all the casual patterns from the explanatory variables to the implied volatility and volatility risk premium series and vice versa. Tables 3.4 and 3.5 report the summary of these relationships for the implied volatility, while Tables 3.6 and 3.7 for the volatility risk premium. The low frequency GC columns show the causality relationship at monthly frequency in which temporal aggregation, end-of-the-month, is applied. The mixed frequency GC columns show the results obtained by running a MF-VAR with the six low frequency variables used in this chapter. In the MF case, one lag is selected and we control for the forecasting horizon h, where $h \in \{1, \ldots, 4\}$. The high frequency GC columns show the results for the HF-VAR run only for those variables available at daily frequency, which in turn include mostly financial conditions variables.

3.6.1 Granger Causality at Different Frequencies: Implied Volatilities

Regarding the implied volatilities, among the LF variables, market sentiment is found to be caused by all the VIX indexes, whereas a unilateral Granger causality is detected only from VIX^+ to inflation and only from VIX^- to unemployment rate. Among the other variables, we find VIX , VIX^- and VIX^+ to Granger cause both TED and EPU. Actually, a bidirectional relationship is found between VIX^- and the EPU index confirming the importance of the VIX^- as a channel for transmitting the economic and policy uncertainty into the volatility market. We find that credit market is informative, in turn, in predicting all the VIX series, whereas the equity market predicts VIX and VIX^- . There is no Granger causality between the S&P 500 index and VIX^+ at low frequency which is, instead, uncovered by HF Granger causality. In general, for the low frequency, we find that some lagged macroeconomic variables are, most of the time, unable to predict implied volatility indexes, especially when lagged beyond the first month, but, in turn, also lagged implied volatility indexes are rarely found to be informative for predicting macroeconomics. While we interpret the first as a mismatch in information containers between macro variables and implied volatilities, one attached to a slower economic state and the other to faster and more contemporaneous investors' beliefs, we believe that for the forward looking implied volatilities the informative power in predicting financial and macroeconomic variables should emerge more strongly (e.g. Diebold and Yilmaz, 2008).

We correct this low frequency limitation identified in the literature (see Ghysels et al., 2016; Ghysels, 2016) by performing a mixed frequency Granger causality test with the main aim being to uncover possible causality relationships which we are unable to detect when using temporal aggregation. The

MF analysis sheds light on several causality chains among low frequency macro variables and daily implied volatility indexes that we find hidden in the low frequency state, aligning the results more with those we detected in the stepwise regression analysis in the previous section. For instance, VIX is now found to be able to predict inflation, money supply and unemployment rate, relationships robust for three out of four forecasting horizons, while VIX Granger causes GDP and IP for $h = 2$ and $h = 3$. Beltratti and Morana (2006) observed the existence of a causal linkage running from stock market volatility to macroeconomics, however with short lived effects, a reason as to why LF Granger is found not to uncover these relationships. They are also found to be more in line with previous studies, such as Paye (2012), who found that lagged volatility provides an efficient indicator of the economic state due to the relationship between volatility and business conditions, Vu (2015) who found that past innovations in stock market volatility contain significant information about future changes in output growth and Bekaert and Hoerova (2014) who found that implied volatility is able to predict future economic activity. In the other direction, we detect causality chains going from IP, M1 and SENT to VIX for the majority of forecasting horizons.

With respect to VIX^- , we mainly confirm the unidirectional causality from VIX^- to unemployment rate and market sentiment as for the low frequency, and we uncover robust relationships from industrial production and market sentiment towards VIX^- . With regards to VIX^+ , we show a bilateral relationship with market sentiment and unilateral relationships from VIX^+ to unemployment rate and from industrial production to VIX^+ . Market sentiment confirms its simultaneous role next to the volatility indexes (maximum one month lag selected), but a bilateral relationship is found between the two only with the MF-VAR approach. This might be interpreted as a mismatch in the market sentiment information frequency which needs a higher frequency in order to be detected.

The high frequency Granger causality also captures linkages which we are not able to capture with monthly aggregation. Interestingly, for all the VIX series, we find evidence of a bilateral relationship with the JPY-USD exchange rate which reflects the currency trading activity impacting on the options trading and vice versa. Relationships from VIX to credit and liquidity proxies and to uncertainty and geopolitical risk indexes are also detected for VIX and VIX^- , while for VIX^+ there is no causality towards the GPR index.

There is evidence of a significant two way feedback between the EPU index and volatilities, however this causality chain being stronger when going from the VIX series towards the EPU index. This can be explained from the way the EPU index is computed from newspaper articles which have a minimum lag of one day compared to the options market. The relationship between EPU and VIX is quite contemporaneous (see Amengual and Xiu, 2017), while credit spread requires a little more time, namely more than ten days, to impact on the volatility indexes, thus the causality relationship which is detected monthly is lost at a daily frequency. This is in line with the results from Table 3.3 in which the

Table 3.4: **Pairwise Granger Causality Test for Mixed Frequencies: From Implied Volatilities to Selected Variables ($\triangle$ VIX $\nRightarrow$ $\triangle$ X)**

Aggregate Implied Volatility: VIX								
	Low Frequency GC		High Frequency GC		Mixed Frequency GC			
HP	l	P-Value	l	P-Value	$h=1$	$h=2$	$h=3$	$h=4$
$\triangle$ VIX $\nRightarrow$ $\triangle$ CPI	2	0.834			0.159	**0.057**	**0.015**	**0.000**
$\triangle$ VIX $\nRightarrow$ $\triangle$ GDP	3	0.327			0.654	**0.047**	**0.018**	0.106
$\triangle$ VIX $\nRightarrow$ $\triangle$ IP	3	0.830			0.788	**0.000**	**0.005**	0.525
$\triangle$ VIX $\nRightarrow$ $\triangle$ UR	3	0.148			0.106	**0.000**	**0.010**	**0.000**
$\triangle$ VIX $\nRightarrow$ $\triangle$ M1	3	0.265			**0.067**	**0.013**	0.162	**0.002**
$\triangle$ VIX $\nRightarrow$ $\triangle$ SENT	1	**0.002**			0.106	**0.016**	0.118	**0.000**
$\triangle$ VIX $\nRightarrow$ $\triangle$ TS	1	0.348	8	0.358				
$\triangle$ VIX $\nRightarrow$ $\triangle$ OIL	2	0.309	8	**0.099**				
$\triangle$ VIX $\nRightarrow$ $\triangle$ ER	1	0.566	8	**0.014**				
$\triangle$ VIX $\nRightarrow$ $\triangle$ GOLD	1	0.387	11	0.175				
$\triangle$ VIX $\nRightarrow$ $\triangle$ SPX	1	0.665	18	0.167				
$\triangle$ VIX $\nRightarrow$ $\triangle$ CRE	1	0.699	10	**0.000**				
$\triangle$ VIX $\nRightarrow$ $\triangle$ TED	2	**0.000**	21	**0.038**				
$\triangle$ VIX $\nRightarrow$ $\triangle$ EPU	2	**0.000**	8	**0.000**				
$\triangle$ VIX $\nRightarrow$ $\triangle$ GPR	3	0.356	14	**0.004**				
Downside Implied Volatility: VIX^-								
$\triangle$ VIX^- $\nRightarrow$ $\triangle$ CPI	2	0.897			0.127	0.489	**0.012**	**0.000**
$\triangle$ VIX^- $\nRightarrow$ $\triangle$ GDP	3	0.486			0.343	0.124	**0.000**	**0.026**
$\triangle$ VIX^- $\nRightarrow$ $\triangle$ IP	2	0.414			0.264	**0.067**	**0.000**	0.254
$\triangle$ VIX^- $\nRightarrow$ $\triangle$ UR	2	**0.080**			**0.043**	**0.094**	**0.003**	**0.000**
$\triangle$ VIX^- $\nRightarrow$ $\triangle$ M1	3	0.318			**0.001**	0.171	0.503	0.153
$\triangle$ VIX^- $\nRightarrow$ $\triangle$ SENT	1	**0.001**			**0.009**	0.208	**0.012**	**0.000**
$\triangle$ VIX^- $\nRightarrow$ $\triangle$ TS	1	0.313	7	0.456				
$\triangle$ VIX^- $\nRightarrow$ $\triangle$ OIL	3	0.319	7	0.174				
$\triangle$ VIX^- $\nRightarrow$ $\triangle$ ER	1	0.744	7	**0.049**				
$\triangle$ VIX^- $\nRightarrow$ $\triangle$ GOLD	1	0.574	11	**0.043**				
$\triangle$ VIX^- $\nRightarrow$ $\triangle$ SPX	1	0.493	18	0.887				
$\triangle$ VIX^- $\nRightarrow$ $\triangle$ CRE	1	0.691	10	**0.006**				
$\triangle$ VIX^- $\nRightarrow$ $\triangle$ TED	2	**0.000**	19	**0.076**				
$\triangle$ VIX^- $\nRightarrow$ $\triangle$ EPU	2	**0.000**	7	**0.000**				
$\triangle$ VIX^- $\nRightarrow$ $\triangle$ GPR	3	0.255	14	**0.021**				
Upside Implied Volatility: VIX^+								
$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ CPI	3	**0.001**			0.751	0.664	**0.035**	**0.016**
$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ GDP	3	0.332			0.877	0.465	0.137	0.510
$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ IP	2	0.467			**0.046**	0.347	0.416	0.813
$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ UR	2	0.123			0.262	**0.090**	**0.003**	**0.000**
$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ M1	1	0.181			0.468	0.251	**0.042**	0.280
$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ SENT	1	**0.002**			**0.062**	**0.055**	0.164	**0.000**
$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ TS	1	0.594	8	0.411				
$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ OIL	1	0.218	8	0.462				
$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ ER	1	0.481	8	**0.070**				
$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ GOLD	1	0.272	9	0.327				
$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ SPX	1	0.394	18	0.227				
$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ CRE	1	0.890	10	**0.000**				
$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ TED	1	**0.004**	20	**0.036**				
$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ EPU	3	**0.004**	8	**0.000**				
$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ GPR	3	0.515	14	0.231				

Notes: This table shows the VAR Granger causality tests performed through equation (3.10), (3.11) and (3.15) for low, high and mixed frequency variables, respectively. The direction of the causality chains goes from the implied volatility series, VIX VIX^- and VIX^+ , towards the macroeconomic and financial variables ($\triangle$ VIX $\nRightarrow$ $\triangle$ X). Lags are selected according to the minimum value between AIC and SIC tests for LF and HF, while fixed to one for MF. MF-VAR controls for forecasting horizon $h = 1, 2, 3, 4$. Null hypotheses: $X \nRightarrow_{LF} Y$, $X \nRightarrow_{HF} Y$ and $X \nRightarrow_{MF} Y$. In bold the Granger Causality relations at 10% level. The total time period is from 04-01-1996 to 29-09-2016. Frequency is according to the model and variables frequency availability.

Table 3.5: **Pairwise Granger Causality Test for Mixed Frequencies: From Selected Variables to Implied Volatilities ($\triangle$ X $\nRightarrow$ $\triangle$ VIX)**

Aggregate Implied Volatility: VIX								
	Low Frequency GC		High Frequency GC		Mixed Frequency GC			
HP	l	P-Value	l	P-Value	$h=1$	$h=2$	$h=3$	$h=4$
$\triangle$ CPI $\nRightarrow$ $\triangle$ VIX	2	0.329			0.200	**0.066**	0.926	0.224
$\triangle$ GDP $\nRightarrow$ $\triangle$ VIX	3	0.231			0.606	0.820	0.782	0.603
$\triangle$ IP $\nRightarrow$ $\triangle$ VIX	3	0.219			**0.000**	**0.098**	**0.000**	0.225
$\triangle$ UR $\nRightarrow$ $\triangle$ VIX	3	0.971			0.541	**0.008**	**0.098**	0.264
$\triangle$ M1 $\nRightarrow$ $\triangle$ VIX	3	0.672			**0.000**	**0.035**	**0.002**	**0.016**
$\triangle$ SENT $\nRightarrow$ $\triangle$ VIX	1	0.905			**0.000**	**0.001**	0.347	**0.000**
$\triangle$ TS $\nRightarrow$ $\triangle$ VIX	1	0.882	8	0.458				
$\triangle$ OIL $\nRightarrow$ $\triangle$ VIX	2	0.113	8	0.901				
$\triangle$ ER $\nRightarrow$ $\triangle$ VIX	1	0.436	8	**0.035**				
$\triangle$ GOLD $\nRightarrow$ $\triangle$ VIX	1	0.831	11	0.463				
$\triangle$ SPX $\nRightarrow$ $\triangle$ VIX	1	**0.067**	18	**0.000**				
$\triangle$ CRE $\nRightarrow$ $\triangle$ VIX	1	**0.006**	10	0.394				
$\triangle$ TED $\nRightarrow$ $\triangle$ VIX	2	0.635	21	0.743				
$\triangle$ EPU $\nRightarrow$ $\triangle$ VIX	2	0.221	8	**0.083**				
$\triangle$ GPR $\nRightarrow$ $\triangle$ VIX	2	0.244	14	0.589				
Downside Implied Volatility: VIX^-								
$\triangle$ CPI $\nRightarrow$ $\triangle$ VIX^-	2	0.195			0.124	0.761	0.691	0.329
$\triangle$ GDP $\nRightarrow$ $\triangle$ VIX^-	3	0.210			0.853	0.876	0.876	0.360
$\triangle$ IP $\nRightarrow$ $\triangle$ VIX^-	3	0.536			**0.000**	**0.060**	**0.000**	**0.065**
$\triangle$ UR $\nRightarrow$ $\triangle$ VIX^-	2	0.742			0.153	**0.006**	0.171	0.564
$\triangle$ M1 $\nRightarrow$ $\triangle$ VIX^-	3	0.668			**0.000**	0.430	**0.012**	0.213
$\triangle$ SENT $\nRightarrow$ $\triangle$ VIX^-	1	0.746			**0.002**	**0.010**	0.354	**0.027**
$\triangle$ TS $\nRightarrow$ $\triangle$ VIX^-	1	0.515	7	0.578				
$\triangle$ OIL $\nRightarrow$ $\triangle$ VIX^-	3	0.162	7	0.315				
$\triangle$ ER $\nRightarrow$ $\triangle$ VIX^-	1	0.506	7	**0.017**				
$\triangle$ GOLD $\nRightarrow$ $\triangle$ VIX^-	1	0.756	11	0.542				
$\triangle$ SPX $\nRightarrow$ $\triangle$ VIX^-	1	**0.054**	18	**0.000**				
$\triangle$ CRE $\nRightarrow$ $\triangle$ VIX^-	1	**0.007**	10	0.587				
$\triangle$ TED $\nRightarrow$ $\triangle$ VIX^-	2	0.610	19	0.716				
$\triangle$ EPU $\nRightarrow$ $\triangle$ VIX^-	2	**0.098**	7	**0.073**				
$\triangle$ GPR $\nRightarrow$ $\triangle$ VIX^-	3	0.238	14	0.810				
Upside Implied Volatility: VIX^+								
$\triangle$ CPI $\nRightarrow$ $\triangle$ VIX^+	3	0.659			0.751	0.576	0.562	0.587
$\triangle$ GDP $\nRightarrow$ $\triangle$ VIX^+	3	**0.087**			0.877	0.489	0.137	0.330
$\triangle$ IP $\nRightarrow$ $\triangle$ VIX^+	2	0.201			**0.046**	**0.039**	**0.000**	**0.000**
$\triangle$ UR $\nRightarrow$ $\triangle$ VIX^+	2	0.775			0.262	0.925	**0.009**	0.807
$\triangle$ M1 $\nRightarrow$ $\triangle$ VIX^+	1	0.846			0.469	**0.011**	0.890	0.440
$\triangle$ SENT $\nRightarrow$ $\triangle$ VIX^+	1	0.552			**0.000**	**0.023**	0.605	0.298
$\triangle$ TS $\nRightarrow$ $\triangle$ VIX^+	1	0.697	8	0.785				
$\triangle$ OIL $\nRightarrow$ $\triangle$ VIX^+	1	0.113	8	0.816				
$\triangle$ ER $\nRightarrow$ $\triangle$ VIX^+	1	0.400	8	**0.094**				
$\triangle$ GOLD $\nRightarrow$ $\triangle$ VIX^+	1	0.781	9	0.185				
$\triangle$ SPX $\nRightarrow$ $\triangle$ VIX^+	1	0.254	18	**0.000**				
$\triangle$ CRE $\nRightarrow$ $\triangle$ VIX^+	1	**0.001**	10	0.410				
$\triangle$ TED $\nRightarrow$ $\triangle$ VIX^+	1	0.689	20	0.398				
$\triangle$ EPU $\nRightarrow$ $\triangle$ VIX^+	3	0.463	8	**0.019**				
$\triangle$ GPR $\nRightarrow$ $\triangle$ VIX^+	3	0.353	14	0.356				

Notes: This table shows the VAR Granger causality tests performed through equation (3.10), (3.11) and (3.15) for low, high and mixed frequency variables, respectively. The direction of the causality chains goes from the macroeconomic and financial variables towards the implied volatility series, VIX VIX^- and VIX^+ ($\triangle$ X $\nRightarrow$ $\triangle$ VIX). Lags are selected according to the minimum value between AIC and SIC tests for LF and HF, while fixed to one for MF. MF-VAR controls for forecasting horizon $h = 1, 2, 3, 4$. Null hypotheses: $X \nRightarrow_{LF} Y$, $X \nRightarrow_{HF} Y$ and $X \nRightarrow_{MF} Y$. In bold the Granger Causality relations at 10% level. The total time period is from 04-01-1996 to 29-09-2016. Frequency is according to the model and variables frequency availability.

lagged credit variable emerged significant at its first lag in the post-crisis period. Credit spread is found to be caused, rather than a cause, by the volatility changes (e.g. Zhang et al., 2009).

Overall, this analysis also highlights how more refined information carried by the options trading behind the VIX might be able to reflect investors' expectations regarding daily frequency variables, such as exchange rate, liquidity and EPU index, which are in turn connected to several tradable assets echoing the actual market participants beliefs, both exuberance and fear. Lastly, we detect a poor predictive power of the implied volatility for future stock market returns, S&P 500 , regardless of the volatility component and the VAR frequency we select, a finding in line with (see Bekaert and Hoerova, 2014). To conclude, for the implied volatility series, we can confirm **Hypothesis 3** and **Hypothesis 4**. Lag selection for financial variables shows how their impact on volatility, or vice versa, most of the time cannot be captured at monthly frequency given that it dissolves within a few days or weeks. For the macroeconomic variables, we show how some of the relationships they have with implied volatilities can be detected only with MF VAR models, whereas forward looking volatility indexes are scarcely responsive to lagged macro-variables at low frequency.

Consistent with the previous Section, a sub-sample analysis has been performed also for the Granger causality test. The results are found to be confirming some of the main findings from Table 3.3. Macroeconomic variables such as CPI, M1 and IP are found to Granger cause the VIX indexes also at lower frequency in the pre-crisis period. Interestingly, market sentiment (SENT) is found to be Granger causing all the VIX series at any frequency. The dot-com bubble event may provide an interpretation for this result which is highlighted even more in a sub-sample analysis. In the crisis period[9] variables such CRE, S&P 500 and EPU are detected as the main causes of future levels of VIX , with higher impact on VIX^{-} . Macroeconomic variables are hardly found significant in the crisis period. Similar results are detected in the post-crisis sub-sample for macroeconomics variables. On the other hand, if we look only at the post-crisis period, EPU, TED, CRE, S&P 500 and ER are the main variables able to impact on future levels of VIX and decomposed VIX^{-} and VIX^{+} . In the other way, we observe an increased (decreased) significance for VIX^{-} (VIX^{+}) in predicting both macroeconomic and also financial variables in the post-financial crisis sub-sample.

3.6.2 Granger Causality at Different Frequencies: Volatility Risk Premia

Table 3.7 shows that macroeconomic variables barely cause VRP series in low frequency with the exception of market sentiment towards the downside and upside risk premia. For instance, the inflation growth rate is found to have no effect on realized volatility (see Engle and Rangel, 2008) which is reflected, in our case, in the risk premia given that the risk premia contain a mixture of information between implied and realized volatilities. All the VRP series are able to Granger cause inflation, VRP

[9] We select an extended crisis period spanning from 2007 to 2010 is considered for having a reasonable number of observation in the analysis.

is found to Granger cause also money supply, while VRP^+ Granger causes inflation, GDP, money supply and market sentiment, being connected to future levels of macro variables.

When MF-VAR is applied the picture changes, and we are now able to detect a more informative role for the risk premia in predicting the future level of macro variables. Not only can we confirm the Granger causality relationships already detected at low-frequency, but we also uncover variables which were hidden at low frequency. For instance, all the VRP series are found to Granger cause inflation and market sentiment, VRP and VRP^+ are found to have a unidirectional relationship towards money supply, while only VRP^- is found to Granger cause unemployment rate and only VRP^+ industrial production. In the other direction, with MF-VAR model, we uncover unilateral relationships from industrial production and market sentiment towards all the VRP series, while money supply is able to Granger cause only VRP^+ .

Looking at the variables available at daily frequency, we find unilateral Granger causality from VRP towards term structure, oil price, gold price and liquidity, both when these relationships are studied at low frequency and also at high frequency. However, the causality linkage expands also to S&P 500 and the EPU index when high frequency VAR is considered. On the other hand, the financial variables which are more informative for future VRP levels are S&P 500 , credit and exchange rate at both low frequency and high frequency and also EPU when high frequency is selected. For the VRP^- , we detect an unilateral Granger causality towards gold at both high and low frequency, whereas towards credit and liquidity proxies only at the first frequency and towards term structure, oil and exchange rate only at the second frequency. Exchange rate, S&P 500 and EPU are also able to Granger cause the VRP^- at both low and high frequencies, while we uncover causality relationships from oil and credit towards VRP^- at high frequency. Lastly, VRP^+ is found to Granger cause term structure and TED spread, while it is Granger caused by S&P 500 index, credit, TED spread and EPU index, at low frequency. However, with HF Granger causality, VRP^+ is found to have a bilateral causality link with many of the financial conditions variables, such as, exchange rate, S&P 500 , EPU index and GPR index, while VRP^+ is predicted by variables, such as, term structure and credit.

A sub-sample Granger causality analysis has been undertaken also for the VRP . The results show, also in this case, how macroeconomic variables cause changes in future levels of VRP mainly in the pre-crisis sub-sample. In the financial crisis period we notice mixture of macroeconomic-financial variables which Granger cause VRP . Among the main variables impacting on VRP , at any frequency, we find S&P 500 , CRE, ER, IP and SENT, in line with the results on the total sample analysis. A role for oil in impacting on future levels of VRP during crisis is detected only at mixed-frequency. In line with the findings for VIX , in the post-crisis period, we notice an increase role for financial variables also in impacting on future levels of VRP . On the other hand, VRP^+ is found the VRP component which is able to impact on macroeconomic variables as well as S&P 500 the most, regardless to the

Table 3.6: **Pairwise Granger Causality Test for Mixed Frequencies: From Volatility Risk Premia to Selected Variables ($\triangle$ VRP $\nRightarrow$ $\triangle$ X)**

Aggregate Volatility Risk Premium: VRP								
	Low Frequency GC		High Frequency GC		Mixed Frequency GC			
HP	l	P-Value	l	P-Value	$h=1$	$h=2$	$h=3$	$h=4$
$\triangle$ VRP $\nRightarrow$ $\triangle$ CPI	3	**0.000**			**0.084**	0.124	**0.028**	**0.015**
$\triangle$ VRP $\nRightarrow$ $\triangle$ GDP	3	0.198			0.128	0.110	0.164	**0.098**
$\triangle$ VRP $\nRightarrow$ $\triangle$ IP	3	0.349			0.206	0.102	**0.000**	0.237
$\triangle$ VRP $\nRightarrow$ $\triangle$ UR	3	0.982			0.122	**0.000**	0.201	0.109
$\triangle$ VRP $\nRightarrow$ $\triangle$ M1	4	**0.021**			**0.000**	**0.038**	**0.001**	**0.009**
$\triangle$ VRP $\nRightarrow$ $\triangle$ SENT	3	0.405			**0.002**	**0.030**	**0.000**	**0.000**
$\triangle$ VRP $\nRightarrow$ $\triangle$ TS	2	**0.090**	19	**0.001**				
$\triangle$ VRP $\nRightarrow$ $\triangle$ OIL	3	**0.084**	11	**0.063**				
$\triangle$ VRP $\nRightarrow$ $\triangle$ ER	3	0.586	11	0.150				
$\triangle$ VRP $\nRightarrow$ $\triangle$ GOLD	2	**0.038**	18	**0.005**				
$\triangle$ VRP $\nRightarrow$ $\triangle$ SPX	2	0.622	19	**0.002**				
$\triangle$ VRP $\nRightarrow$ $\triangle$ CRE	3	0.313	13	0.554				
$\triangle$ VRP $\nRightarrow$ $\triangle$ TED	3	**0.005**	10	**0.091**				
$\triangle$ VRP $\nRightarrow$ $\triangle$ EPU	3	0.828	18	**0.039**				
$\triangle$ VRP $\nRightarrow$ $\triangle$ GPR	2	0.601	18	0.229				
Downside Volatility Risk Premium: VRP^-								
$\triangle \mathrm{VRP}^- \nRightarrow \triangle$ CPI	4	**0.008**			**0.053**	0.513	**0.000**	**0.035**
$\triangle \mathrm{VRP}^- \nRightarrow \triangle$ GDP	4	0.577			0.115	0.211	0.305	**0.035**
$\triangle \mathrm{VRP}^- \nRightarrow \triangle$ IP	4	0.166			0.202	**0.053**	0.200	0.105
$\triangle \mathrm{VRP}^- \nRightarrow \triangle$ UR	3	0.870			**0.000**	**0.007**	**0.000**	**0.000**
$\triangle \mathrm{VRP}^- \nRightarrow \triangle$ M1	4	0.289			0.120	0.573	**0.040**	0.136
$\triangle \mathrm{VRP}^- \nRightarrow \triangle$ SENT	2	0.571			**0.035**	0.249	**0.000**	**0.000**
$\triangle \mathrm{VRP}^- \nRightarrow \triangle$ TS	2	0.488	14	**0.037**				
$\triangle \mathrm{VRP}^- \nRightarrow \triangle$ OIL	3	0.169	11	**0.005**				
$\triangle \mathrm{VRP}^- \nRightarrow \triangle$ ER	2	0.281	7	**0.029**				
$\triangle \mathrm{VRP}^- \nRightarrow \triangle$ GOLD	3	**0.064**	18	**0.026**				
$\triangle \mathrm{VRP}^- \nRightarrow \triangle$ SPX	3	0.649	18	0.202				
$\triangle \mathrm{VRP}^- \nRightarrow \triangle$ CRE	2	**0.003**	19	0.770				
$\triangle \mathrm{VRP}^- \nRightarrow \triangle$ TED	3	**0.005**	18	0.239				
$\triangle \mathrm{VRP}^- \nRightarrow \triangle$ EPU	3	0.966	20	0.345				
$\triangle \mathrm{VRP}^- \nRightarrow \triangle$ GPR	3	0.567	19	0.496				
Upside Volatility Risk Premium: VRP^+								
$\triangle \mathrm{VRP}^+ \nRightarrow \triangle$ CPI	3	**0.000**			0.762	**0.000**	**0.048**	**0.002**
$\triangle \mathrm{VRP}^+ \nRightarrow \triangle$ GDP	3	**0.010**			0.320	**0.000**	**0.000**	**0.012**
$\triangle \mathrm{VRP}^+ \nRightarrow \triangle$ IP	4	0.198			**0.002**	0.244	**0.080**	**0.007**
$\triangle \mathrm{VRP}^+ \nRightarrow \triangle$ UR	3	0.907			0.299	0.342	**0.000**	0.220
$\triangle \mathrm{VRP}^+ \nRightarrow \triangle$ M1	4	**0.000**			**0.000**	**0.000**	**0.002**	**0.012**
$\triangle \mathrm{VRP}^+ \nRightarrow \triangle$ SENT	2	**0.088**			**0.003**	**0.000**	**0.014**	**0.019**
$\triangle \mathrm{VRP}^+ \nRightarrow \triangle$ TS	3	**0.009**	10	0.222				
$\triangle \mathrm{VRP}^+ \nRightarrow \triangle$ OIL	3	0.111	12	0.310				
$\triangle \mathrm{VRP}^+ \nRightarrow \triangle$ ER	2	0.301	10	**0.002**				
$\triangle \mathrm{VRP}^+ \nRightarrow \triangle$ GOLD	2	0.319	8	0.274				
$\triangle \mathrm{VRP}^+ \nRightarrow \triangle$ SPX	2	0.658	20	**0.000**				
$\triangle \mathrm{VRP}^+ \nRightarrow \triangle$ CRE	2	0.220	14	0.746				
$\triangle \mathrm{VRP}^+ \nRightarrow \triangle$ TED	2	**0.082**	18	**0.038**				
$\triangle \mathrm{VRP}^+ \nRightarrow \triangle$ EPU	3	0.664	15	**0.003**				
$\triangle \mathrm{VRP}^+ \nRightarrow \triangle$ GPR	2	0.743	18	**0.062**				

Notes: This table shows the VAR Granger causality tests performed through equation (3.10), (3.11) and (3.15) for low, high and mixed frequency variables, respectively. The direction of the causality chains goes from the variance risk premium series, VRP VRP^- and VRP^+ , towards the macroeconomic and financial variables ($\triangle$ VRP $\nRightarrow$ $\triangle$ X). Lags are selected according to the minimum value between AIC and SIC tests for LF and HF, while fixed to one for MF. MF-VAR controls for forecasting horizon $h = 1, 2, 3, 4$. Null hypotheses: $X \nRightarrow_{LF} Y$, $X \nRightarrow_{HF} Y$ and $X \nRightarrow_{MF} Y$. In bold the Granger Causality relations at 10% level. The total time period is from 04-01-1996 to 29-09-2016. Frequency is according to the model and variables frequency availability.

sub-sample period considered. VRP^- is detected as the main component driving EPU and CRE during the financial crisis.

In general, this comparative frequency Granger causality test further confirms **Hypothesis 3** and **Hypothesis 4** also for the volatility risk premia. Our findings are in part in line with Bekaert and Hoerova (2014) with regards to finding the aggregate VRP unable to Granger cause economic activity (IP), neither at lower frequency nor in mixed frequency. However, by decomposing the VRP mea-

Table 3.7: **Pairwise Granger Causality Test for Mixed Frequencies: From Selected Variables to Volatility Risk Premia ($\triangle$ X $\nRightarrow$ $\triangle$ VRP)**

Aggregate Volatility Risk Premium: VRP								
	Low Frequency GC		High Frequency GC		Mixed Frequency GC			
HP	l	P-Value	l	P-Value	$h=1$	$h=2$	$h=3$	$h=4$
$\triangle$ CPI $\nRightarrow$ $\triangle$ VRP	3	0.153			0.106	0.485	0.719	0.353
$\triangle$ GDP $\nRightarrow$ $\triangle$ VRP	3	0.580			0.382	0.776	0.982	0.850
$\triangle$ IP $\nRightarrow$ $\triangle$ VRP	3	0.616			**0.000**	**0.000**	**0.000**	0.112
$\triangle$ UR $\nRightarrow$ $\triangle$ VRP	3	0.247			0.132	**0.008**	0.250	0.280
$\triangle$ M1 $\nRightarrow$ $\triangle$ VRP	4	0.153			**0.000**	0.440	0.647	**0.043**
$\triangle$ SENT $\nRightarrow$ $\triangle$ VRP	3	0.191			**0.000**	**0.051**	0.113	**0.022**
$\triangle$ TS $\nRightarrow$ $\triangle$ VRP	2	0.447	19	0.214				
$\triangle$ OIL $\nRightarrow$ $\triangle$ VRP	3	0.256	11	0.301				
$\triangle$ ER $\nRightarrow$ $\triangle$ VRP	3	**0.056**	11	**0.000**				
$\triangle$ GOLD $\nRightarrow$ $\triangle$ VRP	2	0.694	18	0.118				
$\triangle$ SPX $\nRightarrow$ $\triangle$ VRP	2	**0.000**	19	**0.000**				
$\triangle$ CRE $\nRightarrow$ $\triangle$ VRP	3	**0.001**	17	**0.000**				
$\triangle$ TED $\nRightarrow$ $\triangle$ VRP	3	0.261	10	0.174				
$\triangle$ EPU $\nRightarrow$ $\triangle$ VRP	3	0.380	18	**0.000**				
$\triangle$ GPR $\nRightarrow$ $\triangle$ VRP	2	0.655	18	0.930				
Downside Volatility Risk Premium: VRP^-								
$\triangle$ CPI $\nRightarrow$ $\triangle$ VRP^-	4	0.195			0.244	0.107	0.371	0.146
$\triangle$ GDP $\nRightarrow$ $\triangle$ VRP^-	4	0.309			0.995	0.740	0.977	0.782
$\triangle$ IP $\nRightarrow$ $\triangle$ VRP^-	4	0.754			**0.002**	**0.000**	**0.000**	0.592
$\triangle$ UR $\nRightarrow$ $\triangle$ VRP^-	3	0.165			0.414	**0.084**	**0.000**	0.801
$\triangle$ M1 $\nRightarrow$ $\triangle$ VRP^-	4	0.387			**0.000**	0.719	0.202	0.631
$\triangle$ SENT $\nRightarrow$ $\triangle$ VRP^-	2	**0.042**			**0.002**	**0.000**	**0.000**	**0.005**
$\triangle$ TS $\nRightarrow$ $\triangle$ VRP^-	2	0.660	14	0.208				
$\triangle$ OIL $\nRightarrow$ $\triangle$ VRP^-	3	0.147	11	**0.000**				
$\triangle$ ER $\nRightarrow$ $\triangle$ VRP^-	2	**0.019**	7	**0.000**				
$\triangle$ GOLD $\nRightarrow$ $\triangle$ VRP^-	3	0.158	18	0.138				
$\triangle$ SPX $\nRightarrow$ $\triangle$ VRP^-	3	**0.000**	18	**0.000**				
$\triangle$ CRE $\nRightarrow$ $\triangle$ VRP^-	2	0.168	19	**0.008**				
$\triangle$ TED $\nRightarrow$ $\triangle$ VRP^-	3	0.817	18	0.120				
$\triangle$ EPU $\nRightarrow$ $\triangle$ VRP^-	3	**0.007**	20	**0.00**2				
$\triangle$ GPR $\nRightarrow$ $\triangle$ VRP^-	3	0.933	19	0.378				
Upside Volatility Risk Premium: VRP^+								
$\triangle$ CPI $\nRightarrow$ $\triangle$ VRP^+	3	0.166			0.152	0.375	0.252	**0.060**
$\triangle$ GDP $\nRightarrow$ $\triangle$ VRP^+	3	0.774			0.500	**0.004**	0.289	0.228
$\triangle$ IP $\nRightarrow$ $\triangle$ VRP^+	4	0.341			**0.000**	**0.000**	**0.000**	**0.000**
$\triangle$ UR $\nRightarrow$ $\triangle$ VRP^+	3	0.383			0.219	0.366	**0.003**	**0.008**
$\triangle$ M1 $\nRightarrow$ $\triangle$ VRP^+	4	0.179			**0.001**	**0.055**	0.641	**0.064**
$\triangle$ SENT $\nRightarrow$ $\triangle$ VRP^+	2	**0.050**			**0.000**	**0.000**	**0.045**	0.171
$\triangle$ TS $\nRightarrow$ $\triangle$ VRP^+	3	0.796	10	**0.041**				
$\triangle$ OIL $\nRightarrow$ $\triangle$ VRP^+	3	0.324	12	0.302				
$\triangle$ ER $\nRightarrow$ $\triangle$ VRP^+	2	0.477	10	**0.000**				
$\triangle$ GOLD $\nRightarrow$ $\triangle$ VRP^+	2	0.729	8	0.238				
$\triangle$ SPX $\nRightarrow$ $\triangle$ VRP^+	2	**0.000**	20	**0.000**				
$\triangle$ CRE $\nRightarrow$ $\triangle$ VRP^+	2	**0.000**	14	**0.000**				
$\triangle$ TED $\nRightarrow$ $\triangle$ VRP^+	2	**0.020**	18	0.759				
$\triangle$ EPU $\nRightarrow$ $\triangle$ VRP^+	3	**0.011**	15	**0.000**				
$\triangle$ GPR $\nRightarrow$ $\triangle$ VRP^+	2	0.425	18	**0.079**				

Notes: This table shows the VAR Granger causality tests performed through equation (3.10), (3.11) and (3.15) for low, high and mixed frequency variables, respectively. The direction of the causality chains goes from the macroeconomic and financial variables towards the variance risk premium series, VRP VRP^- and VRP^+ ($\triangle$ X $\nRightarrow$ $\triangle$ VRP). Lags are selected according to the minimum value between AIC and SIC tests for LF and HF, while fixed to one for MF. MF-VAR controls for forecasting horizon $h = 1, 2, 3, 4$. Null hypotheses: $X \nRightarrow_{LF} Y$, $X \nRightarrow_{HF} Y$ and $X \nRightarrow_{MF} Y$. In bold the Granger Causality relations at 10% level. The total time period is from 04-01-1996 to 29-09-2016. Frequency is according to the model and variables frequency availability.

sure, we detect some predictive power for the VRP^+ in explaining future economic activity in mixed frequency.

Overall, our results about the main determinants of the VRP , when a MF-VAR model is employed, are found to be in line with previous literature looking at the linkage between volatility risk premia and macroeconomics. For instance, the Granger causality relationship we detect from industrial production towards all the VRP series is consistent with Corradi et al. (2013) who found a countercyclical variation

of the risk premium for the risk in fluctuations of industrial production.

In addition, with regard to the relationship between macroeconomics and volatility risk premium, Bollerslev et al. (2011) stated that macro-finance shock coefficients are important in understanding the time-variation of the volatility risk premium. Our results with respect to credit and industrial production are found to be in line with their findings. Such findings emphasize even more the usefulness of the mixed-frequency Granger causality approach as well as the VRP decomposition. We also confirm the findings in Bollerslev et al. (2009), Bollerslev et al. (2011) and Bekaert and Hoerova (2014) in relation to stock market returns by detecting the VRP as a significant predictor of stock market returns (S&P 500), and also the findings in Feunou et al. (2017) who found superior ability of the VRP^{+} in explaining future excess market returns when compared to VRP^{-} . On the other hand, we detect a major role for the S&P 500 in driving the upside volatility risk premium, VRP^{+} (see Feunou et al., 2017; Kilic and Shaliastovich, 2018).

3.7 The Link Between Decomposed Volatilities and Economic, Political and Geopolitical Uncertainty

The role of economic and political uncertainty as one of the main determinants of stock market volatility is not a new concept in the financial literature. Political factors and episodes have been recognized as a cause of change in stock market returns, outputs and volatility (Bloom, 2009; Pastor and Veronesi, 2012, 2013). Nowadays political events are more shrouded with uncertainty and unstable consequences compared to the past. This insecurity arising from governments and future political plans is transmitted onto the financial markets and into macroeconomic policies. This is the rational as to why this section focuses on the relationship between volatilities and, not only, the EPU index but also the geopolitical risk index (GPR) and the Partisan Conflict Index (PCI), as these indexes can potentially capture factors and events that are able to drive the model-free volatilities in this chapter[10]. We believe that the link between the economic, political and geopolitical uncertainty together with the financial market "uncertainty", measured through model-free volatilities deserve further commentary. Here, we build up a more in-depth analysis also based on the results obtained in the previous sections of this chapter.

In order to measure the economic policy uncertainty we adopt the EPU index developed by Baker et al. (2016), an index computed from news associated with the ten most important American newspapers, reflecting the concerns and uncertainty in the news surrounding specific economic or political events.[11]. The EPU index is significant in explaining the implied market volatility with a positive re-

[10]Events such as the Asian financial crisis, the dot-com bubble, the 9/11 terrorist attack, the Iraq invasion, the 2008 financial crisis and the Lehman Brother crash, the European sovereign debt crisis, the tension between Russia and Ukraine, the Chinese Yuan collapse and the Brexit vote, are only some of the various political, economic and financial events in the U.S. and worldwide which are included within our time-frame spanning from 1996 to 2016.

[11]The words that the newspapers' articles should contain in order to be relevant include, in brief, "uncertainty", "economics",

lationship shown. This is consistent with Pastor and Veronesi (2012, 2013) who advocated that equity volatility and returns are affected by changes in government policy, and therefore, when new policies are introduced uncertainty and risk premia will increase, leading to more volatile stock returns. This relationship is already partially described in Baker et al. (2016) with respect to the aggregate VIX in which they related the EPU index finding a correlation of around 58%. During the time frame we adopt for our study we find EPU index and VIX to be positively correlated at 42%. However, we have also explored the impact that the EPU index has on the decomposed implied volatilities. The EPU index shows a correlation of 40% with VIX^{+} and 45% with VIX^{-} .

The empirical results in Section 3.5 describe that the EPU effect is stronger in relation to the downside component of the implied volatility indexes, thereby reflecting investors' fear regarding political uncertainty, and consequently investors' willingness to hedge themselves against it. The EPU index is significant in explaining implied volatility, especially in a contemporaneous framework with coefficients decreasing in significance when the first lag is considered (see Table 3.3). The Granger analysis shows that the relationships between the EPU index and volatility measures are more oriented towards the downside component, especially in relation to the implied volatility extracted from puts, VIX^{-} . This highlights how the EPU index can drive investors' uncertainty concerns and, therefore, their willingness to hedge through equity index Put options. Moreover, there is evidence of a significant two way feedback between the EPU index and volatilities. In fact, the causal relationship from volatility to the EPU index suggests that investors transmit the feeling of "fear" and uncertainty, trading equity put options for the month ahead based on their expectations at time t-1 and revealed in the EPU index through economic and financial news. Thus, we find a significant two way feedback between the EPU index and volatilities which is stronger when going from the VIX series towards the EPU index. This can be explained from the way the EPU index is computed from newspaper articles which have a minimum lag of one day compared to the options market. This relationship is quite contemporaneous and does not last beyond the first lag (see Amengual and Xiu, 2017). The results from Table 3.3 show that there is a positive relationship also between the EPU index and risk premia, found again to be stronger in relation to the VRP^{-} . Similar results are found for RVOL measures (see Appendix A.2).

In this chapter, we also examine the link with the geopolitical risk index by Caldara and Iacoviello (2018). This index is computed in a similar way to Baker et al. (2016) counting the frequency of articles associated with geopolitical risk and events from the major international newspapers having global coverage[12]. Caldara and Iacoviello (2018) found the GPR index to spike in response to events such as the Gulf War, the 9/11 terrorist attack, the 2003 invasion of Iraq and the Ukraine-Russia conflict. The only peak the GPR index shares with the VIX index is the recession period in 2000-2001 and after

"congress", "deficit", "Federal Reserve", "legislation" along with other policy related words.

[12]The selected newspapers adopted to build up this index total eleven, consisting of six U.S., four British and one Canadian. The macro-categories for the words they have looked for include geopolitical threats, nuclear threats, war threats, terrorist threats, acts of war and terrorist acts.

the 9/11 terrorist attack, while it appears quite neutral to financial turbulence, not responding to the global financial crisis and dot-com bubble, periods in which both the volatility indexes and EPU index reacted instead. The geopolitical index captures events such as wars, terrorist attacks, financial crisis and global conflicts[13].

GPR index is significant in explaining the implied volatility indexes, and its role is more relevant towards the VIX^- as found for the EPU index. The description of the index together with the findings shown by Caldara and Iacoviello (2018) justify the negative relationship that we find between the index and the volatility measures (see Tables 3.3). Indeed, the GPR index misses crucial financial events during our time period such as the Asian financial crisis, the LTCM, the global financial crisis, the Lehman Brother failure and the sovereign debt crisis in Europe, to mention but a few. While for the EPU index a positive sign was expected given that this reacts to most of the economic downturn and financial crisis, there is no such expectation with respect to the GPR index where an average negative sign is detected. The GPR index mainly spikes in relation to events which are not related to economic and financial activity, however it appears to be significant in the regression analysis and informative in predicting volatility changes given the Granger analysis results. Economic uncertainty derived from geopolitical risk might turn into depression in economic activity and stock prices, thus, into pessimistic and negative expectations about future market conditions (see Caldara and Iacoviello, 2018), a reason why GPR index seems to be mostly related and priced in the put options. It is significant in explaining Put portfolios especially in the all sample, before crisis period, while not many geopolitical events have been occurred in the post-crisis reducing the impact of this variable at minimum.

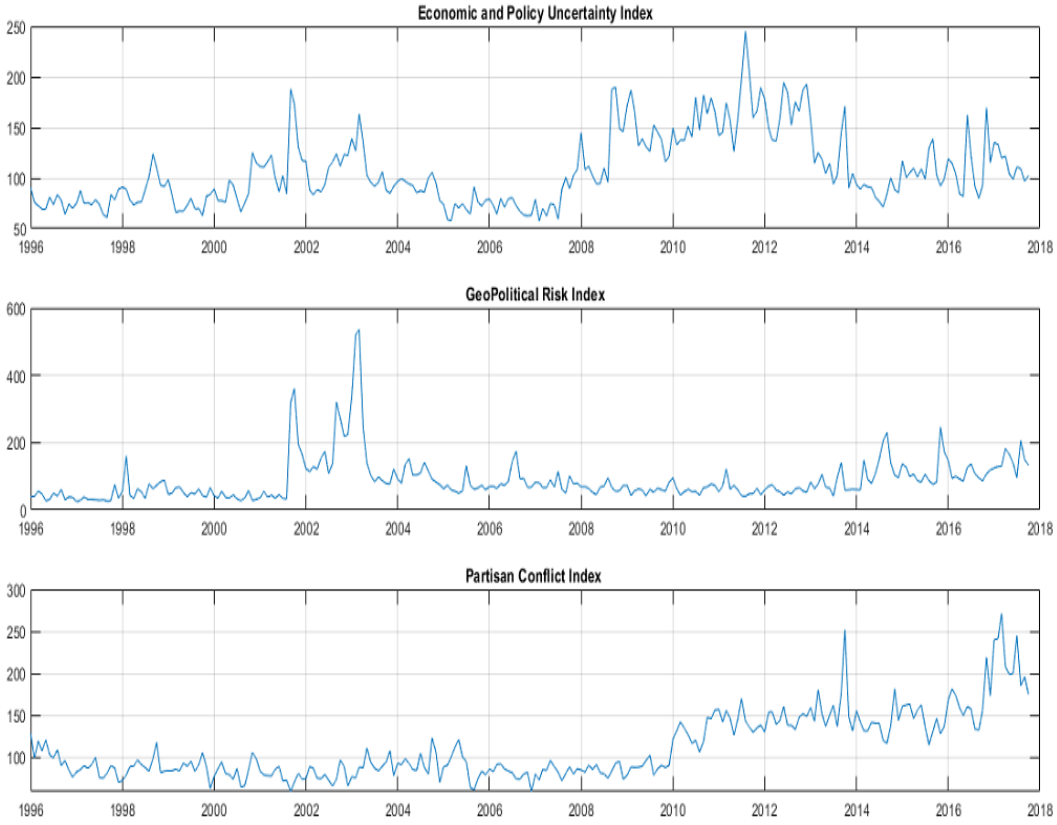
The GPR index appears not to react to political events and presidential elections (Caldara and Iacoviello, 2018). For this reason we also examine, in this chapter, the role of the Partisan Conflict index (PCI) by Azzimonti (2017)[14]. This index reflects the partisan conflicts that have characterized U.S. politics in recent years and it is considered more as a pure political uncertainty proxy. We test this index as an alternative to the EPU index since they share common information and spike in response to similar events. It is computed adopting a methodology similar to Baker et al. (2016), but considers only newspaper articles regarding political disagreement about presidential elections and government policy. Thus, we test whether or not pure political uncertainty has any effect on U.S. volatility measures when incorporated in place of the EPU index into equation 3.9. The three indexes are illustrated in Figure 3.4 for ease and comparison.

We find that the R^2 decreases when PCI is included as a variable in place of the EPU index and that it is not found to be significant in explaining either the VIX or its components either for the total time period or both sub-periods. For instance, in the total time period, for VIX the R^2 reduced to 0.564 and

[13]The GPR index appears to carry an additional source of risk compared to the EPU index allowing us to test both together in a common model avoiding problems of multi-collinearity.

[14]The Partisan Conflict Index is available at `https://www.philadelphiafed.org/research-and-data/real-time-center/partisan-conflict-index`.

Figure 3.4: **EPU, GPR and PCI Series**



Notes: This figure depicts the Economic and Policy Uncertainty (EPU) (upper panel), the GeoPolitical Risk index (GPR) (middle panel) and the Partisan Conflict Index (PCI) (bottom panel). The selected period goes from 01-1996 to 12-2017, at monthly frequency.

the adjusted R^2 to 0.532, for VIX^- to 0.481 and 0.443, respectively, and for VIX^+ they remained the same since the EPU index is also found not to be significant (see Table 3.3). Similar results are found for the volatility risk premia. Such findings show that implied volatilities and risk premia do not react much to political events and elections, while a slightly higher impact is found on the RVOL measures, mainly on RVOL^- (see Appendix A.2). These results are in line with Azzimonti (2017) who revealed that the relationship between PCI and the EPU index has an inverted U-shape. Hence, increases on PCI injects policy uncertainty only when the level of political discord is moderate.

This section has further explored the link between volatility measures and some common indexes of economic, political and geopolitical uncertainty. These results obtained further highlight the crucial role played by the EPU index in explaining and influencing volatility, mainly from its economic uncertainty component rather than from its policy uncertainty component. Indeed, only when a pure political sphere is considered do we fail to find such a strong impact on our volatility measures. In other words, pure political activities and party conflicts do not appear to be that relevant for financial market volatility if they are not linked to economic or financial policies. On the other hand, geopolitical uncertainty might drive changes in volatility especially when detected as a potential threat to economic of financial

instability. These linkages from the uncertainty indexes to the volatilities measures, or vice versa, are mainly placed in the puts activity, VIX^{-} , or VRP^{-} .

3.8 Conclusion

This chapter considered the relationship between model-free stock market volatilities and a renewed set of variables that included not only macro-variables, but also variables which are able to track financial market conditions, market sentiment and economic and geopolitical uncertainty, variables which have often been overlooked in the literature. Given the progress over the years in the volatility and risk premium literature we took the opportunity to further develop the research in the field of macro-finance. We contribute to the existing literature by presenting a new volatility point of view, decomposing volatility associated with positive stock market movements from volatility generated by negative stock market movements, for both the forward looking volatility (implied) and, by combining them with the backward looking volatilities (realized), also for the risk premia, all computed model-free. The empirical analysis has produced different results depending upon the volatility components, upon the time period and upon the data frequency considered.

Overall, we found that variables that are more closely related with financial conditions, in particular those with of a more financial market implication, such as, equity, credit, market sentiment, liquidity and economic policy uncertainty, are found to be robust and stronger determinants of implied volatility and risk premia. In contrast, more macroeconomic variables are found to be less informative in driving volatility. We find evidence of a different behaviour with respect to the upside and downside components of the volatility series in the U.S. financial market when they are decomposed and related to this new set of potential driving factors. Upside implied volatility, VIX^{+} , is affected more by macroeconomic variables, especially those linked with investments and consumption, such as inflation and GDP. Changes in volatility due to economic and geopolitical uncertainty have been found to be placed mainly in the puts activity given that VIX^{-} mirrors the fears and concerns perceived from investors related to negative stock market returns.

A comparative exercise between pre-crisis and post-crisis sub-periods has shown a shift from the information related to the two implied volatility components. There was a shift from calls to puts going from pre to post financial crisis explained by the fact that investors were more concerned about financial market losses, thereby began to actively hedge their equity portfolios by trading put options. Furthermore, while macroeconomic variables appeared to impact more strongly on the volatility and risk premium series in the pre-crisis period, we observe a shift in favor of financial conditions variables emerging more significant in the post financial crisis.

A better structured mixed frequency VAR model allowed us to answer further research questions

still open in the literature. For instance, by aligning the frequency of the macroeconomic information to the volatilities and risk premia we were able to uncover precious information contained in the latter which is actually able to predict macroeconomic variable changes. Vice versa, we uncovered several variables which are found to be able to predict future level of implied volatility and risk premia. This picture is even more refined and improved when we looked at upside and downside components of our volatility series. Forward looking implied volatilities are found to predict future levels of economic activity, output growth and inflation rate, whereas volatility risk premia is found to be an informative predictors of future levels of stock returns.

Lastly, this chapter opened up for new potential trading strategies which may be developed starting from the decomposition of the volatility measures. The CBOE introduced VIX Futures and VIX Options which make the trade of VIX possible. The VIX index derivatives are well known to be efficient hedger tools in downturns and crises. However, in light of the findings of this chapter new research – which is beyond the scope of this thesis – should explore the possibility of trading the decomposed VIX components and adding them to portfolios. VIX^{-} can be traded by buying/selling a portfolio containing S&P 500 OTM put options, whereas VIX^{+} can be traded by buying/selling a portfolio containing OTM call options. Preliminary assumptions of trading strategies which may be designed by using the decomposed VIX may result in a more directional bet which may drive to higher pay offs. For instance, in bearish times, having a mixture of OTM S&P 500 puts as a synthetic position in VIX^{-} could reduce portfolio losses due to a drop in equity market. Trading a portfolio of OTM S&P 500 calls with different strike prices (VIX^{+}) may provide both higher portfolio returns in bullish times and may also provide hedging. Further potential research linked to the VIX decomposition will be discussed in the final Chapter.

Chapter 4

The SKEW Index: Extracting What Has Been Left

So what are policymakers to do? First and foremost, reduce uncertainty. Do so by removing tail risk and the perception of tail risk.

- Oliver Blanchard - Chief Economist - IMF. The Economist, Jan 2009.

4.1 Introduction

Is the implied skewness index able to enhance the information set already contained in options data and revealed from other financial risk and volatility measures? Is there anything *left out* that can be useful to investors through disentangling the implied skewness index? Can these newly decomposed implied skewness indexes contribute to the equity risk premium as well as economic activity predictability?

In this paper, we show that a more refined directional construction of the implied skewness enriches the information that is extracted from equity index option prices in the U.S. In order to conduct our analysis, we first construct a model-free measure of implied skewness following the methodology of Bakshi et al. (2003), and then decompose it into its *positive* and *negative* components by employing only calls and only puts, respectively. We identify different sets of information associated with the two decomposed implied skewness measures. According to Gao et al. (2018), it would be of interest to study the contribution to pricing of investors' time-varying beliefs vs. their time-varying risk aversion associated with the tail risk. In this chapter, we present an innovative approach to investigating this area

by studying the implied skewness decomposed into its two components. We find that SKEW^{+} captures investors' beliefs and therefore it can be linked to market sentiment, whereas SKEW^{-} captures features that are related to tail risk. The former is found to be a strong equity risk premium predictor, while the latter is shown empirically to predict market downturns well.

After the Black Monday 1987, the fear of other possible crashes led to a higher weighting for events in the left side of equity return distributions. Furthermore, the 2008 financial crisis has accentuated even more the interest in tail events and outliers. Barberis (2013) advocated that investors consistently overestimate extreme events when they have a suitable set of information or memories of some similar event still present in their mind. When the information set is limited or when similar tail events have never taken place before, investors may also underestimate their likelihood. The usefulness of implied volatility measures extracted model-free from equity indexes options data has been highlighted in the literature (see Bakshi and Madan, 2000; Jiang and Tian, 2005; Bakshi and Madan, 2006). Du and Kapadia (2014) pointed out that the volatility indexes underestimate the real stock market volatility when the period is bearish and jumpy. In order to capture adequately the tail risk implied skewness measures could enhance the set of information revealed by the implied volatility.

Recently, different measures have been proposed to gauge this missing risk on the equity market taking into account jumps and variance risk premium (see Bollerslev and Todorov, 2011; Du and Kapadia, 2014; Bollerslev et al., 2015; Andersen et al., 2019); and taking a different approach based on cross-sectional portfolio returns (see Kelly and Jiang, 2014; Almeida et al., 2017). The CBOE proposed a SKEW Index computed from the S&P 500 options following the methodology outlined in Bakshi et al. (2003), henceforth (BKM). While the VIX is the market measure reflecting the "likely", the SKEW measure is more related to the extreme market fear measurement reflecting the "unlikely". More about this strand of literature is described in Chapter 2.

Our aim is to extract useful forward looking information about the decomposed implied skewness measures which can be linked to the tail risk, downside risk and market sentiment areas. We show that the positive skew index is, most of the time, related to the optimistic market sentiment generated by the call options. Information coming from market sentiment indicators is rarely influencing the SKEW^{-} which appears to be more closely related to macro fundamentals and it is proposed as a tail risk proxy.

The tail risk literature and the higher risk-neutral moments literature are getting intertwined[1], better explaining the overall risk in the financial markets. The seminal papers by Bakshi and Madan (2000), Bakshi et al. (2003) and Bakshi and Madan (2006) opened a new area of research focused on extracting

[1]The literature on skewness is spanned by two main approaches of calculation as described by Liu (2016). First, there is the raw approach applied by Dennis and Mayhew (2002), Conrad et al. (2013) and Bali and Murray (2013), using the data without filtering or modification. The above studies found that the skew is more negative in period of high market volatility and that the skew for index options tends to be more negative than the skew for individual stock options. The second approach (see Hansis et al., 2010) works with smoothed data, either by data interpolation between OTM puts with lowest strike and OTM calls with highest strike or by data extrapolation between the highest and lowest strike prices. Another methodology that has been applied to calculate the skew is the non-parametric approach applied by Xing et al. (2010) and Mixon (2011).

valuable information about moments of the risk-neutral distribution from option prices. Harvey and Siddique (2000) and Mitton and Vorkink (2007) linked the higher risk neutral moments to asset pricing and portfolio management. Xing et al. (2010) found that the implied volatility smirk has a predictive power for future equity returns. Other studies such as Han (2008), Rehman and Vilkov (2012) and Conrad et al. (2013) concluded that higher moments can increase the accuracy of future asset prices' estimation. Christoffersen et al. (2013) surveyed the available methods for extracting forward looking information from option markets for forecasting purposes.

Our paper has been inspired by the recent growing strand of financial volatility literature that decomposes volatility as well as variance risk premium into positive and negative components (Barndorff-Nielsen et al., 2010; Segal et al., 2015; Feunou et al., 2017; Patton and Sheppard, 2015; Kilic and Shaliastovich, 2018). Motivated by these studies we separate the implied skewness into a *positive* implied SKEW index (henceforth SKEW^{+}) and a *negative* implied SKEW index (henceforth SKEW^{-}), calculated from the relevant class of equity index options, calls and puts, respectively.

We contribute to the literature on equity risk premium predictability by investigating decomposed implied skewness index predictability in relation to stock market premium (Neely et al., 2014; Rapach et al., 2016), thus linking this paper to the literature on market return predictability using information extracted from options (e.g. **?**Driessen et al., 2009; Bakshi et al., 2011; **?**). We hypothesize that SKEW^{+} and SKEW^{-} may be able to enrich equity risk premium predictability, especially for short horizons. The literature on equity returns prediction through model-free skewness measures, computed using the methodology of Bakshi et al. (2003) does not always convey a homogeneous set of conclusions (e.g., Bali and Murray, 2013; Conrad et al., 2013; Stilger et al., 2016). One possible explanation for this is that the link may be time-varying, carrying a different information set related to the belief factor and the risk-based factor (e.g., Friesen et al., 2012), but it may also be due to the existence of two different components (SKEW^{+} and SKEW^{-}) that drive the aggregate SKEW .

In our analysis, we find that SKEW^{+} can predict future S&P 500 equity risk premia well at horizons between 1 and 3 months. The predictive power of SKEW^{+} persists even after controlling for principal components extracted from the 14 Goyal and Welch (2008) macroeconomic variables. Moreover, the predictive ability of SKEW^{+} is preserved out-of-sample when the in-sample window embraces the global financial crisis. We find evidence that disentangling the SKEW index into its positive and negative components allows us to extract additional information on other risk and tail risk measures already studied in the literature. The information content of SKEW^{+} in relation to predicting the equity risk premium is incremental to that of the decomposed VIX , the decomposed VRP (Kilic and Shaliastovich, 2018) and the correlation risk premium (Driessen et al., 2009). The predictive ability of SKEW^{+} is preserved out-of-sample when the in-sample window embraces the global financial crisis. An individual stock predictability exercise shows how the decomposed SKEW indexes are

useful predictors also for the majority of the 30 largest and 30 smallest stocks in the S&P 500 . The predictability of the decomposed SKEW indexes is improved when compared to the aggregate SKEW . The decomposed SKEW indexes are found more useful than the aggregate SKEW also in a Fama-French asset pricing exercise. Furthermore, we show that SKEW^{-} is useful to predict uncertainty indicators and the NBER recession periods at different horizons up to one year.

The strong predictive power of SKEW^{+} in relation to stock market premium *calls* for a market sentiment hypothesis that is based on the literature on risk-neutral skewness and market sentiment (Buraschi and Jiltsov, 2006; Han, 2008; Garleanu et al., 2009; Friesen et al., 2012; Lemmon and Ni, 2014; Stilger et al., 2016). We test the relationship between the decomposed SKEW indexes and market sentiment proxies developed in the financial literature, finding a strong link between market sentiment indicators and SKEW^{+} . Therefore, we hypothesize that market sentiment may be one of the main drivers of SKEW^{+} , being largely responsible for the incremental stock return predictability that is associated with the SKEW^{+} , in line with studies establishing a significant link between market sentiment and equity returns (e.g., Baker and Wurgler, 2006; **?**). Buraschi and Jiltsov (2006) claimed that optimistic investors demand OTM calls, whereas pessimistic investors demand OTM puts, a contention also made by Xing et al. (2010). A new option pricing model with an underlying equity index that follows distinct upside and downside semivariance dynamics was recently introduced by Feunou and Okou (2019).

The aggregate implied skewness is calculated using both SKEW^{-} and SKEW^{+} , with the positive part possibly dampening the real level of risk expressed purely by the negative part. Therefore, taking the SKEW^{-} extracted from OTM puts into account may help investors to better gauge tail risk and avoid under-estimating it. We advocate using SKEW^{-} as a relevant measure of tail risk, focusing on the left side of the risk-neutral distribution and removing investors' beliefs implied from calls that are more attached to market sentiment.

The remainder of this chapter is organized as follows. Section 4.2 describes the methodology behind our analysis for decomposing the implied skewness, the data set used in the study together with the evolution of the decomposed implied SKEW indexes. Section 4.3 positions the decomposed implied skewness measures within some of the already existing financial literature on risk, volatility and tail risk measures. Section 4.4 makes a connection between the implied skewness indexes and various market sentiment measures. Section 4.5 looks at the in-sample predictive power of the decomposed SKEW indexes with relation to S&P 500 and international stock market indexes future risk premia. Robustness exercises when controlling for other predictors as well as out-of-sample predictability are also reported. Section 4.6 shows the predictability results with relation to the largest and smallest S&P 500 individual stocks. Section 4.7 links the decomposed SKEW indexes with the Fama-French portfolios in an asset pricing exercise. Section 4.9 discusses the predictive power of the SKEW indexes in rela-

tion to macroeconomic and uncertainty indicators. The last section concludes the chapter. Additional material on this Chapter is reported in Appendix B.

4.2 Extracting the Positive and Negative Skewness

Du and Kapadia (2014) argued that the VIX seems not to take into account stock returns jumps, missing relevant information for investors during these situations. The interest in the tail risk has increased after the 2008 financial crisis. Investors and academics realized the wrong habit of under-estimating extreme events. The CBOE introduced a SKEW index as a benchmark providing additional market risk information (see CBOE, 2011). The level of the index has also increased after the financial crisis suggesting that options traders expect a higher tail risk.

Our chapter is inspired by a recent line of research in Feunou et al. (2013), Patton and Sheppard (2015) and Bollerslev et al. (2017) who have explicitly modelled upside and downside volatilities[2] and by Bollerslev et al. (2015) who separated the jump tail risk into a left tail component and a right tail component. The idea of decomposing important concepts in asset pricing has been carried forward also by Feunou et al. (2017) who decomposed the variance risk premium into upside and downside components introducing a measure of skewness risk premium as their difference and by Kilic and Shaliastovich (2018) who decomposed “good" and “bad" variance risk premia in order to improve excess market returns predictability. Our research is expanding on these previous ideas and measures focusing on the implied skewness.

4.2.1 The BKM Methodology

For the calculation of the cubic risk-neutral moment, we employ the following result from Bakshi et al. (2003). It allows us to connect in a model-free manner the differential pricing of stocks options and the moments of the risk neutral distribution. It relies on the results in Bakshi and Madan (2000) that underpins our methodology for extracting skewness from options prices without imposing any structure on the underlying process:

Theorem 1: Under all martingale pricing measures, the following contract prices can be recovered from the market prices of OTM European calls and puts: The t-period risk neutral return skewness,

[2]Bekaert and Wu (2000) advocated that volatility in equity markets is asymmetric in the sense that returns and conditional volatility are negatively correlated. Downside volatilities have been proposed both for realized volatility as in Barndorff-Nielsen et al. (2010) and also as in Patton and Sheppard (2015) and Bollerslev et al. (2017) who used high-frequency intra-day data to decompose asset return realized volatility into good and bad volatility associated with positive and negative price increments, respectively, but also as a model-free option implied volatility as discussed in Andersen and Bondarenko (2007).

SKEW(t,T) is given by:

$$SKEW(t,T) \equiv \frac{\mathbb{E}_t[(R(t,T) - \mathbb{E}_t[R(t,T)])^3]}{[\mathbb{E}_t(R(t,T) - \mathbb{E}_t[R(t,T)])^2]^{3/2}} = \frac{e^{rt}W(t,T) - 3\mu(t,T)e^{rt}V(t,T) + 2\mu(t,T)^3}{(e^{rt}V(t,T) - \mu(t,T)^2)^{3/2}} \tag{4.1}$$

The price of volatility and cubic contracts will be, respectively:

$$V(t,T) = 2\int_{S_t}^{\infty} \frac{1 - ln(\frac{K}{S_t})}{K^2} C(t,T;K)dK + 2\int_0^{S_t} \frac{1 + ln(\frac{S_t}{K})}{K^2} P(t,T;K)dK \tag{4.2}$$

$$W(t,T) = \int_{S_t}^{\infty} \frac{6(ln(\frac{K}{S_t})) - 3(ln(\frac{K}{S_t}))^2}{K^2} C(t,T;K)dK - \int_0^{S_t} \frac{6(ln(\frac{S_t}{K})) + 3(ln(\frac{S_t}{K}))^2}{K^2} P(t,T;K)dK \tag{4.3}$$

They can each be formulated through a portfolio of options indexes by their strikes, K (see Bakshi et al. (2003) for more details).

4.2.2 SKEW Index and its Decomposition

CBOE has introduced the SKEW Index as complementary to the VIX , computed from the same range of options (see also Chapter 3 Section 3.2.1). The final formula that is applied is the following:

$$SKEW = 100 - 10S \tag{4.4}$$

where S is the statistical skew $S = \mathbb{E}[(\frac{R-\mu}{\sigma})^3]$ and R is the 30 days log-return of S&P 500 , μ is its expected value and σ is its standard deviation. Following Bakshi et al. (2003) and expanding equation 4.1, S is calculated starting from a portfolio of S&P 500 options with a pay off reflecting the skewness payoff:

$$Skew = S = \frac{\mathbb{E}[R^3] - 3\mathbb{E}[R]\mathbb{E}[R^2] + 2\mathbb{E}[R]^3}{(\mathbb{E}[R^2] - \mathbb{E}^2[R])^{3/2}} \tag{4.5}$$

Simplifying the notation $S = \frac{P_3 - 3P_1P_2 + 2P_1^3}{(P_2 - P_1^2)^{3/2}}$ and the calculation of P_1, P_2 and P_3 from the options market is as follows (see CBOE (2011)):

$$P_1 = \mathbb{E}[R_t] = -e^{rT}\sum_i \frac{Q_K\delta_K}{K_i^2} + \varepsilon_1 \tag{4.6}$$

$$P_2 = \mathbb{E}[R_t^2] = 2e^{rT}\sum_i \frac{(1 - \ln(\frac{K_i}{F_0}))Q_K\delta_K}{K_i^2} + \varepsilon_2 \tag{4.7}$$

$$P_3 = \mathbb{E}[R_t^3] = 3e^{rT}\sum_i \frac{2\ln\left(\frac{K_i}{F_0}\right) - \ln^2\left(\frac{K_i}{F_0}\right)Q_K\delta_K}{K_i^2} + \varepsilon_3 \tag{4.8}$$

where all the variables are as for the VIX computation – with T being the expiration date, F_0 is the forward of S&P 500 calculated from the put-call parity as $F_0 = e^{rT}[c(K,T) - p(K,T)] + K$, where K is the reference price, the first exercise price less or equal to the forward level $F_t(K \leq F_t)$ and K_i is the strike price of *i*-out of the money options used in the calculation, r is the risk free rate with expiration T, $\Delta(K_i)$ is the sum divided by two of the two nearest prices to the exercise price K, $Q(K)$ is a generic price of a European call or put with strike price respectively above or below K, the first strike price below F_0 – except ε_i that represents adjustments for the difference between the reference price and the forward price given by:

$$\varepsilon_1 = -\left(1 + \ln(\frac{F_0}{K_0}) - \frac{F_0}{K_0}\right). \tag{4.9}$$

$$\varepsilon_2 = 2\ln\left(\frac{K_0}{F_0}\right)\left(\frac{F_0}{K_0} - 1\right) + \frac{1}{2}\ln^2\left(\frac{K_0}{F_0}\right) \tag{4.10}$$

$$\varepsilon_3 = 3\ln^2\left(\frac{K_0}{F_0}\right)\left(\frac{1}{3}\ln\left(\frac{K_0}{F_0}\right) - 1 + \left(\frac{F_0}{K_0}\right)\right) \tag{4.11}$$

These equations are applied both for the near term expiration and also for the far term expiration date. The target is to interpolate these two expirations around 30-days, as done for the VIX (see Chapter 3 Section 3.2.1 for more details). When less than 2 days are left to the expiration date, the considered maturity is rolled and the 2nd and the 3rd months options are used instead of the first month. The option maturity selected changes every month in correspondence to the third Friday of the month[3]. The same set of S&P 500 options used for VIX index is also used for SKEW with the same filters' rules. As in Dennis and Mayhew (2002), we use a trapezoidal approximation, consisting of a discrete sum of our available options prices instead of the integrals in formulae (4.6), (4.7) and (4.8). Options are filtered leaving out options with BID price equal to zero, options with prices below or above two consecutive zero BID prices and options with less than 2 days expiration (CBOE, 2009). In order to compute the negative and positive SKEW indexes, the aggregate SKEW index is decomposed into two components: the positive SKEW computed from S&P 500 calls only, called SKEW^+ and the negative SKEW index computed from S&P 500 puts only, called SKEW^- . For SKEW^+ we keep calls only when $K_i \geq K_0$, while for SKEW^- we keep puts only when $K_i \leq K_0$. These filters on the strike prices and on $Q(K_i)$ are applied to formulae from 4.6 to 4.8. Applying these model-free methodologies we obtain three daily indexes series: SKEW , SKEW^+ and SKEW^- extracted from the same set of S&P 500 options.

[3]After 2014, the U.S. volatility and skewness indexes are calculated as a weighted average of the prices of S&P 500 options with weekly expirations. Before 2014, monthly S&P 500 options are used, with the closest interpolated maturity to 30 days since the available S&P 500 Weekly options volume was small and the strike prices available not enough for the VIX and SKEW methodology. Usually, the weighted average in this case is between 1-month and 2-month expirations.

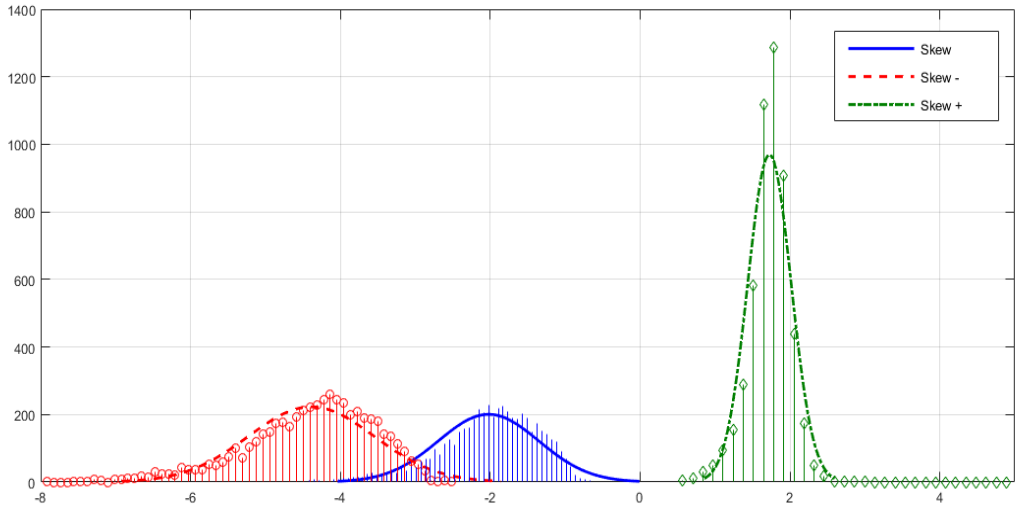
4.2.3 Data and Time Series Preliminary Findings

Daily S&P 500 options prices and daily S&P 500 index prices are collected from OptionMetrics for the time period from January 1996 to December 2017. Daily interest rates for USD are obtained from FRED. The sample we select includes several turbulent events, two recession periods according to the NBER's definition[4], one in correspondence to the aftermath of the dot-com bubble burst in early 2000 and the other in correspondence to the 2007-2009 global financial crisis. Our time period includes also other volatile events worldwide, such as, the Asian financial crisis, the Russian financial crisis, the 9/11 terrorist attack, the Eurozone sovereign debt crisis, the Chinese Yuan crisis and the UK Brexit vote. Even if they were not explicitly U.S. based, they spread volatility and uncertainty in the U.S. impacting on its equity and options market returns and, thus, on the SKEW indexes.

The aggregate skewness - Skew - is a difference between an equity calls portfolio and an equity puts portfolio as shown in formula (4.3). In order to clarify, we refer with Skew, $Skew^{+}$ and $Skew^{-}$ to the statistical skewness measures computed with 4.5. Skew is recognized as the risk neutral version of a coefficient of statistical skewness, but it is also the expectation of market price of a skewness payoff (see Bakshi et al., 2003). It is a measure of the slope of the S&P 500 implied volatility curve. When transformed in SKEW indexes through 4.4 we refer to them as SKEW , SKEW^{+} and SKEW^{-} , respectively. For the S&P 500 this difference appears to be placed entirely in the left skewed area, which drags the aggregate skewness to the left, as illustrated in Figure 4.1. Bakshi et al. (2003) affirmed that for return distributions that are left-shifted, all OTM put options will be priced at a premium relative to OTM calls. The cost of the short position in the linear combination of OTM puts will then exceed the one in calls. Mitton and Vorkink (2007) advocates that returns of under-diversified portfolios are more positively skewed than those of diversified portfolios. According to them, diversification is a two edged sword: it eliminates undesired volatility but, at the same time, it eliminates also desired skewness. The latter is the right skewness that is reduced when stocks are added, so when diversification is amplified the stocks are contributing in a negative way to the portfolio co-skewness. Harvey and Siddique (2000) points out that decreasing the portfolio skewness will command higher expected returns due to the higher risk of the portfolio, and vice-versa. The positive $Skew^{+}$ bell is representative for the long calls investors and it has a positive range. On the other hand, the negative $Skew^{-}$ bell extracted from puts extends in a wider range negative area and it is the most dispersed among the skew distributions.

[4]The NBER does not define a recession in terms of two consecutive quarters of decline in real GDP. Rather, a recession is a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production. Available at: `http://www.nber.org/cycles.html`.

Figure 4.1: Skew, Skew^- and Skew^+ Relationship

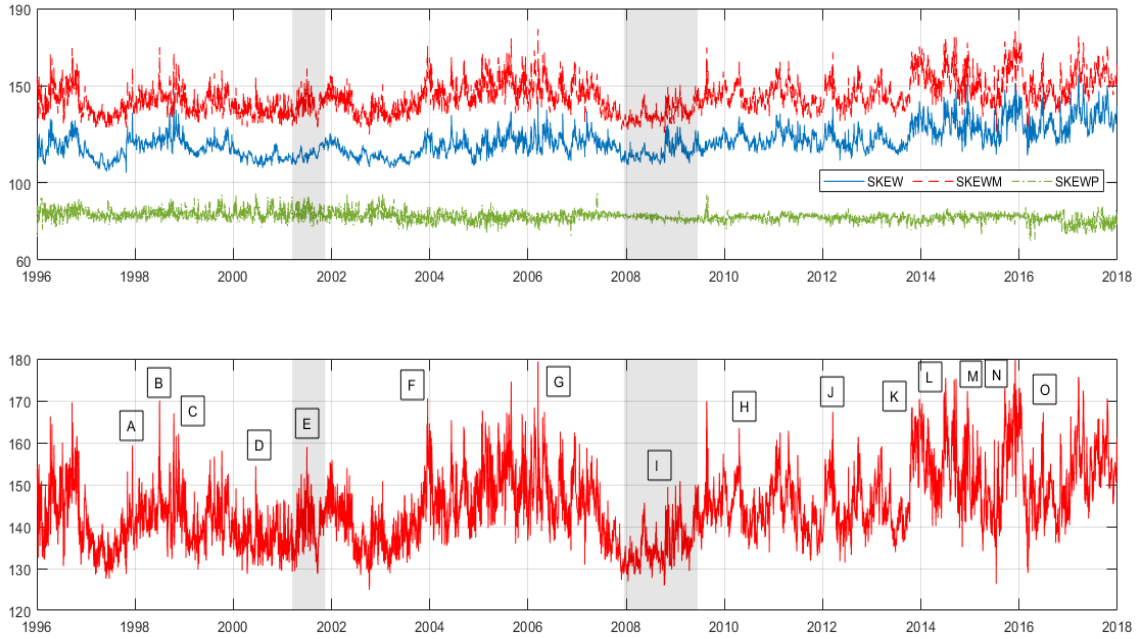


Notes: The three bells plot illustrates the decomposed statistical skew distributions. The aggregate statistical skew is computed using Formula 4.5: $S = \frac{E[R^3]-3E[R]E[R^2]+2E[R]^3}{(E[R^2]-E^2[R])^{3/2}}$. The distribution of Skew^- is computed from the same Formula by inputting puts only, while the distribution of Skew^+ is computed from calls only. The selected period is from 04-01-1996 to 29-12-2017, at daily frequency.

Figure 4.2 illustrates the historical evolution and the relationship between the aggregate SKEW index and its positive and negative components at daily frequency. In Figures 4.1 and 4.2 our series are shown at daily frequency to better highlight their trends and events in the time period. Following standard practice in the literature, in the rest of the chapter, we rely on monthly frequency, end-of-the month, for ease when compared with other financial risk measures and macroeconomic and financial variables as well as for the return predictability regressions. SKEW^- plays a main role in determining the trend for the SKEW series, laying always above the aggregate, while the role of SKEW^+ is usually more marginal becoming important only occasionally. We isolate the negative SKEW^- trend in the bottom panel of Figure 4.2 highlighting some of the main events along our selected time period. SKEW and SKEW^- appear to react in a similar way to events such as the Asian financial crisis, the LTCM collapse, the Iraq invasion, the U.S. housing market bubble in 2006, Lehman Brother failure in September 2008, during the two stages of the Eurozone sovereign debt crisis, the Chinese Yuan crisis and during the more recent UK Brexit vote. On the other hand, SKEW^- appears to react to events such as the Russian crisis in August 1998, the dot-com bubble burst in March 2000, the 9/11 terrorist attack, in the aftermath of the 2008-2009 recession period, possibly anticipating the Eurozone sovereign debt crisis inception and during the Syria was and ISIS escalation. Thus, SKEW and SKEW^- indexes show a similar trend, with the latter reacting more in correspondence of unpredictable events, events which reflected the likelihood of outliers and increased investors' tail risk perception compared to the aggregate SKEW . SKEW^- reached one of its highest levels in March 2006 underlying a period of

increasing concern due to U.S. housing market bubble and its possible bursting as a preamble for the sub-prime crisis. This behaviour is due to the fact that it is a forward looking measure computed from puts tracking more closely the investors' fear of future extreme negative outcomes. Interestingly, the SKEW and SKEW^- level was surprisingly low during the 2008-2009 recession while being volatile before turbulent times and before and after the recession periods. This behaviour during the global financial crisis might be due to the fact that investors view as unlikely another extreme market events when they are already in the midst of it.

Figure 4.2: **Decomposed SKEW Indexes**



Notes: This graph shows the decomposed SKEW indexes, namely, SKEW , SKEW^- and SKEW^+ , computed through formula (4.4): $SKEW = 100 - 10S$ in the upper panel and only the SKEW^- as a tail risk measure proxy in the bottom panel. NBER recession periods are highlighted in grey. Some of the main events in which SKEW^- has reacted along the selected period are also highlighted with letters: [A] Asian Financial Crisis [B] Russian Financial Crisis [C] LTCM Collapse [D] Dot-com Bubble Burst [E] 9/11 Terrorist Attack [F] Iraq Invasion [G] U.S. Housing Market Bubble [I] Lehman Brother Failure [H] [J] First and Second Stage Eurozone Sovereign Debt Crisis [K] Syria War Escalation [L] Ukraine-Russia Conflict [M] ISIS Escalation [N] Chinese Yuan Crisis [O] UK Brexit Vote. The selected period is from 04-01-1996 to 29-12-2017, at daily frequency.

According to Kelly and Jiang (2014), the absence of an increase in tail risk during the recent financial crisis, although surprising, is consistent with Brownlees et al. (2011) arguing that the financial crisis was characterized by soaring volatility which was, however, predictable over short horizons by standard volatility forecasting models. SKEW and SKEW^- get closer in calm periods, while the distance between them becomes wider during high market sentiment periods. SKEW appears more influenced by the positive SKEW^+ index in the pre financial crisis period and during the dot-com bubble optimistic time possibly contributing in dragging down the aggregate SKEW index.

Our idea of tail risk measure is, then, to rely only on the SKEW^- component, disregarding the information coming from the calls side representing the optimistic views. This new measure of tail risk

can be considered a more prudent forward looking measure of extreme market fear, tail risk aversion and investors hedging willingness. SKEW^{-} can be defined as a *perceived* measure of tail risk which increases when market participants increase their probability of a catastrophic market decline.

While there is evidence in the literature about the key role of the equity index OTM puts as shelter against equity market drop (see Dennis and Mayhew, 2002; Han, 2008; Bondarenko, 2014), the role of the equity indexes OTM calls is less studied and is more commonly associated with optimistic beliefs (Buraschi and Jiltsov, 2006). Hence, it is of interest to study the relationship between the SKEW indexes and other risk and tail risk measures in the literature and between the SKEW indexes and market sentiment. Section 4.3 and 4.4 present these findings.

4.3 Positioning the SKEW Indexes in Relation to Other Risk Measures

In this section we position the newly decomposed implied skewness indexes next to some of the already existing financial risk measures and tail risk measures. We describe more in depth some of the properties shown by the decomposed SKEW indexes as well as comparing them with other risk measures more common in the financial literature.

4.3.1 Comparison with Volatility and Risk Premium Measures

In order to perform a cross-sign comparison, we decompose the VIX into its upside and downside components, applying the Bakshi et al. (2003) – BKM – model-free approach to S&P 500 daily options, with the same OTM options selection and filter rules as in 4.2.2 (see Appendix for more details). Plotting the decomposed VIX series in Panel A of Figure 4.3, we notice that VIX^{-} has a prevalent role in the total VIX , in line with Bollen and Whaley (2004) and **?** showing that investors weigh differently downside losses versus upside gains. Consequently, VIX changes are driven more by the downside volatility component (S&P 500 puts) in comparison to the upside volatility component (S&P 500 calls). In general, VIX^{-} is higher than VIX^{+} , with the opposite true only in rare circumstances such as bullish and optimistic periods characterized by positive investors' expectations and calls trading stimulation. VIX^{-} follows mainly the trend of VIX especially when put options are more in need for hedging strategies and it can be considered as a proxy of downside risk[5]. Results are in line with previous studies decomposing implied volatility indexes (e.g. Fu et al., 2016; Kilic and Shaliastovich, 2018). During

[5]For instance, the implied volatility series spiked during the Asian financial crisis (end of 1997), during the Russian financial crisis and Long-Term Capital Management (LTCM) collapse in 1998, during the dot-com bubble, and in the middle of the 2001-2002 NBER recession period). The implied volatility indexes reached their all time high levels during the 2008 financial crisis in response to the Lehman Brother collapse in September 2008. Other noteworthy peaks are found in correspondence of the Eurozone sovereign debt crisis (2011 and 2012), Chinese Yuan crisis in summer 2015 and, finally, the UK Brexit vote in June 2016.

negative times the S&P 500 puts are more expensive than the S&P 500 calls (Bondarenko, 2014) and in more demand. The upside out-looking volatility helps the market attenuate the fear relative to equity shortfall and market losses. A more in-depth analysis between these three indexes, namely, equity, volatility and skewness is contained in Appendix B.1. Results of a Granger causality analysis among the series are reported in Section B.1.1 and Section B.1.2 in Appendix B.1.

The decomposed SKEW indexes are also compared with the newly proposed decomposed good and bad variance risk premia by Kilic and Shaliastovich (2018). The good variance risk premium predicts future assets returns with a positive sign, whereas the bad variance risk premium with a negative sign. The three variance risk premium series are shown in Panel B of Figure 4.3. According to Kilic and Shaliastovich (2018), both components of the variance risk premium should be considered in order to obtain a higher return predictability in the long-term horizon. They define the total variance risk premium as total vp, the good variance risk premium component as vp good and the downside variance risk premium component as vp bad. Their series are available at `https://sites.google.com/view/metekilic/`. In our chapter we slightly change the notation for consistency with the other decomposed measures. We will refer as to the vp total as VRP , to the vp good as VRP^+ and to the vp bad as VRP^- .

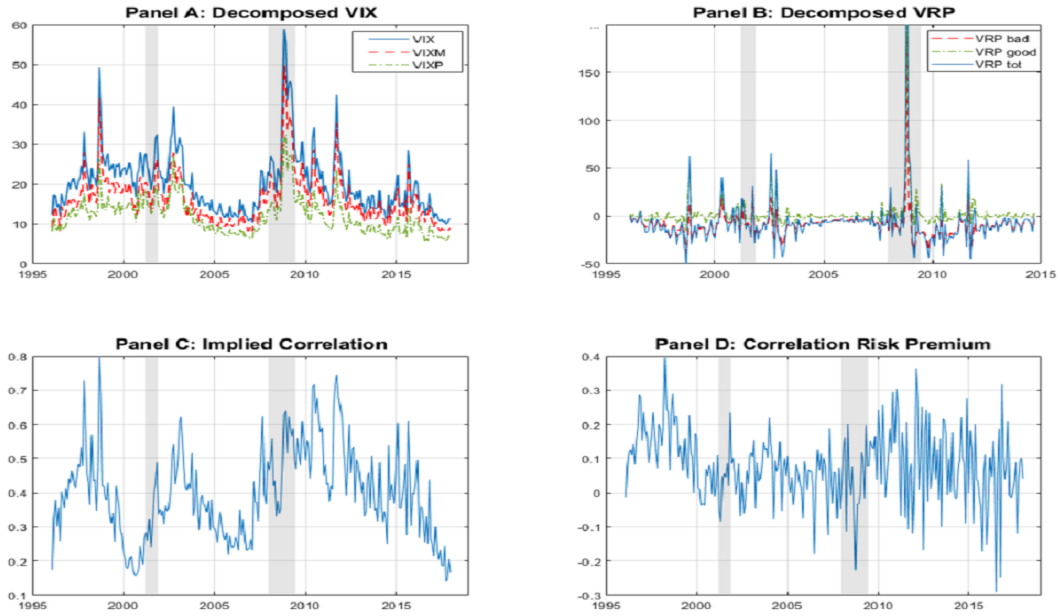
In addition, we analyze together the implied skewness indexes, the measures of implied and realized correlation and the correlation risk premium by Driessen et al. (2009) computed from options with a 1-month maturity[6]. The implied correlation is constructed as the average expected correlation among the stocks contained within an index. Thus, it is extracted from the price of index options corresponding to that of individual stock options[7]. The correlation risk premium at time t is defined as the difference between the risk-neutral and physical correlation measures: $CRP_t = IC_t - RC_t$. Figure 4.3 shows the plots for the implied correlation and the correlation risk premium in Panel C and Panel D, respectively.

Table 4.1 shows the correlation analysis among the three decomposed SKEW indexes, three decomposed VIX indexes, three decomposed VRP , the implied and realized correlation measures, and the correlation risk premium. Our correlation analysis confirms the conclusions in Han (2008), Dennis and Mayhew (2002) and Conrad et al. (2013), highlighting a negative relationship between VIX and SKEW and also between VIX and SKEW^- . When market volatility is high, the negative skewness for S&P 500 is reduced. Even if they are both calculated from the same S&P 500 options, the two indexes carry different information and they have a low correlation being them complementary measures of risk. When VIX spikes, SKEW remains around its average and vice-versa. Furthermore, there is a positive relationship between VIX and SKEW^+ . When VIX spikes the positive SKEW component does the same. We provide some interpretations of these findings in Section 4.4 by taking into account

[6]We thank Grigory Vilkov for kindly sharing the correlation measures at: `http://www.vilkov.net/index.html`

[7]An increase in the price of index options leads to an increase in the implied index variance, in turn, raising the implied correlation. Conversely, an increase in the prices of individual stock options leads to an increase in the implied stock variances, leading to a lower implied correlation (see Buss et al., 2018)

Figure 4.3: **Risk Measures Plots**



Notes: This graph shows the decomposed volatility indexes series, namely VIX , VIX^- and VIX^+ , in Panel A, the decomposed variance risk premium series, namely, VRP total, VRP good and VRP bad as in Kilic and Shaliastovich (2018) in Panel B, the implied correlation in Panel C and correlation risk premium in Panel D. We do not report the extreme values the indexes reached during the financial crisis, namely, 409.10, 221.64 and 188.64 for VRP , VRP^+ and VRP^- , respectively in order to keep a more compact scale allowing an easier comparison. The correlation measures are computed from 1-month options. The selected period is from 01:1996 to 12:2017, at monthly frequency. The selected period for risk premia is from 01:1996 to 08:2014. The NBER recession periods are highlighted in grey.

the market sentiment in relation with the SKEW indexes. The results are also confirmed in Figure B1 in Appendix in which we compare the decomposed SKEW indexes and the decomposed VIX indexes. SKEW is positively correlated with SKEW^- while negatively correlated with SKEW^+ . The two skewness components, SKEW^- and SKEW^+ have an almost nil correlation. The high correlation coefficients among the three decomposed VIX indexes as well as among the three variance risk premia is in line with the previous literature Kilic and Shaliastovich (2018). Lower, but still positive, correlation is found between the implied volatilities and risk premia.

Table 4.1: **Decomposed SKEW and Other Risk Measures: Correlation Analysis**

	SKEW	SKEW^+	SKEW^-	VIX	VIX^+	VIX^-	VRP	VRP^+	VRP^-	IC	RC	CRP
SKEW	1											
SKEW^+	-0.20***	1										
SKEW^-	0.78***	0.03	1									
VIX	-0.23***	0.05	-0.49***	1								
VIX^+	-0.37***	0.14**	-0.52***	0.97***	1							
VIX^-	-0.14**	-0.02	-0.46***	0.98***	0.93***	1						
VRP	0.01	-0.07*	-0.07*	0.28***	0.23***	0.31***	1					
VRP^+	0.02	-0.08*	-0.14**	0.45***	0.39***	0.48***	0.96***	1				
VRP^-	0.01	-0.05	-0.02	0.08*	0.05	0.09*	0.96***	0.86***	1			
IC	0.05	-0.09*	-0.27***	0.60***	0.53***	0.64***	-0.01	0.15**	-0.18***	1		
RC	-0.03	-0.03	-0.28***	0.56***	0.50***	0.58***	0.21***	0.33***	0.06	0.73***	1	
CRP	0.11**	-0.07*	0.03	-0.01	-0.04	0.01	-0.31***	-0.28***	-0.32***	0.26***	-0.46***	1

Notes: This table presents the correlation analysis between the total and decomposed skewness indexes (SKEW , SKEW^+ and SKEW^-), implied volatility indexes (VIX , VIX^+ and VIX^-), variance risk premia (VRP , VRP^+ and VRP^-) and the correlation measures (IC, RC, CRP). The comparison is shown for the common time period among the selected measures, namely, between Jan 1996 and Aug 2014, at monthly frequency. Significance levels: $*\quad p < 0.1, **\quad p < 0.05, ***\quad p < 0.01$.

A positive correlation between the implied volatility indexes and risk premia is also found. The

correlation between the decomposed VIX series and IC is also positive. These findings are in line with the correlation analysis in Buss et al. (2018). Low or even negative correlation is instead found between the decomposed SKEW indexes and the correlation measures. Thus, it appears that the SKEW indexes contain additional information not enclosed in the other sets of financial risk measures. The decomposed SKEW indexes appear also to contain different information from each other.

4.3.2 Comparison with Other Tail Risk Measures

In this section, we compare the implied SKEW measures with some of the tail and financial risk measures have been proposed in the literature, namely, Kelly and Jiang (2014) tail index, Almeida et al. (2017) nonparametric tail risk, the Allen et al. (2012) aggregate systemic risk measure – CATFIN – and the CRASH index. Kelly and Jiang (2014) tail index is computed from a cross-section of equity returns assuming that the lower tail distribution of asset return i at time t follows the probability law:

$$P_t(R_{i,t+1} < r \mid R_{i,t+1} < u_t) = \left(\frac{r}{u_t}\right)^{\frac{-a_i}{\lambda_t}} \tag{4.12}$$

where $P_t(\cdot)$ denotes the conditional probability on the information set F_t at time t, $r < u_t < 0$ and λ_t is the time varying tail exponent estimated by the Hill estimator: $\lambda_t^{Hill} = \frac{1}{K_t}\sum_{k=1}^{K_t} ln\frac{R_{k,t}}{u_t}$, where $R_{k,t}$ is the day k-th return below an extreme value threshold u_t in month t and K_t measures how many times such exceedance happens in month t across firms conditioning to the information set F_t. They assume that even if different firms are subjected to different risk, they can be aggregated into a single process, assuming similarity in the risk dynamics. The relationship between tail risk and individual stock returns is positive under their model, coherent with the fact that investors are tail risk averse.

The Almeida et al. (2017) Hellinger nonparametric tail risk is also based on a cross-sectional approach on assets' returns. It is based on the risk neutral excess expected shortfall (ES) of portfolios returns being the aggregate tail risk the average of the single portfolio ES defined for every asset i as:

$$TR_{i,t} = E^Q[R_{i,\tau} - VaR_\alpha(R_{i,\tau})|R_{i,\tau} \leq VaR_\alpha(R_{i,\tau})], \tag{4.13}$$

where t is the selected month for the tail risk calculation, τ is the possible state of nature, Q is the risk neutral density (RND) over the return space R, and α is the VaR threshold. The Hellinger tail risk is computed with five principal components from the 25 Fama and French Size and Book-To-Market portfolios, employing a Hellinger risk neutral density given by $\gamma = -0.5$.

The macro index of systemic risk – CATFIN – by Allen et al. (2012) is constructed using value-at-risk (VaR) and expected shortfall (ES) methods estimated using both nonparametric and parametric approaches. The parametric distributions to estimate the 99% VaR and the 1% ES are the generalized

Pareto distribution (GPD) and the skewed generalized error distribution (SGED). The nonparametric methods are measured as a cut off point of the left tail lower one percentile of the monthly excess returns for the VaR and as an average of the extreme financial firms returns beyond the 1% nonparametric VaR. This catastrophic risk measure for the financial sector is then constructed as an average of the three VaR and ES measures. The measure is negative most of the time. We consider this measure as a proxy of the financial sector systemic risk and we investigate the possible connection with our SKEW indexes.

Lastly, the CRASH index measures the probability of another catastrophic stock market crash in the U.S. in the next 6 months with regards to institutional investors' expectations taken with regards to institutional investors[8]. Table 4.2 shows the correlation analysis among the selected measures.

Table 4.2: SKEW **Indexes and Other Tail Measures: Correlation Analysis**

	SKEW	$SKEW^+$	$SKEW^-$	TAIL	HELLINGER	CATFIN	CRASH
SKEW	1						
$SKEW^+$	-0.19***	1					
$SKEW^-$	0.75***	0.04	1				
TAIL	0.02	0.01	0.18***	1			
HELLINGER	0.01	-0.03	-0.20***	-0.46***	1		
CATFIN	-0.06	-0.02	-0.33***	-0.55***	0.56***	1	
CRASH	0.01	-0.02	0.22***	0.13**	-0.27***	-0.50***	1

Notes: This table presents the correlation analysis between the aggregate and decomposed skewness indexes, SKEW , $SKEW^+$ and $SKEW^-$ and other tail risk and financial risk indexes, at monthly frequency. TAIL is the Kelly and Jiang (2014) tail index, HELLINGER is the Almeida et al. (2017) Hellinger tail risk, CATFIN is the Allen et al. (2012) catastrophic financial systemic risk, CRASH index is from the Yale School of Management. We conduct the comparison for the common period among the selected measures, namely, between 01:1996 and 04:2014, at monthly frequency. Significance levels: $*\quad p < 0.1, **\quad p < 0.05, ***\quad p < 0.01$.

Our results indicate that the $SKEW^-$ is the most connected among the SKEW indexes, with a positive correlation (18%) to the Kelly and Jiang (2014) tail index. Kelly and Jiang (2014) found a -30% correlation between TAIL and the option-implied skewness suggesting that TAIL is closely associated with tail risks perceived by option market participants. The negative correlation they found is in relation to the statistical skewness (as presented in Figure 4.1 in this chapter) which has opposite sign compared to the SKEW index. We find evidence of lack of correlation between our series, SKEW and $SKEW^+$, and the Hellinger tail risk. $SKEW^-$ is, negatively correlated (-20%) with Hellinger.

Our SKEW measures are also negatively correlated with Allen et al. (2012) CATFIN with the $SKEW^-$ showing a noticeable negative relationship (-33%). We follow the interpretation in Almeida et al. (2017) explaining the negative correlation between the Hellinger tail risk and the Kelly and Jiang (2014) tail risk. This can be explained from the fact that in the latter, they use the whole individual raw returns below 5% threshold, in Hellinger tail risk 25 portfolios sorted by Size and Book-to-Market are used. In addition, since the Hellinger tail risk is based on excess expected shortfall, this gives values which are, most of the time, negative. Our SKEW measures assume only positive values due to the

[8]The Crash index is available at: `https://som.yale.edu/faculty-research/our-centers-initiatives/international-center-finance/data/stock-market-confidence`. The questions that this index answers is the following: *What do you think is the probability of a catastrophic stock market crash in the U. S., like that of October 28, 1929 or October 19, 1987, in the next six months, including the case that a crash occurred in the other countries and spreads to the U. S.?*

transformation in equation 4.4, instead. If taken in absolute values, Hellinger tail risk shows the highest positive correlation with SKEW^{-} , further reinforcing the intuition of the latter proposed as tail risk measure in this chapter. The high level of correlation between Hellinger tail risk and CATFIN can be explained on the fact that both measures are based on VaR and ES methodologies. The same negative implied SKEW index appears the most correlated with the CRASH index (22%), thus sharing some similar information on catastrophic stock market risk.

Other measures such as the Bollerslev and Todorov (2011) realized aggregate and decomposed jumps have been compared with the SKEW indexes. According to them, the realized variance measure consists of two different components: a variation due to the continuous sample price path (continuous variation, CV) and a variation coming from jumps (jump variation, JV). The latter can be further split into positive and negative jumps (RJV and LJV). Eventually, they define $RV_t = CV_t + RJV_t + LJV_t$. The correlation analysis between the jumps and the SKEW indexes spans the all period from 01:1996 to 12:2017, thus not shown in Table 4.2. The correlation between the SKEW indexes and the jump measures is found to be, overall, small and negative, for all the three considered jumps measures, thus not changing our conclusion. The CBOE Volatility of Volatility, VVIX, is also compared with our SKEW indexes. It is calculated by applying the same VIX methodology to a wide range of OTM VIX options. Sometimes VVIX is associated with the tail risk concept. Park (2015) argued that the volatility of the stochastic volatility could be a different way to measure the tail risk and that VVIX, as a mixture of volatility of volatility and also volatility jump risk, is more reliable than VIX in measuring market extreme events. This index is only available for a more recent time period, after 2007. When compared with our SKEW indexes for the last decade, we find that SKEW^{-} and SKEW^{+} indexes are almost uncorrelated with the VVIX, while the aggregate SKEW shows a positive correlation (17%).

Overall, we find that the SKEW indexes do not appear to be highly correlated with other tail risk measures implying that the SKEW indexes extracted from options may carry additional information compared to cross-sectional market returns tail indexes (e.g. Almeida et al., 2017). The results in Table 4.2 confirm that SKEW^{-} is the closest to other existing tail risk measures, hence it is proposed as a new tail risk measure in this chapter. Due to its forward looking properties, SKEW^{-} may also be considered a measure of implied – or *perceived* – tail risk in the financial markets. This might explain the low correlation with other tail risk measures and its trend highlighted in Figure 4.2.

4.4 SKEW Indexes and Market Sentiment

Drawing upon the findings from the previous sections, we hypothesize a market sentiment interpretation connected to the robust predictive power of SKEW^{+} . This hypothesis relies on literature that links investor sentiment to stock prices (e.g. Baker and Wurgler, 2006; **?**) and on literature that links risk-

neutral skewness to market sentiment (e.g. Buraschi and Jiltsov, 2006; Han, 2008; Garleanu et al., 2009; Friesen et al., 2012; Lemmon and Ni, 2014; Stilger et al., 2016). Our hypothesis is that market sentiment affects the price of equity options, thus changing implied skewness.

Baker and Wurgler (2000, 2006, 2007) asserted how investor sentiment is impacting on the stock prices and Han (2008) confirmed that there is a link between risk neutral skewness and market sentiment; when the investor sentiment is bearish the index option volatility smile is steeper and the risk neutral skewness is more negative, while when the investor sentiment is bullish, the volatility smile is flatter and the skewness less negative. Thus, the market sentiment affects equity index options' prices, changing market implied volatility and skewness. The relationship between the skew and market sentiment was also tested by Dennis and Mayhew (2002), in the form of a link between the skew and the put-call ratio, finding a positive, but not significant relationship between the two.

We ask, firstly, whether or not the SKEW indexes extracted from options are affected by market sentiment and, secondly, whether or not SKEW indexes are able to predict changes in investor sentiment. The sentiment proxies we select are some of the most common market sentiment indicators in the financial literature: the investor sentiment index by Huang et al. (2015) (ZHOU), the Baker and Wurgler (2006) Sentiment Index (BW), the put/call Ratio from CBOE (PCRatio), the AAII American Association of Individual Investors' survey data (AAII), the Confidence Index (CONF) and the Sentiment Index from University of Michigan Consumer Sentiment (SENT). More specifically, ZHOU is the investor sentiment index by Huang et al. (2015) available at `http://apps.olin.wustl.edu/faculty/zhou/useful_links`, BW is the Baker and Wurgler (2006) sentiment index available at `http://people.stern.nyu.edu/jwurgler/`. The latter is one of the earliest sentiment index has been developed applying a principal component analysis to six underlying sentiment proxies while Huang et al. (2015) improved this measure extracting the most relevant information for the stock returns from the same six sentiment proxies but discarding their approximation errors. PCRatio is the put-call ratio from CBOE, commonly used as a sentiment proxy (see Dennis and Mayhew, 2002); AAII is the sentiment index from the American Association of Individual Investors's survey (`http://www.aaii.com/sentimentsurvey`). The Confidence Index represents the confidence in the financial market, Dow Jones Industrial, in the following months up to 10 years[9]. SENT is the University of Michigan Consumer Sentiment retrieved from FRED: `https://fred.stlouisfed.org/series/UMCSENT`.

First, we analyze how implied skewness measures extracted from options are affected by market sentiment. Investors are trading index options based on their directional information (Ni et al., 2008). It is common in the literature to distinguish between two groups of investors, influenced by opposite

[9]It can be downloaded from: `https://som.yale.edu/faculty-research/our-centers-initiatives/international-center-finance/data/stock-market-confidence` and the question this index answers is the following - *How much of a change in percentage terms do you expect in the following months/years (fill with $+/-$ before the number to indicate expected increase or decrease)?* - This is taken with regards to institutional investors.

market expectations. According to Brown and Cliff (2005), investors are divided into “fundamentalist", trading according to the asset fundamentals, and “speculators", more influenced by market sentiment. Another investors categorisation by Lemmon and Ni (2014) is between institutional investors and “noise traders" or individual investors. The latter are referred to be more influenced by sentiment and behavioural biases compared to the first (see also Dennis and Strickland, 2002). Index OTM puts are traded as insurance assets against equity market drops (see Bollen and Whaley, 2004; Han, 2008; Bondarenko, 2014) and their trading is driven mainly by hedging demand from institutional investors (Lakonishok et al., 2007). In our view, this opens for potential market sentiment impact on the other side of the equity options market, the calls side. We test the impact of market sentiment on SKEW indexes in a contemporaneous framework, where the dependent and independent variables are matched for their available data. We run the following OLS regression:

$$SKEW_n^i = \alpha + \beta_1 MarkSent_j + \epsilon \quad with \quad i = Tot, +, -. \tag{4.14}$$

where $MarkSent_j$, is one of the market sentiment proxies, ZHOU, BW, PCRatio, AAII, CONF, SENT.

Table 4.3: **Regression Analysis Skewness Indexes on Investor Sentiment Indexes**

	ZHOU			BW			PCRatio		
Predictor	Coef	t-stat	$R^2(\%)$	Coef	t-stat	$R^2(\%)$	Coef	t-stat	$R^2(\%)$
SKEW	-0.029**	[-1.901]	1.3	-0.019***	[-4.632]	4.5	-0.092*	[-1.657]	1.3
SKEW^+	0.005***	[2.524]	2.6	0.006***	[2.875]	2.7	0.032*	[1.679]	1.5
SKEW^-	-0.028**	[-2.001]	2.1	-0.015*	[-1.503]	1.8	-0.023**	[-2.118]	6.2
	AAII			CONF			SENT		
Predictor	Coef	t-stat	$R^2(\%)$	Coef	t-stat	$R^2(\%)$	Coef	t-stat	$R^2(\%)$
SKEW	-0.013***	[-3.781]	3.7	-0.012	[-0.162]	0.1	-0.051*	[-1.462]	0.7
SKEW^+	-0.031	[0.085]	0.1	0.020	[1.034]	0.3	0.024***	[2.836]	1.4
SKEW^-	0.041*	[-1.556]	0.2	-0.084	[-1.107]	0.7	-0.019*	[-1.290]	0.1

Notes: This table presents the output of the regression analysis between our dependent variables, SKEW , SKEW^- and SKEW^+ and some of the most common market sentiment indicators in the literature as independent variables by running regression 4.14. The sentiment indicators which are selected with the corresponding available time period are the following: the sentiment index by Huang et al. (2015) (ZHOU) (from 01:1996 to 12:2016), the sentiment index by Baker and Wurgler (2006) (BW) (from 01:1996 to 09:2015), the put-call ratio (PCRatio) (from 10:2003 to 12:2017) and the American Association of Individual Investors' survey index (AAII), the Confidence Index (CONF) and the University of Michigan Consumer Sentiment (SENT) for the all time period of this study, from 01:1996 to 12:2017. Data frequency is monthly. Regressions intercepts are not reported to save on space. The regression coefficients, Newey-West t-statistics in square brackets and R^2 in percentage are reported. Significance levels: $*\quad p < 0.1, **\quad p < 0.05, ***\quad p < 0.01$.

The results of the estimated contemporaneous OLS regression presented in Table 4.3 indicate that the impact of market sentiment is negative for SKEW and SKEW^- and positive for SKEW^+ , with the only exception for AAII. The difference in coefficients' signs for AAII is due to the fact that it is a sentiment proxy from a survey about investors' market opinions (bullish, bearish, neutral) and it is measured as the difference between bearish opinion and bullish opinion. It is also considered as a proxy of institutional investors sentiment due to the panel of interviewed investors. Thus, the market sentiment proxies have a positive influence on the OTM calls trade, with coefficients significant in four cases out of six. The aggregate SKEW is impacted negatively by market sentiments in all cases, whereas SKEW^-

in five cases out of six. Overall, we find that SKEW^- is impacted less by market sentiment, only in two cases out of six, one of them being the put-call ratio computed from the same S&P 500 options. More specifically, Baker and Wurgler (2006) (BW) and Consumer Sentiment (SENT), two of the most common sentiment proxies in the financial literature, do not show statistically significant relationship with SKEW^- . When found significant, the negative coefficients decrease from SKEW to SKEW^- meaning that there is a stronger marginal relationship with SKEW^- . We find evidence that the put-call ratio, considered as a proxy of market sentiment and trading pressure, is significant in explaining all the three SKEW indexes. Overall, the regression coefficients indicate how puts and calls portfolios react in an opposite direction to market sentiment reflecting pessimistic and optimistic views, respectively. No relationship between the decomposed SKEW indexes and the Confidence index are detected.

Furthermore, we consider whether or not the SKEW indexes have some predicting power with respect to the selected sentiment indicators similar to Neely et al. (2014). The dependent variable is selected among one of the sentiment indicators and the decomposed SKEW indexes are treated as predictors as:

$$MarkSent_{t+1,j} = \alpha + \beta_{1,i} SKEW^i + \epsilon_{t+1,j} \quad with \quad i = Tot, +, -. \tag{4.15}$$

where $MarkSent_{t+1,j}$ is, now, the next month level of one of the selected sentiment indicators, namely, ZHOU, BW, PCRatio, AAII, CONF, SENT. Table 4.4 shows the results of the predictive OLS regression.

Table 4.4: **Market Sentiment and** SKEW **Indexes: Predictive Regression**

	ZHOU			BW			PCRatio		
Predictor	Coef	t-stat	$R^2(\%)$	Coef	t-stat	$R^2(\%)$	Coef	t-stat	$R^2(\%)$
SKEW	-0.169*	[-1.554]	0.7	-0.023***	[-3.496]	4.4	-0.002***	[-2.620]	2.9
SKEW^+	0.691***	[2.642]	1.9	0.040***	[2.455]	2.6	0.005	[0.204]	0.0
SKEW^-	-0.039	[-0.403]	0.0	-0.010	[-1.061]	1.3	-0.002***	[-3.654]	6.2
	AAII			CONF			SENT		
Predictor	Coef	t-stat	$R^2(\%)$	Coef	t-stat	$R^2(\%)$	Coef	t-stat	$R^2(\%)$
SKEW	-0.003***	[-4.427]	5.9	-0.025	[-0.313]	0.1	-0.027	[-0.296]	0.0
SKEW^+	-0.006***	[-3.088]	3.3	0.175	[0.982]	0.4	0.582**	[2.309]	1.3
SKEW^-	0.001**	[2.107]	1.3	-0.049	[-0.670]	0.3	-0.910	[0.942]	0.3

Notes: This table presents the output of the OLS predictive regression between the independent variables, SKEW , SKEW^- and SKEW^+ and the next month level of the selected market sentiment indicators, this time as dependent variables. The OLS predictive regression is estimated through equation 4.15. The sentiment indicators which are selected with the corresponding available time period are the following: the sentiment index by Huang et al. (2015) (ZHOU) (from 01:1996 to 12:2016), the sentiment index by Baker and Wurgler (2006) (BW) (from 01:1996 to 09:2015), the put-call ratio (PCRatio) (from 10:2003 to 12:2017) and the American Association of Individual Investors' survey index (AAII), the Confidence Index (CONF) and the University of Michigan Consumer Sentiment (SENT) for the all time period of this study, from 01:1996 to 12:2017. Data frequency is monthly. Regressions intercepts are not reported to save on space. The regression coefficients, Newey-West t-statistics in square brackets and R^2 in percentage are reported. Significance levels: $*\quad p < 0.1, **\quad p < 0.05, ***\quad p < 0.01$.

Our empirical evidence confirms that SKEW^+ shows the best next month market sentiment predictability in four cases out of six, namely ZHOU, BW, AAII and SENT according to the Newey-West t-statistic. SKEW^+ shows a higher R^2 compared to SKEW and SKEW^- . The coefficients carried

by the SKEW indexes are similar to the ones found in Table 4.3.

Our regression results reveal how SKEW^{+} can be seen as that component being influenced by market sentiment the most and, in turn, it contains useful information in order to predict future levels of some of the most tracked market sentiment indicators, mainly, ZHOU and SENT. This may be due to the fact that in high sentiment market, when the information provided by the tail risk index should be more reliable, OTM index puts are expensive (see Bondarenko, 2014; Han, 2008). For this reason investors with a bullish expectation in equity market can go long in OTM index calls. Investors who are “end-users" have a net long position in S&P 500 options, (Garleanu et al., 2009). The correlation signs in Table 4.1 confirm the positive relationship between SKEW^{+} , and VIX and VIX^{+} . The first is, sometimes, used as a market sentiment proxy, whereas the latter is a proxy of market exuberance (see Segal et al., 2015; Bollerslev et al., 2015). To conclude, market sentiment can have an undesired effect on SKEW dragging it towards the “bright" side thus creating an *optimistic illusion* carried from investors’ positive expectations.

4.5 Decomposed SKEW Indexes and Equity Risk Premium Predictability

In this section we study whether the information content of our SKEW , SKEW^{+} and SKEW^{-} indexes can help in predicting the equity risk premium. This section is motivated by the vast recent literature which has been attempting to predict future excess stock returns by considering different sets of predictors such as financial market variables, macroeconomic variables and technical indicators (see Pástor and Stambaugh, 2009; Bakshi et al., 2011; Bakshi and Panayotov, 2013; Pettenuzzo et al., 2014; Neely et al., 2014; Rapach et al., 2016); and Rapach and Zhou (2013) for an exhaustive survey of this literature.

This section is also well anchored in the financial literature looking at skewness measures as possible containers of information useful to predict the future equity returns and risk premia (see Chang et al., 2013; Bali and Murray, 2013; Amaya et al., 2015). Given that our SKEW indexes are extracted from options, we believe they may improve the equity risk premium predictability (e.g. Bakshi et al., 2011). By disentangling the information content enclosed in upside and negative measures may also be found to improve their predictability (see Kilic and Shaliastovich, 2018). We also position our decomposed implied SKEW measures next to other macroeconomic predictors common in the literature (e.g. Goyal and Welch, 2008) and next to other financial volatility measures based on options, namely, VIX and volatility risk premium with the aim of checking whether or not the SKEW indexes are still informative when other control variables are added to the predictive models.

We describe the dependent variables and the selected predictors in subsection 4.5.1. We show the

results for the in-sample bivariate and multivariate predictive exercise with regards to the S&P 500 equity risk premium and international markets in subsection 4.5.2 and 4.5.5, respectively. Another set of predictors including the decomposed VIX and variance risk premia is considered in the subsection 4.5.3. The out-of-sample analysis as a robustness check is reported in subsection 4.5.4. Section 4.6 studies the predictability of the decomposed SKEW indexes with relation to sets of individual stocks.

4.5.1 Selected Predictors and Descriptive Statistics

In order to show the predictive power of the SKEW indexes, we compare the newly proposed decomposed SKEW indexes to a more consolidated and common set of financial market predictors as the one by Goyal and Welch (2008). This allows us to relate our results to the vast literature on equity risk premium predictability. The data set are available from Amit Goyal's webpage at: `http://www.hec.unil.ch/agoyal/`.

In particular, the common set of 14 macroeconomic variables by Goyal and Welch (2008) we use as predictors of the equity risk premium returns are the following:

- The log dividend price ratio (DP) computed as the log of a 12-month moving sum of dividends paid on S&P 500 minus the log of the S&P 500 stock prices.
- The log dividend yield (DY) computed as the log of a 12-month moving sum of dividend minus the log of lagged S&P 500 stock prices.
- The log earnings-price ratio (EP) computed as the log of a 12-month moving sum of earning on the S&P 500 minus the log of stock prices.
- The log dividend-payout ratio (DE) computed as the log of a 12-month moving sum of dividends minus the log of a 12-month moving sum of earnings.
- The excess stock return volatility (RVOL) computed as a 12-month moving standard deviation estimator (see Mele, 2007; Rapach et al., 2016)[10].
- The book-to-market ratio (BM) computed as the book-to-market value ratio for the Dow Jones Industrial Average.
- The net equity expansion (NTIS) computed as the ratio of a 12-month moving sum of net equity issues by NYSE-listed stocks to the total end-of-year market capitalization of NYSE stocks.
- The treasury bill rate (TBL): interest rate on a three-month T-bill.
- The long-term yield (LTY): long-term government bond yield.

[10]The RVOL measure is computed as a 12-month moving standard deviation estimator (see Mele, 2007; Rapach et al., 2016) and it differs from the measure of stock return volatility used in Goyal and Welch (2008) (sum of squared daily excess stock returns during the month). It has shown to yield better estimation results (see Rapach et al., 2016).

- The long-term return (LTR): return on long-term government bonds.
- The term spread (TMS) computed as the difference between the long-term yield and the T-bill rate.
- The default yield spread (DFY) computed as the difference between Moody's BAA- and AAA-rated corporate bond yields.
- The default return spread (DFR) computed as the long-term corporate bond return minus the long-term government bond return.
- The inflation rate (INFL) computed from the CPI for all urban consumers.

The SKEW indexes, namely, SKEW , SKEW^{+} and SKEW^{-} , computed and decomposed as illustrated in section 4.2.2 represent our main three predictors. All the variables are considered at monthly frequency as standard practice in the predictability literature. Further details on the correlation between the selected variables are described in Appendix B. The dependent variable, the equity risk premium (log) is computed as the difference between the log stock market returns, r_{t+1} on S&P 500 , and the log return on a risk-free bill, r_t^* (see Bakshi et al., 2011; Neely et al., 2014):

$$ln(1 + r_{t+1}^{S\&P500}) - ln(1 + r_t^*) \tag{4.16}$$

The following Table 4.5 shows the selected variables and equity risk premium (log) descriptive statistics.

Table B4 in Appendix shows the correlation coefficients for the Goyal and Welch (2008) 14 macroeconomic variables and for the SKEW indexes. The latter are taken at first difference thus showing different results than Table 4.1. We find that the selected macroeconomic predictors show strong correlations within each other (e.g. DP and DY, EP and DE, LTY and TBL), whereas the coefficients decrease considerably with regards to the SKEW indexes. The implied SKEW indexes appear unrelated to the common set of macroeconomic variables. The highest correlation coefficient is found between SKEW^{-} and DFR (18%). This suggests that the information content of the SKEW indexes is different from the one of the 14 macroeconomic predictors. We also extract principal components from the set of Goyal and Welch (2008) 14 macroeconomic predictors in order to group the dispersed information they contain. The predictors are standardized. $X_t = (X_{1,t}, ...X_{N,t})'$ is the N-vector ($N = 14$) of the selected predictors and the vector of the first K principal components extracted from X_t is denominated as $\hat{F}_t^P = (F_{1,t}^{GW}, ..., F_{K,t}^{GW})'$ where GW implies that these are extracted from the Goyal and Welch (2008) 14 predictors. We select only the first four principal components as selected by Akaike information criterion and reasonable number of components in order to keep the model parsimonious. Figure B2 in Appendix shows the main four principal components.

Table 4.5: **Equity Risk Premium and Predictors Summary Statistics**

Variable	Mean	Std. Dev	Min	Max	Skewness	Kurtosis	Sharpe
Equity Risk Premium (log)	0.01	0.04	-0.18	0.10	-0.82	4.66	0.12
SKEW (log)	4.79	0.06	4.66	4.97	0.66	3.30	
SKEW^{+} (log)	4.41	0.03	4.30	4.54	0.58	5.03	
SKEW^{-} (log)	4.96	0.05	4.84	5.15	0.50	3.00	
DP	-4.01	0.20	-4.52	-3.28	-0.04	3.96	
DY	-4.00	0.20	-4.53	-3.29	-0.16	3.81	
EP	-3.15	0.38	-4.83	-2.56	-2.04	8.76	
DE	-0.85	0.43	-1.24	1.37	3.23	14.98	
RVOL	0.14	0.05	0.05	0.31	0.53	2.79	
BM	0.26	0.07	0.12	0.44	-0.27	2.17	
NTIS	0.01	0.01	-0.05	0.03	-0.86	3.32	
TBL	0.02	0.02	0.01	0.06	0.41	1.50	
LTY	0.04	0.01	0.01	0.07	-0.08	1.98	
LTR	0.01	0.03	-0.11	0.14	0.07	5.43	
TMS	0.02	0.01	-0.01	0.04	-0.13	2.03	
DFY	0.01	0.01	0.01	0.03	2.95	14.35	
DFR	0.01	0.01	-0.09	0.07	-0.48	9.33	
INFL	0.01	0.01	-0.01	0.01	-0.90	7.58	

Notes: The table reports the summary statistics for the log equity risk premium, the log of the decomposed SKEW indexes predictor variables computed as illustrated in Section 4.2 and the 14 predictor variables from Goyal and Welch (2008): the log dividend price ratio (DP), the log dividend yield (DY), the log earnings-price ratio (EP), the log dividend-payout ratio (DE), the excess stock return volatility (RVOL), the book-to-market ratio (BM), the net equity expansion (NTIS), the treasury bill rate (TBL), the long-term yield (LTY), the long-term return (LTR), the term spread (TMS), the default yield spread (DFY), the default return spread (DFR) and the inflation rate (INFL). More details on their computations are illustrated in subsection 4.5.1. TBL, LTY, TMS, DFY and INFL are measured in annual percent. The Sharpe ratio for the equity risk premium is computed as the mean of the log equity risk premium divided by its standard deviation. The time period is from 1996:01 to 2017:12.

4.5.2 In-Sample Stock Market Predictive Exercise

In the spirit of Bakshi et al. (2011) and Rapach et al. (2016), in this subsection we test the predictability power of the selected variables at different horizons, namely, monthly ($h = 1$), quarterly ($h = 3$), semi-annual ($h = 6$) and annual ($h = 12$). Several studies have been questioning the assets' predictability beyond the first month horizon (see Cutler et al., 1991; Hodrick, 1992; Campbell, 2001; Ang et al., 2006; Boudoukh et al., 2008). We, first, estimate a bivariate predictive regression models with relation to the future S&P 500 equity risk premium as follows:

$$r_{t:t+h} = \alpha + \beta_i X_{i,t} + \epsilon_{t:t+h} \quad for \quad t = 1, ..., T - h \tag{4.17}$$

where r_{t+1} is the equity risk premium computed as the continuously compounded return on the S&P 500 from time t to $t + h$ in excess of the risk-free rate. $X_{i,t}$ is one of the selected predicting variable at time t among the Goyal and Welch (2008) predictors and the first difference of SKEW indexes. $\epsilon_{t:t+h}$ is a zero-mean disturbance term (see Rapach and Zhou, 2013; Neely et al., 2014). Secondly, in order to incorporate the macroeconomic variables information, we estimate a predictive regression based on principal components (see Ludvigson and Ng, 2007, 2009; Neely et al., 2014; Rapach et al., 2016) as:

$$r_{t:t+h} = \alpha + \beta_{SKEW} SKEW_t^k + \sum_{j=1}^{4} \beta_{f,j} \hat{F}_{j,t}^{GW} + \epsilon_{t:t+h}, \tag{4.18}$$

where $\hat{F}_{1,t}^{GW}$, $\hat{F}_{2,t}^{GW}$, $\hat{F}_{3,t}^{GW}$, $\hat{F}_{4,t}^{GW}$ are the first four principal components extracted from the Goyal and Welch (2008) set of 14 macroeconomic predictors and where $k = Tot, +, -$ represent one of the implied skewness indexes, namely, SKEW , SKEW$^+$ and SKEW$^-$. In this way, we are able to isolate and to better test the predictive power of each of the selected SKEW indexes after controlling for the four principal components proxy for the information contained in the 14 selected predictors and allowing to test more parsimonious models. Ultimately, the role of the pairwise SKEW indexes is also checked by estimating the following predictive regressions:

$$r_{t:t+h} = \alpha + \beta_{SKEW} SKEW_t + \beta_{SKEW^+} SKEW_t^+ + \epsilon_{t:t+h}. \tag{4.19}$$

$$r_{t:t+h} = \alpha + \beta_{SKEW} SKEW_t + \beta_{SKEW^-} SKEW_t^- + \epsilon_{t:t+h}. \tag{4.20}$$

$$r_{t:t+h} = \alpha + \beta_{SKEW^+} SKEW_t^+ + \beta_{SKEW^-} SKEW_t^- + \epsilon_{t:t+h}. \tag{4.21}$$

The three SKEW indexes are also tested together as final robustness check. In every predictive model, the SKEW indexes are taken at first difference for avoiding stationarity issues. Panel A of Table 4.6 reports the in-sample S&P 500 risk premium predictive results of the bivariate OLS regression at horizons (1, 3, 6, 12) estimated through equation 4.17. As common practice to facilitate the comparison across predictors, these are standardized as to have a standard deviation of one and negative values for NTIS, TBL, LTY and INFL are taken. Panel B reports the multivariate OLS estimation in which we control for the four principal components (see equation 4.18), whereas in Panel C we report the multivariate results estimated through equations from 4.19 to 4.21, when SKEW indexes are considered in pairs. Table 4.6 reports the predictive regression coefficients, the two-sided heteroskedasticity and autocorrelation robust Newey (1987) t-statistic (t_{NW}) and Hodrick (1992) t-statistic (t_H) with automatic selected lag (see Newey and West, 1994). The predictive regression R^2 are reported in percentage.

From Panel A of Table 4.6, we observe that the aggregate SKEW index is not able to predict future levels of equity risk premia at any horizons. On the other hand, SKEW$^+$ and SKEW$^-$ show predictability power with relation to the next month ($h = 1$) S&P 500 equity premium. Only SKEW$^+$ is found to significantly predict the equity premium with regards to the next three months horizon ($h = 3$). Poor predictive performance is shown for all the SKEW indexes after the first quarter with decreasing R^2.

Table 4.6: **In-Sample Predictive Regression Results**

Panel A: Bivariate Predictive Regression

	$h=1$				$h=3$				$h=6$				$h=12$			
Predictor	Coef.	t NW	t HH	$R^2(\%)$	Coef.	t NW	t HH	$R^2(\%)$	Coef.	t NW	t HH	$R^2(\%)$	Coef.	t NW	t HH	$R^2(\%)$
SKEW	-0.056	[-1.101]	(-1.084)	0.3	-0.023	[-0.856]	(-0.969)	0.1	-0.003	[-0.163]	(-0.186)	0	-0.005	[-0.289]	(-0.397)	0
SKEW$^+$	0.106	[1.853]	(2.044)	1.1	0.034	[1.667]	(1.744)	0.4	0.016	[0.843]	(2.043)	0.1	0.006	[0.447]	(-9.612)	0
SKEW$^-$	0.065	[1.669]	(1.743)	0.6	-0.007	[-0.328]	(-0.401)	0	0.001	[0.070]	(0.084)	0	-0.004	[-0.309]	(-0.410)	0
DP	0.026	[1.427]	(1.331)	1.7	0.027	[2.148]	(1.802)	5.1	0.030	[3.652]	(3.032)	10.8	0.031	[6.573]	(5.426)	21.2
DY	0.029	[1.772]	(1.686)	2.1	0.029	[2.521]	(2.133)	5.8	0.031	[4.158]	(3.473)	11.6	0.032	[7.311]	(6.059)	22.8
EP	0.006	[0.621]	(0.556)	0.3	0.003	[0.469]	(0.390)	0.3	0.002	[0.390]	(0.322)	0.2	0.003	[0.814]	(0.669)	0.8
DE	0.001	[0.118]	(0.107)	0	0.003	[0.600]	(0.504)	0.4	0.005	[1.300]	(1.082)	1.4	0.004	[2.026]	(1.677)	2.1
RVOL	0.025	[0.576]	(0.546)	0.1	0.029	[0.876]	(0.738)	0.4	0.027	[1.083]	(0.902)	0.6	0.024	[1.244]	(1.027)	0.8
BM	0.043	[1.088]	(1.140)	0.5	0.061	[2.281]	(1.960)	3	0.080	[4.438]	(3.729)	9.1	0.081	[6.091]	(5.031)	16.7
NTIS(-)	0.219	[1.068]	(0.967)	1	0.263	[1.663]	(1.387)	3.8	0.267	[2.091]	(1.731)	6.9	0.209	[2.299]	(1.891)	7.5
TBL(-)	0.096	[0.780]	(0.798)	0.2	-0.105	[-1.186]	(-1.005)	0.7	-0.127	[-1.936]	(-1.610)	1.9	-0.175	[-3.262]	(-2.685)	6.5
LTY(-)	0.235	[1.448]	(1.511)	0.6	-0.223	[-1.868]	(-1.591)	1.5	-0.225	[-2.419]	(-2.017)	2.6	-0.206	[-2.513]	(-2.068)	3.8
LTR	0.047	[0.530]	(0.720)	0.1	-0.025	[-0.413]	(-0.410)	0.1	0.022	[0.577]	(0.590)	0.1	0.008	[0.307]	(0.319)	0
TMS	-0.029	[-0.136]	(-0.131)	0	0.015	[0.091]	(0.077)	0	0.080	[0.625]	(0.518)	0.3	0.243	[2.663]	(2.196)	4.5
DFY	-0.760	[-0.687]	(-0.619)	0.6	-0.405	[-0.487]	(-0.406)	0.5	0.082	[0.156]	(0.129)	0	0.409	[1.500]	(1.239)	1.5
DFR	0.184	[0.686]	(0.665)	0.6	0.106	[0.748]	(0.720)	0.5	0.085	[0.778]	(0.743)	0.6	0.067	[1.158]	(1.21)	0.7
INFL(-)	1.117	[1.207]	(1.124)	0.9	-0.440	[-0.629]	(-0.554)	0.4	-0.863	[-1.895]	(-1.679)	2.5	-0.627	[-2.360]	(-2.119)	2.4

Panel B: Principal Components and SKEW Indexes Regression

	$h=1$				$h=3$				$h=6$				$h=12$			
Predictor	Coef.	t NW	t HH	$R^2(\%)$	Coef.	t NW	t HH	$R^2(\%)$	Coef.	t NW	t HH	$R^2(\%)$	Coef.	t NW	t HH	$R^2(\%)$
SKEW $\|PC$	-0.061	[-1.151]	(-1.138)	1.3	-0.032	[-1.137]	(-1.263)	5.7	-0.035	[-1.304]	(-1.662)	5.8	-0.019	[-0.873]	(-1.062)	5.6
SKEW$^+$ $\|PC$	0.107	[2.031]	(1.718)	2	-0.009	[-0.433]	(-0.481)	13.2	0.016	[0.858]	(1.359)	13.3	-0.008	[-0.502]	(-0.626)	13.2
SKEW$^-$ $\|PC$	0.062	[1.685]	(1.727)	1.4	-0.010	[-0.619]	(-0.967)	20.2	0.006	[0.479]	(1.005)	20.2	-0.012	[-1.102]	(-2.158)	20.3

Panel C: Pairwise SKEW Indexes Regression

SKEW	-0.050	[-1.014]	(-0.996)		-0.022	[-0.806]	(-0.907)		-0.002	[-0.118]	(-0.134)		-0.001	[-0.076]	(-0.087)	
SKEW$^+$	0.103	[1.817]	(2.004)	1.3	0.033	[1.669]	(1.710)	0.4	0.016	[0.828]	(1.901)	0.1	0.017	[0.831]	(1.808)	0.1
SKEW	-0.223	[-1.503]	(-1.456)		-0.035	[-0.873]	(-1.035)		-0.008	[-0.303]	(-0.401)		-0.007	[-0.260]	(-0.341)	
SKEW$^-$	0.200	[2.570]	(2.553)	0.9	0.013	[0.424]	(0.546)	0.2	0.006	[0.266]	(0.376)	0	0.005	[0.237]	(0.336)	0
SKEW$^+$	0.092	[1.633]	(1.837)		0.038	[1.622]	(1.958)		0.017	[0.916]	(2.291)		0.018	[0.925]	(2.254)	
SKEW$^-$	0.046	[1.031]	(1.042)	1.3	-0.015	[-0.688]	(-0.828)	0.4	-0.002	[-0.147]	(-0.168)	0.1	-0.002	[-0.152]	(-0.174)	0.1

Notes: The table presents the regression results for the bivariate predictive regression model estimated through equation 4.17 for the SKEW indexes and the 14 macroeconomic variables (Panel A). Panel B reports the estimation for the multivariate regression model 4.18 in which only the SKEW indexes predictability is shown after controlling for the four principal components extracted from the 14 macroeconomic variables. In Panel C we report the multivariate predictive regression in which the SKEW indexes are taken in pairs. The results are reported for monthly ($h=1$), quarterly ($h=3$), semi-annual ($h=6$) and annual ($h=12$) horizons. The log equity risk premia (in percent) are taken at monthly frequency from 01-1996 to 12-2017. Regressions intercepts are not reported to save on space. Newey-West [t NW] and Hodrick t-stats (t HH) are reported in square brackets and parentheses, respectively, to account for heteroskedasticity and overlap in the regressions. R^2 (in percent) of every regression are reported in the last column for each horizon.

Opposite results are found with relation to the other 14 macroeconomic predictors which increase their predictability with time horizons. DP, DY, BM and LTY present significant predictive power at the 3 months horizon. The same variables with the addition of NTIS, TBL and INFL show significance for the semi-annual horizon. The same variables plus DE and TMS are able to predict next year equity premium. For some of the macroeconomic variables, the increase in predictability power over longer than monthly horizons is captured by the higher values for their R^2, in line with Boudoukh et al. (2008).

Our results are in line with previous studies showing that the log of dividend yield (DY), the treasury bill rate (TBL), the long-term yield (LTY) and the term spread (TS) are among the variables performing better in predicting equity returns (see Rapach and Zhou, 2013; Neely et al., 2014; Rapach et al., 2016). Neely et al. (2014) found predictive power for macroeconomic variables as interest rates between 1951 and 2010, while almost no role is detected here. Dividend variables are also found strong predictors. This is confirmed from our results as well as by Kelly and Jiang (2014) using the same set of variables. However, we find that the dividend-price ratio is the only other predictor with performance comparable to the decomposed SKEW indexes in the first month horizon (see Kelly and Jiang, 2014).

Overall, the R^2 statistics are found to be small, exceptions being DP and DY when the time horizon increases. This might be due to the fact that monthly stock returns contain unpredictable information (see Neely et al., 2014), thus a monthly R^2 close to 0.5% can actually be considered economically significant for predicting equity risk premium (see Campbell and Thompson, 2007). Both SKEW^+ and SKEW^- exceed this benchmark at $h = 1$, whereas SKEW^+ is 0.4% at $h = 3$.

Panel B of Table 4.6 reports the principal components predictive regression results estimated through equation 4.18. The selected four principal components are used as a proxy for capturing the common information enclosed in the 14 macroeconomic variables. We find that decomposed SKEW indexes still show predictability power at one-month horizon. Thus, they contain additional or complementary information not entirely captured by the principal components in the short term. The SKEW indexes predictability ability dissolves after the first month also when we control for the principal components.

Lastly, Panel C shows the results of the predictive regression which includes the SKEW indexes in pairs. Interestingly, the best combination in this exercise appears to be the ones including SKEW^+ , thus, SKEW - SKEW^+ and SKEW^- - SKEW^+ for the one-month horizon showing both a R^2 equal to 1.3%. SKEW^- is found to be significant when next to the total SKEW implying that it contains additional information not enclosed in SKEW . When SKEW^- and SKEW^+ are coupled, only the last is found significant. In the pairwise regressions, we still find SKEW^+ being the only index significant at the three-months horizon[11]. We also estimate a predictive regression with the SKEW indexes added all together finding a significant predictive ability for SKEW^+ at $h = 1$ and the group of SKEW predictors is able to explain 3.1% of the next month equity risk premium.

[11] We have performed bivariate as well as multivariate predictive regressions for horizons longer than the annual one, however the SKEW indexes have shown no predictive power in the long-term.

With regards to the signs of the coefficients, we find that future levels of risk premium might be increased by past increase in the SKEW^{+} . There might be a market sentiment and exuberance behind this relationship as we have shown in Section 4.4. We find a negative relationship between SKEW and the future equity premium in line with the findings in Amaya et al. (2015). Mixed and time-varying results are found for the relationship between equity market and SKEW^{-} . The coefficients' signs are, overall, positive when SKEW^{-} is significantly predicting future equity premium. This relationship builds on the interpretation that higher tail risk should command higher risk premia (see Almeida et al., 2017). The relationship between SKEW^{-} and future risk premium is negative mainly at longer horizons. The magnitude of the SKEW^{+} coefficients is found higher compared to the others.

Overall, the decomposed SKEW indexes predict well the future S&P 500 equity premium at one-month horizon in the bivariate regression. Their predictability in the short run is found to be better than most of the individual macroeconomic variables. The options based SKEW indexes are better predictors at short term horizons with decreasing predictive power when the time horizon increases (see Bakshi et al., 2011). Our results echo the conclusions of Amaya et al. (2015) that realized skewness contains important information on predicting future stock returns. In our case, decomposed SKEW indexes being implied measures, predict well the short-term future equity premium, losing their predictive ability after the first month.

As illustrated in Table 4.6, variables tracking dividend yields and dividend payout, namely, DP and DY, are among the most important predictors for the equity market premium (see Bollerslev et al., 2015). Thus, here, we briefly check whether or not the SKEW indexes might still improve the predicting models' performance when added next to dividend proxies. The results of this robustness exercise are reported in Table 4.7 only for the first-month horizon.

Table 4.7: SKEW **Indexes and Dividend Variables Predictive Regression**

Panel A: SKEW Indexes, Dividend price ratio and Dividend yield											
Predictor	Coef.	t NW	$R^2(\%)$	Predictor	Coef.	t NW	$R^2(\%)$	Predictor	Coef.	t HH	$R^2(\%)$
SKEW	-0.073	[-1.338]		SKEW^{+}	0.124	[2.082]		SKEW^{-}	0.049	[1.010]	
DP	-0.075	[-0.865]		DP	-0.083	[-0.954]		DP	-0.049	[-0.537]	
DY	0.104	[1.288]	3	DY	0.111	[1.686]	3.9	DY	0.078	[0.911]	2.8
Panel B: SKEW Indexes and OptionMetrics Dividend yield											
Predictor	Coef.	t NW	$R^2(\%)$	Predictor	Coef.	t NW	$R^2(\%)$	Predictor	Coef.	t HH	$R^2(\%)$
SKEW	-0.076	[-1.355]		SKEW^{+}	0.105	[1.743]		SKEW^{-}	0.057	[1.232]	
DYOP	0.012	[2.086]	2.7	DYOP	0.012	[2.071]	3.2	DYOP	0.012	[2.050]	2.6

Notes: The table presents the regression results for the multivariate predictive regression model in which we keep the decomposed SKEW indexes and only DP and DY among the 14 macroeconomic variables The results are reported only for the first month ($h = 1$). The log equity risk premia (in percent) are taken at monthly frequency from 01-1996 to 12-2017. Regressions intercepts are not reported to save on space. Newey-West (t NW) are reported in square brackets. R^2 (in percent) of every regression are reported in the last column for each horizon.

In Panel A of Table 4.7, we find that SKEW^{+} is still able to predict future levels of equity risk premium at $h = 1$. SKEW and SKEW^{-} are found to have no predictive power in these models. Interestingly, even thought DY is found significant in Table 4.6 for $h = 1$, it loses its statistical sig-

nificance, according to NW t-statistics, when next to SKEW and SKEW^- [12]. In Panel B, results for SKEW^+ appear robust when we replace DP and DY with the dividend yield variable collected from OptionMetrics (DYOP).

4.5.3 SKEW Indexes Relation to Other Predictors

In this section, we investigate the robustness of our findings when other predictors, more related to the options market and financial market risk, namely, implied volatility and variance risk premium. These are found to be important in the context of Brunnermeier et al. (2008) and Kilic and Shaliastovich (2018). According to the latter, variance risk premium is considered to disclose useful information for return predictability when its upside component is taken into account. Thus, in their spirit, we also study the upside and downside components of these risk measures, thus allowing us to perform a cross-sign comparison with our decomposed SKEW indexes. The VIX index is decomposed as described in Section 4.3.1 and in Chapter 3. The decomposed variance risk premia are the Kilic and Shaliastovich (2018) measures as described in Section 4.3.1. They are considered at their first difference. The aim is to further check whether or not the implied skewness indexes are still able to provide additional information not enclosed in the VIX index, risk premium and their components when it comes to future equity risk premium predictability. The results are reported in Table 4.8 for the implied volatility indexes and in Table 4.9 for the variance risk premia. Results are reported only with regards to the first month which we have shown to be the horizon in which the SKEW indexes are more informative.

Table 4.8: **Decomposed** SKEW **and** VIX **Indexes Predictive Regression**

Panel A: Decomposed SKEW and VIX Indexes Predictive Regression											
Predictor	Coef.	t NW	$R^2(\%)$	Predictor	Coef.	t NW	$R^2(\%)$	Predictor	Coef.	t NW	$R^2(\%)$
SKEW	-0.055	[-1.065]		SKEW^+	0.113	[1.801]		SKEW^-	0.064	[1.408]	
VIX	0.039	[0.284]		VIX	-0.057	[-0.404]		VIX	0.009	[0.073]	
VIX^+	-0.014	[-0.242]		VIX^+	0.019	[0.335]		VIX^+	-0.001	[-0.023]	
VIX^-	-0.026	[-0.301]	0.3	VIX^-	0.037	[0.412]	1.1	VIX^-	-0.008	[-0.101]	0.6
Panel B: SKEW and VIX Indexes Corresponding Signs Predictive Regression											
Predictor	Coef.	t NW	$R^2(\%)$	Predictor	Coef.	t NW	$R^2(\%)$	Predictor	Coef.	t NW	$R^2(\%)$
SKEW	-0.056	[-1.094]		SKEW^+	0.107	[1.829]		SKEW^-	0.065	[1.439]	
VIX	-0.007	[-0.066]	0.3	VIX^+	-0.012	[-0.117]	1.1	VIX^-	-0.001	[-0.011]	0.6

Notes: The table presents the regression results for the multivariate regression model in which decomposed SKEW indexes, namely, SKEW , SKEW^+ and SKEW^- and decomposed VIX indexes, namely, VIX , VIX^+ and VIX^- are compared. Panel A reports the estimation for the multivariate regression model between each one of the three SKEW indexes controlling for the decomposed VIX indexes. Panel B reports the multivariate predictive regression in which the SKEW indexes and VIX indexes are taken in pairs according to their signs, namely, total SKEW and total VIX , positive SKEW^+ and upside VIX^+ and negative SKEW^- and VIX^- . The results are reported only for monthly ($h = 1$) horizon. The log equity risk premia (in percent) are taken at monthly frequency from 01-1996 to 12-2017. Regressions intercepts are not reported to save on space. Newey-West (t NW) are reported in square brackets. R^2 (in percent) of are reported in the last column for each regression.

Table 4.8 shows that SKEW^+ predicts the next month S&P 500 equity risk premium also when aggregate and decomposed VIX indexes are added in the same predictive regression. Interestingly,

[12] Hodrick (1992) t-statistics are not reported to save on space, however they lead to the same findings. The predictability power of SKEW indexes does not last after the first month, whereas dividend variables confirm their increasing predictive power at longer horizons. The models including SKEW indexes and the dividend-price ratio achieve impressive levels of predictability in terms of R^2 at longer horizons in line with Kelly and Jiang (2014).

the implied volatility indexes are not found to be significant in predicting future levels of equity risk premium (see Bekaert and Hoerova, 2014), neither in the bivariate regression nor in the multivariate with SKEW indexes. We also show the predictability power of the SKEW indexes compared to the decomposed variance risk premia by Kilic and Shaliastovich (2018) in Table 4.9. We control for the aggregate VRP and the decomposed VRP^+ and VRP^- in different regressions due to multi-collinearity issues. We find that the informative role of VRP in predicting equity returns is in line with previous studies on the relationship between equity returns and risk premium (e.g. Bekaert and Hoerova, 2014; Kilic and Shaliastovich, 2018). In Panel C, we also find superior ability of the VRP^+ in explaining future excess market returns when compared to VRP^- (see Feunou et al., 2017)[13]. We still show how decomposed SKEW indexes are still informative in predicting future equity premium even after we control for variance risk premia. We observe a prevalent role of SKEW^- next to the variance risk premia observing higher R^2 when the index is enclosed in the predictive model. Hence, the negative SKEW index contains tail risk information useful to predict future stock returns which are not incorporated in the VRP indexes. SKEW^+ is still significantly predicting future equity risk premia, but it loses part of its predictive ability when next to VRP^+ meaning the two indexes contain a similar set of information.

Table 4.9: **Decomposed** SKEW **and VRP Indexes Predictive Regression**

Panel A: Decomposed SKEW and VRP Indexes Predictive Regression											
Predictor	Coef.	t NW	$R^2(\%)$	Predictor	Coef.	t NW	$R^2(\%)$	Predictor	Coef.	t NW	$R^2(\%)$
SKEW	-0.058	[-1.016]		SKEW^+	0.082	[1.710]		SKEW^-	0.082	[1.646]	
VRP^+	-0.001	[-0.040]		VRP^+	-0.001	[-0.048]		VRP^+	-0.001	[-0.064]	
VRP^-	-0.005	[-1.185]	4.6	VRP^-	-0.006	[-1.309]	5.1	VRP^-	-0.006	[-1.262]	5.1
Panel B: Total SKEW and Total VRP Index Predictive Regression											
Predictor	Coef.	t NW	$R^2(\%)$	Predictor	Coef.	t NW	$R^2(\%)$	Predictor	Coef.	t NW	$R^2(\%)$
SKEW	-0.058	[-1.005]		SKEW^+	0.092	[1.394]		SKEW^-	0.080	[1.674]	
VRP	-0.003	[-3.695]	4.3	VRP	-0.003	[-3.794]	4.8	VRP	-0.004	[-3.677]	4.9
Panel C: SKEW and VRP Indexes Corresponding Signs Predictive Regression											
Predictor	Coef.	t NW	$R^2(\%)$	Predictor	Coef.	t NW	$R^2(\%)$	Predictor	Coef.	t NW	$R^2(\%)$
SKEW	-0.058	[-1.005]		SKEW^+	0.093	[1.416]		SKEW^-	0.082	[1.647]	
VRP	-0.003	[-3.695]	4.3	VRP^+	-0.005	[-3.179]	4.1	VRP^-	-0.006	[-3.966]	5.1

Notes: The table presents the regression results for the multivariate regression model in which decomposed SKEW indexes, namely, SKEW , SKEW^+ and SKEW^- and decomposed variance risk premium indexes, namely, VRP , VRP^+ , VRP^- (see Kilic and Shaliastovich, 2018), are compared. Panel A reports the results of the estimated multivariate regression model between the decomposed SKEW indexes and the decomposed VRP indexes. Panel B reports the results of the estimated multivariate regression model between the decomposed SKEW indexes and the total VRP . We control for the decomposed VRP and the total VRP in different multivariate regression due to multi-collinearity issues. Panel C reports the multivariate predictive regression in which the SKEW indexes and VRP indexes are taken in pairs according to their signs, namely, total SKEW and total VRP , SKEW^+ and VRP^+ and SKEW^- and VRP^- . The results are reported only for monthly ($h = 1$) horizon. The log equity risk premia (in percent) are taken at monthly frequency from 01-1996 to 08-2014. Regressions intercepts are not reported to save on space. Newey-West (t NW) are reported in square brackets. R^2 (in percent) of are reported in the last column for each regression.

Empirical evidence has also shown the important role of implied correlation and correlation risk premium in predicting future market returns (see Driessen et al., 2009; Buss and Vilkov, 2012; **?**), with correlation measures predictability significant for horizons up to 1 year. We test for predictability power of the decomposed SKEW indexes when controlling for correlation measures. The results are

[13]Indeed, the VRP^+ and VRP^- in Feunou et al. (2017) correspond to the VRP^- and VRP^+ , respectively, in Kilic and Shaliastovich (2018) since they are computed in the opposite way.

reported in Table 4.10. IC and CRP predict well future market returns, whereas the predictive power of the realized correlation is weak. However, even after controlling for the correlation measures as well as for CRP, the decomposed SKEW measures still contain significant predictive information.

Table 4.10: **SKEW Indexes and CRP Predictive Regression**

Panel A: SKEW Indexes and Correlation Risk Premium											
Predictor	Coef.	t NW	$R^2(\%)$	Predictor	Coef.	t NW	$R^2(\%)$	Predictor	Coef.	t NW	$R^2(\%)$
SKEW	-0.051	[-1.026]		SKEW^+	0.102	[1.950]		SKEW^-	0.075	[1.784]	
CRP	0.062	[2.090]	2.7	CRP	0.062	[2.069]	3.5	CRP	0.065	[2.175]	3.2
Panel B: SKEW Indexes and Implied Correlation											
Predictor	Coef.	t NW	$R^2(\%)$	Predictor	Coef.	t NW	$R^2(\%)$	Predictor	Coef.	t NW	$R^2(\%)$
SKEW	-0.050	[-1.011]		SKEW^+	0.108	[1.971]		SKEW^-	0.078	[1.747]	
IC	0.056	[2.324]	2.6	IC	0.050	[2.304]	3.4	IC	0.053	[2.489]	3.2
Panel C: SKEW Indexes and Realized Correlation											
Predictor	Coef.	t NW	$R^2(\%)$	Predictor	Coef.	t NW	$R^2(\%)$	Predictor	Coef.	t NW	$R^2(\%)$
SKEW	-0.055	[-1.095]		SKEW^+	0.106	[2.041]		SKEW^-	0.066	[1.667]	
RC	0.007	[0.301]	0.4	RC	0.007	[0.286]	1.2	RC	0.008	[0.329]	0.8

Notes: The table presents the regression results for the multivariate predictive regression model in which decomposed SKEW indexes, namely, SKEW , SKEW^+ and SKEW^- and the correlation risk premium (CRP) are compared. The results are reported only for the first month ($h = 1$). The log equity risk premia (in percent) are taken at monthly frequency from 01-1996 to 12-2017. Regressions intercepts are not reported to save on space. Newey-West (t NW) are reported in square brackets. R^2 (in percent) of every regression are reported in the last column.

As a robustness check we have also studied the predictability of other tail risk measures as illustrated in subsection 4.3.2 next to our decomposed SKEW indexes[14]. The bivariate analysis shows that SKEW^+ and SKEW^- are still significant in predicting the next month S&P 500 log equity premium. Kelly and Jiang (2014) TAIL index and Hellinger tail risk by Almeida et al. (2017) also contain information useful to predict the next month equity premium. The bivariate predictive regression estimation shows that SKEW^+ and SKEW^- are able to significantly predict the next month log equity premium with Newey t-statistic of 1.8 and 1.69, respectively and R^2 (in percentage) equal to 1.1% and 0.9%, respectively. Among the other measures which we found significant in predicting future levels of equity premium, TAIL shows a t-statistic of 2.56 with R^2 equal to 3.1% and Hellinger shows t-statistic of 1.67 and R^2 equal to 1.8%. No significant role for CATFIN, JV, RJV, LJV and CRASH index is found instead. This results are found to be in line with Almeida et al. (2017). When we control for the other tail risk measures in a multivariate predictive regression, we still find SKEW^+ and SKEW^- containing additional information useful to predict future levels of equity risk premium. The multivariate regression carries a total R^2 equal to 7.5%. To conclude this section, we observe that the presence of additional predictors tracking financial market risk and volatility does not appear to diminish the predictive ability of our decomposed SKEW indexes.

[14]The time period is the common period available to all the selected tail risk measures, namely, from 01:1996 to 04:2014 at monthly frequency, due to data availability.

4.5.4 Out-of-sample Predictive Analysis

As a further robustness check, we test the out-of-sample predictive power of the SKEW indexes and of the 14 macroeconomic variables. We compute the equity risk premium predictive regression forecast as:

$$\hat{r}_{t:t+h} = \hat{\alpha}_t + \hat{\beta}_t \chi_t, \tag{4.22}$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the OLS estimates of α and β, respectively, from the beginning of the sample until month t. Different approaches can be used when it comes to the sample split selection (see Goyal and Welch, 2008; Hansen and Timmermann, 2012). In this chapter, we follow the approach of Rapach et al. (2010) in which multiple out-of-sample periods are considered. We show the forecasting performance of our models for each sample selection. The following sample splits are selected for the in-sample period leaving the rest as out-of-sample evaluation forecast period: 1996-1999, 1996-2007 and 1996-2013[15]. The natural forecast benchmark is the average excess return from the beginning of the sample through month t (see Campbell and Thompson, 2007).

$$\hat{r}_{t+1}^{HA} = \frac{1}{t} \sum_{i=1}^{t} r_i. \tag{4.23}$$

We evaluate the out-of-sample forecast performance of our predictors based on the Campbell and Thompson (2007) R^2_{OS}, namely, $R^2_{OS} = 1 - (MSFE_i/MSFE_0)$ which measures the reduction in mean squared forecast errors (MSFE) for the OLS predictive regression against the historical mean benchmark forecast over the forecast evaluation period. We compare the two mean squared forecast errors where, $MSFE_i$ is the forecast error of the predictive regression over the forecast evaluation period and $MSFE_0$ is the forecast error of the historical average benchmark forecast. Thus, the out-of-sample R^2 measures the reduction in MSFE for the predictive regression forecast compared to the historical average. When $R^2_{OS} > 0$ means that the predictive regression forecast is more accurate than the historical average in terms of forecast errors, meaning $MSFE_i < MSFE_0$. In addition, to test whether or not the predictive regression forecast produces a significant improvement in the MSFE, we report the Clark and West (2007) MSFE-adjusted statistic. It tests the null hypothesis that the historical average MSFE is less than or equal to the predictive regression MSFE against the alternative hypothesis that the historical average MSFE is greater than the predictive regression MSFE which correspond to $H_0 : R^2_{OS} \leq 0$ against $H_A : R^2_{OS} > 0$.

Table 4.11 shows the out-of-sample predictive results with relation to different choice of in-sample and out-of-sample forecasting periods. The selected in-sample periods are reported at the top of each

[15]Since our total time period is 22-years long, the first sample split results in a in-sample period of only few observation. In order to expand our in-sample period as well as keeping the out-of-sample estimation period relatively long, we select a second in-sample forecast window length from January 1996 to December 2007. Lastly, we sacrifice the length of the out-of-sample period for a more reasonable and precise estimation in-sample by increasing the number of in-sample observation from January 1996 to December 2013 leaving a evaluation out-of-sample period of 4 years.

multi-column. Panel A reports the out-of-sample bivariate predictive regression forecast, Panel B the out-of-sample results for the principal components predictive regression forecast as follows:

$$\hat{r}_{t:t+h} = \hat{\alpha}_t + \hat{\beta}_{SKEW,t}\hat{SKEW}_t^j + \sum_{k=1}^{4} \hat{\beta}_{PC,t,k}\hat{F}_{1:t,k,t}, \tag{4.24}$$

where $\hat{F}_{1:t,k,t}$ are the principal components extracted from the 14 macroeconomic variables with $k \in 1, 2, 3, 4$ through time t and with $\hat{\beta}_{PC,t,k}$ being the OLS coefficients estimated regressing the historical average on the 4 principal components and a constant. $\hat{SKEW}_t^j$ are the SKEW indexes with $j = Tot, +, -$ and with $\hat{\beta}_{SKEW,t}$ estimated through OLS as well. Panel C and Panel D report the out-of-sample forecast results of the predictive regression with SKEW pairwise indexes and all SKEW indexes together, respectively.

The results from Table 4.11 show that the out-of-sample forecast performance depends on how our data set is split (see Hansen and Timmermann, 2012). In Panel A, the bivariate predictive regression forecast based on individual macroeconomic variables and SKEW indexes perform poorly when only few years are selected as in-sample period. Only DY shows a positive R^2_{OS}. When the R^2_{OS} is found to be positive it means that the predictive regression forecast outperforms the historical average in terms of MSFE, viceversa when negative. SKEW indexes are not able to outperform the historical average benchmark in the first 1996-1999 in-sample period choice. These results echo Goyal and Welch (2008) who stated that, most of the time, individual variables fail to outperform the historical average forecast which can be considered as a rigorous out-of-sample benchmark.

In the first sample selection, all the three SKEW indexes show MSFEs less than the ones of the historical average, however showing negative R^2_{OS}[16]. When 1996 - 2007 in-sample period is selected, we still find limited out-of-sample predictive ability for the majority of the individual variables, however SKEW^+ shows a positive R^2_{OS} and carries a lower MSFE than the historical average forecast. When the out-of-sample period is chosen to be a small proportion than the in-sample period, the individual variables forecasting performance improves. Several are, in this case, the individual variable showing positive R^2_{OS}. SKEW^+ shows a positive R^2_{OS} as well as a significant MSFE-adjusted statistic. Among the macroeconomic variables, significant results are found with relation to DP, DY, EP, BM and DFY. Difference in results in the forecast evaluation may be dictated by the number of observations in our time period and by the occurrence of the global financial crisis in the midst of it.

[16] Similar results are found in Neely et al. (2014) with respect to TBL, LTY and TMS. According to them, these results can be possible when comparing nested model forecasts (Clark and West, 2007; McCracken, 2007).

Table 4.11: **Out-of-Sample Predictive Regression Results**

Panel A: Bivariate Predictive Regression												
	In-Sample Window: 1996-1999				In-Sample Window: 1996-2007				In-Sample Window: 1996-2013			
Predictor	MSFE	$R^2_{OS}(\%)$	MSFE adj.	p value	MSFE	$R^2_{OS}(\%)$	MSFE adj.	p value	MSFE	$R^2_{OS}(\%)$	MSFE adj.	p value
SKEW	18.109	-0.421	0.260	0.397	18.412	-0.098	0.588	0.277	7.905	-3.308	-0.254	0.600
$SKEW^+$	18.109	-0.310	1.027	0.152	18.287	0.576	0.984	0.162	7.428	2.919	1.324	0.098
$SKEW^-$	18.229	-0.976	0.741	0.229	18.597	-1.107	-0.071	0.528	7.763	-1.452	0.114	0.454
DP	18.134	-0.449	0.773	0.219	19.341	-5.148	-1.027	0.84	7.225	5.584	1.924	0.027
DY	17.974	0.434	1.158	0.123	19.001	-3.236	-0.466	0.679	7.246	5.298	1.832	0.033
EP	18.534	-2.667	0.840	0.200	19.743	-7.337	-0.433	0.667	7.511	1.832	2.136	0.016
DE	19.253	-6.649	-0.022	0.508	19.683	-7.010	0.172	0.431	7.664	-0.159	-1.281	0.899
RVOL	18.196	-0.795	-1.010	0.843	18.483	-0.485	-0.245	0.597	8.046	-5.156	-2.208	0.986
BM	18.521	-2.592	0.145	0.442	18.586	-1.047	-0.830	0.796	7.406	3.207	1.719	0.042
NTIS(-)	18.361	-1.706	0.744	0.228	18.549	-0.842	0.668	0.251	8.222	-7.451	-0.867	0.807
TBL(-)	18.761	-3.924	-0.616	0.731	18.560	-0.903	-0.212	0.584	7.523	1.673	1.270	0.101
LTY(-)	18.303	-1.385	-0.088	0.535	18.493	-0.538	0.197	0.421	7.361	3.762	1.559	0.059
LTR	18.319	-1.472	-1.217	0.888	18.641	-1.342	-1.472	0.929	7.605	0.608	0.735	0.231
TMS	18.470	-2.311	-0.555	0.710	18.502	-0.589	-0.605	0.727	7.665	-0.178	-1.346	0.910
DFY	18.698	-3.573	0.775	0.219	19.218	-4.479	0.775	0.219	7.470	2.373	1.641	0.050
DFR	18.883	-4.601	-1.083	0.860	19.363	-5.268	-0.792	0.786	8.016	-4.792	-1.857	0.968
INFL(-)	18.278	-1.247	-0.049	0.519	18.358	0.195	0.571	0.283	7.694	-0.559	0.297	0.382
Panel B: SKEW Indexes and Principal Components Predictive Regression												
SKEW |PC	20.989	-16.266	-0.225	0.589	20.763	-12.881	-0.179	0.571	7.886	-3.065	0.433	0.332
$SKEW^+$ |PC	21.159	-17.204	0.233	0.407	20.710	-12.593	-0.082	0.532	7.385	3.476	1.438	0.075
$SKEW^-$ |PC	21.092	-16.831	-0.006	0.502	21.098	-14.700	-0.238	0.594	7.624	0.363	0.889	0.186
Panel C: SKEW Indexes Pairwise Predictive Regression												
SKEW - $SKEW^+$	18.21	-0.914	0.937	0.174	18.30	0.466	1.066	0.143	7.61	0.443	0.756	0.224
SKEW - $SKEW^-$	17.88	0.919	1.979	0.023	18.226	0.910	1.361	0.086	8.21	-1.324	0.017	0.495
$SKEW^+$ - $SKEW^-$	18.29	-1.354	0.993	0.160	18.47	-0.434	0.487	0.312	7.52	1.650	1.270	0.092
Panel D: All SKEW Indexes Predictive Regression												
All SKEW	18.11	-0.369	1.718	0.042	18.24	0.796	1.277	0.100	8.14	-6.432	0.047	0.480

Notes: The table presents the S&P 500 risk premium out-of-sample predictive regression results for both the bivariate predictive regression and also multivariate predictive regressions. Panel A presents the results for the bivariate out-of-sample predictive regression estimated through equation 4.22 for the all 14 macroeconomic variables and the three SKEW indexes. Panel B presents the results for the multivariate out-of-sample predictive regression estimated through equation 4.24 in which the four principal components are extracted from the 14 macroeconomic variables and added as control variables in the same predictive model next to one of the three SKEW indexes. Only the SKEW indexes out-of-sample predictability is shown after controlling for the four principal components. Panel C presents the out-of-sample multivariate predictive regression in which the SKEW indexes are taken in pairs. Panel D presents the results of the out-of-sample multivariate predictive regression with all three the SKEW indexes. The historical average (HA) forecast is computed through equation 4.23. The out-of-sample results are presented with relation to three in-sample period horizon choice, namely, 1996-1999, 1996-2007 and 1996-2013 for a total number of observation accounting for 48, 132 and 204, respectively. MSFE is the mean squared forecast error, R^2_{OS} (see Campbell and Thompson, 2007) measures the reduction in MSFE with respect to the historical average forecast benchmark shown in the first column of every selected in-sample period horizon. The Clark and West (2007) MSFE-adjusted statistic tests the null hypothesis that the historical average (HA) forecast MSFE is $\leq$ than the competing forecast MSFE against the one-sided alternative hypothesis that the historical average (HA) forecast MSFE is $>$ greater than the competing forecast MSFE. P-values are shown in the last column of each forecast in-sample period.

In Panel B of Table 4.11, the only combination of variables that show positive R^2_{OS} and MSFE significantly less than the historical average is SKEW^+ after controlling for the four principal components. This result is found only in correspondence of the last in-sample period choice, namely 1996-2013. The other results show poor out-of-sample forecast performance. In Panel C, we present the out-of-sample results when SKEW indexes are taken in pair.

Interestingly, the SKEW -SKEW^- combination shows positive R^2_{OS} in the 1996-1999 and 1996-2007 in-sample selected period with MSFE significantly less than the historical average MSFE according to the Clark and West (2007) MSFE-adjusted statistic. Also SKEW -SKEW^+ together show positive R^2_{OS} in the last two in-sample periods. The SKEW^+ - SKEW^- combination shows positive R^2_{OS} and MSFE significantly less than the historical average MSFE only in the 1996-2013 in-sample window. In all cases, the MSFEs for these combinations are found higher than the historical average MSFE.

Overall, we find that the choice of window length leads to different results. When the sample split for the out-of-sample forecast evaluation is chosen from 2013 to 2017, with the crisis included in the in-sample estimation period, we detect better out-of-sample performance of our models. Poor performance is found when the in-sample period is selected as a small proportion of the out-of-sample in the bivariate case. In this case, only few variables show a positive R^2_{OS} and the decomposed SKEW indexes appear to perform as well as the majority of the individual macroeconomic variables. When the in-sample period increases in proportion to the out-of-sample, SKEW^+ show better out-of-sample forecast result in terms of MSFE-adjusted statistic. The out-of-sample robustness check further shows that SKEW^+ appears to perform as well as, or better, than the individual macroeconomic variables.

As a robustness exercise, in this subsection we compare the out-of-sample predictability power of the selected models as obtained through Clark and West (2007) MSFE-adjusted statistic with a second statistical test based on the Diebold and Mariano (2002) (DM) test. In order to compare the forecast models which are nested, Clark and West (2007) developed the MSFE-adjusted statistic by modifying the familiar Diebold and Mariano (1995) statistic as to have an approximately standard normal asymptotic distribution when comparing forecasts from nested models (e.g. Rapach et al., 2010; Neely et al., 2014). According to Neely et al. (2014), comparing a predictive regression forecast to the historical average entails comparing nested models, because the predictive regression model reduces to the constant expected equity risk premium model under the null hypothesis.

In other words, the popular Diebold and Mariano (1995) statistic for comparing predictive accuracy has a nonstandard distribution when comparing forecasts from nested models (e.g. McCracken, 2007; Rapach et al., 2010). Clark and West (2007) modify this statistic so that it has an approximately standard distribution when comparing forecasts from nested models.

Therefore, we compare nested models by using the Clark and West (2007) test, whereas the Diebold

and Mariano (1995) test is computed for not nested models in which the three SKEW indexes are tested[17]. We apply the test in order to compare the predictive accuracy of the three different SKEW indexes in different models. The test is not used when the forecasting models are nested.

When the three SKEW indexes are input in the forecast model next to the four principal components, we confirm the superiority of the model with SKEW^+ . For the Diebold and Mariano (2002) test, we get values equal to 2.11, 1.83, 1.90 for the models with SKEW , SKEW^+ and SKEW^- , respectively. We confirm, once more, the greater predictive accuracy of the decomposed SKEW in terms of equity excess returns also when we control for the four principal components.

4.5.5 The SKEW Indexes Predictability of International Markets

Inspired by Bollerslev et al. (2015), Almeida et al. (2017) and Andersen et al. (2019), in this section we perform a predicting exercise looking at the relationship between the SKEW indexes and international stock market premium. The aim is to further test the usefulness of the the SKEW indexes in predicting stock market index premia in a more global framework, for stock indexes which differ from the S&P 500 . The six selected stock market indexes are three U.S. based and three international, namely, Dow Jones Industrial Average (DJIA), Wilshire 5000 (WI), Nasdaq Composite Index (NAC) for the U.S. and Nikkei 225 (NIK) for Japan, EUROSTOXX 50 (SXE) for Europe and Hang Seng Index (HSI) for China. Their prices and corresponding risk free rates are collected from Bloomberg. The equity risk premium (log) is computed as in Section 4.5.1 as the difference between the log stock market returns on the index and the log return on a risk-free bill. The U.S. risk-free t-bill rate is used for computing the Dow Jones, Wilshire 5000 and Nasdaq risk premia, while specific country 1M risk-free rates are collected from Bloomber for the other three stock market indexes. Specifically, Japanese LIBOR - ICE LIBOR JPY 1M is used for Nikkei 225, LIBOR for the EUROSTOXX 50 and CHIBOR 1M for the Hang Seng Index. The results of this predictive exercise are reported only with respect to the first month, $h = 1$[18]. The following bivariate regression is estimated for the international stock indexes:

$$r_{t,t+1,q} = \alpha_{i,j} + \beta_{i,j} X_{i,t,j} + \varepsilon_{t,t+1,q} \tag{4.25}$$

where $r_{t,t+1,q}$ is the stock market excess return with q indexed for DJIA, WI, NAC, NIK, SXE or HSI, j is one of the predictors including the SKEW indexes. The results are reported in Table 4.12 and 4.13 for the bivariate predictive regressions.

[17] Diebold and Yilmaz (2015) affirmed that however the fact that $MSE(SKEW) < MSE(SKEW^+)$in a particular sample realization does not mean that the model including SKEW is necessarily truly better than the model including SKEW^+ in population. Whereas, the forecasting literature is filled with such horse races, with associated declarations of superiority based on outcomes, however in any particular sample realization $t = 1, ..., T$ or forecast horizon, one or the other models must *win*, so the question arises in any particular sample as to whether the first model is truly superior or merely lucky. Diebold and Mariano (2002) proposed a test for answering that question, allowing one to assess the significance of apparent predictive superiority

[18] Results for other horizons ($h = 3$, $h = 6$, $h = 12$) show a similar picture as found in subsection 4.5.2 for the S&P 500 index. The SKEW indexes are not able to predict longer term horizons risk premia showing decreasing t-statistics and R^2 when the returns horizon increases.

We find evidence that SKEW^{+} is able to predict two of the U.S. stock market indexes risk premia, namely, Wilshire 5000 and Nasdaq, with R^2 close to 1%. SKEW^{-} predicts well the next month Nasdaq risk premium among the U.S. based stock indexes (R^2 equal to 0.7%), while no predictive role is found for SKEW confirming the results of Table 4.6. For the other stock market indexes, we find poor predictive ability for SKEW indexes, only exception being SKEW^{-} in significantly predicting the next month EUROSTOXX50 risk premium with R^2 equal to 1.4%. Among the macroeconomic variables, we detect a poor predictability power in the short term, especially with regards to the U.S. stock indexes. Term structure related variables predict well the NIKKEI 225 future risk premia.

Panel A of Table 4.14 shows the predictive results of the principal components regression estimated as in equation 4.18. Panel B of Table 4.14 shows the pairwise predictive regression for the SKEW indexes as estimated in equation from 4.19 to 4.21.

The excess stock market return, $r_{t,t+1,q}$, is now indexed with q one among DJIA, WI, NAC, NIK, SXE or HSI and only at monthly horizon ($h = 1$). From Panel A, we observe how SKEW^{+} confirms its predictive ability with regards to the U.S. based stock market indexes, namely, Dow Jones and Wilshire 5000, also when we control for the four principal components. SKEW^{-} confirms its significant predictive power for the Eurozone stock market index future risk premium. When we estimate the pairwise regressions, we still find a predominant role for the SKEW^{+} in predicting Wilshire 5000 and Nasdaq risk premia. Interestingly, SKEW and SKEW^{-} show significant predictability for the U.S. based stock market indexes only when coupled together. SKEW^{-} appears to be the only one able to carry information for forecasting the Nikkei 225 next month equity premium. Noticeable, is the strong role of SKEW^{-} in relation to the European stock market index, EUROSTOXX 50, with R^2 of 1.5% and 3.7% when coupled with SKEW^{+} and SKEW , respectively. We can conclude that SKEW^{+} keeps its predictive ability for the U.S. stock market indexes also when we control for the principal components. Same conclusion applies for SKEW^{-} in relation to EUROSTOXX 50 future risk premium. Similar results are found for the out-of-sample analysis, however SKEW^{-} is found carrying a positive R^2_{OS} and MSFE significantly less than the historical average for all the selected in-sample periods and also when we control for principal components.

Table 4.12: **In-Sample Predictive Regression Results Other U.S. Stock Indexes**

Bivariate Predictive Regression												
	DOW JONES				WILSHIRE 5000				NASDAQ			
Predictor	Coef.	t NW	t HH	$R^2(\%)$	Coef.	t NW	t HH	$R^2(\%)$	Coef.	t NW	t HH	$R^2(\%)$
SKEW	-0.059	[-1.187]	(-1.142)	0.3	-0.067	[-1.268]	(-1.248)	0.4	-0.064	[-0.768]	(-0.801)	0.2
SKEW^+	0.078	[1.382]	(1.481)	0.6	0.102	[1.662]	(1.864)	0.9	0.173	[1.674]	(1.960)	1.1
SKEW^-	0.044	[0.996]	(0.974)	0.3	0.060	[1.273]	(1.286)	0.4	0.135	[1.685]	(1.798)	0.7
DP	0.019	[1.065]	(1.004)	0.9	0.025	[1.244]	(1.150)	1.3	0.051	[1.591]	(1.495)	2.4
DY	0.022	[1.323]	(1.271)	1.2	0.029	[1.629]	(1.534)	1.9	0.055	[1.777]	(1.710)	2.8
EP	0.006	[0.624]	(0.564)	0.3	0.006	[0.573]	(0.513)	0.3	0.006	[0.512]	(0.464)	0.1
DE	0.001	[0.038]	(0.034)	0	0.001	[0.103]	(0.093)	0	0.006	[0.691]	(0.637)	0.2
RVOL	0.016	[0.376]	(0.358)	0	0.027	[0.582]	(0.549)	0.1	0.041	[0.657]	(0.634)	0.1
BM	0.030	[0.773]	(0.815)	0.3	0.043	[1.026]	(1.051)	0.5	0.095	[1.228]	(1.208)	1
NTIS(-)	0.162	[0.840]	(0.774)	0.5	0.220	[0.968]	(0.869)	0.9	0.251	[0.912]	(0.833)	0.5
TBL(-)	0.065	[0.559]	(0.587)	0.1	0.119	[0.899]	(0.900)	0.3	0.298	[1.221]	(1.190)	0.8
LTY(-)	0.227	[1.411]	(1.483)	0.6	0.256	[1.504]	(1.528)	0.7	0.426	[1.442]	(1.407)	0.8
LTR	0.018	[0.191]	(0.252)	0	0.037	[0.411]	(0.558)	0.1	0.002	[0.023]	(0.026)	0
TMS	0.104	[0.518]	(0.516)	0.1	0.008	[0.037]	(0.035)	0	0.292	[0.714]	(0.685)	0.3
DFY	0.915	[0.851]	(0.774)	0.8	-0.780	[-0.670]	(-0.603)	0.5	-0.297	[-0.240]	(-0.218)	0
DFR	0.173	[0.721]	(0.700)	0.5	0.242	[0.801]	(0.773)	0.9	0.189	[0.541]	(0.526)	0.2
INFL(-)	1.209	[1.206]	(1.095)	0.01	1.032	[1.046]	(0.982)	0.7	0.356	[0.307]	(0.306)	0

Notes: The table presents the regression results for the bivariate predictive regression model estimated through equation 4.25 for the SKEW indexes and the 14 macroeconomic variables with regards to six stock market index worldwide. The one shown in this table are the three U.S. based: Dow Jones Industrial Average (DJIA), Wilshire 5000 (WI) and Nasdaq Composite Index (NAC). The log equity risk premia (in percent) are taken at monthly frequency from 01-1996 to 12-2017. Regressions intercepts are not reported to save on space. The results are reported only for monthly ($h = 1$) horizon. Newey-West [t NW] and Hodrick t-stats (t HH) are reported in square brackets and parentheses, respectively, to account for heteroskedasticity and autocorrelation in the regressions. R^2 (in percent) of every regression are reported in the last column for each regression.

Table 4.13: **In-Sample Predictive Regression Results International Stock Indexes**

Bivariate Predictive Regression												
	NIKKEI 225				EUROSTOXX 50				HSI			
Predictor	Coef.	t NW	t HH	$R^2(\%)$	Coef.	t NW	t HH	$R^2(\%)$	Coef.	t NW	t HH	$R^2(\%)$
SKEW	0.082	[1.087]	(1.086)	0.4	-0.030	[-0.429]	(-0.440)	0.1	-0.042	[-0.562]	(-0.559)	0.1
SKEW^+	-0.077	[-0.991]	(-1.027)	0.3	0.078	[1.098]	(1.231)	0.3	0.012	[0.150]	(0.171)	0
SKEW^-	0.090	[1.355]	(1.365)	0.6	0.133	[2.109]	(2.106)	1.4	-0.011	[-0.170]	(-0.177)	0
DP	0.022	[1.063]	(1.002)	0.7	0.011	[0.549]	(0.505)	0.2	0.029	[1.140]	(1.059)	0.7
DY	0.029	[1.473]	(1.393)	1.2	0.019	[0.949]	(0.878)	0.5	0.029	[1.169]	(1.086)	0.7
EP	0.004	[0.408]	(0.357)	0.1	0.006	[0.527]	(0.475)	0.2	-0.005	[-0.439]	(-0.406)	0.1
DE	0.001	[0.170]	(0.149)	0	-0.002	[-0.206]	(-0.186)	0	0.011	[0.989]	(0.915)	0.5
RVOL	-0.049	[-0.812]	(-0.756)	0.2	-0.006	[-0.106]	(-0.102)	0	-0.021	[-0.260]	(-0.245)	0
BM	0.080	[1.596]	(1.575)	1	-0.001	[-0.035]	(-0.033)	0	0.079	[1.212]	(1.228)	0.6
NTIS(-)	0.032	[0.112]	(0.103)	0	0.257	[1.056]	(0.981)	0.8	0.106	[0.334]	(0.310)	0.1
TBL(-)	-0.303	[-1.867]	(-1.887)	1.2	0.105	[0.665]	(0.643)	0.2	-0.093	[-0.402]	(-0.398)	0.1
LTY(-)	-0.577	[-2.465]	(-2.430)	2	-0.067	[-0.300]	(-0.294)	0	-0.301	[-0.977]	(-0.995)	0.3
LTR	-0.180	[-1.724]	(-2.080)	0.9	0.056	[0.494]	(0.628)	0.1	-0.043	[-0.295]	(-0.314)	0
TMS	0.114	[0.424]	(0.424)	0.1	-0.377	[-1.368]	(-1.293)	0.7	-0.122	[-0.352]	(-0.332)	0
DFY	-0.149	[-0.126]	(-0.114)	0	-1.313	[-1.062]	(-0.957)	1	0.860	[0.607]	(0.551)	0.3
DFR	0.406	[1.028]	(0.995)	1.5	0.125	[0.441]	(0.430)	0.2	0.323	[0.794]	(0.799)	0.6
INFL(-)	0.723	[0.613]	(0.617)	0.2	0.788	[0.693]	(0.643)	0.3	-0.596	[-0.503]	(-0.507)	0.1

Notes: The table presents the regression results for the bivariate predictive regression model estimated through equation 4.25 for the SKEW indexes and the 14 macroeconomic variables with regards to six stock market index worldwide. The ones reported in this table are the international stock market indexes: NIKKEI 225 (NIK) for Japan, EUROSTOXX 50 (SXE) for Europe and Hang Seng Index (HSI) for China. The log equity risk premia (in percent) are taken at monthly frequency from 01-1996 to 12-2017. Regressions intercepts are not reported to save on space. The results are reported only for monthly ($h = 1$) horizon. Newey-West [t NW] and Hodrick t-stats (t HH) are reported in square brackets and parentheses, respectively, to account for heteroskedasticity and autocorrelation in the regressions. R^2 (in percent) of every regression are reported in the last column for each regression.

Table 4.14: **In-Sample Multivariate Predictive Regression International Markets**

Panel A: Principal Components and SKEW Indexes Regression												
	DOW JONES				WILSHIRE 5000				NASDAQ			
Predictor	Coef.	t NW	t HH	$R^2(\%)$	Coef.	t NW	t HH	$R^2(\%)$	Coef.	t NW	t HH	$R^2(\%)$
SKEW $\|PC$	-0.043	[-1.507]	(-1.618)	4.5	-0.036	[-1.230]	(-1.385)	4.2	-0.018	[-0.418]	(-0.535)	6.1
SKEW$^+$ $\|PC$	0.037	[1.687]	(1.740)	4.3	0.036	[1.667]	(1.721)	6.2	0.043	[0.808]	(1.437)	6.3
SKEW$^-$ $\|PC$	-0.027	[-1.197]	(-1.403)	4.2	-0.022	[-0.955]	(-1.191)	6.2	-0.005	[-0.147]	(-0.184)	6.4
	NIKKEI 225				EUROSTOXX 50				HSI			
Predictor	Coef.	t NW	t HH	$R^2(\%)$	Coef.	t NW	t HH	$R^2(\%)$	Coef.	t NW	t HH	$R^2(\%)$
SKEW $\|PC$	-0.021	[-0.571]	(-0.666)	9	-0.016	[-0.435]	(-0.547)	2.5	-0.067	[-1.393]	(-1.514)	2.8
SKEW$^+$ $\|PC$	-0.009	[-0.233]	(-0.328)	9	0.051	[1.315]	(1.899)	2.8	0.007	[0.142]	(0.200)	2.4
SKEW$^-$ $\|PC$	-0.042	[-1.259]	(-1.635)	9.3	-0.004	[-2.136]	(-2.180)	3.4	-0.053	[-1.187]	(-1.277)	2.7
Panel B: SKEW Indexes Pairwise Regression												
	DOW JONES				WILSHIRE 5000				NASDAQ			
SKEW	-0.056	[-1.122]	(-1.079)		-0.063	[-1.193]	(-1.171)		-0.056	[-0.681]	(-0.704)	
SKEW$^+$	0.075	[1.334]	(1.429)	0.9	0.099	[1.621]	(1.819)	1.2	0.170	[1.662]	(1.935)	1.2
SKEW	-0.195	[-2.257]	(-2.192)		-0.237	[-2.450]	(-2.414)		-0.307	[-1.930]	(-2.050)	
SKEW$^-$	0.162	[2.150]	(2.123)	2.1	0.203	[2.423]	(2.437)	2.9	0.290	[2.147]	(2.234)	2.3
SKEW$^+$	0.069	[1.260]	(1.395)		0.089	[1.484]	(1.693)		0.150	[1.496]	(1.806)	
SKEW$^-$	0.029	[0.689]	(0.688)	0.7	0.040	[0.889]	(0.910)	1.1	0.073	[1.094]	(1.128)	1.3
	NIKKEI 225				EUROSTOXX 50				HSI			
SKEW	0.078	[1.058]	(1.065)		-0.026	[-0.375]	(-0.382)		-0.046	[-0.556]	(-0.553)	
SKEW$^+$	-0.073	[-0.956]	(-0.999)	0.6	0.076	[1.082]	(1.206)	0.4	0.009	[0.121]	(0.137)	0.1
SKEW	0.012	[0.114]	(0.113)		-0.285	[-2.709]	(-2.702)		-0.075	[-0.615]	(-0.624)	
SKEW$^-$	0.083	[0.860]	(0.862)	0.6	0.305	[3.305]	(3.246)	3.7	0.033	[0.336]	(0.355)	0.1
SKEW$^+$	-0.112	[-1.412]	(-1.450)		0.040	[0.572]	(0.681)		0.016	[0.205]	(0.227)	
SKEW$^-$	0.114	[1.684]	(1.678)	1.2	0.124	[1.918]	(1.971)	1.5	-0.015	[-0.218]	(-0.221)	0

Notes: The table presents the regression results for the multivariate predictive regression for U.S. and international stock market indexes. The top three of each panel are U.S. based stock market indexes: Dow Jones Industrial Average (DJIA), Wilshire 5000 (WI) and Nasdaq Composite Index (NAC). The bottom three of each panel are international stock market indexes: NIKKEI 225 (NIK) for Japan, EUROSTOXX 50 (SXE) for Europe and Hang Seng Index (HSI) for China. The log equity risk premia (in percent) are taken at monthly frequency from 01-1996 to 12-2017. The results are reported only for monthly ($h = 1$) horizon. In Panel A are presented the predictive results for the multivariate regression model estimated through equation 4.18 in which only the SKEW indexes predictability is shown after controlling for the four principal components extracted from the 14 macroeconomic variables. In Panel B we report the multivariate predictive regression in which the SKEW indexes are taken in pairs. Regressions intercepts are not reported to save on space. Newey-West [t NW] and Hodrick t-stats (t HH) are reported in square brackets and parentheses, respectively, to account for heteroskedasticity and overlap in the regressions. R^2 (in percent) of every regression are reported in the last column for each regression.

4.6 Individual Stocks Analysis

In this section, we report the results of the in-sample and out-of-sample predictive exercise with regards to the excess returns of the 30 largest individual stocks in the S&P 500 by market capitalization. This data set is similar to the one selected in other studies (see Bakshi et al., 2003; Bollerslev et al., 2016)[19]. In addition, we select a novel individual stocks data set formed by the 30 smallest stocks in the S&P 500 index by market capitalization. We show the descriptive statistics for the selected individual stocks in Table B5 in the Appendix. The selected 30 largest and 30 smallest stocks in the S&P 500 by market capitalization are ranked as at the end of 2017. Only stocks with prices available for our entire time period, namely from 01:1996 to 12:2017 are included in our data sets[20]. We study the predictability of the SKEW indexes for the 30 largest and 30 smallest stocks in the U.S. market, first, in-sample in subsection 4.6.1 and then out-of-sample in subsection 4.6.2.

4.6.1 Largest and Smallest Stocks In-Sample Predictive Exercise

We compute the individual stock risk premium as the difference between the log return on the 30 largest (30 smallest) stocks in the S&P 500 index, end-of-the-month, and the log return on the U.S. risk free rate, T-bill rate as in equation 4.16. r_{t+1} is, now, replaced by r_{t+1,i_L,i_S} with i being either one of the 30 largest or one of the 30 smallest selected individual stocks' returns. The aim of this predictive exercise is to check whether or not the decomposed SKEW indexes are able to add additional information to the more common stock returns predictors in the literature (e.g. Goyal and Welch, 2008; Neely et al., 2014), when individual stock risk premia are taken into account. The results for the in-sample predictive exercise for the 30 largest individual stocks included in the S&P 500 are reported in Table 4.15. To save space, the results are reported only for the three SKEW indexes as the output of the predictive regression in which we control for the 4 principal components extracted from the Goyal and Welch (2008) macroeconomic variables. The results are reported only for the one-month horizon since we have shown in Section 4.5.2 that the SKEW indexes contain information useful to predict stock equity risk premia in the short-term.

According to the Newey (1987) t-statistics, Table 4.15 shows that the aggregate SKEW is able to predict the future month log equity premium only for 5 companies out of 30. These companies are one in the consumer discretionary sector, Home Depot Inc., and four financial companies, namely, Bank of America, Citigroup, J.P. Morgan and Wells Fargo & Company. All the financial stocks present negative relationship with SKEW . All the financial stocks are found to be positively skewed (see Table B5). This is in line with Conrad et al. (2013) affirming that negatively (positively) skewed stocks

[19] 11 out of 30 of our individual stocks match the ones in Bakshi et al. (2003). Their data set was collected as of May 1998 while ours is as of December 2017. 18 out of 30 individual stocks match Bollerslev et al. (2016) data set.

[20] This is the reason why, we left out large stocks as, for instance, Berkshire Hathaway, Amazon and Google which IPOs took place in May 1996, May 1997 and Aug 2004, respectively.

Table 4.15: **30 Largest S&P 500 Stocks: Multivariate Predictability**

	SKEW |PC			SKEW^{+} |PC			SKEW^{-} |PC		
Ticker	Coef.	t NW	$R^2(\%)$	Coef.	t NW	$R^2(\%)$	Coef.	t NW	$R^2(\%)$
AAPL	-0.120	[-0.770]	1.8	0.271	[1.697]	2.13	0.166	[0.901]	1.93
ABT	0.062	[0.841]	1.62	-0.018	[-0.189]	1.44	0.031	[0.449]	1.49
ADBE	-0.174	[-0.996]	0.63	0.035	[0.195]	0.29	-0.095	[-0.664]	0.42
AMGN	0.089	[0.733]	0.29	0.118	[0.959]	0.45	0.144	[1.752]	0.83
BA	0.102	[0.994]	1.89	-0.030	[-0.223]	1.67	0.174	[1.759]	2.61
BAC	-0.226	[-1.687]	9.77	0.209	[1.737]	9.7	0.072	[0.561]	9.4
C	-0.238	[-1.714]	10.13	0.138	[0.520]	9.93	0.165	[1.713]	10.03
CMCSA	0.034	[0.316]	0.95	0.158	[1.674]	1.61	0.115	[1.879]	1.42
CSCO	0.017	[0.126]	0.28	0.224	[1.727]	0.98	0.212	[1.828]	1.15
CVX	0.021	[0.291]	0.61	-0.060	[-0.698]	0.78	0.024	[0.353]	0.63
DIS	0.041	[0.432]	1.49	-0.050	[-0.398]	1.52	0.135	[1.670]	2.2
DWDP	-0.141	[-1.208]	1.25	-0.052	[-0.332]	0.95	-0.018	[-0.173]	0.91
HD	-0.241	[-2.484]	2.51	0.087	[0.730]	0.95	-0.059	[-0.717]	0.86
INTC	-0.019	[-0.149]	0.72	0.240	[1.840]	1.43	0.213	[1.660]	1.49
JNJ	-0.013	[-0.214]	0.61	0.066	[0.930]	0.89	0.075	[1.389]	1.11
JPM	-0.248	[-2.149]	2.79	0.227	[1.670]	2.59	0.096	[0.923]	1.88
KO	-0.006	[-0.096]	2.04	0.067	[0.704]	2.25	-0.001	[-0.002]	2.04
MCD	0.046	[0.625]	1.7	0.061	[0.695]	1.77	0.119	[1.706	2.49
MDT	-0.057	[-0.675]	0.81	0.106	[1.258]	1.13	0.063	[0.839]	0.9
MO	-0.010	[-0.122]	0.9	-0.094	[-0.654]	1.17	-0.011	[-0.120]	0.9
MRK	-0.017	[-0.189]	0.22	0.015	[0.135]	0.22	0.007	[0.075]	0.21
MSFT	0.004	[0.036]	1.68	0.302	[2.527]	3.53	0.166	[1.669]	2.46
PFE	-0.021	[-0.254]	0.27	0.067	[0.763]	0.45	0.068	[0.949]	0.53
PG	0.042	[0.647]	0.66	0.033	[0.374]	0.63	0.002	[0.046]	0.58
T	-0.002	[-0.030]	1.69	0.072	[0.722]	1.88	0.077	[1.074]	1.98
UNH	0.050	[0.458]	1.87	0.078	[0.583]	1.94	0.115	[0.902]	2.19
VZ	0.088	[0.988]	1.81	0.069	[0.697]	1.69	0.056	[0.785]	1.67
WFC	-0.163	[-1.816]	6.96	0.074	[1.660]	6.47	0.040	[0.510]	6.39
WMT	-0.035	[-0.445]	1.55	0.087	[0.911]	1.84	0.013	[0.176]	1.5
XOM	0.041	[0.635]	1.12	0.014	[0.227]	1.01	0.052	[0.857]	1.27

Notes: The table presents the regression results for the multivariate predictive regression model estimated through equation 4.18 for the 30 largest individual stocks in the S&P 500 . The individual log equity premium is computed as in equation 4.16 for each one of the 30 largest individual stocks at monthly frequency from 01-1996 to 12-2017. The individual stocks' tickers are shown in the first column. The multivariate predictive regression is based on the four principal components extracted from the 14 macroeconomic variables and one of the three SKEW indexes. Only the SKEW indexes predictability results are shown after controlling for the four principal components. The results are reported only for monthly ($h = 1$) horizons. Regressions intercepts are not reported to save on space. Newey-West [t NW] are reported next to the SKEW indexes coefficients. R^2 (in percent) of every regression are reported in the last column.

yield subsequent higher (lower) returns. SKEW^{+} predicts well 8 of the 30 largest individual stocks in the S&P 500 mainly included in the financial sector (e.g. Bank of America, J.P. Morgan and Wells Fargo & Company) and in the IT sector (e.g. Apple Inc., Cisco System Inc., Intel Corp. and Microsoft Corp.). Finally, SKEW^{-} predicts 9 individual stock across several sectors. Stocks with high predictive loadings on tail risk will be discounted more steeply and thus have higher expected returns; stocks with low or negative tail risk loadings serve as effective hedges and will have comparatively higher prices and lower expected returns (see Kelly and Jiang, 2014). Thus, in the bivariate predictive regression, SKEW^{-} is found to perform better than SKEW and SKEW^{+} . The decomposed SKEW indexes, however, perform better than the majority of the macroeconomic variables. For instance, DY predicts only 5 individual stocks' future risk premia as well as LTY. INFL predicts 8 of the individual future risk premia mainly in the consumer discretionary and staples sectors (e.g. Home Depot and Walmart Inc.) and in the financial sectors (e.g. Bank of America and Citigroup). Our results show that the SKEW indexes contain information useful to predict some of the 30 largest stocks' future month risk premia,

especially in the financial sector and their predictability power increases when decomposed.

Table 4.16: **30 Smallest S&P 500 Stocks: Multivariate Predictability**

	SKEW |PC			SKEW^+ |PC			SKEW^- |PC		
Ticker	Coef.	t NW	$R^2(\%)$	Coef.	t NW	$R^2(\%)$	Coef.	t NW	$R^2(\%)$
AIV	-0.126	[-1.043]	0.84	0.227	[1.651]	1.54	0.044	[0.468]	0.57
ALK	-0.092	[-0.660]	1.31	0.174	[1.156]	1.65	0.060	[0.480]	1.26
AOS	-0.015	[-0.128]	2.63	-0.108	[-0.689]	2.86	-0.032	[-0.290]	2.66
AVY	-0.144	[-1.499]	0.77	-0.032	[-0.258]	0.17	0.060	[0.690]	0.29
BF.B	-0.013	[-0.169]	0.79	0.123	[1.814]	1.51	0.084	[1.835]	1.26
BWA	0.027	[0.232]	0.72	-0.083	[-0.601]	0.84	-0.001	[-0.001]	0.71
CPB	0.013	[0.143]	2.11	0.085	[0.881]	2.44	0.072	[0.944]	2.43
DISH	-0.159	[-0.923]	3.63	0.231	[1.096]	3.91	0.211	[1.732]	4
FL	-0.179	[-0.953]	0.58	0.041	[0.209]	0.25	0.051	[0.345]	0.28
FLIR	0.062	[0.382]	0.29	0.419	[1.896]	2.12	0.329	[2.374]	1.84
GPS	-0.048	[-0.319]	0.6	0.240	[1.647]	1.33	0.155	[1.189]	1.010
HOG	-0.304	[-2.208]	2.62	0.227	[1.867]	1.93	-0.012	[-0.113]	1.09
HP	-0.465	[-2.992]	3.37	-0.011	[-0.070]	0.46	-0.192	[-1.912]	1.14
HRB	-0.048	[-0.391]	0.49	0.088	[0.794]	0.63	0.030	[0.314]	0.46
JEF	-0.232	[-1.904]	2.04	0.117	[1.128]	1.17	0.001	[0.001]	0.87
KIM	-0.256	[-2.229]	4.93	0.084	[0.745]	3.57	-0.058	[-0.700]	3.51
LB	-0.268	[-1.955]	1.58	0.256	[1.767]	1.46	0.084	[0.765]	0.53
LEG	-0.170	[-1.615]	1.76	0.156	[1.669]	1.62	0.053	[0.605]	1.06
MAC	-0.287	[-1.841]	1.41	0.271	[1.891]	1.3	-0.011	[-0.109]	0.48
NFX	-0.210	[-1.287]	1.39	-0.158	[-0.942]	1.12	-0.219	[-1.670]	1.68
NKTR	-0.252	[-0.998]	0.68	-0.099	[-0.345]	0.4	-0.116	[-0.542]	0.44
PBCT	-0.169	[-1.885]	1.78	0.032	[0.315]	0.68	-0.020	[-0.254]	0.67
PHM	-0.139	[-0.940]	0.38	-0.184	[-1.028]	0.57	0.091	[0.626]	0.27
RHI	0.131	[1.082]	1.3	0.008	[0.065]	0.99	0.063	[0.613]	1.09
ROL	-0.208	[-2.470]	3	0.282	[2.705]	4.51	-0.014	[-0.207]	1.16
SCG	0.056	[0.737]	0.37	0.029	[0.351]	0.22	-0.013	[-0.227]	0.19
UNM	-0.038	[-0.292]	4.25	0.303	[2.249]	5.6	0.169	[1.753]	4.82
WHR	-0.182	[-1.314]	1.57	0.093	[0.653]	1.19	0.076	[0.684]	1.18
XRAY	-0.042	[-0.549]	0.33	0.180	[2.154]	1.73	0.127	[1.802]	1.26
XRX	0.094	[0.622]	1.02	-0.196	[-0.869]	1.37	0.003	[0.003]	0.91

Notes: The table presents the regression results for the multivariate predictive regression model estimated through equation 4.18 for the 30 smallest individual stocks in the S&P 500 . The individual log equity premium is computed as in equation 4.16 for each one of the 30 smallest individual stocks at monthly frequency from 01-1996 to 12-2017. The individual stocks tickers are shown in the first column. The multivariate predictive regression is based on the four principal components extracted from the 14 macroeconomic variables and one of the three SKEW indexes. Only the SKEW indexes predictability results are shown after controlling for the four principal components. The results are reported only for monthly ($h = 1$) horizons. Regressions intercepts are not reported to save on space. Newey-West [t NW] are reported next to the SKEW indexes coefficients. R^2 (in percent) of every regression are reported in the last column.

Table 4.16 shows the predictive regression results with respect to the 30 smallest stocks in the S&P 500 . The results of the in-sample predictive exercise are estimated in an analogous way as for the 30 largest stocks. We control for the 4 principal components extracted from the 14 macroeconomic variables and the single stocks' return is, now, r_{t+1,i_B}, computed for every stock among the 30 smallest in the S&P 500 . SKEW predicts 8 among the 30 smallest stocks future risk premia with stocks spanning different sectors, e.g. financial, consumer discretionary and real estate. We find that SKEW^+ performs better than SKEW^- . The first is able to predict 11, whereas SKEW^- predicts 7 among the 30 smallest stocks operating in all sectors. Despite the change in the internal ranking regarding the predictability power of the three SKEW indexes, we confirm that they also carry information useful to predict smaller market capitalization stocks also when controlling for the four principal components. In the bivariate predictive regression, we find that the aggregate SKEW performs in the same way as in the principal components regression, whereas SKEW^- and SKEW^+ under-perform compared

to the multivariate regression when we control for the 4 principal components. However, they are still found to predict the individual smallest 30 stocks risk premia better compared to the majority of the macroeconomic variables. Exception being only TS and INFL which appear to predict as well as or better some among the individual 30 smallest stocks, 4 and 9, respectively. The individual stocks predicted well by the inflation rate are mainly in the consumer staples and discretionary.

We have also estimated predictive regressions in which the SKEW indexes are taken in pairs as in equations from 4.19 to 4.21 for predicting the future levels of the individual stocks risk premia[21]. The best model appears to be the one with SKEW and SKEW^- paired together. A relevant role for SKEW^- is found in the in-sample predictability of the 30 smallest individual stocks, however this decreasing when SKEW^- is coupled with SKEW^+ confirming once more that the prevalent role of SKEW^+ over SKEW and SKEW^- . When the three SKEW indexes are tested together in the same multivariate predicting model, we find that SKEW , SKEW^+ and SKEW^- forecast future risk premia in 7, 4 and 9 cases out of 30 for the largest individual stocks, while in 11, 7 and 15 cases out of 30 for the smallest, respectively. These findings show how SKEW^- appears to strengthen its predictive power when added next to other SKEW indexes predictors.

As a final robustness check, we also add the SKEW indexes next to VIX and VRP in predicting individual stocks. The SKEW indexes performance is still robust when we control for these. VIX appears to predict as well as or less than the aggregate SKEW . Among the decomposed measures, SKEW^+ is found to be significantly predict the future risk premia better than VIX^+ for both the 30 largest or 30 smallest S&P 500 stocks. Interestingly, SKEW^- is found to be the best predictor among the six for the 30 largest stocks, whereas VIX^- is found more useful to predict the 30 smallest stocks. Also when we control for VRP indexes, we still find a predictive role for the decomposed SKEW indexes. SKEW^- appears to predict the 30 largest stocks as well as than VRP^- . SKEW^+ predicts the 30 smallest stocks better than VRP and VRP^- . Among these indexes, superior ability in explaining individual stock returns is found for VRP^+ in line with Feunou et al. (2017) and Kilic and Shaliastovich (2018) and as found in Section 4.5.3.

[21] With relation to the 30 largest stocks, SKEW and SKEW^+ predict well the future risk premia in only 6 and 3 cases out of 30, respectively, when added in the same predictive model. SKEW and SKEW^- appear to strengthen their predictability power when coupled in the same regression, predicting well in 7 and 11 cases, respectively. SKEW^+ and SKEW^- are able to predict, in both cases, only 4 stocks out of 30. With regards to the 30 smallest individual stocks, we find that SKEW^+ and SKEW are able to significantly predict future level of risk premia in 10 and 7 cases out of 30, respectively, when paired. SKEW and SKEW^- are found to be significant in 14 and 16 cases, respectively, out of 30. When SKEW^+ and SKEW^- are combined in the same multivariate regression, they are significant predictors in 8 cases and 4 cases out of 30, respectively.

Table 4.17: **30 Largest S&P 500 Stocks: Out-of-Sample Predicting Regression**

	SKEW |PC				SKEW^{+} |PC				SKEW^{-} |PC			
Ticker	MSFE	$R^2_{OS}(\%)$	MSFE adj.	p value	MSFE	$R^2_{OS}(\%)$	MSFE adj.	p value	MSFE	$R^2_{OS}(\%)$	MSFE adj.	p value
AAPL	5.402	-21.043	-0.089	0.535	4.648	-4.155	1.145	0.126	4.727	-5.938	1.006	0.157
ABT	3.202	-0.092	0.541	0.294	3.236	-1.178	0.048	0.480	3.225	-0.809	0.211	0.416
ADBE	3.463	-7.907	-0.384	0.649	3.139	2.178	1.321	0.093	3.175	1.357	1.213	0.155
AMGN	4.432	-1.027	-0.262	0.603	4.366	0.470	0.524	0.299	4.289	2.217	1.252	0.128
BA	3.924	6.133	2.417	0.007	3.939	5.795	2.457	0.006	3.904	6.613	2.305	0.010
BAC	2.833	0.115	0.973	0.165	2.815	1.750	1.273	0.165	2.89	-1.884	0.823	0.205
C	3.878	-4.594	-0.285	0.612	3.922	-5.756	-1.026	0.847	3.954	-6.620	-1.241	0.892
CMCSA	2.280	-15.207	0.023	0.490	1.943	1.819	1.264	0.122	2.032	-2.667	0.235	0.406
CSCO	3.644	1.988	1.350	0.124	3.890	-4.632	0.272	0.392	3.708	0.857	1.235	0.155
CVX	6.670	-11.061	0.649	0.258	6.382	-6.266	0.993	0.160	6.348	-5.696	0.993	0.160
DIS	5.546	-11.716	0.503	0.307	5.437	-9.522	0.537	0.295	5.622	-13.239	0.372	0.354
DWDP	2.493	-0.670	0.293	0.384	2.471	0.215	0.661	0.254	2.461	0.651	0.768	0.221
HD	3.120	0.238	0.355	0.360	3.241	-3.640	-0.051	0.520	3.442	-10.050	-0.394	0.653
INTC	3.025	-6.428	-1.741	0.959	3.006	-5.769	-1.253	0.895	3.007	-5.802	-1.649	0.950
JNJ	1.332	-0.040	0.354	0.361	1.298	2.486	1.670	0.047	1.287	3.325	1.629	0.051
JPM	3.173	3.534	1.314	0.094	3.118	5.208	1.550	0.060	3.157	4.010	1.434	0.075
KO	1.475	-13.542	-0.766	0.778	1.497	-15.252	-0.785	0.783	1.476	-13.608	-0.754	0.774
MCD	1.263	3.099	1.442	0.074	1.257	3.821	1.577	0.057	1.214	6.821	1.772	0.038
MDT	2.421	-3.608	-0.877	0.809	2.374	-1.598	-0.091	0.536	2.370	-1.401	-0.161	0.564
MO	2.437	1.723	1.019	0.153	2.549	-2.792	0.105	0.457	2.446	1.365	1.2712	0.165
MRK	2.304	-0.964	0.030	0.487	2.287	-0.224	0.288	0.386	2.290	-0.351	0.231	0.408
MSFT	3.707	-2.152	0.300	0.381	3.885	-7.058	0.298	0.382	3.702	-2.019	0.669	0.251
PFE	1.864	-3.659	-1.083	0.860	1.791	1.408	1.233	0.332	1.783	1.886	1.350	0.257
PG	1.276	-5.907	-0.878	0.810	1.270	-5.381	-0.726	0.766	1.282	-6.404	-1.115	0.867
T	2.325	-0.458	0.559	0.287	2.345	-1.330	0.462	0.321	2.309	0.258	0.843	0.199
UNH	2.529	-16.948	-1.121	0.868	2.495	-15.375	-1.006	0.843	2.505	-15.855	-0.730	0.767
VZ	2.335	0.580	0.827	0.203	2.342	0.309	0.690	0.244	2.341	0.352	0.685	0.246
WFC	2.607	-12.188	0.371	0.355	2.614	-12.505	0.061	0.475	2.648	-13.953	-0.165	0.565
WMT	2.330	-2.426	-0.016	0.506	2.253	1.979	1.217	0.206	2.264	1.759	1.304	0.240
XOM	1.941	-12.421	-1.602	0.945	1.858	-7.608	-1.174	0.879	1.884	-9.096	-1.190	0.883

Notes: The table presents the S&P 500 30 largest individual stocks risk premium out-of-sample predictive regression. We present only the results for the multivariate out-of-sample predictive regression estimated through equation 4.24. The four principal components are extracted from the 14 macroeconomic variables and added as control variables in the same predictive model next to one of the three SKEW indexes. Only the SKEW indexes out-of-sample predictability is shown after controlling for the four principal components. The out-of-sample results are presented only with relation to the 1996-2013 in-sample period horizon selection. The 30 largest individual stocks tickers are listed in the first column. MSFE is the mean squared forecast error, R^2_{OS} (see Campbell and Thompson, 2007) measures the reduction in MSFE with respect to the historical average forecast benchmark shown in the first column of every selected in-sample period horizon. The Clark and West (2007) MSFE-adjusted statistic tests the null hypothesis that the historical average (HA) forecast MSFE is $\leq$ than the competing forecast MSFE against the one-sided alternative hypothesis that the historical average (HA) forecast MSFE is $>$ greater than the competing forecast MSFE. P-values are shown in the last column of each forecast in-sample period.

Table 4.18: **30 Smallest S&P 500 Stocks: Out-of-Sample Predicting Regression**

	SKEW |PC				SKEW^{+} |PC				SKEW^{-} |PC			
Ticker	MSFE	$R^2_{OS}(\%)$	MSFE adj.	p value	MSFE	$R^2_{OS}(\%)$	MSFE adj.	p value	MSFE	$R^2_{OS}(\%)$	MSFE adj.	p value
AIV	2.945	-24.063	-1.828	0.966	2.323	2.161	1.254	0.170	2.467	-3.931	-0.448	0.673
ALK	7.923	-0.744	0.426	0.334	7.627	3.014	1.378	0.119	7.799	0.834	1.323	0.234
AOS	3.951	-6.782	-0.155	0.561	4.196	-13.403	-1.140	0.872	3.989	-7.807	-0.284	0.612
AVY	2.697	-9.748	-1.015	0.845	2.604	-5.978	-3.095	0.999	2.548	-3.674	-1.254	0.895
BF.B	2.549	-2.443	-0.292	0.615	2.395	3.752	1.778	0.037	2.428	2.397	1.264	0.102
BWA	8.479	-7.354	-1.949	0.974	8.383	-6.134	-1.834	0.966	8.511	-7.760	-1.873	0.969
CPB	3.306	-7.807	-0.607	0.728	3.164	-3.162	0.252	0.400	3.402	-10.941	-0.814	0.792
DISH	4.917	-9.642	0.007	0.496	5.070	-13.056	-0.469	0.680	4.850	-8.154	0.610	0.270
FL	9.563	-2.510	-0.215	0.585	9.466	-1.480	-0.298	0.617	9.503	-1.873	-0.405	0.657
FLIR	3.810	-1.650	-0.242	0.595	3.718	0.798	1.389	0.082	4.462	-19.043	-0.692	0.755
GPS	11.842	-7.947	-2.429	0.992	12.097	-10.273	-1.936	0.973	12.026	-9.623	-2.232	0.987
HOG	4.295	2.965	1.256	0.104	4.409	0.403	0.844	0.199	4.518	-2.066	0.127	0.449
HP	9.076	7.592	2.409	0.007	10.069	-2.512	-1.019	0.846	9.837	-0.157	0.434	0.331
HRB	6.916	-4.490	-2.043	0.979	6.828	-3.158	-1.251	0.894	6.895	-4.174	-1.738	0.958
JEF	4.151	-1.974	0.482	0.314	3.978	2.272	1.465	0.167	4.055	0.381	0.417	0.338
KIM	4.144	-11.854	0.128	0.448	3.694	2.293	1.226	0.152	3.762	-1.563	0.655	0.256
LB	7.350	-0.191	0.400	0.344	7.519	-2.491	-0.340	0.633	7.751	-5.653	-2.113	0.982
LEG	2.988	-9.109	-0.898	0.815	2.898	-5.813	-0.366	0.643	3.055	-11.551	-1.682	0.953
MAC	3.743	-6.733	0.729	0.232	3.435	2.050	1.448	0.073	3.525	-0.506	0.541	0.294
NFX	9.755	-4.582	-0.530	0.702	9.815	-5.221	-1.256	0.895	9.684	-3.818	-0.274	0.608
NKTR	36.560	-2.185	-0.931	0.824	36.574	-2.225	-1.632	0.948	36.615	-2.339	-1.533	0.937
PBCT	2.224	0.765	0.956	0.169	2.274	-1.498	-0.052	0.521	2.281	-1.795	-0.131	0.552
PHM	5.080	-3.311	-0.652	0.743	5.205	-5.841	-1.350	0.911	5.142	-4.567	-1.296	0.902
RHI	5.044	-3.725	-0.342	0.634	5.068	-4.200	-1.034	0.849	5.062	-4.082	-0.937	0.825
ROL	1.991	-9.709	0.502	0.307	1.645	9.338	2.151	0.015	1.764	2.834	1.534	0.062
SCG	3.374	-1.051	-0.403	0.656	3.391	-1.577	-0.761	0.776	3.389	-1.503	-0.523	0.699
UNM	4.264	2.001	1.160	0.122	4.090	5.999	1.704	0.044	4.432	-1.863	0.914	0.180
WHR	7.417	-12.164	-2.477	0.993	7.170	-8.440	-2.508	0.993	7.235	-9.425	-2.367	0.991
XRAY	2.635	-3.832	-1.076	0.859	2.454	3.275	1.547	0.060	2.545	-0.295	0.547	0.291
XRX	4.310	0.936	1.275	0.164	4.304	1.071	1.364	0.193	4.418	-1.558	0.548	0.291

Notes: The table presents the S&P 500 30 smallest individual stocks risk premium out-of-sample predictive regression. We present only the results for the multivariate out-of-sample predictive regression estimated through equation 4.24. The four principal components are extracted from the 14 macroeconomic variables and added as control variables in the same predictive model next to one of the three SKEW indexes. Only the SKEW indexes out-of-sample predictability is shown after controlling for the four principal components. The out-of-sample results are presented only with relation to the 1996-2013 in-sample period horizon selection. The 30 smallest individual stocks tickers are listed in the first column. MSFE is the mean squared forecast error, R^2_{OS} (see Campbell and Thompson, 2007) measures the reduction in MSFE with respect to the historical average forecast benchmark shown in the first column of every selected in-sample period horizon. The Clark and West (2007) MSFE-adjusted statistic tests the null hypothesis that the historical average (HA) forecast MSFE is $\leq$ than the competing forecast MSFE against the one-sided alternative hypothesis that the historical average (HA) forecast MSFE is $>$ greater than the competing forecast MSFE. P-values are shown in the last column of each forecast in-sample period.

4.6.2 Largest and Smallest Stocks Out-of-Sample Predictive Exercise

Table 4.17 reports the S&P 500 30 largest individual stocks out-of-sample predictive results. The selected predictors are the SKEW indexes added in the multivariate predictive regressions when controlling for the 4 principal components extracted from the 14 macroeconomic variables. The results are reported only for the 1996-2013 in-sample period choice which is found to lead to the best out-of-sample results in Section 4.5.4. This sample choice includes enough observation in the forecasting model evaluation spanning the last four years of our total time period and includes the global financial crisis in the in-sample window. For the 30 largest S&P 500 stocks, we find that the SKEW^{+} and SKEW^{-} are the best predictors. SKEW^{+} carries additional information in order to predict the selected individual stocks in 9 cases out of 30 with positive R^2_{OS}, as well as, MSFE significantly less than the historical average. SKEW^{-} shows positive R^2_{OS} in correspondence of 13 stocks and the Clark and West (2007) MSFE-adjusted statistic test shows a significant error less than the historical average in 10 cases out of 30. The aggregate SKEW out-of-sample predictability power appears weaker, with R^2_{OS} found to be positive in 8 cases out of 30.

Table 4.18 shows the S&P 500 30 smallest individual stocks out-of-sample predictive results. We find that SKEW and SKEW^{-} perform poorly showing a positive R^2_{OS} in correspondence of a MSFE less than the historical average only in 3 cases out of 30. SKEW^{+} is found to predict better out-of-sample showing a positive R^2_{OS} and a MSFE significantly less than the historical average in 11 cases out of 30 in relation to the 30 smallest individual stocks in S&P 500 . We can conclude that the decomposed SKEW indexes perform as well as or better than the aggregate SKEW for both the 30 largest and 30 smallest individual stocks in the S&P 500 for the out-of-sample forecasting evaluation. In addition, the decomposed SKEW indexes appear to include information useful for out-of-sample predictability which are not captured by the four principal components.

4.7 SKEW Indexes and Asset Pricing

In this section, we investigate the connection between stock portfolios returns, the skewness index and its positive and negative components. We expand the Fama and French (1993) three-factors and Fama and French (2017) five-factors models by testing the explanatory power of the third moment's indexes when added next to them. According to Fama and French (2017), this model is found to perform better than the traditional Fama and French (1993) three-factors model where market excess return, return of value portfolios minus average return on growth portfolios (HML) and return on small portfolios minus average return on big portfolios (SMB) are considered. The five factors include market excess return, as a difference between market portfolio return and risk-free rate of 1m T-bills, the average return on value portfolios minus average return on growth portfolios (HML), the average return on small

portfolios minus average return on big portfolios (SMB), the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios (RMW) and the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios (CMA).[22]

This section is based on a series of studies advocating the role of stock returns higher moments in asset pricing models in the literature. The strand of literature incorporating skewness in asset pricing models is also vast and it has a long history. This literature has started from the seminal work by Kraus and Litzenberger (1976) and has been progressively expanded, see Friend and Westerfield (1980); Kraus and Litzenberger (1983); Harvey and Siddique (2000); Brunnermeier et al. (2007); Mitton and Vorkink (2007); Boyer et al. (2009); Rehman and Vilkov (2012); Conrad et al. (2013).

Some studies have analyzed this relationship using historic expected skewness measures (e.g. Boyer et al., 2009) while some others have used ex ante forward looking skewness extracted from options (e.g. Rehman and Vilkov, 2012; Conrad et al., 2013). In our chapter we follow the second strand of literature by using implied skewness measures. In particular, Harvey and Siddique (2000) has included a conditional skewness measure in asset pricing model to better understand the cross-sectional variation of asset returns. Among the most recent, Conrad et al. (2013) focused on both individual securities' risk neutral volatility and skewness and their linkages with future returns, and Rehman and Vilkov (2012)– using ex ante forward looking skewness extracted from options– found that risk-averse investors dislike negative skewness and they require compensation with higher returns in order to invest in these left skewed stocks. More specifically we want to test whether or not the negative and positive skewness indexes (SKEW^{-} and SKEW^{+}) are more informative than the aggregate, SKEW in explaining our selected portfolios returns.

The portfolios we select are the daily bivariate U.S. 25 stocks portfolios sorted on Size and Book-to-Market, constructed at the end of each June and representing the intersections of five portfolios formed on size (Market Equity, ME) and five portfolios formed on the ratio of book equity to market equity (BE/ME). Moreover, we analyze the informative power of our series in relationship to the bivariate 100 portfolios sorted on Size and Book-to-Market and we verify the results when using 12 industry portfolios[23]. All the selected portfolios are taken as average value weighted returns[24]. The results of these robustness exercises are reported in Appendix B.2.

Specifically, we conduct an asset pricing exercise with the full sample and sub-samples, performing a Fama and MacBeth (1973) two steps regression analysis.[25] This provides information about the

[22]For further details on the methodology for computing these five factors see Kenneth R. French Data Library at: `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html` from where the data have been collected.

[23]The 12 industries comprehend Consumer Non Durable, Consumer Durable, Manufacturing, Energy, Chemicals, Hi-Tech, Telecommunication, Shops. Health-Care, Utility, Money and Others.

[24]For more details available at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

[25]The Fama and MacBeth (1973) allows us to test which factors can better explain stock market returns. Thus, we test whether our risk factors, the decomposed second and third moments, can provide better results when added to the standard factors by

premium that compensates investors from their exposure to these factors. Finally, we explore how fundamental factors together with implied indexes affect average stock returns during turbulent periods in our study. The first step of the methodology involves the system of equations where there are the n selected portfolios returns and the factors we test on the left and the right side, respectively, as[26].

$$\begin{aligned} R_{1,t} - r_{f,t} &= \alpha_1 + \beta_{1,F_1} F_{1,t} + \beta_{1,F_2} F_{2,t} + ... + \beta_{1,F_m} F_{m,t} + \epsilon_{1,t} \\ R_{2,t} - r_{f,t} &= \alpha_2 + \beta_{2,F_1} F_{1,t} + \beta_{2,F_2} F_{2,t} + ... + \beta_{2,F_m} F_{m,t} + \epsilon_{2,t} \\ &\vdots \\ R_{n,t} - r_{f,t} &= \alpha_n + \beta_{n,F_1} F_{1,t} + \beta_{n,F_2} F_{2,t} + ... + \beta_{n,F_m} F_{m,t} + \epsilon_{n,t} \end{aligned} \tag{4.26}$$

where each equation represents a regression for a different return $R_{i,t}$ of portfolio or asset i (from 1 to n) at time t and minus the risk free rate (excess market return), $F_{j,t}$ is the factor j (from 1 to m) at time t, with β_{i,F_m} are the factor loadings expressing the exposure of each asset or portfolio of assets to that specific factor, and t goes from 1 to T[27]. In the second step we compute T cross-sectional regressions of the returns on the m estimates of the βs ($\hat{\beta}$) calculated from the first step.

$$\begin{aligned} R_{i,1} - r_{f,1} &= \gamma_{1,0} + \gamma_{1,1} \hat{\beta}_{i,F_1} + \gamma_{1,2} \hat{\beta}_{i,F_2} + ... + \gamma_{1,m} \hat{\beta}_{i,F_m} + \epsilon_{i,t} \\ R_{i,2} - r_{f,2} &= \gamma_{2,0} + \gamma_{2,1} \hat{\beta}_{i,F_1} + \gamma_{2,2} \hat{\beta}_{i,F_2} + ... + \gamma_{2,m} \hat{\beta}_{i,F_m} + \epsilon_{i,2} \\ &\vdots \\ R_{i,T} - r_{f,T} &= \gamma_{T,0} + \gamma_{n,1} \hat{\beta}_{i,F_1} + \gamma_{n,2} \hat{\beta}_{i,F_2} + ... + \gamma_{n,m} \hat{\beta}_{i,F_m} + \epsilon_{i,T} \end{aligned} \tag{4.27}$$

where the $R_{i,t} - r_{f,t}$ excess market returns are the same as before and γ are the coefficients measuring the risk premium expressed by each factor over time T, with i from 1 to n.

We start with the standard Fama and French (1993) three-factor model:

$$R_{i,t} - r_{f,t} = \beta_{0,i} + \beta_{1,i}(R_{M,t} - r_{f,t}) + \beta_{2,i} HML_t + \beta_{3,i} SMB_t + \epsilon_{i,t} \tag{4.28}$$

where $R_{i,t}$ is the daily portfolio return i for day t minus the risk-free rate for day t, $r_{f,t}$ and R_M the equal weighed market portfolio. The following is the more recent Fama and French (2017) five-factor model, which includes also profitability (RMW) and investment (CMA) factors:

$$R_{i,t} - r_{f,t} = \beta_{0,i} + \beta_{1,i}(R_{M,t} - r_{f,t}) + \beta_{2,i} HML_t + \beta_{3,i} SMB_t + \beta_{4,i} RMW_t + \beta_{5,i} CMA_t + \epsilon_{i,t} \tag{4.29}$$

increasing the significance, coefficients size and sign (I step). Then, in the II step, we test what is the risk premium required by these factors on the asset returns.

[26] In the first step each portfolio's return is regressed against one or more factor time series to determine how exposed it is to each one (the factor exposures). In the second step, the cross-section of portfolio returns is regressed against the factor exposures, at each time step, to give a time series of risk premia coefficients for each factor. The insight of Fama-MacBeth is to then average these coefficients, once for each factor, to give the premium expected for a unit exposure to each risk factor over time.

[27] Each regression uses the same factors F, because the purpose is to determine the exposure of each portfolio's return to a given set of factors.

Skewness measures have also been widely advocated as important variables in explaining the variations of stock returns. Hence, here, we also employ the models taking into account the positive and negative implied SKEW indexes:

$$R_{i,t}-r_{f,t} = \beta_{0,i}+\beta_{1,i}(R_{M,t}-r_{f,t})+\beta_{2,i}HML_t+\beta_{3,i}SMB_t+\beta_{4,i}RMW_t+\beta_{5,i}CMA_t+\beta_{z,i}SKEW_t^q+\epsilon_{i,t} \tag{4.30}$$

where $SKEW_t^q$ is the U.S. SKEW index index with q indexed for $Tot, -, +$. Finally, all the SKEW indexes are tested together in the same regression having a eight factors model as follow:

$$\begin{aligned} R_{i,t} - r_{f,t} = \{&\beta_{0,i} + \beta_{1,i}(R_{M,t} - r_{f,t}) + \beta_{2,i}HML_t + \beta_{3,i}SMB_t + \beta_{4,i}RMW_t + \\ &+\beta_{5,i}CMA_t + \beta_{6,i}SKEW_t + \beta_{7,i}SKEW_t^+ + \beta_{8,i}SKEW_t^- + \epsilon_{i,t}\} \end{aligned} \tag{4.31}$$

Tables 4.19 and 4.20 present the results of the empirical asset pricing analysis from the second step Fama-MacBeth methodology. The analysis is performed for the 25-Size-Book-To-Market and the 100-Size-Book-To-Market sorted portfolios. A robustness exercise is presented in Appendix B.2 for other portfolio selection and different time periods. We verify using the regressions' R^2 and adjusted R^2, whether the outcomes improve by adding the implied decomposed third moments indexes to the five-factor model. In addition, we consider whether the decomposed implied SKEW indexes might carry more useful information in terms of portfolios' returns predictability. The traditional three factor model and the five factors models are reported as well for comparative purposes.

The results in Table 4.19 indicate that incorporating SKEW in the five-factors model does not improve the adjusted R^2. On the other hand, adding the decomposed SKEW^+ and SKEW^- in the same model *does* improve the adjusted R^2 compared to the five-factors model.

SKEW^+ is found to be significant at 10% in regression (4), while SKEW^- is found to be significant at 5% from regression (5). Despite this, the model including SKEW^+ performs slightly better than the one including SKEW^- in terms of R^2 and adjusted-R^2. Both models with decomposed SKEW indexes perform better than regression (3) including the aggregate SKEW which is found not significant. The model including SKEW does not appear to perform better than the stand alone five-factors model. When all the SKEW indexes are added together in the 8-factors models in regression (6), we observe that the model carries a total R^2 and adjusted-R^2 equal to 71% and 56%, respectively. Only SKEW^- is found to be significant in regression (6). The directional information encapsulated into the decomposed indexes improves the regression models performance more than the aggregate indexes.

Table 4.20 presents the results for the 100 Size and Book-to-Market sorted portfolios[28]. We observe

[28]Since the portfolios sorted by Book-to-Market have missing data, interpolation is used. When daily missing data (shown as 99.99 are found), interpolation between the previous and following trading day is used. When there are daily missing data spanning months, we leave out that missing data. The main part of the monthly missing data is found during the financial crisis. This is the reason why a robustness check within the financial crisis is performed on the 100 portfolios sorted by Size-Operational Profitability.

Table 4.19: **Fama-MacBeth Results: 25-Size/Book-to-Market Portfolios**

Coeff	3-Factors	5-Factors	5-Factors & SKEW			Full 8-Factors
	(1)	(2)	(3)	(4)	(5)	(6)
γ_0	1.646^{***}	1.407^{***}	1.376^{**}	1.157^{**}	1.213^{**}	1.174^{**}
	(5.657)	(3.152)	(2.814)	(2.834)	(2.652)	(2.631)
γ_{Mkt-rf}	-0.950^{***}	-0.728	-0.699	-0.433	-0.521	-0.430
	(-3.240)	(-1.625)	(-1.434)	(-1.059)	(-1.157)	(0.997)
γ_{HML}	0.204^{**}	0.164^{**}	0.167^{**}	0.114	0.166^{**}	0.111^{*}
	(3.920)	(2.386)	(2.314)	(1.628)	(2.593)	(2.004)
γ_{SMB}	0.160	0.203^{**}	0.204^{***}	0.180^{**}	0.202^{***}	0.174^{***}
	(2.282)	(3.417)	(3.223)	(2.685)	(3.134)	(3.018)
γ_{RMW}		0.389^{*}	0.397^{*}	0.272	0.415^{*}	0.314^{*}
		(1.834)	(1.824)	(1.415)	(1.872)	(1.753)
γ_{CMA}		0.098	0.077	0.138	-0.007	0.129
		(0.503)	(0.383)	(0.515)	(0.974)	(0.585)
γ_{SKEW}			-0.045			-0.073
			(-0.497)			(-0.610)
γ_{SKEW+}				-0.036^{*}		-0.294
				(-1.782)		(-1.674)
γ_{SKEW-}					-0.022^{**}	-0.027^{**}
					(-2.700)	(-2.673)
R^2	0.5290	0.572	0.574	0.656	0.620	0.711
Adj R^2	0.461	0.460	0.432	0.542	0.494	0.566

Notes: This table shows the results of the second stage of the Fama-MacBeth regression approach in which the portfolios' returns, 25 portfolios based on Size and Book-to-Market, are regressed on the β factor loadings computed in the first step and expressing the exposure of each portfolio of assets to that specific factor as in (4.27). γ coefficients measure the risk premium associated with each selected factor. The regressions' outcome we report are for the simple 3-factors model (1) (Equation (4.28)), for the 5-factors model (2) (Equation (4.29)), for the 6-factors model with skewness indexes (3), (4), and (5) (Equation (4.30)) and the full model with all the three SKEW indexes (Equation 4.31). Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The selected period is the full sample from 04-01-1996 to 29-12-2017, at daily frequency.

that the results are similar to Table 4.19. SKEW^{+} and SKEW^{-} are found improving the regression performance compared to the five-factors model and compared to regression (3) including SKEW . SKEW^{+} and SKEW^{-} are found both significant when added in regressions (4) and (5). SKEW^{+} is improving slightly the regression R^2 and adjusted-R^2 compared to the five-factors model; whereas SKEW^{-} shows a larger improvement in R^2 and adjusted-R^2. When the SKEW indexes are added all together, R^2 and adjusted R^2 are equal to 65% and 62%, respectively.

Other robustness exercises regarding the ability of the decomposed SKEW indexes in asset pricing context as well as their ability in turbulent times are reported in Appendix B.2. In general, we confirm the results of Tables 4.19 and 4.20 also when other portfolios and time period are taken into account. We find that the negative SKEW^{-} emerged as significant and is able to bring extra information and it considerably increases the regression models' R^2 and adjusted R^2.

Overall, the empirical results for the asset pricing exercise show that the six or eight factors models, constructed from the five common factors plus the decomposed implied moments measures as well as from the five common factors plus all the SKEW indexes can better explain the variations of stock returns than the Fama and French (1993) three-factors and than the more recent Fama and French (2017) five-factors models. We observe evidence of the main role played by the decomposed SKEW indexes. As far as our knowledge, it is the first time in the literature that this exercise is conducted and evidence is found in support of directional implied third moments as predictors of stock returns.

This section provides new insights on the investigation of the third higher moment of the market return as pricing factor of stock returns, topic which seems worthwhile (e.g. Ang et al., 2005; Chang

Table 4.20: **Fama-MacBeth Results: 100-Size/Book-to-Market Portfolios**

Coeff	3-Factors	5-Factors	5-Factors & SKEW			Full 8-Factors
	(1)	(2)	(3)	(4)	(5)	(6)
γ_0	6.734^{**}	4.143^{**}	4.278^{**}	4.165^{**}	4.105^{**}	3.805^{**}
	(2.393)	(2.192)	(2.261)	(2.162)	(2.355)	(2.258)
γ_{Mkt-rf}	-6.229^{**}	-3.784^{**}	-3.916^{**}	-3.835^{*}	-3.761^{**}	-3.421^{**}
	(-2.150)	(-1.975)	(-2.027)	(-1.961)	(-2.098)	(-1.998)
γ_{HML}	-0.096	-0.533	-0.514	-0.500	-0.398	-0.380
	(-0.387)	(-1.101)	(-1.130)	(-1.096)	(-1.098)	(-1.123)
γ_{SMB}	0.646	0.845^{*}	0.849^{**}	0.858^{*}	0.796^{**}	0.720^{*}
	(2.170)	(1.857)	(1.992)	(1.845)	(2.085)	(1.913)
γ_{RMW}		1.195^{*}	1.186^{*}	1.231^{*}	$0.973*$	0.722
		(1.742)	(1.876)	(1.744)	(1.741)	(1.327)
γ_{CMA}		2.187^{**}	2.108^{**}	2.152^{**}	1.909^{**}	1.869^{**}
		(2.097)	(2.142)	(2.127)	(2.266)	(2.298)
γ_{SKEW}			0.037			0.033
			(1.153)			(1.139)
γ_{SKEW+}				0.029^{*}		0.019
				(1.907)		(0.074)
γ_{SKEW-}					0.089^{**}	0.096^{**}
					(2.221)	(2.367)
R^2	0.539	0.589	0.600	0.612	0.636	0.650
Adj R^2	0.524	0.567	0.574	0.576	0.612	0.619

Notes: This table shows the results of the second stage of the Fama-MacBeth regression approach in which the portfolios' returns, 100 portfolios based on Size and Book-to-Market, are regressed on the β factor loadings computed in the first step and expressing the exposure of each portfolio of assets to that specific factor as in (4.27). γ coefficients measure the risk premium associated with each selected factor. The regressions' outcome we report are for the simple 3-factors model (1) (Equation (4.28)), for the 5-factors model (2) (Equation (4.29)), for the 6-factors model with skewness indexes (3), (4), and (5) (Equation (4.30)) and the full model with all the SKEW indexes (Equation 4.31). Interpolation is used when missing data is found. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The selected period is the full sample from 04-01-1996 to 29-12-2017.

et al., 2012). More specifically, we examine the pricing factor role of the implied skewness indexes extracted model-free from options. Our results appear to suggest mixed results for the decomposed implied skewness performance according to the selected portfolios. Economic theory provides little guidance on the sign of the price of the market skewness risk; usually investors with reasonable utility functions need to be compensated with higher returns when their portfolios present low skewness, however the interaction among our six or eight factors does not always convey a similar interpretation.

According to Chang et al. (2013) if we follow the interpretation in Bollen and Whaley (2004) and Garleanu et al. (2009) suggesting that the skewness curve is caused by imbalance in supply and demand for options with different strike prices, then would be not straightforward to interpret the relation between option implied skewness and changes in investment opportunities because of the exogenous imbalance in supply and demand. Therefore, they stated, when skewness is used as a pricing factor, the literature does not provide guidance on the sign we should expect a priori. Specifying this sign will be then mainly an empirical exercise. Overall, we find a strong evidence that the decomposed implied skewness indexes are priced risk factors. We provide robustness checks about such finding in the Appendix of Chapter 4.

In other words, interpreting skewness as a pricing factor is less obvious than volatility. Using an argument similar to the one used to explain the inverse relationship between market returns and volatility, the negative correlation may be due to the negative price of market skewness (see Chabi-Yo, 2012). However, the signs of the SKEW coefficients change may vary when the considered portfolios

are different (see Chang et al., 2013)[29].

New insights for investment strategies can be drawn from this section. We can observe that the five-factor plus each SKEW index model captures average returns on the variables and we can observe which variables are positively or negatively correlated to each other. The results also show that our models including SKEW indexes over-perform the Fama-French five-factor model which has been found to explain a great part of the cross-section variance of expected returns for the size, value, profitability and investment portfolios. It has been proven to perform better than the three-factor model (e.g. Fama and French, 1993, 2015). They therefore should not be excluded from the asset pricing model. The empirical results of the complete eight-factor model show that it is better than the models with only a subset of fundamental variables in explaining the variations of stock returns. We can detect an empirical success of the decomposed SKEW indexes in explaining excess returns.

Our eight-factor model is also related to a recent debate in the literature which argues that in reduced-form factors model studied in the literature the sentiment-investor component has been understudied. In other words, there should be a clear distinction between factor pricing and behavioural asset pricing, the second able to capture more distorted beliefs and sentiment driven expectations (see Kozak et al., 2018). Our model confirms how, when these two factors categories, assuming the decomposed SKEW indexes being closely related to market sentiment as deducted by this Chapter, there is still information which can help to price the stocks portfolios.

When components of sentiment-driven factors are studied they are found to be not aligned with standard asset pricing factors, thus containing additional information investors might exploit and consider when pricing their portfolios. This rationale is studied by Kozak et al. (2018) who built a model of a multiasset market in which fully rational risk averse investors, namely arbitrageurs, trade with investors whose asset demands are based on distorted beliefs about the true distribution of returns, namely sentiment investors. In their model all cross-sectional variation in expected returns is caused by distorted beliefs the latter being the dominant factors affects prices because it is risky for arbitrageurs to take the other side. As a result, all deviations of expected returns from the CAPM are caused by sentiment. Thus, further research combining our intuitions on this topic and the model of Kozak et al. (2018) might start to investigate how expectations and market sentiment extracted from options in which investors are classified by being hedgers or speculators might affect the performance of existing asset pricing

[29]The difference in coefficients' sign according to the way portfolios are sorted may be due to the presence of value stocks. For instance, the SKEW indexes signs are found to be negative when values stocks are considered in the sorted portfolios, whereas positive when the value stocks are excluded (e.g. in the 100 book to market). In relation to the 25 size book-to-market, the portfolios are constructed at the end of each June and are the intersections of 5 portfolios formed on size (market equity, ME) and 5 portfolios formed on the ratio of book equity to market equity (BE/ME). With regards to the 100 size book-to-market, the portfolios are the intersections of 10 portfolios formed on size (market equity, ME) and 10 portfolios formed on the ratio of book equity to market equity (BE/ME), instead. Portfolios constructed on size $ME < 0$ are not used and firms with negative book equity are in only the BE < 0 portfolio. If the ratio is above 1 then the stock is undervalued; if it is less than 1, the stock is overvalued. A high ratio is means that the stock is a value stock, that is trading cheaply in the market compared to its book value. More details can be found at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

models.

4.8 Trading the Implied Skewness: General Considerations

In this section, we discuss general trading strategies involving implied skewness. We divide this section into two categories of trading strategies with skewness; based on distribution discrepancies (subsection 4.8.1) and based on skew swaps (subsection 4.8.2).

4.8.1 Trading Skew Based on Distributions Discrepancies

From a skewness point of view, deviations of historical state price densities (SPDs) from implied (SPDs) lead to trading strategies and can be used as market indicators. We provide discussion on options strategies which could be implemented as well as on what option to buy or to sell when deviations from the two estimated SPDs are detected. In order to simplify we consider only European calls and puts. According to Blaskowitz et al. (2004), a skewness trading strategy is supposed to exploit differences in skewness of two distributions by buying options in the range of strike prices where they are underpriced and selling options in the range of strike prices where they are overpriced. We recall here the call and put options pricing equation as in Bakshi et al. (2003). From the option pricing theory we define:

$$P = \exp^{-rt} \int_0^\infty max(K_1 - S_T, 0) q(S_T) dS_T \tag{4.32}$$

$$C = \exp^{-rt} \int_0^\infty max(S_T - K_2, 0) q(S_T) dS_T \tag{4.33}$$

where P and C are put and call prices, respectively, r is the risk-free rate, S_T is the price of the underlying at maturity T, and q is a risk-neutral density. We denote two risk neutral distributions (RNDs) as f^* and g^* where f^* is more negatively skewed than g^*. Then equations 4.32 and 4.33 imply that the price of a European call with strike K_2 computed with density f^* is lower than the price computed with density g^*. This is due to the fact that f^* shows less probability mass to prices $S_T > K_2$ than g^*. Assuming no arbitrage opportunities, there should be only one risk-neutral density. However, when the market are not complete or there are different models we rely on, there are in general many risk-neutral measures. This allows traders to comparing RNDs and models thus entering in positions and trades based on the model and RND they believe to be the correct one.

A possible trading strategy thus follows: if the call is priced using f^*, but investors believe that density g^* is a better approximation of the underlying's distribution, one would buy the option. On the other hand, one would sell a put option with strike K_1. This will result in a risk-reversal portfolio (e.g. Blaskowitz et al., 2004).

The portfolio or investment return will be given by the net cash flow from buying and selling calls

and puts. Usually in a long skew position (buy OTM put and sell OTM call), the implied volatility of the put purchased has a higher implied volatility than the implied volatility sold through the call. Hence, the long skew position presents a cost associated with it, sometimes denominated skew theta (see Bennett, 2014). The implied skewness results to be usually overpriced due to hedging and as a result of investors excessive demand of put options to protect their portfolios against market drops. This intuition further reinforces our previous results in Section 4.5 and 4.4. OTM puts are found to be associated more with pessimistic investors and bearish market views, whereas OTM calls with optimistic investors and bullish market opinions (e.g. Buraschi and Jiltsov, 2006). Another reason for the overpricing of the implied skew is the fact that investors usually enter short volatility-long skew trades thus entering in OTM puts positions which protect themselves against sudden market drops. This is consistent with the discussions in previous sections of this thesis about OTM puts pressure (e.g. Bollen and Whaley, 2004; Bondarenko, 2014).

4.8.2 Trading Skew Swaps

Kozhan et al. (2013) showed how to construct a trading strategy as a pure bet on the desired return moment, in our case, the implied skewness. They defined as risk premium or excess return the expected profit from such a strategy. We follow their notation. Similarly to a variance swap strategy (see Chapter 3), a skew swap strategy can be defined as the difference between the skew physical measure ($\mathbb{P}$) and the forward pricing measure for a maturity T ($\mathbb{Q}$). Following Bakshi and Madan (2000), if calls and puts are available for all strikes, one can buy a portfolio at time t that has payoff at time T equal to $g(r_t, T)$ for an arbitrary function g. Hence, the risk premium associated with this strategy is as follows:

$$E_t^{\mathbb{P}}[g(r_t, T)] - E_t^{\mathbb{Q}}[g(r_t, T)] \tag{4.34}$$

Since $g(r_t, T)$ changes over time, this strategy involves trading in the options as well as in the forward market. The fixed leg of the swap can be replicated from calls and puts as shown in Section 4.2 (see also Bakshi et al., 2003). More specifically the fixed leg is the payoff of a position that is long OTM calls and short OTM puts and its value depends on the options skew in implied volatility. The floating leg of the skew swap can be considered as a daily realized skewness measure as defined in Neuberger (2012) which is determined by the covariance between returns and variance shocks. According to Kozhan et al. (2013), the average realized skew is smaller (in absolute terms) than the average implied skew, thus resulting in the existence of a skew risk premium. Usually monthly options are used for trading strategies which run for a month and when one option expires the strategy is rolled to the next month's expiration date. This is in line with Aıt-Sahalia et al. (2001) stating that such a strategy is designed such that we do not change the resulting portfolio until maturity, thus all the options are kept

until expiration. The realized skewness is rebalanced daily. For more details on a empirical application of this trading strategy see Kozhan et al. (2013).

The application of the aforementioned trading strategies go beyond the scope of this thesis. However, further research should start looking at the potential effect of building up skew swap which account only for half of the asset options distribution (calls and puts) and which consider floating legs based on half of the asset realized returns and shocks being these either positive or negative. Such strategies may allow investors to grasp differences among implied and realized skewness according to the state of the economy and financial market (bullish or bearish). Building up two different skew swaps in the two different sides of the underlying price distribution will also create an asymmetry which may lead to a potential additional skew strategy when the *positive* skew swap and the *negative* skew swap payoffs are combined together.

4.9 The Link with Uncertainty and Macroeconomic Indicators

In this last section, we study the predictability power of the SKEW indexes in relation to uncertainty and macroeconomic indicators. Since the SKEW indexes are computed from options and they are forward looking measures, we believe they may be useful to monitor and anticipate the uncertainty in the economy or its downturns. We aim to provide a broader understanding of the economic relevance of the decomposed forward looking SKEW indexes and their economic predictive power in the spirit of Bakshi et al. (2011), Allen et al. (2012), Bollerslev et al. (2015) and Almeida et al. (2017). Moreover, we test whether or not SKEW^{-} better predicts macroeconomic and uncertainty indicators compared to the aggregate and positive measures. We have shown that SKEW^{-} is more connected with the tail risk measures in the literature, it reacts more in correspondence to extreme events (see Figure 4.2), thus it is the index proposed in this chapter as a tail risk measure. We specifically focus on whether or not it contains useful information to predict future macroeconomic downturns or increase in uncertainty indicators. The role of SKEW and SKEW^{+} in predicting these indicators is also shown for comparison.

We select some of the indicators, commonly used in the literature, which track the economic and macroeconomic activity as well as the macroeconomic, political and geopolitical uncertainty. Data on the following variables are collected according to their available sample at monthly frequency. Among the uncertainty indicators we select the Economic Uncertainty Index (EUI) by Bali et al. (2014), the Economic Policy Uncertainty (EPU) index by Baker et al. (2016), the GeoPolitical Risk (GPR) index by Caldara and Iacoviello (2018), the CBOE VIX index commonly known as the fear gauge, the macroeconomic index by Jurado et al. (2015) (MUI) and the CRASH index, already described in Section 4.3.2 and used here as a proxy for future uncertainty. The Economic Uncertainty Index

(EUI) by Bali et al. (2014) is a measure of economic uncertainty based on the time varying conditional volatility of macroeconomic and financial variables such as default spread, term spread, short term interest rate, dividend yield, equity market index, inflation, unemployment rate and GDP available at http://faculty.msb.edu/tgb27/workingpapers.html. The EPU index by Baker et al. (2016) is computed from news associated with the ten most important American newspapers, reflecting the concerns and uncertainty around specific economic or political events. It is collected from: http://www.policyuncertainty.com/. The GeoPolitical Risk index by Caldara and Iacoviello (2018) (GPR) is an index computed in a similar way to EPU from newspapers articles associated with geopolitical risk and events. The GPR tracks mainly events such as wars, terrorist attacks or international conflicts. It is available at: https://www2.bc.edu/matteo-iacoviello/gpr.htm. VIX from CBOE is commonly considered a proxy of market fear. The macroeconomic index by Jurado et al. (2015) (MUi) is a refined measure of macroeconomic uncertainty from a macro data set including information in hundreds of macroeconomic and financial indicators available at: https://www.sydneyludvigson.com/data-and-appendixes/. For more details on the CRASH Index, see Section 4.3.2. The selected macroeconomic activity indicators are the following: the Aruoba-Diebold-Scotti macroeconomic conditions index by Aruoba et al. (2009) (ADS), the Chicago FED National Activity Index, CFNAI and the NBER recession period indicator. The Aruoba-Diebold-Scotti (ADS) index tracks real business conditions at high frequency and it is based on economic indicators such as initial jobless claims, monthly payroll employment, industrial production, personal income, etc. It is collected from: https://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index. The Chicago FED National Activity Index (CFNAI) is a monthly index which tracks the overall economic activity and the inflationary pressure and it is computed as a weighted average of 85 monthly indicators and it is collected from: https://www.chicagofed.org/publications/cfnai/index. The NBER recession period indicator for the U.S. is a dummy variable taking 1 in recession and 0 in expansion periods according to NBER and it available at: https://fred.stlouisfed.org/series/USREC.

We run the following regression in relation to the uncertainty indicators predictability.

$$Indicators_{Unc,t+i} = \beta_0 + \beta SKEW_t^k + \sum_{i=0}^{11} \gamma_i Indicators_{Unc,t-i} + \epsilon_t, \tag{4.35}$$

where $Indicators_{Unc,t+i}$ is one among the uncertainty indicators, namely, EUI, EPU, GPR, VIX , MUi and CRASH. $i = 1, ..., 12$ is indexed for the forecasting horizon up to one year. We regress the selected indicators on the SKEW indexes, with $k = Tot, +, -$, and we control for up to 12 lags of the endogenous variable. The results are presented in Table 4.21 and Table 4.22. For every horizon up to one year, we report the predictability of SKEW , SKEW^+ and SKEW^- , in this order.

Table 4.21: SKEW Indexes Uncertainty Indicators Prediction (1)

Forecast		EUI	t-stat	R^2	EPU	t-stat	R^2	GPR	t-stat	R^2
1	β	-0.005	[-2.505]	96.4	-0.247	[-1.457]	72.7	0.590	[1.347]	64.4
	β^+	0.004	[0.673]	96.4	-0.284	[-0.760]	72.5	-0.929	[-1.170]	64.1
	β^-	-0.008	[-2.477]	96.4	-0.514	[-3.021]	73.6	0.215	[0.528]	64.1
2	β	-0.010	[-3.291]	92.2	-0.296	[-1.297]	60.5	0.598	[0.883]	34.9
	β^+	0.013	[1.448]	92	-0.022	[-0.045]	60.2	0.314	[0.312]	34.5
	β^-	-0.017	[-2.999]	92.4	-0.515	[-2.415]	61.4	0.172	[0.284]	34.5
3	β	-0.019	[-3.987]	86.9	-0.186	[-0.832]	55.7	0.450	[0.622]	26.2
	β^+	0.009	[0.677]	86.6	0.405	[0.745]	55.6	2.035	[1.256]	26.5
	β^-	-0.029	[-3.651]	87.6	-0.385	[-1.873]	56.2	0.279	[0.474]	26.1
4	β	-0.028	[-3.896]	82.1	-0.153	[-0.683]	52.8	0.544	[0.763]	23.6
	β^+	0.025	[1.545]	81.4	0.416	[0.683]	52.8	3.332	[1.464]	24.9
	β^-	-0.037	[-3.928]	83	-0.406	[-2.065]	53.5	0.722	[1.278]	24
5	β	-0.037	[-3.936]	76.6	-0.1562	[-0.664]	49.6	0.540	[0.731]	22.2
	β^+	0.028	[1.628]	75.3	-0.421	[-0.762]	49.6	2.184	[1.236]	22.5
	β^-	-0.045	[-4.087]	77.7	-0.477	[-2.328]	50.5	0.724	[1.207]	22.6
6	β	-0.043	[-4.066]	71.8	-0.159	[-0.534]	45	0.454	[0.623]	19.7
	β^+	0.055	[2.495]	70.4	0.379	[0.573]	44.9	1.892	[1.130]	20
	β^-	-0.048	[-4.046]	72.8	-0.456	[-1.734]	45.8	0.417	[0.666]	19.7
7	β	-0.048	[-4.144]	66.3	-0.069	[-0.220]	42.1	0.689	[0.939]	17.2
	β^+	0.047	[2.183]	64.4	0.675	[1.133]	42.3	0.891	[0.655]	16.8
	β^-	-0.052	[-4.282]	67.4	-0.383	[-1.383]	42.7	0.389	[0.587]	16.9
8	β	-0.054	[-4.138]	61.4	-0.049	[-0.179]	42.6	0.370	[0.499]	17.5
	β^+	0.062	[2.712]	59.1	0.435	[0.608]	42.7	-1.190	[-0.763]	17.6
	β^-	-0.057	[-4.417]	62.6	-0.285	[-1.162]	43	0.258	[0.419]	17.4
9	β	-0.062	[-3.917]	55.6	-0.010	[-0.037]	42.6	0.426	[0.609]	18.8
	β^+	0.075	[3.121]	52.8	0.299	[0.453]	42.6	0.763	[0.426]	18.7
	β^-	-0.065	[-4.171]	57	-0.329	[-1.408]	43	0.707	[1.298]	19.3
10	β	-0.071	[-3.880]	49.8	-0.144	[-0.509]	41.1	0.751	[1.172]	18.9
	β^+	0.083	[3.338]	46.4	-0.275	[-0.445]	41	0.866	[0.557]	18.4
	β^-	-0.073	[-4.034]	51.7	-0.481	[-2.039]	42	0.927	[1.794]	19.5
11	β	-0.073	[-3.966]	43.9	-0.247	[-0.813]	37.1	0.951	[1.595]	19.1
	β^+	0.081	[3.156]	40	-0.454	[-0.619]	37	-0.884	[-0.787]	18.3
	β^-	-0.078	[-4.028]	46.2	-0.141	[-0.503]	37	0.904	[1.972]	19.3
12	β	-0.082	[-4.144]	39.2	-0.444	[-1.454]	33.8	0.868	[1.559]	19.2
	β^+	0.103	[3.858]	34.8	-0.009	[-0.012]	33.2	0.503	[0.305]	18.4
	β^-	-0.086	[-4.067]	42	-0.051	[-0.197]	33.2	0.856	[2.160]	19.4

Notes: This table presents the results of the predictive regressions estimated through equation 4.35 between the total SKEW and the decomposed SKEW^+ and SKEW^- , and the selected uncertainty proxies, such as, the Economic Uncertainty Index (EUI) by Bali et al. (2014), the Economic and Policy Uncertainty (EPU) by Baker et al. (2016) and the GeoPolitical Risk Index (GPR) by Caldara and Iacoviello (2018). OLS regressions are estimated controlling for 12 lags of the dependent variable and Newey (1987) t-statistics are reported in square brackets. R^2 are shown in percentage. The selected period for all the variables is from 01-1996 to 12-2017.

SKEW and SKEW^- contain useful information to predict future levels of EUI for all the horizons, while SKEW^+ only for 6-12 months horizons. Even if SKEW and SKEW^- show similar predictive ability, higher R^2 are associated with the negative SKEW measure. The Economic Uncertainty Index by Bali et al. (2014) is obtained from the first principal component of eight factors. It is found to be higher during bad states of economy, low output growth and low economic activity. The negative coefficients carried by SKEW^- in predicting future levels of EUI might be justified from the negative correlation the two indexes share (-22%), and from the fact that SKEW^- tends to anticipate the perception of decreasing business conditions being extracted from options. Interestingly, SKEW^- is the only index found to be able to forecast future level of EPU index, mainly from 1-month to 6-month horizons. SKEW^- is also the only implied skewness index which is able to predict the GPR index and the macroeconomic uncertainty index (MUi) mainly at long horizons, from 10 to 12 months and from 9 to 12 months, respectively.

The fact that information coming from the put options are useful to predict well EPU and GPR reflects the investors' fear regarding economic, political and geopolitical uncertainty. Future levels of VIX are predicted well by all the SKEW indexes. SKEW and SKEW^- predict VIX between 2 and 10 months with same negative relationship consistent with Figure B1 and with the findings in Section 4.4. The R^2 carried by SKEW^- are higher than the ones carried by SKEW . SKEW^+ predicts VIX well at almost all the horizons within one year with positive relationship. This is consistent with the market sentiment interpretation illustrated in Section 4.4 since VIX is, sometimes, considered a market sentiment proxy.

The negative correlation between SKEW and SKEW^- and VIX is also shown in Table 4.1 with the one between VIX and SKEW^- almost double the one between VIX and SKEW . On this line, the negative coefficients found, most of the time, between SKEW and SKEW^- , and EPU can be interpreted as a consequence of the negative relationship between SKEW indexes and VIX and the positive between VIX and EPU (see Baker et al., 2016)[30]. On the other hand, the overall positive relationship between SKEW indexes and GPR is consistent with the fact that the geopolitical index show a negative relationship with VIX (see Caldara and Iacoviello, 2018). This might be interpreted from the nature of the events to which the SKEW indexes and these uncertainty indexes react[31]. GPR as well as SKEW^- do not appear to respond to financial events in the same way as VIX and EPU (see also Figure 4.2)[32]. Thus, the positive coefficients between SKEW and SKEW^- , and GPR may be due to the events to which the indexes react which are of a similar nature. SKEW^- is found also the only index containing information to forecast the CRASH index between 2 and 7 months. The coefficients signs between the SKEW indexes and CRASH index confirm the results of Table 4.2. The positive relationship between CRASH and SKEW^- is consistent with the fact that both measures carry information about investors' perceptions about catastrophic events.

We also check the predictability power of the SKEW indexes with regards to some macroeconomic indicators running the following:

$$Indicators_{Macro,t+i} = \beta_0 + \beta SKEW_t^k + \sum_{i=0}^{11} \gamma_i Indicators_{Macro,t-i} + \epsilon_t, \tag{4.36}$$

where $Indicators_{Macro,t+i}$ is one among the macroeconomic indicators, namely, ADS, CFNAI and NBER. $i = 1, ..., 12$ is indexed for the forecasting horizon up to one year. We regress the selected macroeconomic indicators on the SKEW indexes, with $k = Tot, +, -$, and we control for up to 12 lags of the endogenous variable. A probit regression is estimated for the dummy NBER variable. The

[30]Baker et al. (2016) shown VIX to have a correlation of 58% with the EPU index. We find the EPU index and VIX to be positively correlated at 42%.

[31]The GPR index captures events such as wars, terrorist attacks and global conflicts and appears to carry an additional source of risk compared to the EPU index. The GRP index and SKEW^- react to events, such as, 9/11, Iraq invasion, Syria War, Ukraine-Russia conflict and ISIS escalation. See also Figure 4.2.

[32]EPU index as well as VIX react to most of the economic downturn and financial crisis. On the other hand, GPR is found to show an almost nil correlation with VIX and low correlation with EPU.

Table 4.22: SKEW Indexes Uncertainty Indicators Prediction (2)

Forecast		VIX	t-stat	R^2 (%)	MUi	t-stat	R^2 (%)	CRASH	t-stat	R^2 (%)
1	β	-0.028	[-0.830]	71.7	-0.001	[-0.199]	96.4	0.002	[0.133]	93.2
	β^+	0.157	[1.659]	71.9	0.002	[0.531]	96.4	-0.014	[-0.276]	93.2
	β^-	-0.017	[-0.457]	71.7	-0.001	[-0.440]	96.4	0.024	[1.502]	93.3
2	β	-0.093	[-1.840]	51	-0.002	[-0.355]	88.1	0.010	[0.319]	83.1
	β^+	0.193	[1.904]	50.8	0.003	[0.421]	88.1	-0.064	[-0.730]	83.2
	β^-	-0.098	[-1.731]	51.1	-0.002	[-0.419]	88	0.052	[1.822]	83.4
3	β	-0.114	[-1.834]	40.5	-0.005	[-0.694]	76.1	0.032	[0.735]	70.6
	β^+	0.22	[1.935]	40.2	0.005	[0.591]	76	-0.104	[-0.874]	70.7
	β^-	-0.124	[-1.790]	40.8	-0.005	[-1.008]	76.1	0.084	[2.243]	71.2
4	β	-0.152	[-2.290]	35.0	-0.001	[-1.085]	64.6	0.045	[0.886]	57.5
	β^+	0.223	[1.781]	34.1	0.009	[0.880]	64.4	-0.187	[-1.338]	57.7
	β^-	-0.164	[-2.077]	35.5	-0.009	[-1.447]	64	0.101	[2.315]	58.2
5	β	-0.155	[-2.460]	30.4	-0.001	[-1.119]	53.2	0.033	[0.589]	47.6
	β^+	0.438	[2.535]	30.9	0.009	[0.749]	52.9	-0.166	[-1.129]	47.8
	β^-	-0.162	[-2.072]	30.8	-0.001	[-1.710]	53.6	0.102	[2.060]	48.5
6	β	-0.183	[-2.645]	25.9	-0.001	[-0.863]	44.5	0.031	[0.476]	37.5
	β^+	0.516	[1.953]	26.6	0.009	[0.743]	44.3	-0.114	[-0.733]	37.6
	β^-	-0.195	[-2.629]	26.5	-0.001	[-1.493]	45.1	0.109	[1.938]	38.5
7	β	-0.161	[-2.262]	22.8	-0.001	[-0.753]	37.4	0.026	[0.391]	34.3
	β^+	0.401	[1.546]	22.9	0.009	[0.610]	37.2	-0.104	[-0.632]	34.4
	β^-	-0.188	[-2.531]	23.7	-0.001	[-1.290]	38.1	0.100	[1.684]	35.1
8	β	-0.145	[-1.996]	21.3	-0.009	[-0.620]	30.9	0.012	[0.174]	33
	β^+	0.373	[1.864]	21.5	0.002	[0.108]	30.7	-0.059	[-0.340]	33.1
	β^-	-0.173	[-2.371]	22.2	-0.002	[-1.535]	32.3	0.099	[1.622]	33.9
9	β	-0.174	[-2.615]	20.5	-0.008	[-0.571]	25.4	-0.018	[-0.236]	32.3
	β^+	0.441	[1.857]	20.6	0	[-0.018]	25.2	-0.092	[-0.489]	32.3
	β^-	-0.189	[-2.896]	21.2	-0.002	[-1.799]	27.9	0.086	[1.405]	32.9
10	β	-0.164	[-2.340]	19.8	-0.001	[-0.693]	20.5	-0.042	[-0.524]	31.7
	β^+	0.605	[2.277]	22	0.004	[0.259]	20.3	-0.125	[-0.632]	31.7
	β^-	-0.170	[-2.491]	20.3	-0.003	[-2.021]	24	0.066	[1.048]	32
11	β	-0.117	[-1.620]	18.6	-0.001	[-0.738]	15.6	-0.071	[-0.848]	30
	β^+	0.568	[2.570]	21.1	0.001	[0.756]	15.5	-0.178	[-0.853]	30
	β^-	-0.119	[-1.821]	18.7	-0.003	[-2.101]	19.5	0.037	[0.589]	29.8
12	β	-0.112	[-1.531]	17.0	-0.008	[-0.541]	11.5	-0.103	[-1.196]	29
	β^+	0.485	[2.684]	18.7	0.001	[1.127]	11.6	-0.277	[-1.404]	29.1
	β^-	-0.097	[-1.555]	16.9	-0.003	[-2.129]	15.6	0.005	[0.080]	28.4

Notes: This table presents the results of the predictive regressions estimated through equation 4.35 between the total SKEW and the decomposed SKEW^+ and SKEW^- , and the selected uncertainty proxies, such as the macroeconomic uncertainty index (MUi) by Jurado et al. (2015), the VIX index by CBOE and the CRASH index from the Yale School of Management. OLS regressions are estimated controlling for 12 lags of the dependent variable and Newey (1987) t-statistics are reported in square brackets. R^2 are shown in percentage. The selected period for all the variables is from 01-1996 to 12-2017 except for MUi (01-1996 to 09-2011).

results are presented in Table 4.23.

All the SKEW indexes exhibit significant predictive power for ADS from 4-month to 10-month horizons, however SKEW^- and SKEW^+ predict ADS also at longer horizons. SKEW^- is found to predict well future levels of CFNAI at all the horizons up to one year, whereas SKEW^+ only starting at the 4-month horizon and SKEW only between 4-10 months. The probit model estimation shows that SKEW and SKEW^- predicts really well future recessions (NBER recession periods). The predictive power spans all the year with SKEW^- showing higher R^2 compared to the aggregate. SKEW^+ is only able to predict recession from 8 to 12 months horizons. The signs of the coefficients reflect the negative correlation between SKEW and SKEW^+ and the positive correlation between SKEW and SKEW^- . Interestingly, positive coefficients are found between SKEW and SKEW^- and macroeconomic indicators, such as, ADS and CFNAI. This can be due to trading activity reasons. The better the business and economic conditions the higher the investors' trading volume which for S&P 500 is

Table 4.23: SKEW Indexes Macroeconomic Activity Prediction

Forecast		ADS	t-stat	R^2 (%)	CFNAI	t-stat	R^2 (%)	NBER	t-stat	R^2 (%)
1	β	0.001	[0.758]	87.4	0.004	[1.229]	64.9	-0.168	[-2.279]	83
	β^+	0.005	[0.994]	87.4	0.003	[0.306]	64.7	0.06	[0.734]	78
	β^-	0.002	[1.149]	87.4	0.007	[2.001]	65.2	-0.025	[-2.251]	86.4
2	β	0.004	[1.370]	65.4	0.003	[0.769]	62.3	-0.207	[-3.084]	73
	β^+	0.008	[0.090]	65.1	0.002	[0.020]	62.3	0.065	[1.007]	63
	β^-	0.005	[1.491]	65.4	0.006	[1.693]	62.6	-0.240	[-3.452]	78
3	β	0.006	[1.578]	57	0.007	[1.611]	55.3	-0.149	[-3.196]	59.9
	β^+	-0.019	[-1.863]	57	-0.011	[-0.912]	55.0	0.063	[1.107]	51.0
	β^-	0.005	[1.491]	57	0.008	[1.935]	55.5	-0.161	[-3.639]	63.9
4	β	0.008	[1.803]	49.6	0.009	[1.895]	45.8	-0.109	[-3.061]	47.6
	β^+	-0.027	[-2.578]	49.8	-0.036	[-2.487]	46.3	0.063	[1.2]	40.5
	β^-	0.006	[1.736]	49.4	0.010	[2.306]	46.1	-0.127	[-3.640]	52.1
5	β	0.011	[2.195]	41.7	0.010	[1.870]	37.3	-0.105	[-3.222]	39.2
	β^+	-0.019	[-2.113]	41	-0.015	[-1.289]	36.7	0.044	[0.882]	31
	β^-	0.009	[2.086]	41.7	0.012	[2.308]	37.8	-0.136	[-4.016]	46.1
6	β	0.014	[2.496]	34.3	0.012	[2.004]	31.5	-0.103	[-3.360]	32
	β^+	-0.017	[-1.669]	32.9	-0.021	[-1.642]	30.9	0.018	[0.389]	22.7
	β^-	0.011	[2.148]	34	0.013	[2.312]	32	-0.169	[-4.437]	44.1
7	β	0.012	[2.221]	25	0.015	[2.371]	22.9	-0.108	[-3.622]	26.9
	β^+	-0.019	[-1.709]	24.8	-0.027	[-1.773]	22	0.043	[0.977]	16.5
	β^-	0.012	[2.209]	26	0.016	[2.519]	23.5	-0.17	[-4.663]	39.5
8	β	0.012	[2.022]	19.3	0.011	[1.723]	19.9	-0.105	[-3.703]	21.7
	β^+	-0.027	[-2.399]	18.9	-0.027	[-1.940]	19.8	-0.078	[1.890]	12.4
	β^-	0.014	[2.307]	20.3	0.017	[2.632]	21.6	-0.129	[-4.516]	29.5
9	β	0.016	[2.317]	15.9	0.016	[2.161]	16.7	-0.094	[-3.577]	18.1
	β^+	-0.039	[-3.070]	15.5	-0.041	[-2.850]	16.5	0.087	[2.105]	10.6
	β^-	0.016	[2.237]	16.6	0.018	[2.242]	17.6	-0.096	[-4.055]	21.5
10	β	0.014	[2.109]	11.4	0.018	[2.386]	11.8	-0.089	[-3.532]	15.5
	β^+	-0.039	[-3.004]	11.5	-0.043	[-2.904]	11.3	0.106	[-3.822]	9.8
	β^-	0.015	[2.062]	12.2	0.021	[2.509]	13.3	-0.085	[2.582]	17.4
11	β	0.010	[1.637]	7.4	0.011	[1.610]	8.2	-0.082	[-3.390]	12.7
	β^+	-0.036	[-2.922]	8.2	-0.033	[-2.047]	8.3	0.118	[2.848]	8.9
	β^-	0.013	[1.774]	8.4	0.018	[2.155]	10	-0.076	[-3.627]	14.1
12	β	0.010	[1.550]	5	0.013	[1.623]	6	-0.075	[-3.224]	10.1
	β^+	-0.043	[-3.285]	6.5	-0.035	[-2.069]	6	0.124	[3.022]	8.1
	β^-	0.012	[1.711]	5.9	0.019	[2.258]	8.1	-0.076	[-3.448]	11.4

Notes: This table presents the results of the predictive regressions estimated through equation 4.36 between the total SKEW and the decomposed SKEW^+ and SKEW^- , and some macroeconomic conditions indicators such as the Aruoba-Diebold-Scotti Business Conditions Index (ADS), the Chicago FED National Activity Index (CFNAI) and the NBER recession dummy variable (NBER). OLS regressions are estimated controlling for 12 lags of the dependent variable and Newey (1987) t-statistics are reported in square brackets. For NBER, a Probit regression is estimated and the z-statistics are reported in square brackets. R^2 are shown in percentage and for NBER the McFadden R^2, in percentage, are reported. All the indexes are taken at monthly frequency for the full sample from 01:1996 to 12:2017, except for ADS (01:1996 to 04:2014).

mainly generated by puts trading. The positive relationship between macroeconomic indicators and SKEW^- might also come from their correlation being 25% between SKEW^- and CFNAI and 20% between SKEW^- and ADS. When these two macroeconomic indicators (correlated at 90%) decrease, we also find our tail risk measure to be lower. In calm periods, which might coincide with periods of better-than-average business conditions, according to Aruoba et al. (2009) – ADS – index, SKEW^- is found to be higher as well since investors are scared of a possible future tail events. Same intuition may apply for the positive coefficients found between SKEW^- and CFNAI.

There is a negative correlation between SKEW^- and SKEW on one side and the NBER recession indicator, on the other. While NBER dummy variable is activated when the recession has already started, SKEW^- tracks in a forward looking way the tail risk perception associated with the likelihood of the recession occurrence. The negative sign suggests that investors have limited beliefs regarding

another recession when they are in the midst of it (see Figure 4.2). Same considerations may be applied to the negative coefficient sign found between EPU and EUI and SKEW^{-} and it may be associated with the counter-cyclical relationship between current uncertainty measures and the forward looking implied skewness.

4.10 Conclusion

This chapter exploits further information enclosed in the implied skewness extracted model-free from the U.S. equity index options market, by decomposing it into its positive and negative components, namely, SKEW^{+} and SKEW^{-} . These indexes reflect investors' belief characteristics that are uncaptured by other tail risk measures proposed in the literature. These newly proposed indexes can be used to depict an improved financial market risk picture. The information revealed by other risk and tail risk measures in the literature can be augmented by supporting implied skewness measures, especially when these are decomposed.

By disentangling the information contained in the two portfolios of S&P 500 options, provide new insight into the investors' perceptions and associated sentiment reflected in the two components. By relating the SKEW indexes extracted from options with market sentiment proxies, we acknowledge that, most of the time, the aggregate SKEW index may be influenced by the positive information flows coming from the calls market side, leading to a possible bias in the measurement of the market tail risk. Hence, we advocate to separate the market view on skewness that conveys information about the left tail risk from the market view on skewness on the more speculative right tail.

We show how SKEW^{+} extracted from the call side appears to be more connected to the equity market as well. A predictive analysis conducted in this chapter shows that SKEW^{+} is more informative for predicting future equity market premia at short horizons, both in-sample and also out-of-sample. SKEW^{+} predicts well the U.S. financial markets premia, while SKEW^{-} is found helpful for international stock market index predictability. The decomposed SKEW indexes confirm their predictability power even when added next to the principal components extracted from the Goyal and Welch (2008) set of macroeconomic variables. The information content of the decomposed implied skewness indexes is found useful for forecasting a good proportion of individual stocks included in the S&P 500 both from the 30 largest and also from the 30 smallest stocks by market capitalization.

An asset pricing exercise further confirms the superior power of the SKEW^{-} and SKEW^{+} when compared to the aggregate indexes. We found evidence that when we augment the original Fama and French (1993) three-factor model and the more recent Fama and French (2017) five-factors models with the decomposed implied SKEW measures, we obtain improved asset pricing results. Our analysis highlights the role played by SKEW^{+} during the pre-crisis bull market period, that then gyrated

towards SKEW^{-} during the post global financial crisis period.

We find SKEW^{-} to be the index more related to fundamentals, more connected to previous tail risk measures in he financial literature and it has been identified to react more to extreme tail events along our time frame. We proposed employing SKEW^{-} as a more reliable and prudent tail risk index, reflecting the information encapsulated in the puts market, investors' fear and uncertainty. Indeed, the forward looking SKEW^{-} index is found to be useful in explaining future movements of uncertainty indicators as well as a potential recession periods monitoring tool.

There is something *left* to discover about tail risk even after having absorbed the information enclosed in other macroeconomic predictors and financial risk measures. Of great importance is the interaction between implied skewness and implied volatility, risk premia, market sentiment and future equity premium. Our chapter contribute to the existing literature by showing how the decomposed implied skewness measures contain helpful information for asset pricing purposes. Of interest is, also, the monitoring of future macroeconomic and economic conditions as well as of increasing uncertainty and possible recessions for financial stability purposes. Our findings identify this highly valuable informative part as located in the *left* side of the risk-neutral distribution of equity market indexes.

Chapter 5

Asymmetric Connectedness of Fears in the U.S. Financial Sector

5.1 Introduction

Different expectations about future values of stocks extracted from call and put options influence system-wide beliefs in the financial market. A shock to forward-looking market views associated with call options may then propagate through the system with a different strength than a similar shock to put options information. It is of interest to study how investors in the financial system interact and how they can create risk. The unequal impact of "fears" spreading into the system may create asymmetric connections within the financial sector. In this chapter, we highlight the connections' asymmetry on both sides of the stock options market, and we introduce a new connectedness measure derived from the implied volatility extracted from individual financial institutions' options. This tool can be beneficial for monitoring the level of "fear" connectedness in the financial sector by exploiting forward-looking investors' expectations. In particular, we would like to answer the following important research question: *"is there any signal relevant to economic downturns embedded in the asymmetric fears connectedness in the financial sector?"* To answer this question, we first produce a new data set of daily implied volatility-type measures from call options only and put options only, respectively. Then, we assemble a new asymmetric fear connectedness index used as a forward-looking systemic risk monitoring tool.

Our main focus on the connectedness of the main U.S. financial stocks is motivated by the idea that financial institutions have always been under the magnifying glass of investors, practitioners and academics for their pivotal role in systemic risk terms. Excellent discussions along this line can be found in Billio et al. (2012), Diebold and Yılmaz (2014) and Baruník and Křehlík (2018). De Bandt and Hartmann (2002) and Allen et al. (2012) pointed out that the financial sector's systemic risk exposure

may lead to macroeconomic decline and macroeconomic contagion, so it should be closely monitored. Systemic risk in the financial sector has been identified to predict future economic downturns (Allen et al., 2012). In our work, we consider forward-looking information embedded in implied volatility measures extracted from stock call and put options prices. Comparison of the both sides of the market yields an important insight about asymmetric views of market participants about future volatility of the U.S. financial sector that can be used to predict economic downturns as well as periods of exuberance.

The methodological framework for measuring connectedness is anchored in the financial connectedness literature, which is spanned by Diebold and Yilmaz (2009, 2012); Diebold and Yılmaz (2014);s seminal papers. While the literature on volatility spillover and contagion is immense (see Bae et al., 2003; Engle et al., 2012; Beirne and Fratzscher, 2013; Bekaert et al., 2014; Diebold and Yilmaz, 2015) or Gagnon and Karolyi (2006) for an excellent survey, quantifying connectedness via variance decompositions from a vector autoregression approximation model has attracted a great deal of attention recently. We provide a more in-depth overview on the literature about returns spillovers, volatility spillovers and connectedness in Chapter 2.

Previous literature relies on historical volatility measures[1]. We contribute to the existing volatility spillovers literature by replacing the standard methodology used in the original Diebold and Yilmaz (2012) spillovers index to take into account the different reactions of stocks to good or bad news in a separate call-put framework. This allow us to link this research to a growing strand of literature studying the asymmetric characteristics of volatility (see Barndorff-Nielsen et al., 2010; Patton and Sheppard, 2015; Segal et al., 2015; Feunou et al., 2017; Kilic and Shaliastovich, 2018). We believe that a more informative analysis can be achieved by employing information from the stock option prices of individual companies, such that forward-looking measures can be calculated for "fear connectedness". Call and put options carry different information; hence, we further decompose the individual bank's "fear" index VIX into *upside* and *downside* components extracted from calls and puts only (henceforth denoted as VIX^{+} and VIX^{-} , respectively). We refer to "fear" connectedness when fear is generated by the aggregated VIX index, well known as the "fear" index in the literature. Thus, in order not to detach this label from the decomposed implied volatility indexes, we denote upside "fear" connectedness when fear is generated by VIX^{+} and downside "fear" connectedness when fear is generated by VIX^{-} .

We derive the asymmetric fear connectedness (AFC) index from stock option prices and study the interdependence among market expectations about individual institutions to see how they are connected within the financial system network. The "fear" contagion within the financial system depends on the structure of the financial network, its integration and diversification (see Elliott et al., 2014). Thus, we investigate the structural characteristics of the system focusing on directional implied volatility (or

[1]The volatility in Diebold and Yilmaz (2012) is computed using daily high and low assets' prices following Parkinson (1980) methodology: for the asset i on day t the daily variance is: $\widetilde{\sigma}_{it}^2 = 0.361[ln(P_{it}^{max}) - ln(P_{it}^{min})]^2$ where P_{it}^{max} is the high price on day t and P_{it}^{min} is the daily low price. The corresponding annualized daily percent volatility is $\widetilde{\sigma}_{it} = 100\sqrt{365 \times \widetilde{\sigma}_{it}^2}$.

"fear") connectedness.

The main contribution in this chapter is the construction of a forward-looking monitoring tool extracted from stock option prices, that is, an asymmetric fear connectedness measure. When constructed from put options only, the new measure reflects investors' negative future expectations associated with "bad" volatility (e.g., Segal et al., 2015), which could be linked to a possible decrease in economic growth and equity value and an increase in uncertainty (see Baruník et al., 2016; Feunou et al., 2017). Moreover, in some cases, volatility may reflect a upside direction associated with events that may trigger higher returns. Connectedness can create links between the sources and uses of funds, as savings are channeled into investments, international trade, regional and global capital market integration, and the coordination of global financial regulation and accounting standards (see Diebold and Yilmaz, 2015). Thus, there might be some events related to U.S. financial institutions that could be considered harmful because they increase "bad" volatility and can transmit across the system, creating the downside connectedness. However, other events that will increase "good" volatility and transmit across the system can create upside connectedness (see Segal et al., 2015; Baruník et al., 2016; Feunou et al., 2017). For instance, Kilic and Shaliastovich (2018) found a "synergy" between the good and bad components of the variance risk premium when they are included in the same model, increasing return predicability compared to the aggregate measure of the variance premium. In addition, they found that the variance premium decomposition uncovers long-horizon return predictability, where the aggregate variance premium fails instead.

Since connectedness measures may be directly related to network theory and to systemic risk measures (Diebold and Yılmaz, 2014), this study also contributes to the systemic risk literature. Fundamental information transmission from one bank to another has also been considered as a source of banks' connectedness. Correlated returns among banks can make depositors and investors run from one bank to another, generating panic (Chen, 1999). Banks might be further linked through deposits or asset liquidity (see Dasgupta, 2004; Cespa and Foucault, 2014). Systemic risk may also come from the interaction between asset commonality and funding maturity through an informational channel. This systemic risk is higher, especially when bad information about banks' future solvency arrives in the economy and the asset structures are clustered (see Allen et al., 2012). All these market situations can be better understood in a more general framework for banks' information contagion based on volatility, since good or bad news in relation to the bank influences the banks' stock volatility.

In contrast to the previous literature measuring systemic risk, we provide an ex ante systemic risk *alarm bell* extracted from the individual U.S. financial stock option prices in order to anticipate the propagation of systemic risk in the financial sector. Other measures of systemic risk that are based on interconnectedness and network spillovers among banks and financial institutions are discussed in Billio et al. (2012), Diebold and Yılmaz (2014), Hautsch et al. (2014) Härdle et al. (2016) and Geraci

and Gnabo (2018). Baruník and Křehlík (2018) argue that changes in investors' expectations will have a significant impact on the market. Thus, by considering decomposed implied volatility indexes, we can shed new light on directional forward-looking connectedness measures.

We focus on the separate behavior of the connectedness of single equity VIX indexes. Our analysis indicates that the downside implied volatility inflates mainly during turbulent periods, reflecting "fear" among investors. Employing the asymmetric fear connectedness measure for the ten main U.S. financial institutions, we identify a clear predominance of "fear" connectedness coming from upside implied volatility. We examine the predictive power of our connectedness measures with respect to macroeconomic and uncertainty indicators in the spirit of Allen et al. (2012), and we find that the decomposed fear connectedness measures perform better than the aggregate measure and they can predict future economic activity, recession and VIX level. We also provide a ranking of the top ten financial institutions in the U.S. by classifying them into net upside or net downside transmitters or receivers. In addition, we confirm the different roles played by VIX^{+} and VIX^{-} on the net fear connectedness indexes, especially when we focus on specific company events.

The remainder of this chapter is organized as follows. Section 5.2 describes the data and it illustrates the calculation of the individual financial stocks' implied volatility indexes and their decomposition into upside and downside measures. Section 5.3 introduces the computation of ex ante asymmetric fear connectedness measure. Section 5.4 reports the results for the static and dynamic analyses in relation to the aggregate implied volatility measures, while Section 5.5 shows the static and dynamic results with regards to the upside and downside asymmetric measures. We also investigate the net upside and net downside connectedness for specific financial institutions. In Section 5.6, a series of results are reported, highlighting the predictive power of the "fear" connectedness measures for future levels of economic indicators and uncertainty proxies. Finally, Section 5.8 concludes the chapter. Additional material for this Chapter is reported in Appendix C.

5.2 Data and Implied Volatility Decomposition

Implied volatility reveals the market's expectations and is often used as an ex ante measure of investor sentiment. Since we aim to measure the ex ante connectedness of the U.S. financial sector, we apply the VIX methodology (see CBOE, 2009) to create a proxy "VIX Index" for the ten main U.S. banks.

5.2.1 Data on U.S. Financial Institutions

The study focuses on the following ten major financial institutions representing the financial sector of the U.S. economy: J.P. Morgan (JPM), Bank of America (BAC), Wells Fargo (WFC), Citigroup (C), Goldman Sachs (GS), Morgan Stanley (MS), U.S. Bancorp (USB), American Express (AXP),

PNC Group (PNC) and Bank of New York Mellon (BK). Daily option prices were collected from OptionMetrics[2] for each of the banks, while financial information and market prices are collected from Bloomberg. The same set of firms has already been studied in the previous literature (see Diebold and Yılmaz, 2014; Baruník and Křehlík, 2018) and, therefore, by keeping the same sample, we can compare our findings to those of previous studies. The dataset ranges from 03-01-2000 to 29-12-2017, covering the most recent crisis and the remarkable boom that occurred after the crisis. Our sample contains 4528 daily observations for each series.

Table 5.1 describes the characteristics of the U.S. financial companies in our sample. The company tickers are reported in the second column and their main business area in the third column. Market capitalization and stock price are considered both as the average values over the 2000-2017 period and as a 2017-only value.

Table 5.1: **U.S. Financial Companies Description**

Company	Ticker	Business	MktCap		Stock Price	
			Average	2017	Average	2017
JP Morgan Chase & Co.	JPM	Com Bank	165.046	371.052	46.91	106.94
Bank of America Corp.	BAC	Com Bank	155.131	307.912	26.33	29.52
Wells Fargo Co.	WFC	Com Bank	160.769	298.755	34.07	60.67
Citigroup Inc.	C	Com Bank	175.757	196.740	233.62	74.41
Goldman Sachs	GS	Inv Bank	70.304	99.816	141.35	254.76
Morgan Stanley	MS	Inv Bank	58.660	94.860	38.92	52.47
US Bancorp	USB	Com Bank	58.212	88.916	31.09	53.58
American Express	AXP	Credit Card	64.119	86.201	53.06	99.31
PNC Group	PNC	Com Bank	30.020	68.653	67.33	144.29
Bank of New York Mellon	BK	Com Bank	35.747	55.154	35.94	53.86

Notes: This table shows the main characteristics of each selected U.S. financial institution, including their tickers, their business (commercial bank or investment bank), their market capitalization (in billions of U.S. dollars) and their stock prices. These last two areas of financial information are reported both for the average period between 2000 and 2017 or only for the end-of-the-year 2017.

5.2.2 Individual Upside and Downside Implied Volatilities of U.S. Financial Institutions

We apply the CBOE VIX index methodology as already described in details in Chapter 3 to a set of out-of-the-money (OTM) financial stocks options for the ten main U.S. financial institutions. The calculation is based on the weighted average of 1-month and 2-month expirations. When less than 3 days are left to the expiration date, the considered maturity is rolled and the 2nd and the 3rd months options are used instead of the first month. The option maturity changes every month in correspondence to the third Friday of the month. The same OTM options selection and filter rules discussed in Chapter 3 in order to screen out options as for the CBOE VIX methodology are applied here: options are filtered leaving out options with bid price equal to zero, options with prices below or above two consecutive

[2]Data on U.S. stocks' options are specifically collected from IvyDBUS/v3.1/History/IVYOPPRCD and IvyDBUS/v3.1.1/History/IVYOPPRCD at `ftp.ivydb.com`.

zero bid prices and options with less than 2 days expiration. We compute the individual equity VIX index for the $j = 1, \ldots, 10$ banks.

$$\mathrm{VIX}_j = 100\sqrt{\frac{365}{30}\left[T_1\sigma^2_{\mathrm{VIX}_j}(T_1)\frac{N_2-30}{N_2-N_1} + T_2\sigma^2_{\mathrm{VIX}_j}(T_2)\frac{30-N_1}{N_2-N_1}\right]}. \tag{5.1}$$

In order to compute the upside and downside components of the single stock VIX_j, we consider call options and put options separately. Using call options (i.e., $K_i \geq K_0$) in the equation allows us to define the upside or *positive* implied volatility index for a given stock VIX_j^+. Employing put options instead (i.e., $K_i \leq K_0$) allows us to define the downside or *negative* implied volatility index for a given stock VIX_j^-. Finally, the two implied volatility components VIX_j^+ and VIX_j^- are determined from the following formulae

$$\mathrm{VIX}_j^+ = 100\sqrt{\frac{365}{30}\left[T_1\sigma^2_{\mathrm{VIX}_j^+}\frac{N_2-30}{N_2-N_1} + T_2\sigma^2_{\mathrm{VIX}_j^+}\frac{30-N_1}{N_2-N_1}\right]}, \tag{5.2}$$

$$\mathrm{VIX}_j^- = 100\sqrt{\frac{365}{30}\left[T_1\sigma^2_{\mathrm{VIX}_j^-}\frac{N_2-30}{N_2-N_1} + T_2\sigma^2_{\mathrm{VIX}_j^-}\frac{30-N_1}{N_2-N_1}\right]}. \tag{5.3}$$

Hence, we obtain three daily implied volatility indexes: VIX_j, VIX_j^+, and VIX_j^- for every bank considered in our sample which are related through the following approximate relationship[3]: $\mathrm{VIX}_j^2 \simeq \left(\mathrm{VIX}_j^+\right)^2 + \left(\mathrm{VIX}_j^-\right)^2$. More details on the construction and decomposition of the VIX index are provided in Chapter 3.

Table 5.2 reports the descriptive statistics for the VIX, VIX^+, and VIX^- of the ten main financial institutions. Bank of America carries the highest aggregate VIX and VIX^+ average values, followed by Citigroup, while Morgan Stanley presents the highest VIX^- average value. Bank of America also presents the highest maximum values for VIX and VIX^+ , while PNC Group shows the highest maximum value for VIX^- . The lowest minimum values for all the implied volatility series are found for American Express. The VIX^- indexes are also the most volatile series.

The time dynamic of implied volatility series is illustrated in Figure 5.1. Overall, all the ten financial institutions' volatility indexes spike in alignment with the global financial crisis, which is found to be a common denominator of uncertainty and volatility increases. There are also more idiosyncratic jumps in volatility indexes. For instance, J.P. Morgan Chase VIX indexes are found to spike in 2000, when Chase Manhattan Corp. merged with J.P. Morgan & Co., becoming J.P. Morgan Chase, and to increase the company's volatility until late 2001, when the deal was finalized. The main volatility peak for Bank of America is found during the financial crisis due to its acquisition of Merrill Lynch in September

[3]We decided not to weight downside information extracted from puts more than upside information extracted from calls. For this reason, this relationship is not always exact, as when VIX index is decomposed, $K_i = K_0$ might result in an ATM options price that is excluded from calculations of the VIX^- or VIX^+ measures on one or another side of the distribution, whereas for the aggregate VIX , it is always taken into account in the total distribution of prices as the average between the ATM call and put prices relative to the strike price.

Table 5.2: **Aggregate and Decomposed Implied Volatility Indexes - Descriptive Statistics**

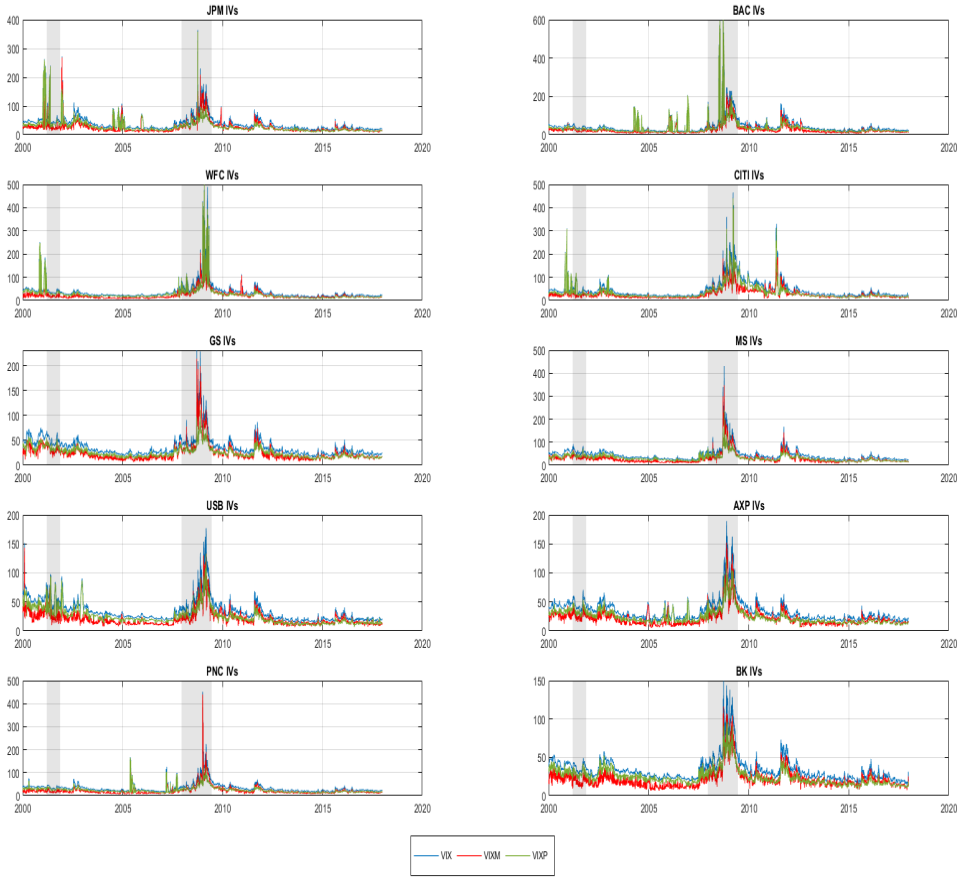
		Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis
JPM	VIX	41.01	31.38	363.61	13.30	30.30	3.39	19.13
	VIX^+	28.37	21.77	358.61	8.15	23.01	5.29	45.30
	VIX^-	26.98	20.62	268.63	7.55	22.03	3.92	24.34
BAC	VIX	46.89	34.01	643.87	14.79	51.73	6.05	52.57
	VIX^+	35.22	25.27	618.23	10.87	46.85	7.70	76.86
	VIX^-	26.55	18.97	319.89	6.60	24.84	3.86	24.98
WFC	VIX	38.69	27.36	543.12	12.40	41.53	5.61	42.97
	VIX^+	28.18	20.55	532.00	7.72	35.02	7.05	65.05
	VIX^-	23.36	16.58	325.87	7.57	24.13	5.97	53.63
C	VIX	46.53	32.22	465.24	15.41	40.75	3.51	20.74
	VIX^+	34.47	22.99	440.82	9.95	34.06	4.36	31.53
	VIX^-	28.07	20.25	262.44	6.29	22.90	3.31	19.14
GS	VIX	36.16	29.81	231.30	15.84	19.75	3.47	21.69
	VIX^+	25.03	21.68	111.24	10.04	10.77	1.95	9.11
	VIX^-	24.59	19.79	214.05	6.46	17.31	4.11	27.91
MS	VIX	44.20	36.60	430.83	17.92	27.60	4.24	31.80
	VIX^+	30.86	26.89	239.04	10.99	14.98	2.96	22.51
	VIX^-	29.35	23.22	347.55	7.18	24.20	4.59	33.27
USB	VIX	34.62	27.89	177.17	12.56	19.90	2.32	10.59
	VIX^+	25.02	20.61	132.94	6.71	14.91	2.09	8.76
	VIX^-	21.66	17.25	143.38	6.39	13.89	3.00	15.81
AXP	VIX	34.36	28.35	189.25	12.05	19.42	3.02	16.02
	VIX^+	24.25	19.67	123.65	6.54	12.88	2.42	11.60
	VIX^-	22.76	19.08	152.17	5.23	14.92	3.34	19.44
PNC	VIX	34.48	28.16	451.50	12.69	24.42	6.22	69.37
	VIX^+	24.13	20.73	165.13	9.05	13.31	3.81	26.75
	VIX^-	22.40	17.14	439.61	6.95	21.54	8.24	115.14
BK	VIX	34.01	29.73	149.53	12.78	16.29	2.83	13.62
	VIX^+	24.66	21.93	96.45	8.17	11.20	2.22	10.38
	VIX^-	21.70	18.64	116.43	6.68	12.71	3.03	15.27

Notes: The table shows the main descriptive statistics for the daily implied volatility indexes series for the aggregate VIX and for the upside (VIX^+) and downside (VIX^-) decomposed measures for the selected ten main U.S. financial institutions (tickers in the table) between 03-01-2000 and 29-12-2017, for a total of 4528 observations for each series.

2008. In October 2000, Wells Fargo bought First Security Corp., becoming one of the largest banks in the West, leading to an increase in the WFC's implied volatility index. In mid 2001, Citigroup acquired European American Bank and Banamex, resulting in an increase in Citi's volatility indexes, which spiked again in March 2012, when the Federal Reserve reported that Citigroup was one of the few main banks that failed the stress tests. U.S. Bancorp began the 2000 era with a high level of volatility caused by the acquisitions of Peninsula Bank in September 1999, with price renegotiations until January 2000. We observe how companies' idiosyncratic news, such as M&A deals, restructuring and negotiations contribute to their changes in implied volatility. The latter, however, is found to react to macro events as well, such as the dot-com bubble burst, the Enron scandal, the 9/11 terrorist attack, the global financial crisis and the European sovereign debt crisis. A mixture of idiosyncratic and systemic events is found to affect the financial stock implied volatility through the options market.

Having computed an implied volatility index for the individual banks, we also define a financial sector implied volatility index (WVIX), reflecting the ten main stock volatility indexes. This index is

Figure 5.1: **Upside and Downside Implied Volatilities of the U.S. Financial Sector**



Notes: The figure shows the single stock VIX and the decomposed volatility indexes VIX^+ and VIX^- for the ten main U.S. financial institutions. The NBER recession periods are highlighted in grey. The selected period spans from 03-01-2000 to 29-12-2017 at a daily frequency.

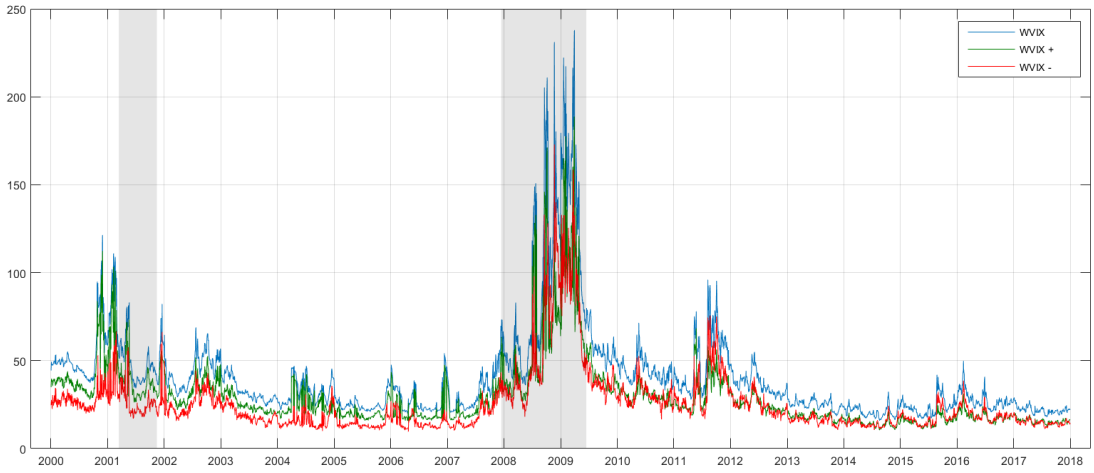
computed as the sum of their single stock VIX weighted for their average market capitalizations as

$$\text{WVIX} = \sum_{j=1}^{10} w_j \text{VIX}_j, \tag{5.4}$$

where w_j are the weights based on the 2000-2017 average market capitalizations, as shown in Table 5.1, and VIX_j represents the aggregate implied volatility index. Analogous upside and downside implied volatility measures WVIX^+ and WVIX^- can be computed from equation (5.4) using VIX_j^+ and VIX_j^- instead of VIX_j, respectively. The WVIX indexes, namely, aggregate, upside and downside are plotted in Figure 5.2. Even though the main component of the aggregate single stock VIX is generated by the call options, most of the time, we observe that in the case of financial market downturns, the downside component also increases in size, overpowering the upside component. The figure also shows that before the financial crisis, the implied upside volatility is found to be above the implied downside volatility, whereas the two decomposed implied volatility series become more intertwined in the post-crisis period, highlighting the role of implied downside volatility during crises and reflect-

ing the investors' increasing concern for other potentially similar events. This characteristic is also supported by the graphs illustrated in Figure 5.1.

Figure 5.2: **The U.S. Financial Sector** VIX **Indexes**



Notes: The figure shows the aggregate, upside and downside WVIX indexes for the ten major financial institutions, as computed through formula (5.4) as a market cap weighted average of the selected ten financial companies in the U.S. The NBER recession periods are highlighted in grey. The selected period spans from 03-01-2000 to 29-12-2017 at a daily frequency.

5.3 Asymmetric Fear Connectedness

System connectedness can be characterized well through variance decompositions from a vector autoregression approximation model (Diebold and Yilmaz, 2009, 2012)[4]. Variance decompositions provide useful information about how much of the future variance of variable j is due to shocks in variable k. Aggregating variance decompositions then yields a simple way to measure how the system is interconnected. Diebold and Yılmaz (2014) further argue that variance decompositions are closely linked to modern network theory[5] and recently proposed measures of various types of systemic risk, such as marginal expected shortfall (Acharya et al., 2017) and delta CoVaR (Adrian and Brunnermeier, 2016). However, the literature as a whole examines how shocks to volatility measured ex post are transmitted across the system.

Employing forward-looking implied volatility measures, we aim to derive informatively different measures of interconnectedness. Option prices reflect market participants' expectations of future movements of the underlying asset; hence, volatility implied by option prices carry forward-looking information superior to ex post volatility (see Christensen and Prabhala, 1998). Individual equity VIX indexes as derived in the previous section essentially measure the risk-neutral expected volatility. We are naturally interested in knowing how a shock to the expected volatility of a stock j will transmit to future

[4] According to Diebold and Yılmaz (2014), a financial system characterized through variance decomposition can be seen as a more sophisticated form of financial network.

[5] Networks can accelerate and amplify the way shocks propagate through the financial system. The nature and extent of the interrelationship between actors and markets influence the manner by which the positive feedback loops grip the entire system.

expectations about the volatility of a stock k. Aggregating this information can provide a system-wide measure of forward-looking connectedness measuring how strongly the investors' expectations are interconnected.

To construct the asymmetric fear connectedness measures, we use the implied volatility indexes computed for the main financial institutions in combination with connectedness measures based on generalized variance decompositions of a vector autoregressive (VAR) approximation model due to Diebold and Yilmaz (2012). In particular, we consider a covariance stationary N-variate process $\mathbf{VIX}_t^* = (\mathrm{VIX}_{1,t}^*, \ldots, \mathrm{VIX}_{N,t}^*)'$ at $t = 1, \ldots, T$ described by the VAR model of order p as

$$\mathbf{VIX}_t^* = \mathbf{\Phi}_1 \mathbf{VIX}_{t-1}^* + \mathbf{\Phi}_2 \mathbf{VIX}_{t-2}^* + \ldots + \mathbf{\Phi}_p \mathbf{VIX}_{t-p}^* + \boldsymbol{\epsilon}_t, \tag{5.5}$$

with $\mathbf{\Phi}_1, \ldots, \mathbf{\Phi}_p$ coefficient matrices, and $\boldsymbol{\epsilon}_t$ being white noise with a (possibly non-diagonal) covariance matrix $\mathbf{\Sigma}$. In this model, each variable is regressed on its own p lags, as well as the p lags of all of the other variables in the system; hence, matrices of the coefficients contain complete information about the connections between variables. It is useful to work with $(N \times N)$ matrix lag-polynomial $\mathbf{\Phi}(L) = [\boldsymbol{I}_N - \mathbf{\Phi}_1 L - \ldots - \mathbf{\Phi}_p L^p]$ with $\boldsymbol{I}_N$ identity matrix, as the model can be written concisely as $\mathbf{\Phi}(L)\mathbf{VIX}_t^* = \boldsymbol{\epsilon}_t$. Assuming that the roots of $|\mathbf{\Phi}(z)|$ lie outside the unit circle, the VAR process has the following vector moving average (i.e., MA(∞)) representation: $\mathbf{VIX}_t^* = \mathbf{\Psi}(L)\boldsymbol{\epsilon}_t$, where $\mathbf{\Psi}(L)$ matrix of infinite lag polynomials can be calculated recursively from $\mathbf{\Phi}(L) = [\mathbf{\Psi}(L)]^{-1}$ and is key to understanding dynamics. Since $\mathbf{\Psi}(L)$ contains an infinite number of lags, it must be approximated with the moving average coefficients $\mathbf{\Psi}_h$ calculated at $h = 1, \ldots, H$ horizons. The connectedness measures rely on variance decompositions, which are transformations of the $\mathbf{\Psi}_h$ and allow the measurement of the contribution of shocks to the system.

To construct connectedness measures of aggregate, as well as decomposed implied volatility, we consider different vectors $\mathbf{VIX}_t^* \in \left\{\mathbf{VIX}_t, \mathbf{VIX}_t^+, \mathbf{VIX}_t^-\right\}$. Since a shock to a variable in the model does not necessarily appear alone, *i.e.*, orthogonally to shocks to other variables, an identification scheme is a crucial step in the calculation of variance decompositions. Standard approaches relying on Cholesky factorization depend on the ordering of the variables and complicate the measures. The generalized identification proposed by Pesaran and Shin (1998) produces variance decompositions that are invariant to ordering. Generalized variance decompositions can be written in the form[6]

$$\left(\boldsymbol{\theta}^H\right)_{j,k} = \frac{\sigma_{kk}^{-1} \sum_{h=0}^{H} \left((\mathbf{\Psi}_h \mathbf{\Sigma})_{j,k}\right)^2}{\sum_{h=0}^{H} (\mathbf{\Psi}_h \mathbf{\Sigma} \mathbf{\Psi}_h')_{j,j}}, \tag{5.6}$$

where $\mathbf{\Psi}_h$ is a $(N \times N)$ matrix of moving average coefficients at lag h defined above, and $\sigma_{kk} = (\mathbf{\Sigma})_{k,k}$.

[6] $(\boldsymbol{A})_{j,k}$ denotes the jth row and kth column of matrix $\boldsymbol{A}$ denoted in bold. $(\boldsymbol{A})_{j,\cdot}$ denotes the full jth row; this is similar for the columns. A $\sum A$, where A is a matrix that denotes the sum of all elements of the matrix A.

The $\left(\boldsymbol{\theta}^H\right)_{j,k}$ denotes the contribution of the kth variable to the variance of forecast error of the element j, at horizon h. As the rows of the variance decomposition matrix $\boldsymbol{\theta}^H$ do not necessarily sum to one, each entry is normalized by the row sum as

$$\left(\widetilde{\boldsymbol{\theta}}^H\right)_{j,k} = \left(\boldsymbol{\theta}^H\right)_{j,k} / \sum_{k=1}^{N} \left(\boldsymbol{\theta}^H\right)_{j,k}.$$

Now the $\sum_{j=1}^{N} \left(\widetilde{\boldsymbol{\theta}}^H\right)_{j,k} = 1$ for any k and the sum of all elements in $\widetilde{\boldsymbol{\theta}}^H$ is equal to N, by construction. Note that $\left(\widetilde{\boldsymbol{\theta}}^H\right)_{j,k}$ provides a pairwise measure of connectedness from j to k at horizon H. Note that the variance decomposition can be used to form a network adjacency matrix defining a network. Hence, all the connectedness measures defined later can be viewed as a network connectedness directly (see Diebold and Yılmaz, 2014). The connectedness measure is then defined as the share of variance in the forecasts contributed by errors other than own errors or as the ratio of the sum of the off-diagonal elements to the sum of the entire matrix (Diebold and Yilmaz, 2012)

$$\mathcal{C}^H = 100 \cdot \frac{1}{\sum \widetilde{\boldsymbol{\theta}}^H} \cdot \sum_{j \neq k} \left(\widetilde{\boldsymbol{\theta}}^H\right)_{j,k}, \tag{5.7}$$

where the denominator signifies the sum of all elements of the $\widetilde{\boldsymbol{\theta}}^H$ matrix. Hence, the connectedness is the relative contribution to the forecast variances from the other variables in the system.

Similarly to the overall aggregate connectedness measure that infers the system-wide connectedness, we can define measures that will reveal when an individual bank in the system is a volatility transmitter or receiver. The directional connectedness that measures how much of each bank's j variance is due to other banks $j \neq k$ in the system is given by

$$\mathcal{C}^H_{j \leftarrow \bullet} = 100 \cdot \frac{1}{\sum \widetilde{\boldsymbol{\theta}}^H} \cdot \sum_{k=1, j \neq k}^{N} \left(\widetilde{\theta}^H\right)_{j,k}, \tag{5.8}$$

defining the so-called FROM connectedness. Likewise, the contribution of asset j to variances in other variables is computed as

$$\mathcal{C}^H_{j \rightarrow \bullet} = 100 \cdot \frac{1}{\sum \widetilde{\boldsymbol{\theta}}^H} \cdot \sum_{k=1, j \neq k}^{N} \left(\widetilde{\theta}^H\right)_{k,j}, \tag{5.9}$$

and this is the so-called TO connectedness. These two measures show how other assets contribute to the risk of asset j, and how asset j contributes to the riskiness of others, respectively. Further, a measure showing the discrepancy between how much of the variance is received, so-called NET connectedness, can be calculated as

$$\mathcal{C}^H_{j,\text{NET}} = \mathcal{C}^H_{j \rightarrow \bullet} - \mathcal{C}^H_{j \leftarrow \bullet}. \tag{5.10}$$

The NET connectedness measures whether a bank is inducing more risk than it receives from the other

banks in the system. Finally, one might be interested in pairwise relations of risk that can further be described by the PAIRWISE connectedness measure given by

$$\mathcal{C}^{H}_{j,k} = 100 \cdot \frac{1}{\sum \widetilde{\boldsymbol{\theta}}^{H}} \cdot \left(\left(\widetilde{\theta}^{H} \right)_{k,j} - \left(\widetilde{\theta}^{H} \right)_{j,k} \right). \tag{5.11}$$

As discussed before, our main aim is to compare the connectedness of investors with fundamentally different beliefs revealed by VIX^{+} and VIX^{-} . In the spirit of Baruník et al. (2016), who define asymmetric spillover measures based on the ex post realized semivariance, we consider the vectors $\mathbf{VIX}^{*}_{t} \in \left\{ \mathbf{VIX}_{t}, \mathbf{VIX}^{+}_{t}, \mathbf{VIX}^{-}_{t} \right\}$ holding information about aggregate, upside, and downside implied volatility and use it in the framework described above. The measures of respective connectedness $\mathcal{C}$ for aggregate fear, $\mathcal{C}^{+}$ for upside, and $\mathcal{C}^{-}$ downside fear in the system can be readily calculated by using appropriate $\mathbf{VIX}^{*}$ measures. When $\mathcal{C}^{+} \neq \mathcal{C}^{-}$, we have asymmetry in connectedness due to different investors' expectations, which we define as the measure of asymmetric fear connectedness ($\mathcal{AFC}$)

$$\mathcal{AFC} = \mathcal{C}^{+} - \mathcal{C}^{-}. \tag{5.12}$$

In other words, when $\mathcal{AFC} > 0$, connectedness due to VIX^{+} is greater than connectedness due to VIX^{-} , and vice versa. In order to shed new light on the nature and sign of the transmitted or received volatility for every financial institution in the system, we compute the upside directional NET as the difference between upside TO and FROM, as

$$\mathcal{C}^{+}_{j,\text{NET}} = \mathcal{C}^{+}_{j\rightarrow\bullet} - \mathcal{C}^{+}_{j\leftarrow\bullet}, \tag{5.13}$$

and the downside directional NET as the difference between downside TO and FROM as

$$\mathcal{C}^{-}_{j,\text{NET}} = \mathcal{C}^{-}_{j\rightarrow\bullet} - \mathcal{C}^{-}_{j\leftarrow\bullet}. \tag{5.14}$$

Finally, we compute the asymmetric directional NET as the difference between $\mathcal{C}^{+}_{j,\text{NET}}$ and $\mathcal{C}^{-}_{j,\text{NET}}$ as

$$\mathcal{AFC}_{j,\text{NET}} = \mathcal{C}^{+}_{j,\text{NET}} - \mathcal{C}^{-}_{j,\text{NET}}. \tag{5.15}$$

In computations, we follow the previous literature and use the logarithmic of the volatility series, a forecast horizon of twelve days, and a VAR order equal to four (Diebold and Yilmaz, 2012; Diebold and Yılmaz, 2014; Baruník et al., 2016). We report the static forecast error variance decomposition matrix results both for the aggregate measures and for the decomposed upside and downside measures in Section 5.4 and Section 5.5, respectively. These connectedness measures are also studied dynamically

over a 200-day rolling window[7]

5.4 Fear Connectedness in the Financial Sector

We begin the empirical analysis by studying the aggregate level of the transmission of shocks to expectations within the financial sector. The aggregate connectedness investigated in subsection 5.4.1 shows how individual banks contributed to the distribution of "fear" in the financial system between 2000 and 2017. In addition, we will also identify net fear transmitters and net fear receivers in the system (e.g. Härdle et al., 2016). Looking at dynamic connectedness, we follow (subsection 5.4.2) on the time dynamics of connections.

5.4.1 Fear Connectedness: Static Analysis

Table 5.3 reports the static analysis of "fear" connectedness for the ten main U.S. financial institutions. The diagonal values in the Table 5.3 indicate that the future volatility of a stock is impacted by own shocks to expectations, which range from 29.91% to 56.06%. Furthermore, the off-diagonal elements reveal how "fear" spreads from one bank to other banks in the financial sector. The directional FROM connectedness measure ranges from 43.93% for Bank of America to 70.08% for Bank of New York Mellon. The directional FROM contribution accounts to 100% minus the companies' own total forecast error variance in the main diagonal or, in other words, to the sum of the other pairwise directional connectedness elements in the (N- 1) off-diagonal entries for every company. The directional TO connectedness measure in the bottom row of the table ranges from 19.92% for Bank of America to 108.85% for Goldman Sachs. The directional TO contribution is not limited to 100% and it can exceed 100% and it really depends on how many assets are considered in the system.

The FROM directional connectedness, which measures the exposure of a single bank j to shocks FROM the system, is similar, in systemic risk terms, to the Marginal Expected Shortfall ($MES^{j|mkt}_{T+1|T}$) (see Acharya et al., 2017), while the TO connectedness, which measures the contribution of the individual bank TO the volatility spillovers in the system is similar to the delta CoVaR measure ($\Delta CoVaR^{mkt|i}_{T+1|T}$) (see Adrian and Brunnermeier, 2016). The delta CoVar measures the systemic risk contribution conditional on market events to financial firms' events – exactly in the opposite direction of MES (see Diebold and Yılmaz, 2014).

The pairwise values in the off-diagonal matrix entries indicate the directional connectedness between the two companies crossing that entry. The highest pairwise connectedness appears to be from Goldman Sachs to Morgan Stanley (20.29%). In other words, 20.29% of the future variation of VIX for Morgan Stanley is expected to be generated by the shocks from Goldman Sachs. The second-highest

[7] We have also examined the static analysis within a range of different VAR lags and forecast horizons, respectively, such as $p \in \{2, 3, 4, 5\}$, and $h \in \{4, 6, 10, 14\}$, together with different rolling window sizes. The results do not change materially.

Table 5.3: **Static Fear Connectedness in the Financial Sector**

	VIX Connectedness										
	JPM	BAC	WFC	CITI	GS	MS	USB	AXP	PNC	BK	FROM
JPM	46.98	2.16	3.58	3.26	10.36	9.46	8.69	6.63	2.06	6.77	53.01
BAC	4.03	56.06	3.04	3.28	8.20	7.05	5.67	4.99	1.65	5.98	43.93
WFC	6.93	1.78	44.41	4.61	11.11	6.37	7.19	5.63	5.66	6.26	55.58
CITI	5.23	2.09	3.44	54.67	8.92	7.20	5.69	5.44	2.33	4.94	45.32
GS	6.34	2.25	4.81	5.54	35.55	18.29	9.35	7.36	2.29	8.19	64.44
MS	6.91	2.58	4.12	5.11	20.29	34.34	8.59	6.40	2.86	8.74	65.65
USB	8.23	2.26	4.97	4.34	13.62	9.67	36.33	7.67	3.48	9.39	63.66
AXP	7.14	2.51	4.21	4.45	12.65	11.47	10.42	35.71	3.02	8.37	64.28
PNC	5.82	1.34	4.93	3.11	8.69	7.53	6.85	4.22	49.89	7.57	50.10
BK	7.19	2.90	4.25	4.21	14.97	14.50	10.38	7.77	3.87	29.91	70.08
TO	57.86	19.92	37.38	37.96	108.85	91.57	72.87	56.14	27.25	66.25	TOTAL
NET	4.84	-24.01	-18.19	-7.35	44.40	25.92	9.21	-8.13	-22.84	-3.82	**57.61**

Notes: The table contains a decomposition of forecast error variance computed for the aggregate VIX indexes for the ten main U.S. financial institutions. Elements in the off-diagonal entries are the pairwise directional connectedness, while the diagonal elements (in grey) are the financial institutions' own variance. The off-diagonal row and column sum to TO and FROM connectedness, respectively. The NET row at the bottom is the difference between TO and FROM. The bottom-right element is the total connectedness index in the considered system. Selected VAR lags = 4 and Forecast Horizon = 12 days. The selected time period spans from 03-01-2000 to 29-12-2017.

number is in the opposite direction, going from Morgan Stanley to Goldman Sachs (18.29%). The bottom row in the table shows the total directional NET computed as difference between directional TO and directional FROM fear connectedness. A positive difference reveals that the company can be classified as a "fear" transmitter, while a negative number identifies a "fear" receiver. The main net aggregate "fear" transmitter is found to be Goldman Sachs (44.4%) followed by Morgan Stanley (25.92%). J.P. Morgan Chase and U.S. Bancorp are also net aggregate "fear" transmitters. However, we find that Bank of America, Wells Fargo and PNC Bank are, on average, the main aggregate "fear" receivers in the system. The total "fear" connectedness index, bottom-right element, is found to be equal to 57.61%, which means that, on average, more than half of the implied volatility (or "fears") for these ten main financial institutions has been generated from fear spillovers in the financial system.

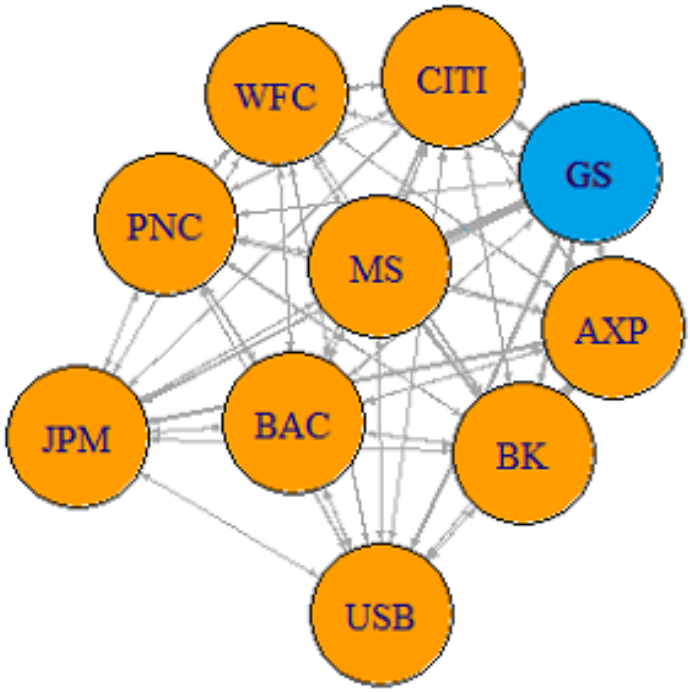
In Figure 5.3 we plot the total "fear" connectedness network in which the ten main financial institutions are linked to each other. We represent thicker lines for banks which are more connected to each other. The highlighted bank is the one showing the highest *to* pairwise connectedness, in the aggregate VIX case this is Goldman Sachs towards Morgan Stanley.

5.4.2 Fear Connectedness: Time Dynamics

While the static analysis provides an average overview of the "fear" connectedness within the system, we are further interested in gauging how the aggregate VIX connectedness evolves over time.

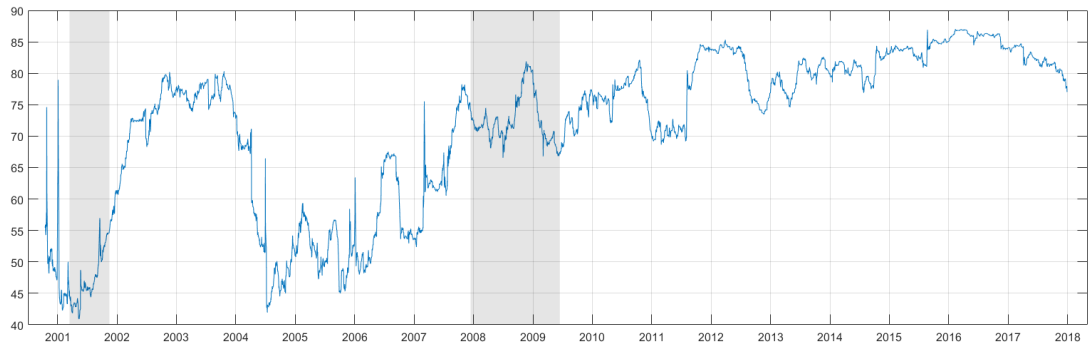
Figure 5.4 illustrates how the total "fear" connectedness index spiked twice in the early 2000s due to several specific news and M&A deals in which some of the banks in our sample were involved and to the burst of the dot-com bubble in March 2000. These events, in addition to others, such as the 9/11 terrorist attack, the Enron scandal and the MCI WorldCom scandal, are found to have increased

Figure 5.3: **Total Fear Connectedness Network**



Notes: This figure shows the total "fear" connectedness for the ten main financial institutions' aggregate VIX indexes as a network. Highlighted in blue is the main VIX pairwise transmitter.

Figure 5.4: **Total Fear Connectedness Index**



Notes: This figure shows the total "fear" connectedness for the ten main financial institutions' aggregate VIX indexes. Selected VAR lags = 4 and forecast horizon = 12. The rolling window length is equal to 200 days. The NBER recession periods are highlighted in grey. The selected period spans from 03-01-2000 to 29-12-2017 at a daily frequency.

the total "fear" connectedness index at the end of 2001 from 45% to 75% in only one year. The index remained at high levels, close to 80%, for a few years until it decreased in mid-2004. This period was followed by several smaller cycles corresponding to the U.S. tightening of monetary policy and

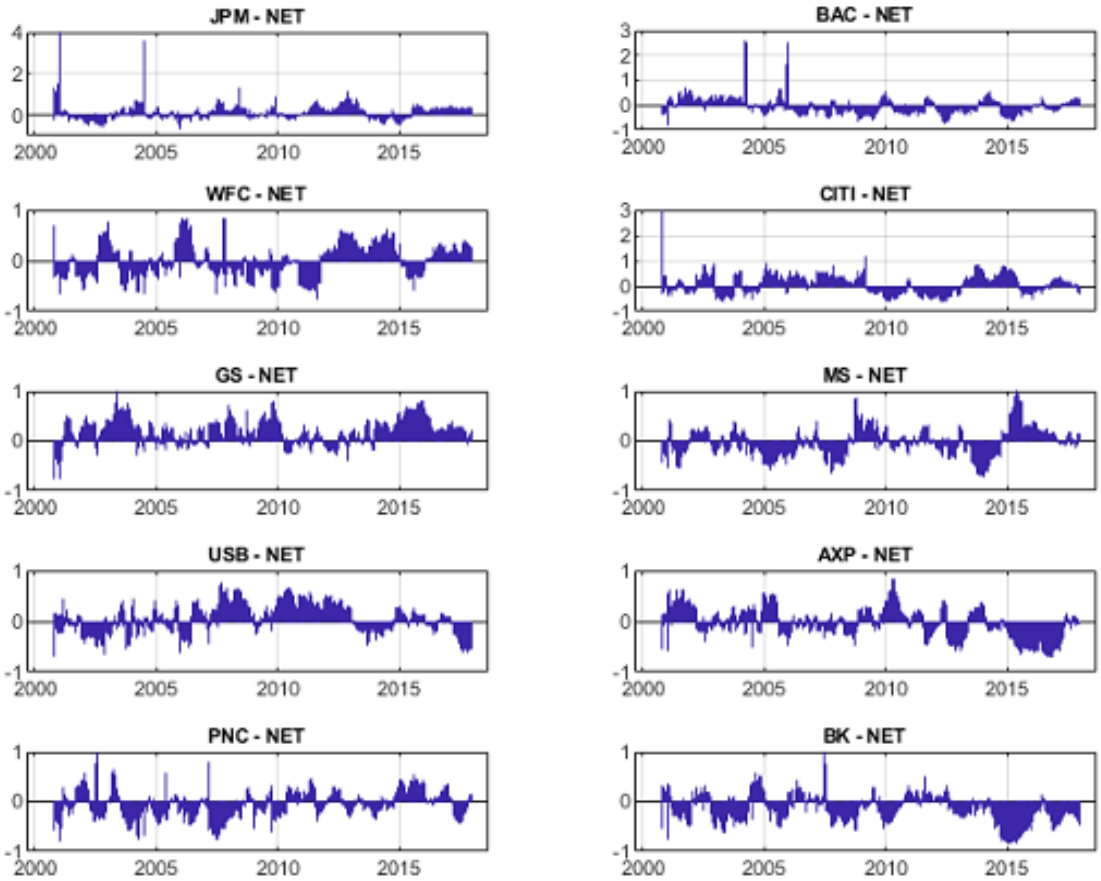
increases in long-term interest rates (see Diebold and Yılmaz, 2014). The total connectedness index rose again in February 2007 in alignment with the beginning of the sub-prime crisis. After decreasing for few months, it jumped up in mid-2007, increasing by more than 20% to levels near 80%. In the middle of the global financial crisis, the index spiked again in accordance with the losses of Merrill Lynch and the collapse of Lehman Brothers in September 2008. The index level remained high until 2011, given the intensification of the Eurozone sovereign debt crisis, which reached its record high of 85% at that moment. Eventually, after the global financial crisis and the sovereign debt crisis, the "fear" connectedness average value rose well above the pre-crisis range. This level is found to increase even further, in line with Grexit and the Chinese Yuan crisis in mid-2015, before decreasing in 2017. Overall, the dynamics show that shocks to expectations in individual banks play an increasingly important role in the financial system.

5.4.3 Net Fear Receivers and Transmitters

Time-varying NET directional fear connectedness provides a more detailed analysis of the connections among banks. We show the dynamic aggregate VIX net directional volatility connectedness for all the main ten banks in the system. This measure is rolled along our time frame selecting a 200-days window length. Table 5.4 reports a cumulative ranking for the directional NET measures, describing the main aggregate "fear" transmitters or receivers within the system.

Figure 5.5 shows the financial institutions which contribute to transmit aggregate implied volatility (area above 0) or to receive aggregate implied volatility (area below 0). We detect a clear aggregate volatility transmitter role for J.P. Morgan Chase and Goldman Sachs. These two together with Morgan Stanley, Citigroup and U.S. Bancorp are found to be aggregate implied volatility transmitters also during the 2007-2008 global financial crisis, whereas, on the other hand, Wells Fargo and Bank of America are found to suffer the turbulent crisis time by receiving volatility. Citigroup and Bank of America are found to take volatility during the sovereign debt crisis. U.S. Bancorp shows a stable period of volatility transmission from the sub-prime crisis until the end of the European sovereign debt crisis. Morgan Stanley and American Express alternate their roles many times during the selected market period, whilst Bank of America, PNC and Bank of New York Mellon can, overall, be classified as main aggregate volatility receivers within the system.

Figure 5.5: **Net Fear Connectedness**



Notes: This figure shows the aggregate net "fear" connectedness for the ten main financial institutions. The NET directional connectedness is computed as the difference between the TO and the FROM. Selected VAR lags = 4 and forecast horizon = 12. The rolling window length is equal to 200 days. The selected period spans from 03-01-2000 to 29-12-2017 at a daily frequency.

Table 5.4: **Cumulative Net Fear Receivers and Transmitters**

Period	JPM		BAC		WFC		CITI		GS		MS		USB		AXP		PNC		BK	
	T	R	T	R	T	R	T	R	T	R	T	R	T	R	T	R	T	R	T	R
Annual Cumulative Net Fear Receivers and Transmitters																				
2000	57.80	-0.26	0	-13.67	2.21	-7.14	11.79	-3.20	0	-19.51	0	-12.96	1.86	-5.41	2.81	-1.42	0	-20.99	8.87	-0.75
2001	29.48	-21.50	60.86	-4.26	1.96	-47.50	7.63	-30.40	33.88	-13.03	10.25	-46.91	9.42	-15.33	81.36	-1.99	21.01	-20.98	4.71	-58.67
2002	0.41	-71.95	40.70	-1.41	41.33	-39.74	65.17	-12.29	56.27	-1.30	31.66	-6.04	0.12	-76.52	12.17	-21.35	21.55	-41.24	20.33	-17.87
2003	23.24	-8.20	57.94	0	28.72	-38.30	17.34	-86.36	129.73	0	15.85	-17.74	13.37	-36.21	10.75	-12.31	25.37	-41.64	1.02	-82.57
2004	63.63	-7.91	19.14	-18.63	0.45	-48.02	12.29	-32.27	39.80	-2.48	6.17	-31.01	15.45	-9.75	33.86	-9.50	1.12	-53.79	50.23	-28.79
2005	12.14	-19.01	54.52	-20.75	21.54	-20.53	94.45	-3.87	19.49	-5.13	0	-85.59	15.65	-13.29	56.75	-20.68	7.17	-40.40	1.87	-54.35
2006	7.01	-27.15	10.15	-60.18	77.82	-5.75	66.88	-0.64	12.66	-6.57	3.04	-27.03	29.14	-39.80	3.01	-20.50	1.96	-45.70	28.55	-6.90
2007	65.34	-4.75	3.39	-47.70	8.53	-35.04	85.51	0	52.68	-3.07	5.26	-48.59	68.88	-4.33	2.25	-24.26	2.50	-107.86	13.98	-32.72
2008	55.38	-5.18	0.58	-65.76	1.41	-56.22	56.47	-0.14	49.41	-1.21	35.86	-33.93	91.68	-0.06	8.06	-35.02	7.89	-31.33	0	-77.88
2009	27.06	-4.06	9.53	-71.84	2.31	-56.59	25.20	-44.95	89.58	0	49.97	-2.68	17.58	-9.47	27.87	-6.81	5.67	-36.50	6.17	-28.04
2010	3.45	-15.55	12.85	-45.87	2.73	-28.11	2.85	-88.99	17.18	-17.09	7.84	-11.67	111.55	0	81.18	-1.30	21.74	-17.98	9.47	-44.28
2011	72.00	-0.04	16.91	-36.84	6.13	-98.45	1.97	-72.49	17.37	-6.80	12.28	-5.83	86.64	0	13.23	-36.78	24.59	-17.80	25.37	-1.47
2012	101.98	0	0	-86.04	83.08	0	0	-96.20	7.40	-24.90	0.29	-37.32	80.27	0	19.05	-56.91	19.99	-11.22	14.43	-13.90
2013	53.14	-11.16	3.75	-40.15	67.84	0	84.52	-7.34	27.06	-4.40	9.88	-70.09	1.10	-38.24	27.18	-38.16	2.76	-23.12	0.22	-44.80
2014	2.45	-47.30	43.50	-26.45	82.97	-0.05	90.60	0	69.85	0	5.30	-75.77	6.85	-34.62	6.11	-22.01	7.73	-21.03	0.70	-88.85
2015	40.45	-25.86	0	-82.90	2.59	-52.80	57.67	-30.53	149.01	0	121.89	-0.09	24.39	-1.04	0	-106.31	73.95	0	0	-170.41
2016	59.76	0	7.55	-18.45	32.44	-4.02	8.95	-33.07	71.84	0	50.10	0	7.48	-13.28	0	-142.96	29.70	-1.44	2.07	-56.68
2017	76.22	0	0	-11.06	1.00	0	2.26	-4.97	2.06	-0.43	0.90	-7.03	0.11	-85.15	0	-42.31	3.09	-42.49	0	-68.76
Two Years Cumulative Net Fear Receivers and Transmitters																				
2000-2001	87.28	-21.77	60.86	-17.94	4.18	-54.65	19.42	-33.60	33.88	-32.54	10.25	-59.87	11.28	-20.75	84.18	-3.41	21.01	-41.97	13.59	-59.42
2002-2003	23.65	-80.16	98.64	-1.41	70.06	-78.04	82.52	-98.65	186.00	-1.30	47.51	-23.79	13.50	-112.74	22.93	-33.67	46.92	-82.88	21.35	-100.44
2004-2005	75.78	-26.93	73.67	-39.39	21.99	-68.55	106.75	-36.14	59.30	59.30	6.17	-116.60	31.11	-23.05	90.61	-30.18	8.30	-94.19	52.11	-83.15
2006-2007	72.36	-31.91	13.54	-107.89	86.35	-40.79	152.39	-0.64	65.34	-9.64	8.31	-75.63	98.02	-44.14	5.26	-44.76	4.47	-153.56	42.53	-39.63
2008-2009	82.45	-9.24	10.12	-137.61	3.73	-112.81	81.67	-45.09	139.00	-1.21	85.83	-36.62	109.26	-9.53	35.93	-41.84	13.57	-67.84	6.17	-105.93
2010-2011	75.45	-15.60	29.77	-82.72	8.87	-126.56	4.83	-161.49	34.56	-23.90	20.13	-17.51	198.19	0	94.42	-38.09	46.33	-35.79	34.84	-45.75
2012-2013	155.13	-11.16	3.75	-126.19	150.92	0	84.52	-103.54	34.47	-29.31	10.17	-107.42	81.37	-38.24	46.24	-95.07	22.75	-34.34	14.65	-58.71
2014-2015	42.91	-73.17	43.50	-109.35	85.56	-52.85	148.27	-30.53	218.86	0	127.19	-75.86	31.25	-35.67	6.11	-128.32	81.69	-21.03	0.70	-259.26
2016-2017	135.99	0	32.88	-29.83	87.35	-4.16	41.34	-38.31	123.05	-0.43	58.34	-7.03	8.75	-98.44	4.96	-185.84	39.00	-43.94	2.07	-126.05
Pre, During, Post Crisis Cumulative Net Fear Receivers and Transmitters																				
Pre-Crisis	234.15	-160.78	243.33	-152.60	179.00	-229.27	335.53	-169.05	326.11	-51.08	72.26	-253.24	107.89	-200.68	202.41	-102.95	80.71	-336.80	129.60	-254.53
Crisis	81.74	-8.42	3.98	-132.35	248.60	-89.39	107.23	-12.73	103.14	-1.23	73.34	-56.75	140.51	-7.54	28.06	-44.45	7.89	-88.26	1.78	-112.93
Post-Crisis	435.14	-100.75	119.45	-367.09	334.71	-219.73	278.98	-365.97	464.44	-53.65	228.08	-210.52	334.26	-174.34	160.21	-453.37	195.03	-151.04	56.67	-510.48
Total Period Cumulative Net Fear Receivers and Transmitters																				
2000-2017	751.04	-269.97	366.77	-652.05	519.04	-538.31	721.75	-547.76	893.70	-105.97	373.69	-520.36	582.67	-382.58	390.68	-600.65	283.64	-575.60	188.06	-877.78

Notes: This table shows the cumulative net aggregate fear connectedness receivers and transmitters for the ten main U.S. financial institutions. The aggregate VIX NET directional measure is computed as the difference between aggregate VIX TO and aggregate VIX FROM. When this difference is positive, the financial institution can be classified as a net aggregate fear connectedness transmitter (T), while, when negative, it can be classified as a net aggregate fear connectedness receiver (R). The ranking is reported for every year and every two years, for the pre-crisis, during crisis and post-crisis periods, and for the total period. For every considered period, the main volatility transmitters are highlighted in blue, while the main volatility receivers are highlighted in red. Selected VAR lags = 4 and Forecast Horizon = 12. The rolling window length is equal to 200 days. The selected period spans from 03-01-2000 to 29-12-2017 at a daily frequency.

Table 5.4 documents how the financial institutions change their roles as "fear" transmitters or receivers according to the specific market period. We rank the banks according to their aggregate VIX cumulative net directional connectedness for different time ranges, namely, every year, every two years, in the pre-crisis, during crisis and post-crisis periods and, lastly, over the total time period. Goldman Sachs, J.P. Morgan Chase and Citigroup are classified as the main aggregate net "fear" transmitters, according to the one-year and two-year cumulative rankings.

Bank of New York Mellon, PNC Bank and Bank of America are found to be the main financial institutions receiving "fear" from the system in the one-year and two-year period cumulative ranking. Citigroup and PNC Bank are identified as the main "fear" transmitter and receiver, respectively, in the pre-crisis period. Wells Fargo and Bank of America are the main transmitter and receiver, respectively, during the global financial crisis and Goldman Sachs and Bank of New York Mellon the main transmitter and receiver, respectively, post-crisis. Over the whole period, we observe that the main "fear" transmitters are Goldman Sachs and J.P. Morgan Chase, while the main "fear" receivers are Bank of New York Mellon and Bank of America. A graphical representation of the banks ranking is reported in the Appendix of this Chapter.

In the next Section 5.5, we study whether the financial institutions' roles are confirmed when we take into account upside and downside implied volatility indexes.

5.5 Asymmetric Fear Connectedness in the Financial Sector

5.5.1 Asymmetric Fear Connectedness: Static Analysis

Table 5.5 illustrates the asymmetry of the connectedness results emerging from the forecast error variance decompositions of VIX^{+} and VIX^{-} . The upside "fear" connectedness and the downside "fear" connectedness are reported in the upper and bottom panels, respectively. The overall connectedness from VIX^{+} (33.19%) is smaller than the total connectedness computed using the VIX index. The on-diagonal entries show that more than half of the fear in the system is generated by banks' own shocks to their VIX^{+} rather than external shocks. The upside directional FROM connectedness (right column) is also found to be lower than the aggregate, with values between 19.32% for Citigroup to 46.84% for Morgan Stanley, while the upside directional TO connectedness ranges from 11.81% for Bank of America to 61.02% for Goldman Sachs.

Although the strength of connection is lower, Goldman Sachs is still found to be the main "fear" transmitter in the system (19.33%), followed by Citigroup (9.05%). Morgan Stanley is detected as a upside "fear" receiver (-2.37%). We also find U.S. Bancorp to be a upside "fear" transmitter, while J.P. Morgan Chase is found to be a "fear" receiver. PNC Bank, Bank of America and Bank of New York Mellon can be classified, on average, as the main upside "fear" receivers in the system. The highest

upside pairwise connectedness is from Goldman Sachs to Morgan Stanley (17.76%) and, second, from Morgan Stanley to Goldman Sachs (12.18%) again.

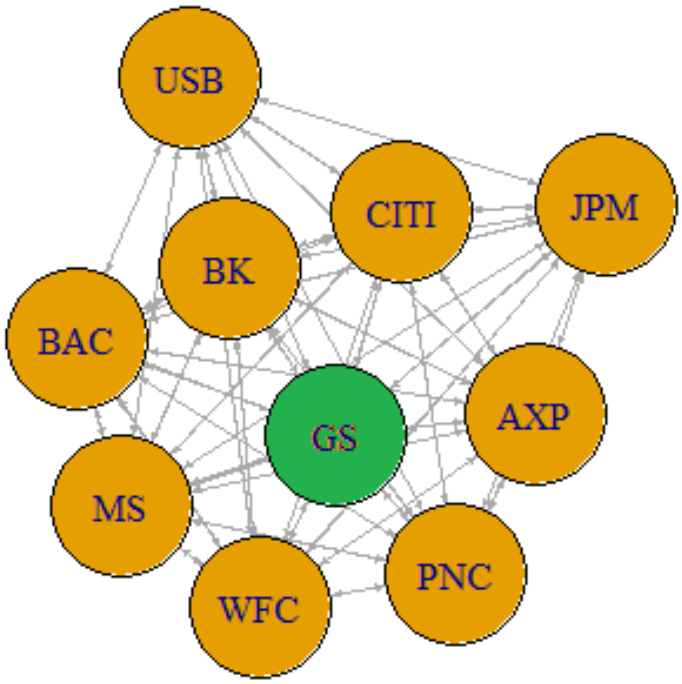
Table 5.5: **Asymmetric Fear Connectedness in the Financial Sector**

	JPM	BAC	WFC	CITI	GS	MS	USB	AXP	PNC	BK	FROM
					VIX^+ **Connectedness**						
JPM	73.69	0.79	1.55	1.67	4.11	5.28	5.53	2.79	0.73	3.82	26.30
BAC	0.90	79.51	1.85	3.36	2.28	2.52	0.80	3.63	0.90	4.20	20.48
WFC	3.04	0.88	72.25	3.53	6.20	1.39	3.80	4.13	1.01	3.70	27.74
CITI	0.72	2.05	2.10	80.67	4.04	1.73	1.48	2.79	1.88	2.49	19.32
GS	2.50	1.09	4.78	4.05	58.31	12.18	5.95	5.31	1.15	4.63	41.68
MS	4.05	1.76	2.39	3.56	17.76	53.15	4.03	3.64	1.88	7.72	46.84
USB	4.72	0.39	4.00	2.94	7.15	2.66	63.83	5.59	2.53	6.13	36.16
AXP	2.70	1.70	3.90	2.83	7.81	4.79	5.98	63.34	1.95	4.96	36.65
PNC	2.61	0.92	2.77	3.78	3.92	3.80	4.90	4.05	68.42	4.77	31.57
BK	3.67	2.17	3.46	2.61	7.71	10.08	6.52	5.98	2.90	54.85	45.14
TO	24.96	11.81	26.85	28.37	61.02	44.46	39.02	37.95	14.97	42.45	TOTAL
NET	-1.33	-8.66	-0.88	9.05	19.33	-2.37	2.85	1.29	-16.59	-2.68	**33.19**
					VIX^- **Connectedness**						
	JPM	BAC	WFC	CITI	GS	MS	USB	AXP	PNC	BK	FROM
JPM	73.08	1.50	0.54	3.86	5.04	3.45	6.28	3.97	0.69	1.54	26.91
BAC	0.89	80.11	3.92	2.68	2.57	4.19	2.79	0.45	0.91	1.45	19.88
WFC	1.79	2.75	73.53	4.57	5.42	1.83	2.08	2.69	2.99	2.29	26.46
CITI	2.43	2.33	2.82	80.73	2.42	2.57	1.71	2.10	1.09	1.76	19.26
GS	1.43	0.91	3.40	2.80	71.83	10.39	4.13	3.01	0.58	1.48	28.16
MS	2.85	2.24	2.25	3.71	15.69	65.02	2.90	1.32	0.83	3.15	34.97
USB	6.54	1.89	1.69	3.07	6.43	3.33	71.05	4.05	0.68	1.20	28.94
AXP	3.13	0.24	3.20	4.96	8.58	2.30	6.58	67.32	1.80	1.84	32.67
PNC	2.57	1.48	2.75	1.61	4.77	0.94	1.32	2.49	80.72	1.28	19.27
BK	1.23	2.60	3.79	3.61	4.04	5.79	1.47	1.82	1.27	74.32	25.67
TO	22.92	15.99	24.37	30.92	55.01	34.84	29.29	21.94	10.87	16.03	TOTAL
NET	-3.98	-3.89	-2.08	11.65	26.84	-0.12	0.35	-10.72	-8.39	-9.64	**26.22**

Notes: The table contains forecast error variance decomposition computed for the VIX^+ andVIX^- indexes for the ten main U.S. financial institutions. Elements in the off-diagonal entries are the pairwise directional connectedness, while the diagonal elements (in grey) are the financial institutions' own variance. The off-diagonal row and column sums to TO and FROM directional connectedness, respectively. The NET row at the bottom is the difference between TO and FROM. The bottom-right element is the total connectedness index in the considered system. Selected VAR lags = 4 and Forecast Horizon = 12 days. The selected time period spans from 03-01-2000 to 29-12-2017.

On the bottom panel of Table 5.5, we observe that the downside "fear" connectedness is even lower, being equal to 26.22%, which implies that only a quarter of all financial institutions' downside "fear" is generated by "fear" transmission within the system. The on-diagonal elements point to an even stronger role of the own shocks. The range of the downside directional FROM values is even narrower than in the case of the upside volatility analysis, with the lowest value equal to 19.26% for Citigroup and the highest value equal to 34.97% for Morgan Stanley. The downside directional TO connectedness is also quite low, except for Goldman Sachs, which transferred to the system most of the downside "fear" , making it the main net volatility transmitter. PNC Bank is found to have the lowest downside directional TO (10.87%), thus being one of the main net downside "fear" receivers, alongside Bank of New York Mellon and American Express. American Express changed its role from upside "fear" transmitter to downside "fear" receiver. In addition, the highest pairwise value of downside "fear" connectedness is found to be the one from Goldman Sachs to Morgan Stanley (15.69%), followed by the pair from Morgan Stanley to Goldman Sachs (10.39%).

Figure 5.6: **Positive Fear Connectedness Network**

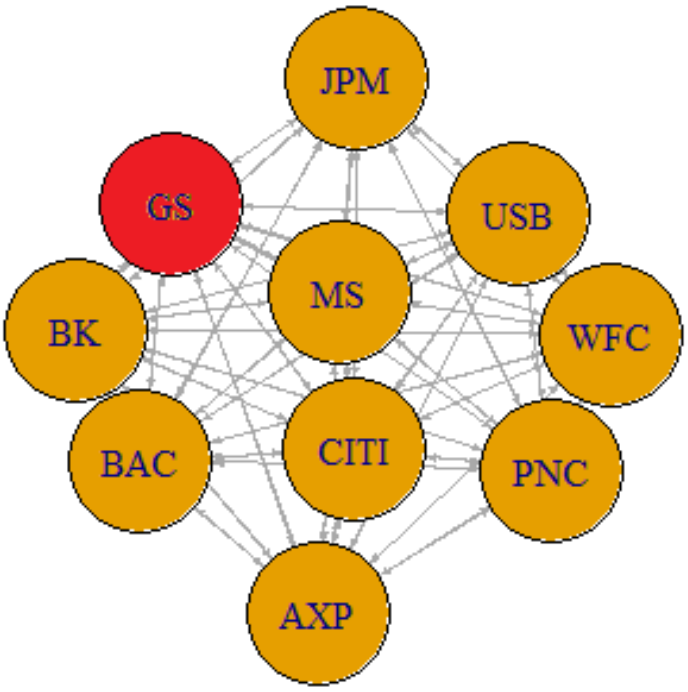


Notes: This figure shows the positive "fear" connectedness for the ten main financial institutions' VIX^{+} indexes as a network. Highlighted in green is the main VIX^{+} pairwise transmitter.

In Figure 5.6 and Figure 5.7 we plot the positive and negative "fear" connectedness network based on VIX^{+} and VIX^{-} , respectively. We represent thicker lines for banks which are more connected to each other. The highlighted banks are the main pairwise connectedness transmitters, being in both cases, Goldman Sachs.

Overall, these results show how some of the selected financial institutions change their roles from a net receiver to a net transmitter, or vice versa, when comparing aggregate to upside and downside implied volatility (or "fear") shocks, confirming asymmetries in the transmission mechanism. For instance, J.P. Morgan Chase is found to be an aggregate "fear" transmitter, whereas separate VIX^{+} and VIX^{-} show that it is found to be a upside and downside "fear" receiver. The opposite is found for Citigroup. Morgan Stanley's role as a "fear" transmitter is confirmed in the aggregate and downside case, while it is also found to be a upside "fear" receiver. Goldman Sachs is found to be the main winner in the financial sector, being an average "fear" transmitter, regardless of the nature of the volatility measure. PNC Bank, Bank of America and Bank of New York Mellon are, on the other hand, the

Figure 5.7: **Negative Fear Connectedness Network**



Notes: This figure shows the negative "fear" connectedness for the ten main financial institutions' VIX^{-} indexes as a network. Highlighted in red is the main VIX^{-} pairwise transmitter.

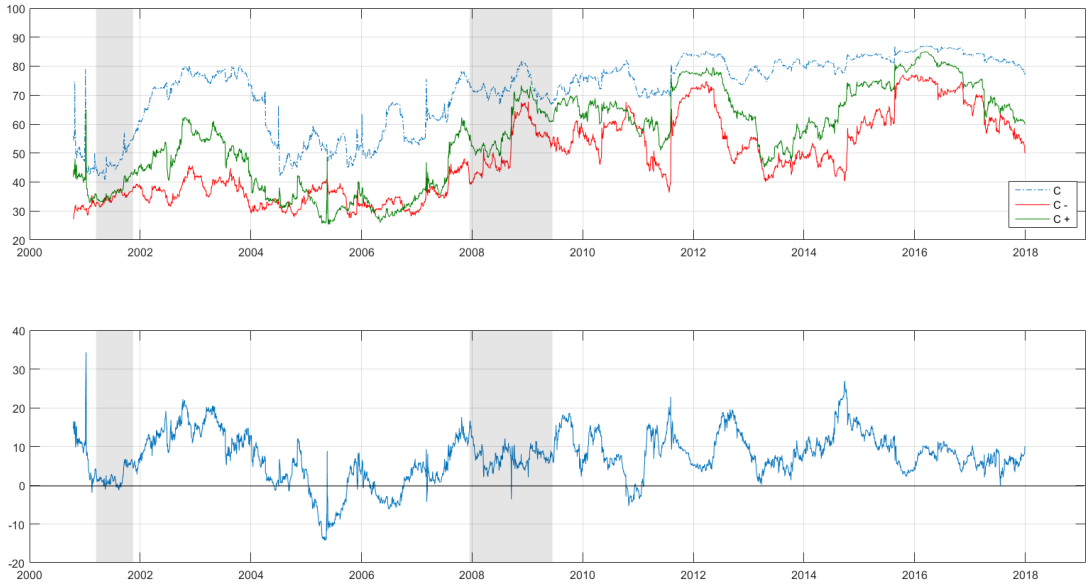
weakest banks, given that they receive volatility from the system, regardless of the volatility measure. The static picture may hide the different roles that upside and downside implied volatility (or "fear") connectedness have in relation to the different market periods. However, the next section 5.5.2 provides a more in-depth understanding of their separate roles by studying their changes over time.

5.5.2 Asymmetric Fear Connectedness: Time Dynamics

In Figure 5.8, we depict the fear connectedness indexes as computed from equation (5.7) and the asymmetric fear connectedness as computed from equation (5.12) over time.

Figure 5.8 confirms our preliminary finding that the connectedness due to upside "fear" plays a stronger role in the financial sector for the entire study period. However, in some specific periods, such as during the two recessions and during the Eurozone sovereign debt crisis, the downside "fear" connectedness increases. The peak in downside connectedness during 2006 can be justified by the extreme uncertainty about a possible U.S. housing bubble burst. The bottom plot in the Figure 5.8 shows

Figure 5.8: **Fear Connectedness Indexes and AFC**



Notes: The figure shows the comparison between the VIX , VIX^{+} , and VIX^{-} connectedness indexes, namely, $\mathcal{C}$, $\mathcal{C}^{+}$ and $\mathcal{C}^{-}$, in the upper panel. The bottom panel shows the asymmetric fear connectedness (AFC). Selected VAR lags = 4 and forecast horizon = 12. The rolling window length is equal to 200 days. The NBER recession periods are highlighted in grey. The selected period spans from 03-01-2000 to 29-12-2017 at a daily frequency.

that upside and downside "fear" connectedness become more intertwined depending on recessions, turbulent periods or crises. Overall, it appears that upside "fear" is the main factor to understand how the volatility of single U.S. financial companies is transmitted.

Further details can be inferred from Figure 5.8 by looking at the evolution of $\mathcal{C}^{+}$ and $\mathcal{C}^{-}$ over time. $\mathcal{C}^{+}$ spikes exactly before the 2000-2001 dot-com bubble, also dragging up the aggregate connectedness index, $\mathcal{C}$. As soon as the bubble burst, the upside connectedness index dropped. $\mathcal{C}^{-}$ is found to be lower than $\mathcal{C}^{+}$ before the recession, while it increased and remained at the same level in the midst of the recession. During 2002 and 2003, $\mathcal{C}^{+}$ was almost 50% higher than $\mathcal{C}^{-}$, but at the end of 2004, this trend inverted, with $\mathcal{C}^{-}$ overcoming $\mathcal{C}^{+}$ until mid-2006. Beginning in 2007, we find an increase in both the upside and downside "fear" connectedness indexes, with the AFC showing a positive-negative break at the end of 2006 and in September 2008. The two indexes spiked again at the beginning of 2011 with $\mathcal{C}^{-}$ overcoming $\mathcal{C}^{+}$, dragging the AFC below zero, in accordance with the Eurozone sovereign debt crisis. After that, the $\mathcal{C}^{-}$ and $\mathcal{C}^{+}$ average values increased even further. We also notice an increase in the $\mathcal{C}^{-}$ index when a crisis, recession or turbulent period impacted the U.S. financial sector. In systemic risk terms and monitoring purposes, $\mathcal{C}^{-}$ appears more in line with the description of an efficient systemic risk monitoring tool as explained in Adrian and Brunnermeier (2016). According to them, systemic risk typically builds up in times of low asset pricing volatility and it materializes during crisis. Thus, a good systemic risk measure should capture this build up.

In order to verify the different behaviors of the "fear" connectedness indexes, we compute a new

ratio as $\mathcal{C}^-$ on $\mathcal{C}^+$, which should better capture the relative role of $\mathcal{C}^-$. Indeed, put options reflect investors' negative expectations and beliefs about future financial and economic downturns since they are traded as insurance assets (e.g., Bollen and Whaley, 2004; Ang et al., 2006; Bondarenko, 2014). The $\mathcal{C}^-/\mathcal{C}^+$ ratio is plotted in the following Figure 5.9. Remarkably, this ratio had an abrupt rise and an equally rapid fall between 2005 and 2006, foreshadowing the subprime crisis.

Figure 5.9: **Asymmetric Fear Connectedness Ratio:** $\mathcal{C}^-/\mathcal{C}^+$

Notes: The figure shows the ratio between the "fear" connectedness index computed from puts only, $\mathcal{C}^-$, and the one computed from calls only, $\mathcal{C}^+$. Selected VAR lags = 4 and forecast horizon = 12. The rolling window length is equal to 200 days. The NBER recession periods are highlighted in grey. The selected period spans from 03-01-2000 to 29-12-2017 at a daily frequency.

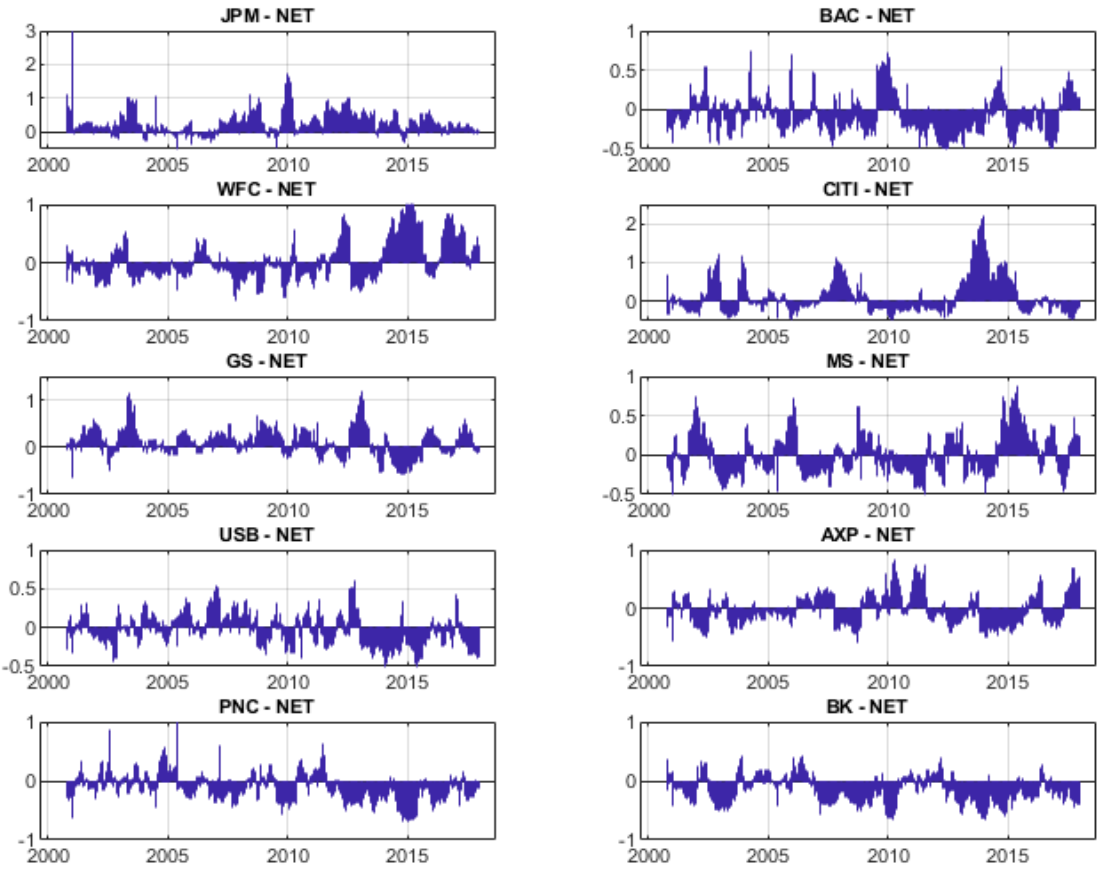
5.5.3 Asymmetric Net Fear Receivers and Transmitters

In this section, we analyze how the financial institutions can be classified as net upside or net downside "fear" transmitters or receivers.

Figures 5.10 and 5.11 show which are the U.S. financial institutions which contribute more to the upside and downside implied volatility connectedness, respectively. With regards to the upside volatility measures, we detect a clear upside volatility transmitter role for J.P. Morgan Chase. Overall, also Goldman Sachs can be classified as upside implied volatility transmitter, exception only for 2014 and 2015. Bank of America alternates its role, however it is found to be a clear upside volatility receiver during the Eurozone sovereign debt crisis. Morgan Stanley, Citigroup and Wells Fargo share the same alternating roles behaviour, but all of them show a noteworthy upside implied volatility transmitter role. Conversely to the aggregate volatility case, Citigroup transmits upside volatility during the global financial crisis, while it absorbs volatility during the sovereign debt crisis. PNC Bank and Bank of New York Mellon can be labelled as the main upside implied volatility receivers within the system.

With regards to the net directional downside implied volatility connectedness, different financial institutions' roles are found. For instance, Bank of America is found, this time, as net downside implied volatility receiver during the global financial crisis. Less clear cut role as volatility transmitter is found for J.P. Morgan Chase. Goldman Sachs behaves in the opposite way by receiving downside volatility during the sovereign debt crisis and transmitting downside volatility from the end of 2014. Not a clear role is found for Citigroup and Wells Fargo, while Morgan Stanley appears to behave as downside

Figure 5.10: **Upside Net Fear Connectedness**

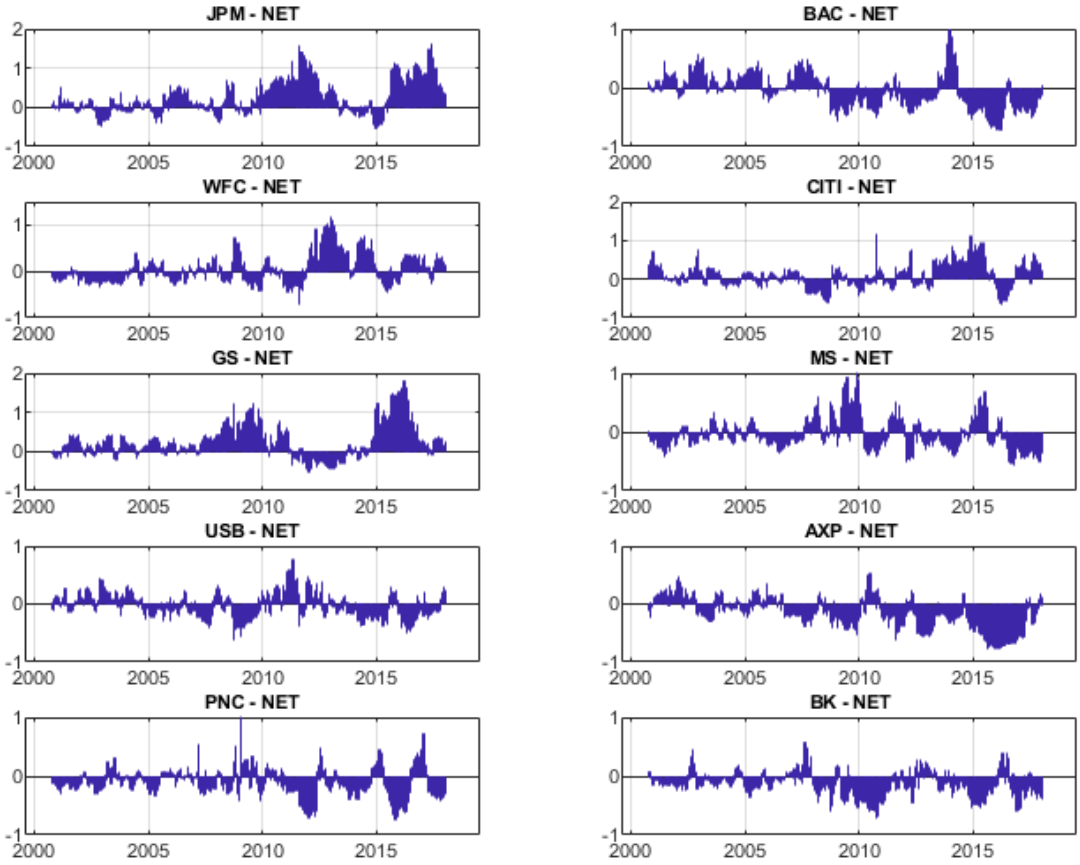


Notes: This figure shows the upside net "fear" connectedness for the ten main financial institutions. The NET upside directional connectedness is computed as difference between the upside TO and the upside FROM. Selected VAR lags = 4 and forecast horizon = 12. The rolling window length is equal to 200 days. The selected period spans from 03-01-2000 to 29-12-2017 at a daily frequency.

implied volatility transmitter during the global financial crisis. U.S. Bancorp, American Express, PNC Bank and Bank of New York Mellon are found to suffer the global financial crisis the most being downside implied volatility receivers.

Tables 5.6 and 5.7 rank the ten main banks according to their cumulative net upside and net downside "fear" transmitter or receiver role. We rank the financial institutions according to the results gathered every year, every two years, during the pre-crisis, crisis and post-crisis periods, and over the total time frame. From Table 5.6, J.P. Morgan Chase confirms its role as a main upside "fear" transmitter within the system at an annual frequency, being the top ranking transmitter over half of the period. Citigroup follows as a second main upside "fear" transmitter on an annual basis. On the other hand, Bank of New York Mellon is found as the main upside "fear" receiver on an annual basis, with PNC Bank and Morgan Stanley ranking next. Repeating this exercise at the two-year grouping, overall, the same ranking is obtained, namely, J.P. Morgan Chase is found to be the main upside "fear" transmitter and Bank of New York Mellon the main upside "fear" receiver. A more refined ranking of banks,

Figure 5.11: **Downside Net Fear Connectedness**



Notes: This figure shows the downside net "fear" connectedness for the ten main financial institutions. The NET downside directional connectedness is computed as difference between the downside TO and the downside FROM. Selected VAR lags = 4 and forecast horizon = 12. The rolling window length is equal to 200 days. The selected period spans from 03-01-2000 to 29-12-2017 at a daily frequency.

in our case according to upside or downside volatility transmitters and receivers, might be useful for regulators as stated in Acharya et al. (2012).

The cumulative main net upside connectedness transmitter for the pre-crisis period is found to be J.P. Morgan Chase, with Goldman Sachs contributing almost the same amount. In the pre-crisis period, the main upside "fear" receiver is Bank of New York Mellon, followed by Morgan Stanley. Interestingly, during the global financial crisis, Wells Fargo is classified as a main upside "fear" transmitter, while Bank of New York Mellon is found to be a upside "fear" receiver. For the post-financial crisis period, J.P. Morgan Chase is found to be the main upside "fear" transmitter, followed by Citigroup, while PNC Bank is found to be the main upside "fear" receiver. The total sample cumulative ranking shows, overall, that J.P. Morgan Chase is the main upside "fear" transmitter, whereas Bank of New York Mellon is the main upside "fear" receiver within the U.S. banking system.

Table 5.6: **Cumulative Net Upside Fear Connectedness Receivers and Transmitters**

Period	JPM		BAC		WFC		CITI		GS		MS		USB		AXP		PNC		BK	
	T	R	T	R	T	R	T	R	T	R	T	R	T	R	T	R	T	R	T	R
Annual Cumulative Net Upside Fear Connectedness Receivers and Transmitters																				
2000	34.62	0	0	-8.42	3.86	-2.63	1.23	-5.47	3.20	-0.25	0	-9.45	1.28	-3.12	0	-6.64	0	-13.43	5.46	-0.23
2001	52.05	-0.20	7.92	-24.05	0.47	-21.60	4.35	-32.46	49.69	-1.93	36.24	-17.55	11.21	-9.59	17.78	-12.39	6.19	-19.25	0.28	-47.13
2002	28.06	-4.08	15.67	-21.23	12.61	-45.76	87.55	-12.71	29.34	-14.87	41.10	-13.36	1.05	-40.24	3.26	-50.19	14.97	-11.09	15.78	-35.83
2003	117.42	-1.48	5.06	-28.69	25.35	-38.53	36.55	-60.45	105.35	-0.95	0.42	-65.88	7.73	-8.22	5.73	-45.92	11.47	-11.83	10.81	-63.54
2004	22.04	-7.06	16.92	-9.64	0	-33.06	18.00	-11.87	9.41	-5.78	10.50	-15.70	14.94	-7.30	0.42	-30.18	34.97	-11.05	15.34	-10.89
2005	5.44	-11.72	9.93	-26.46	0.23	-33.53	23.53	-14.54	33.06	-8.74	39.81	-13.08	28.88	-4.78	0.12	-21.06	23.30	-26.20	5.76	-9.96
2006	0.66	-28.58	11.75	-25.93	33.37	-3.35	0.13	-33.49	21.49	-6.58	23.61	-39.40	25.78	-7.49	25.10	-6.05	3.13	-26.06	35.41	-3.50
2007	62.48	-0.65	1.96	-43.85	0.98	-46.40	87.80	-1.63	41.49	-0.81	4.75	-34.59	42.55	-1.00	44.78	-18.52	1.14	-60.83	0	-79.64
2008	124.07	0	3.21	-36.33	0.04	-68.10	88.18	-0.39	38.50	-2.12	21.06	-15.74	18.83	-15.64	3.13	-69.30	8.19	-22.74	0	-74.84
2009	62.11	-7.60	47.17	-34.16	3.19	-33.70	4.57	-38.17	60.15	-4.50	23.31	-11.87	10.10	-23.00	41.89	-2.97	10.30	-40.29	1.01	-67.56
2010	101.81	-1.41	27.18	-20.80	8.35	-38.87	0	-61.36	47.23	-7.16	0.51	-35.35	14.49	-22.95	60.93	-3.97	17.04	-32.79	5.33	-58.20
2011	107.92	-0.12	0	-55.48	11.84	-25.94	1.23	-37.42	13.99	-16.57	5.51	-54.13	7.50	-27.54	70.42	-11.66	26.76	-14.81	8.69	-10.19
2012	151.02	0	0	-102.13	63.01	-33.45	8.50	-34.72	51.42	-27.26	23.32	-19.39	37.72	-4.16	1.71	-34.87	0.15	-65.18	12.18	-27.87
2013	70.79	-2.01	0.01	-55.81	1.50	-60.83	269.07	0	71.50	-28.11	10.60	-28.60	0	-60.57	10.12	-29.69	0	-68.96	0	-99.00
2014	52.54	-7.73	24.66	-7.60	132.74	0	195.24	0	6.47	-80.79	36.78	-30.47	1.29	-60.99	0	-86.40	0.40	-82.68	0.20	-93.67
2015	77.85	-0.21	0.27	-56.83	127.94	-9.98	48.79	-34.30	20.52	-49.90	106.17	0	0.07	-61.74	5.62	-43.64	0.08	-81.37	0.21	-49.55
2016	36.89	-0.59	1.69	-51.69	91.98	-9.09	5.76	-14.30	19.67	-13.89	35.01	-5.28	3.59	-15.42	28.87	-25.88	0.95	-60.76	6.18	-33.69
2017	23.72	-0.46	35.34	-8.79	69.53	-1.44	0.01	-57.34	49.77	-3.90	20.13	-31.60	8.19	-47.82	56.52	-17.57	2.31	-37.42	0	-59.20
Two Years Cumulative Net Upside Fear Connectedness Receivers and Transmitters																				
2000-2001	86.67	-0.20	7.92	-32.48	4.34	-24.24	5.59	-37.93	52.90	-2.19	36.24	-27.01	12.49	-12.72	17.78	-19.04	6.19	-32.69	5.74	-47.36
2002-2003	145.48	-5.57	20.73	-49.93	37.96	-84.30	124.11	-73.16	134.70	-15.83	41.15	-79.25	8.78	-48.47	9.00	-96.12	26.45	-22.93	26.59	-99.38
2004-2005	27.48	-18.79	26.85	-36.10	0.23	-66.59	41.53	-26.42	42.48	42.48	50.32	-28.78	43.83	-12.09	0.54	-51.25	58.28	-37.26	21.10	-20.85
2006-2007	63.14	-29.24	13.72	-69.79	34.35	-49.76	87.93	-35.12	62.99	-7.40	28.36	-74.00	68.34	-8.50	69.89	-24.58	4.28	-86.90	35.41	-83.15
2008-2009	186.18	-7.60	50.38	-70.50	3.24	-101.81	92.75	-38.56	98.66	-6.63	44.37	-27.62	28.94	-38.64	45.03	-72.27	18.50	-63.04	1.01	-142.41
2010-2011	209.74	-1.53	27.18	-76.28	20.20	-64.81	1.23	-98.78	61.22	-23.74	6.02	-89.49	21.99	-50.50	131.36	-15.63	43.80	-47.60	14.02	-68.39
2012-2013	221.82	-2.01	0.01	-157.95	64.51	-94.29	277.57	-34.72	122.92	-55.37	33.93	-47.99	37.72	-64.73	11.84	-64.57	0.15	-134.14	12.18	-126.87
2014-2015	130.40	-7.95	24.94	-64.44	260.68	-9.98	244.03	-34.30	26.99	-130.69	142.96	-30.47	1.36	-122.73	5.62	-130.05	0.48	-164.05	0.41	-143.22
2016-2017	60.62	-1.05	37.04	-60.49	161.51	-10.53	5.78	-71.64	69.45	-17.79	55.15	-36.88	11.79	-63.25	85.40	-43.45	3.26	-98.19	6.18	-92.89
Pre, During, Post Crisis Cumulative Net Upside Fear Connectedness Receivers and Transmitters																				
Pre-Crisis	296.65	-53.72	67.45	-176.46	76.90	-192.43	200.40	-172.65	286.35	-39.15	151.48	-206.16	117.03	-81.70	93.77	-172.67	95.21	-152.90	88.85	-226.25
Crisis	156.85	-4.38	4.99	-81.24	346.20	-105.24	151.53	-19.39	87.84	-2.94	45.08	-19.38	38.44	-30.44	33.67	-87.63	18.44	-52.26	0.07	-137.30
Post-Crisis	672.65	-15.86	136.46	-344.05	508.77	-209.63	528.76	-259.05	295.44	-234.59	239.37	-219.47	80.93	-308.60	247.85	-259.77	47.56	-482.80	36.70	-460.67
Total Period Cumulative Net Upside Fear Connectedness Receivers and Transmitters																				
2000-2017	1126.16	-73.97	208.92	-601.76	588.15	-507.16	880.70	-451.10	669.63	-276.68	435.94	-444.87	236.41	-420.75	375.30	-520.08	161.22	-687.78	125.64	-823.92

Notes: This table shows the cumulative net upside fear connectedness receivers and transmitters for the ten main U.S. financial institutions. The upside VIX NET directional measure is computed as the difference between upside VIX TO and upside VIX FROM. When this difference is positive, the financial institution can be classified as a net upside fear connectedness transmitter (T), while, when negative, it can be classified as a net upside fear connectedness receiver (R). The ranking is reported for every year and every two years, for the pre-crisis, during crisis and post-crisis periods, and for the total period. For every considered period, the main volatility transmitters are highlighted in blue, while the main volatility receivers are highlighted in red. Selected VAR lags = 4 and Forecast Horizon = 12. The rolling window length is equal to 200 days. The selected period spans from 03-01-2000 to 29-12-2017 at a daily frequency.

Table 5.7: **Cumulative Net Downside Fear Connectedness Receivers and Transmitters**

Period	JPM		BAC		WFC		CITI		GS		MS		USB		AXP		PNC		BK	
	T	R	T	R	T	R	T	R	T	R	T	R	T	R	T	R	T	R	T	R
Annual Cumulative Net Downside Fear Connectedness Receivers and Transmitters																				
2000	1.95	-0.16	0.45	-1.53	0	-8.79	25.44	0	0.02	-4.67	0	-6.08	3.48	-0.60	0.31	-2.36	0	-5.45	0.82	-2.82
2001	19.42	-6.22	28.83	-0.57	0.80	-21.77	30.90	-2.68	39.45	-5.31	0	-50.46	10.77	-7.12	33.13	-0.07	0	-39.00	0	-30.10
2002	12.68	-29.32	43.84	-6.62	0	-52.33	33.48	-5.98	16.49	-3.88	2.67	-21.71	32.24	-2.19	33.36	-5.04	0.87	-33.95	10.57	-25.17
2003	9.99	-27.68	32.94	-3.13	0	-52.42	31.77	-4.96	45.54	-8.64	10.43	-11.47	30.91	-1.76	8.43	-35.24	11.93	-12.70	0.18	-24.13
2004	12.03	-6.76	23.72	-1.25	14.13	-13.77	4.51	-25.11	24.27	-2.76	7.72	-15.40	19.81	-7.25	2.43	-10.71	2.32	-20.28	6.86	-14.50
2005	17.35	-28.12	46.57	-4.40	18.26	-8.40	11.48	-12.31	37.70	-1.90	11.23	-11.63	0.85	-27.46	17.02	-6.07	5.97	-27.90	2.69	-40.91
2006	79.94	-0.05	6.94	-14.20	2.53	-32.44	19.43	-1.99	24.70	-1.35	0	-53.44	4.69	-17.69	12.56	-14.71	6.49	-6.62	1.57	-16.34
2007	10.16	-10.68	55.51	-0.27	17.94	-3.89	13.64	-31.31	51.93	-0.97	13.57	-16.28	4.02	-43.72	0	-53.23	1.89	-39.44	34.35	-3.20
2008	41.83	-18.84	11.01	-27.29	44.22	-20.31	4.24	-73.92	129.45	0	37.06	-7.75	11.24	-34.65	3.89	-25.14	7.33	-28.15	0.88	-55.10
2009	22.21	-13.86	0.18	-69.02	8.19	-51.68	13.91	-18.02	189.41	0	105.63	-1.72	1.75	-53.61	0	-82.85	24.91	-16.10	3.02	-62.35
2010	132.70	0	0	-71.57	14.78	-12.02	10.60	-21.99	65.95	-0.54	10.06	-55.89	27.40	-3.81	36.53	-5.91	7.05	-12.87	0	-120.47
2011	210.89	0	9.12	-13.17	2.20	-69.50	13.88	-17.07	15.61	-31.74	29.90	-6.91	72.93	-12.40	0.08	-68.23	0	-91.17	0.64	-45.05
2012	131.96	0	0	-58.05	141.43	0	23.69	-14.89	0.01	-67.17	4.68	-45.96	27.32	-8.92	3.09	-69.06	9.95	-70.55	16.23	-23.73
2013	29.03	-9.66	45.34	-17.91	108.62	-2.93	70.49	-7.91	3.93	-50.83	0.33	-36.56	2.81	-19.23	0.06	-67.46	1.31	-39.64	6.40	-16.21
2014	2.12	-38.98	40.52	-43.42	99.04	-0.35	135.83	0	36.63	-9.92	5.86	-35.61	0.08	-53.87	2.03	-52.82	6.43	-45.12	0.02	-48.50
2015	98.37	-31.42	0	-116.76	0.26	-49.38	111.12	-1.18	253.76	0	54.77	-11.84	8.24	-30.02	0	-142.70	21.50	-80.67	0	-84.05
2016	194.70	0	1.97	-90.66	50.38	-1.87	12.11	-74.74	228.49	0	5.30	-60.42	1.39	-61.29	0	-169.79	26.77	-49.26	23.59	-36.67
2017	201.89	0	0.07	-81.55	32.31	-5.30	80.31	-1.41	41.72	-1.40	0	-94.73	9.75	-22.89	3.08	-54.29	14.91	-63.09	0.62	-60.00
Two Years Cumulative Net Downside Fear Connectedness Receivers and Transmitters																				
2000-2001	21.38	-6.38	29.29	-2.11	0.80	-30.57	56.35	-2.68	39.47	-9.98	0	-56.54	14.26	-7.72	33.44	-2.44	0	-44.45	0.82	-32.93
2002-2003	22.68	-57.00	76.79	-9.76	0	-104.75	65.26	-10.94	62.04	-12.52	13.11	-33.19	63.15	-3.95	41.80	-40.29	12.80	-46.66	10.75	-49.31
2004-2005	29.39	-34.89	70.29	-5.66	32.39	-22.17	15.99	-37.43	61.98	-4.67	18.96	-27.04	20.67	-34.72	19.45	-16.79	8.29	-48.19	9.55	-55.42
2006-2007	90.10	-10.74	62.46	-14.47	20.47	-36.34	33.07	-33.31	76.63	-2.33	13.57	-69.73	8.72	-61.42	12.56	-67.94	8.39	-46.06	35.92	-19.55
2008-2009	64.04	-32.71	11.19	-96.32	52.42	-72.00	18.16	-91.94	318.86	0	142.70	-9.48	13.00	-88.26	3.89	-108.00	32.25	-44.26	3.90	-117.45
2010-2011	343.59	0	9.12	-84.74	16.98	-81.53	24.49	-39.07	81.57	-32.29	39.97	-62.81	100.33	-16.22	36.62	-74.15	7.05	-104.04	0.64	-165.53
2012-2013	161.00	-9.66	45.34	-75.96	250.06	-2.93	94.18	-22.81	3.95	-118.01	5.01	-82.52	30.13	-28.16	3.15	-136.53	11.26	-110.19	22.64	-39.95
2014-2015	100.50	-70.41	40.52	-160.18	99.30	-49.73	246.96	-1.18	290.39	-9.92	60.64	-47.46	8.33	-83.89	2.03	-195.52	27.94	-125.79	0.02	-132.56
2016-2017	396.59	0	2.05	-172.22	82.70	-7.17	92.42	-76.16	270.21	-1.40	5.30	-155.15	11.15	-84.19	3.08	-224.08	41.68	-112.36	24.21	-96.68
Pre, During, Post Crisis Cumulative Net Downside Fear Connectedness Receivers and Transmitters																				
Pre-Crisis	159.58	-102.11	225.35	-31.97	42.06	-193.81	170.68	-57.96	217.92	-29.52	34.37	-186.44	103.04	-98.19	107.27	-106.85	29.49	-171.36	44.25	-155.81
Crisis	46.22	-38.49	24.50	-70.61	381.86	-35.21	18.16	-101.58	248.87	0	99.02	-9.15	15.01	-84.63	3.89	-86.58	22.38	-45.87	15.97	-87.03
Post-Crisis	1024.36	-81.19	94.65	-531.58	448.44	-179.08	461.28	-155.96	738.17	-162.73	169.54	-346.06	151.25	-225.42	44.69	-673.11	97.84	-463.04	49.27	-461.32
Total Period Cumulative Net Downside Fear Connectedness Receivers and Transmitters																				
2000-2017	1230.17	-221.80	344.50	-634.17	554.53	-408.11	650.13	-315.19	1204.97	-192.25	302.94	-541.66	269.31	-407.92	155.87	-866.30	149.73	-680.09	109.50	-704.17

Notes: This table shows the cumulative net downside fear connectedness receivers and transmitters for the ten main U.S. financial institutions. The downside VIX NET directional measure is computed as the difference between downside VIX TO and downsideVIX FROM. When this difference is positive, the financial institution can be classified as a net downside fear connectedness transmitter (T), while, when negative, it can be classified as a net downside fear connectedness receiver (R). The ranking is reported for every year and every two years, for the pre-crisis, during crisis and post-crisis periods, and for the total period. For every considered period, the main volatility transmitters are highlighted in blue, while the main volatility receivers are highlighted in red. Selected VAR lags = 4 and Forecast Horizon = 12. The rolling window length is equal to 200 days. The selected period spans from 03-01-2000 to 29-12-2017 at a daily frequency.

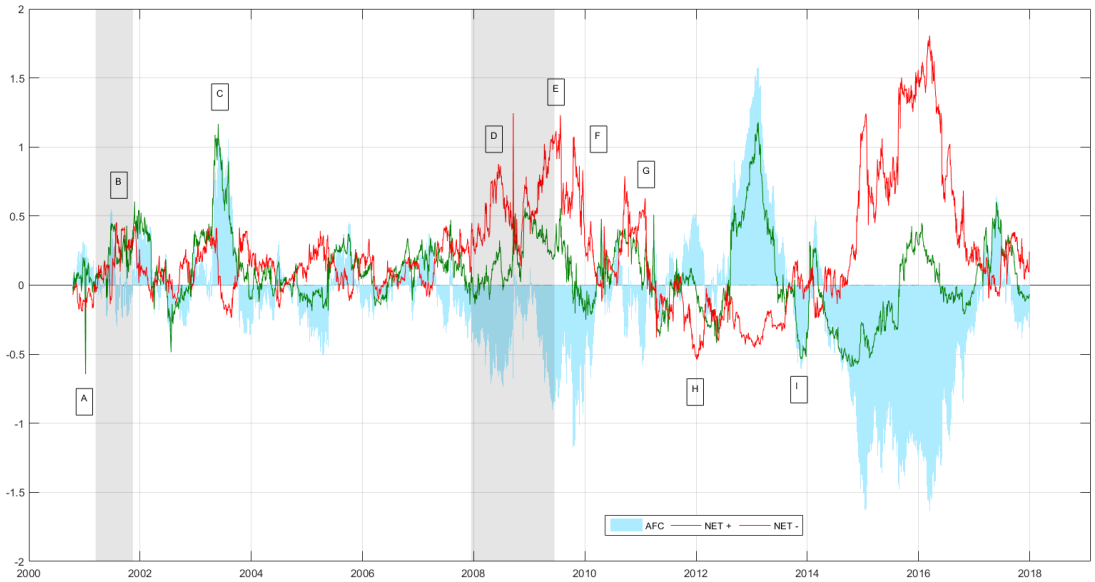
Table 5.7 shows the ranking for the net downside "fear" connectedness. The annual ranking highlights a main contribution in the downside "fear" transmission from Goldman Sachs, followed by J.P. Morgan Chase and Wells Fargo. American Express played the main role in terms of annual downside "fear" reception, followed by Morgan Stanley. For the two-year ranking, we find, again, Goldman Sachs, J.P. Morgan Chase and Wells Fargo to be the main downside "fear" transmitters and a clearer role for American Express and Bank of New York Mellon as downside "fear" receivers. The pre-crisis, crisis and post-crisis periods rankings indicate that Bank of America, Wells Fargo and J.P. Morgan Chase had the main downside "fear" transmitter roles, respectively. Wells Fargo is found to be the main downside "fear" receiver in the pre-crisis period, Citigroup during the financial crisis and American Express in the post-crisis period. Over the total sample period, the downside cumulative "fear" connectedness picture points to J.P. Morgan Chase and Goldman Sachs as the main transmitters of downside "fear" to the system and to American Express as the main institution receiving downside "fear" from the system. A graphical representation of Tables 5.6 and 5.7 is reported in the Appendix of this Chapter.

5.5.4 Additional Analysis of Individual Financial Firm Net Fear Connectedness

This section contains case studies on financial institutions that are found to be the top net aggregate "fear" transmitters and receivers in our previous analysis. We investigate this bank more closely, reporting the dynamics of the connectedness in response to systematic and specific events. We present the net directional "fear" connectedness indexes, together with the net AFC of the single financial institution in order to determine their asymmetric behavior over the studied time period. We denote the net upside "fear" as $\mathcal{C}^{+}_{j,\text{NET}}$ and the net downside "fear" as $\mathcal{C}^{-}_{j,\text{NET}}$. For instance in the Goldman Sachs case, we denote the net upside "fear" as $\mathcal{C}^{+}_{GS,\text{NET}}$ and the net downside "fear" as $\mathcal{C}^{-}_{GS,\text{NET}}$. The same notation will apply for these banks, and major specific company events, along with systematic events, will be reported for the selected time period.

Figure 5.12 captures the net upside and net downside "fear" connectedness and the net AFC for Goldman Sachs. In January 2000, Goldman Sachs and Lehman Brothers were the lead managers for the first internet bond offering for the World Bank, which is found to correspond to one of the highest levels of $\mathcal{C}^{+}_{GS,\text{NET}}$ received by Goldman Sachs. When Goldman Sachs purchased Spear, Leeds and Kellogg in September 2000 for more than \$6 billion, significant upside and downside "fear" was transmitted into the system. In 2003, Goldman Sachs took an almost 50% stake in a joint venture together with JBWere, which resulted in a spike of $\mathcal{C}^{+}_{GS,\text{NET}}$ transmitted, together with an increase in absorbed $\mathcal{C}^{-}_{GS,\text{NET}}$. We find $\mathcal{C}^{-}_{GS,\text{NET}}$ transmission during the financial crisis, especially in 2007, when Goldman Sachs' traders bet against the mortgage market, which gave an alarming pessimistic signal to the U.S. financial sector. In October 2008, Goldman Sachs received a \$10-billion preferred stock investment from the U.S. Treasury as part of the Troubled Asset Relief Program (TARP). This bailout intervention appears to increase the

Figure 5.12: **Net Fear Connectedness and Net AFC - Goldman Sachs**



Notes: The figure shows the net upside "fear" connectedness, $\mathcal{C}^{+}_{GS,\text{NET}}$, and net downside "fear" connectedness, $\mathcal{C}^{-}_{GS,\text{NET}}$ for Goldman Sachs, together with the AFC, computed as difference between the two. The figure also reports the main specific company events during the time period: [A] First Internet Bond Offering [B] Spear, Leeds and Kellogg Acquisitions [C] Joint Venture with JBWere [D] Short-Selling of Subprime Mortgage-Backed Securities [E] $10 Billion Preferred Stock from TARP [F] TARP Repayment [G] JBWere Full Control [H] Global Alpha Fund Shutdown [I] $17 Billion Bond Offering by Apple Inc. Selected VAR lags = 4 and forecast horizon = 12.The rolling window length is equal to 200 days. The NBER recession periods are highlighted in grey. The selected period spans from 03-01-2000 to 29-12-2017 at a daily frequency.

U.S. financial sector instability resulting in an increase in transmitted $\mathcal{C}^{-}_{GS,\text{NET}}$. In June 2009, Goldman Sachs repaid the U.S. TARP investment, resulting in a drop in the transmitted net $\mathcal{C}^{-}_{GS,\text{NET}}$, while in an increase in the received $\mathcal{C}^{+}_{GS,\text{NET}}$ as a sign of recovery. Later on, in 2011, Goldman Sachs took over JBWere, which contributed to the reception of both net upside and net downside "fear" . One of the highest peaks of $\mathcal{C}^{+}_{GS,\text{NET}}$ received is found in April 2013, when Goldman Sachs, together with Deutsche Bank, led a $17 billion bond offering by Apple Inc., one of the largest non-bank bond deals in history. During the same year, Goldman Sachs led Twitter's IPO. Both IPOs resulted in a stable $\mathcal{C}^{+}_{GS,\text{NET}}$ reception and a $\mathcal{C}^{-}_{GS,\text{NET}}$ transmission for Goldman Sachs from that time onwards. The spike of downside volatility between 2014 and 2016 might be due to different reasons: Goldman Sachs might have been detected as a downside volatility transmitter along these two years because of the foreign investments through banks in Malaysia which have been investigated by the U.S. since these deals were found to generate commissions above average. Thus criminal charges against Goldman Sachs were filled. Another potential reason for the downside volatility connectedness increase may be the political exposure that Goldman Sachs had during the president Trump election in 2016.

Figure 5.13 displays the net "fear" connectedness and the net AFC for J.P. Morgan Chase. In September 2000, the merger between J.P.Morgan & Co. and Chase Manhattan combined two of the largest banks in New York City into J.P. Morgan Chase & Co., resulting in a huge spike of transmitted $\mathcal{C}^{+}_{JPM,\text{NET}}$ and optimistic reactions among American investors. Another peak in $\mathcal{C}^{+}_{JPM,\text{NET}}$ transmission

is found in 2004, when J.P. Morgan Chase $ Co. merged with Bank One, enlarging its presence across the U.S.

Figure 5.13: **Net Fear Connectedness and AFC - J.P. Morgan Chase**

Notes: The figure shows the net upside "fear" connectedness, $\mathcal{C}^{+}_{JPM,\text{NET}}$, and net downside "fear" connectedness, $\mathcal{C}^{-}_{JPM,\text{NET}}$ for J.P. Morgan Chase, together with the AFC, computed as difference between the two. The figure reports also the main specific company events along the time period: [A] J.P. Morgan & Co. Merges with Chase Manhattan [B] Merge with Bank One [C] Bank of New York Mellon' Retail Banking Acquisition. [D] Acquisition of Bear Stearns [E] Washington Mutual Takeover [F] Cazenove Group Acquisition Announcement [G] Settlement of Investigations over Mortgage-Backed Securities [H] Commodities Division Sale [I] Legal and Fraudulent News. Selected VAR lags = 4 and forecast horizon = 12. The rolling window length is equal to 200 days. The NBER recession periods are highlighted in grey. The selected period spans from 03-01-2000 to 29-12-2017 at a daily frequency.

In April 2006, J.P.Morgan Chase acquired Bank of New York Mellon's retail banking and regional middle-market businesses, then exited from the retail banking, which resulted in both a transmission of downside and a reception of upside $\mathcal{C}_{JPM,\text{NET}}$. In 2008, due to the deteriorating market conditions and capitalization of Bear Stearns & Co. Inc., J.P. Morgan Chase acquired the bank for only $ 236 million. However, related to this event, we find both upside and downside $\mathcal{C}_{JPM,\text{NET}}$ transmission in the system, meaning investors had different views on this acquisition. A few months later, in September 2008, J.P. Morgan Chase took over Washington Mutual, an event that transmitted mainly $\mathcal{C}^{+}_{JPM,\text{NET}}$ in the financial sector. The spike $\mathcal{C}^{+}_{JPM,\text{NET}}$ transmission at the end of 2009 may be due to the announcement by J.P. Morgan Chase that it would buy the rest of Cazenove Group for 1 billion pounds. In November 2013, J.P. Morgan Chase received downside"fear" from the system when the Justice Department announced that J.P. Morgan Chase had to pay $ 13 billion to settle investigations over mortgage-backed securities. One year later, J.P. Morgan sold its commodities division to Mercuria for a quarter of its initial valuation, which resulted in a $\mathcal{C}^{-}_{JPM,\text{NET}}$ reception. In 2017, J.P. Morgan Chase was found to transmit $\mathcal{C}^{-}_{JPM,\text{NET}}$ in the financial sector due to news in relation to former employee frauds, a former COO's resignation and a lawsuit filed by the Nigerian government with regard to money transfers to a former corrupt minister.

Figure 5.14 shows the net directional upside and downside "fear" connectedness for Citigroup together with its AFC and main events in the selected time period. In 2001, Citigroup acquired European American Bank, in July and Banamex in August. Citigroup spun off its Travelers Property and Casualty insurance in 2002 because Travelers earnings were more seasonal and dependent on large disasters and events such as the September 11 attacks. We find this operation resulted in a upside volatility transmission from the parent company to the system. The number of bad mortgages of Citigroup, some of them resulting of mortgage fraud, started to increase in 2007 exceeding 80% of the volume, thus being subject to external investigation. Moreover, when the crisis began, Citigroup announced a restructuring operation with the aim to eliminate 17,000 jobs, or about 5 percent of its workforce in order to cut costs. When the crisis intensified and worsened, Citigroup announced in January 2008 cutting another 5% to 10% of its 327,000 workforce. In November 2008, Citigroup was insolvent, despite the $25 billion federal TARP funds and announced plans for other new job cuts resulting from four quarters of consecutive losses and reports that it was unlikely to be in profit again before 2010. The stock price responded falling from $540 in mid 2007 to about $20 in February 2009, dropping the Citigroup market capitalization to $6 billion, down from $300 billion of two years before. This resulted in one of the peak of downside "fear" received from Citigroup in all its history. On June 1, 2009, it was announced that Citigroup would be removed from the Dow Jones Industrial Average effective June 8, 2009, due to significant government ownership. Citigroup was replaced by Travelers Co. At the end of November 2008, the U.S. government approved a massive bailout program to rescue Citigroup from bankruptcy by providing $45 billion in TARP funds, this made to prevent a financial sector panic and chaos spread, thus, resulting in a increase in upside "fear" received, first from the system and, later in 2009, from Citigroup which started to recover.

The upside "fear" received was also due to the reorganization of Citigroup in two operating units, also in 2009. By December 2010, Citigroup repaid the emergency aid in full resulting in a spike in upside "fear" transmission as a synonym of stability. In March 2012 was reported that Citigroup was one of the four financial institutions, out of 19 major banks, that failed its stress tests. In March 2014, the Federal Reserve Board of Governors reported that Citigroup was one of the 5 financial institutions that failed its stress tests. In March 2015, Citi has passed its first CCAR test resulting in a increase in received upside "fear" connectedness.

In Figure 5.15, with regard to Bank of America, we observe that the net upside "fear" , $\mathcal{C}^{+}_{BAC,\text{NET}}$, is transmitted to the system when Bank of America agreed to acquire FleetBoston Financial for $47 billion at the end of 2003 and when the merger between Bank of America and the credit card giant, MBNA, for $35 billion was announced in July 2005 and then finalized in January 2006. Furthermore, in May 2006, Bank of America and the Brazilian Banco Itaú entered into a merger agreement. In November 2006, Bank of America announced the purchase of The United States Trust Company from

Figure 5.14: **Net Fear Connectedness and AFC - Citigroup**

Notes: This figure shows the net upside and net downside directional fear connectedness for Citigroup together with net AFC computed as difference between net upside and net downside connectedness. The Figure reports also the main specific company events along the time period: [A] European American Bank and Banamex Acquisition [B] Travelers Property Casualty Insurance Spin off [C] Restructuring and Workforce Cutting [D] Insolvency and Financial Crisis [E] Stock Price and Capitalization Fall [F] U.S. Government TARP Bailout [G] Reorganization in two Units [H] Fund Repayment [I] Stress Test Failure (a) [J] Stress Test Failure (b) [K] CCAR Test. Selected VAR lags = 4 and forecast horizon = 12. The rolling window length is equal to 200 days. NBER recession periods highlighted in grey. The selected period spans between 03-01-2000 to 30-04-2016 at daily frequency.

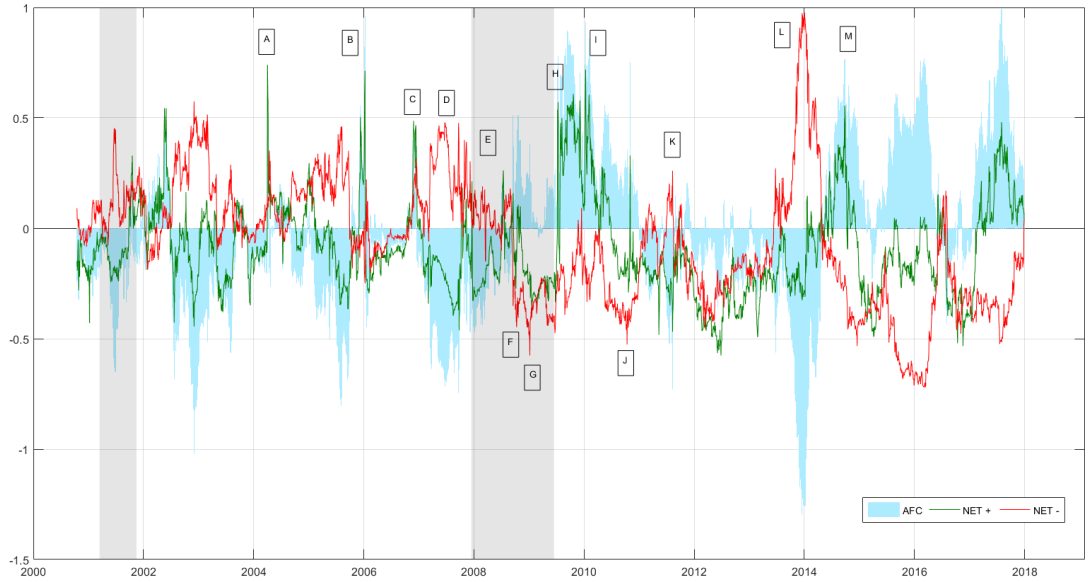
the Charles Schwab Corporation for $3.3 billion, which resulted in a $\mathcal{C}^{-}_{BAC,\text{NET}}$, transmission together with a $\mathcal{C}^{+}_{BAC,\text{NET}}$ reception. The agreement in September 2007 to buy LaSalle Bank Corporation from ABN AMRO for $21 billion increased the level of $\mathcal{C}^{+}_{BAC,\text{NET}}$ received from Bank of America, while different "fear" connectedness is found for two other acquisitions by Bank of America in the midst of the global financial crisis. For instance, in January 2008, Bank of America agreed to a $4 billion acquisition of Countrywide Financial, which resulted in a $\mathcal{C}^{-}_{BAC,\text{NET}}$ reception[8]. We find an even higher level of $\mathcal{C}^{-}_{BAC,\text{NET}}$ received by Bank of America in correspondence to the announcement of the acquisition of Merrill Lynch & Co., Inc. for $50 billion in September 2008. This deal was clearly made with the aim to save Merrill Lynch from bankruptcy, thus reflecting investors' negative expectations and uncertainty about it. Even if this acquisition made Bank of America one of the largest financial services companies in the world, it was not seen in positively by many. Bank of America is found to receive $\mathcal{C}^{-}_{BAC,\text{NET}}$ in January 2009, when its earnings release revealed massive operating loss of $21.5 billion. Due to this, Bank of America received a $20 billion bailout from the U.S. government TARP in January 2009 in addition to the $25 billion it received at the end of 2008, which generated a reception of $\mathcal{C}^{-}_{BAC,\text{NET}}$ together with a transmission of $\mathcal{C}^{+}_{BAC,\text{NET}}$ to the financial sector[9]. Another peak of $\mathcal{C}^{+}_{BAC,\text{NET}}$ transmission is found at the end of 2009, when Bank of America announced the TARP debt repayment.

[8]The acquisition was completed in July 2008, despite the fact that in March 2008, Countrywide was investigated for fraud and the acquisition was thus seen as a maneuver by Bank of America to prevent the target's potential bankruptcy.

[9]The additional bailout was made with the U.S. government's intention to preserve Bank of America's stability and merger operation with Merrill Lynch, thus seen as a stabilizing operation within the financial system.

In 2010, Bank of America was accused of fraud by the U.S. government and, thus, again became a $\mathcal{C}^{-}_{BAC,\text{NET}}$ receiver. From 2011 to 2014, Bank of America went through a reduction in personnel, which contributed to an increase in the received $\mathcal{C}^{+}_{BAC,\text{NET}}$. Lastly, in August 2014, Bank of America agreed with the U.S. Justice Department to pay $17 billion to settle toxic mortgage-linked securities claims, which triggered a peak in $\mathcal{C}^{-}_{BAC,\text{NET}}$ transmission.

Figure 5.15: **Net Fear Connectedness and AFC - Bank of America**



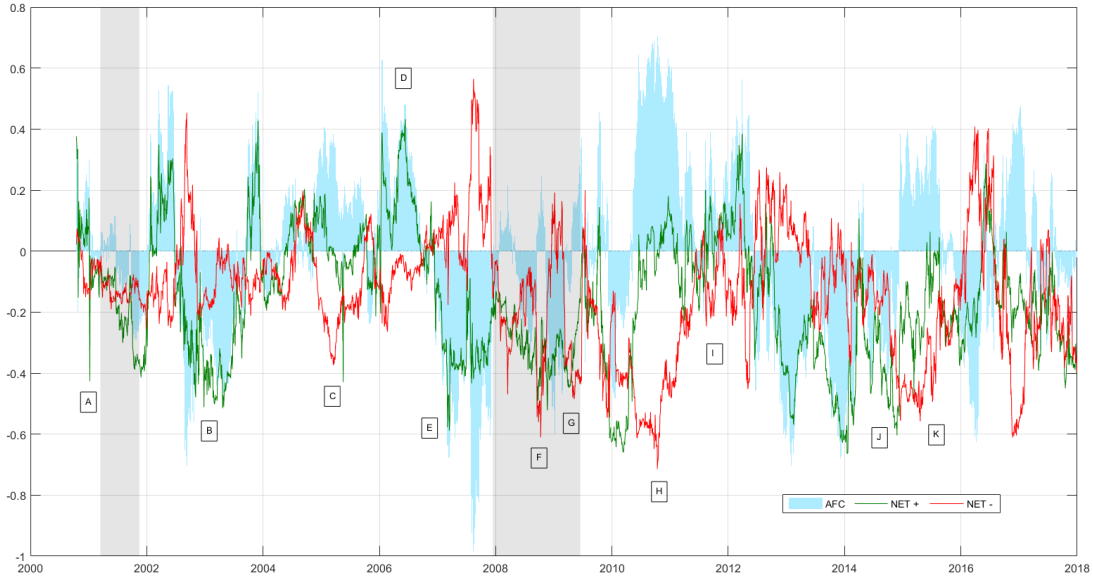
Notes: The figure shows the net upside "fear" connectedness, $\mathcal{C}^{+}_{BAC,\text{NET}}$, and net downside "fear" connectedness, $\mathcal{C}^{-}_{BAC,\text{NET}}$ for Bank of America together with the AFC, computed as difference between the two. The figure also reports the main specific company events during the time period: [A] FleetBoston Acquisition Announcement [B] MBNA Acquisition Announcement [C] Banco Itaú Acquisition Agreement [D] United States Trust Company Acquisition Announcement [E] Acquisition of LaSalle Bank Corporation [F] Acquisition of Countrywide Financial [G] Acquisition of Merrill Lynch [H] U.S. TARP Bailout [I] TARP Debt Repayment [J] Fraud Accusation [K] Downsizing begins [L] Settlement with U.S. Justice Department [M] Scaling Back, Branches Closing. Selected VAR lags = 4 and forecast horizon = 12. The rolling window length is equal to 200 days. The NBER recession periods are highlighted in grey. The selected period spans from 03-01-2000 to 29-12-2017 at a daily frequency.

Finally, Figure 5.16 shows the net "fear" and net AFC for Bank of New York Mellon. The bank was formed only in July 2007 from the merger of The Bank of New York and Mellon Financial Corporation. The first made several acquisitions during the early 2000s, and one of the most important was the acquisition of Ivy Asset Management, which was reflected in a peak in received $\mathcal{C}^{+}_{BK,\text{NET}}$. Both net downside and net upside "fear" are found to be received at the end of 2001, when profits fell, but there was a confident outlook by the management for the bank's future leading position in the financial sector, which may have stimulated the company's calls trading. In 2003, the Bank of New York acquired Credit Suisse First Boston's Pershing LLC for $2 billion, which is reflected in a clear spike in $\mathcal{C}^{+}_{BK,\text{NET}}$ received. In 2005, the bank settled a U.S. federal investigation for money laundering in relation to Russian privatization, resulting in a $\mathcal{C}^{-}_{BK,\text{NET}}$ reception. In April 2006, an asset-swap agreement with J.P. Morgan Chase was announced[10]. This operation was found to result in a $\mathcal{C}^{+}_{BK,\text{NET}}$ transmission and in a

[10]The swap consisted in selling Bank of New York retail and regional middle-market businesses to J.P. Morgan for $ 3.1 billion in return for J.P. Morgan's corporate trust business for $2.8 billion, meaning its exit from retail banking.

$\mathcal{C}^{-}_{BK,\text{NET}}$ reception, meaning that J.P. Morgan Chase likely profited more from the swap than the Bank of New York. In December 2006, the Bank of New York and the Mellon Financial Corporation announced their merger, which was finalized in July 2007, for a value of $16.5 billion, becoming the Bank of New York Mellon Corp. and resulting in a peak of $\mathcal{C}^{+}_{BK,\text{NET}}$ received since the merger contributed to the creation of one of the largest securities servicing and asset management companies. The merger was found to contribute to $\mathcal{C}^{-}_{BK,\text{NET}}$ transmission to the system due to the increase in competition in the financial sector.

Figure 5.16: **Net Fear Connectedness and AFC - Bank of New York Mellon**



Notes: The figure shows the net upside "fear" connectedness, $\mathcal{C}^{+}_{BK,\text{NET}}$, and net downside "fear" connectedness, $\mathcal{C}^{-}_{BK,\text{NET}}$ for Bank of New York Mellon together with the AFC, computed as difference between the two. The figure also reports the main specific company events during the time period: [A] Ivy Asset Management Acquisition [B] CSFB's Pershing Acquisition [C] U.S. Federal Investigation [D] Asset Swaps with J.P. Morgan Chase [E] Bank of New York and Mellon Financial Corporation Merger [F] Financial Crisis [G] Stress Test Result [H] PNC's Global Investment Servicing Acquisition [I] Foreign Currency Fraud Lawsuits [J] BNY Markets Mellon Creation [K] Foreign Currency Fraud Admission. Selected VAR lags = 4 and forecast horizon = 12. The rolling window length is equal to 200 days. The NBER recession periods are highlighted in grey. The selected period spans from 03-01-2000 to 29-12-2017 at a daily frequency.

During the global financial crisis, Bank of New York Mellon fired almost 2,000 employees, accounting for the 4% of its workforce, which generated an increase in $\mathcal{C}^{-}_{BK,\text{NET}}$ received. However, the results of the February 2009 stress test by federal regulators indicated that Bank of New York Mellon was one among only three banks that could have withstood a worsening of the financial situation, and this announcement triggered an increase in $\mathcal{C}^{+}_{BK,\text{NET}}$ received. In August 2009, the bank acquired Insight Investment from Lloyds Banking Group, while in July 2010, it acquired PNC Financial Services' Global Investment Servicing Inc.; the latter, however, resulted in a reception of $\mathcal{C}^{-}_{BK,\text{NET}}$. $\mathcal{C}^{-}_{BK,\text{NET}}$ received by Bank of New York Mellon is also found at the end of 2011 and the beginning of 2012, when the Justice Department filed lawsuits against the bank concerning foreign currency fraud. The creation of the new Markets Group (BNY Markets Mellon) in June 2014, which combined its global markets, global collateral services and prime services, is found to generate $\mathcal{C}^{+}_{BK,\text{NET}}$ received. Conversely, a peak

in $\mathcal{C}^{-}_{BK,\text{NET}}$ is detected again in March 2015, when Bank of New York Mellon admitted to the allegation of misrepresentation of foreign exchange pricing and execution.

Whereas in the total "fear" connectedness analysis, the role of put options is found to be a bit more marginal compared to the role of call options, when we study the behaviour of calls and puts with regards to single banks the picture varies. The received or transmitted, upside or downside, net "fear" connectedness depends more on the specific financial institutions' events and news. Thus, we find that upside and downside "fear" connectedness play a more evident role when taken in their single stock specific context, by signalling events which investors consider or expect to be good or bad for the company. Specifically, we find that events, such as, leading bond offerings and IPOs, TARP repayments, M&A deals which investors believe could have a potential benefit and improving power on the conditions of the bidder company, positive earnings announcements and positive stress tests results all contribute to a increase of net upside "fear" reception spread in the system through calls trading. On the other hand, legal issues with the Department of Justice, fraud issues, money laundering, M&A deals which investors believe could negatively affect the bidder, at least in the short term (e.g. Merrill Lynch), stress tests negative results as well as company losses, they all contribute to the spread of net downside "fear" received from the bank through put options. With regards to the net "fear" transmitted, we find that events, such as, M&A deals which may contribute to an increase in stability in the financial sector (e.g. J.P. Morgan and Chase Manhattan, J.P. Morgan Chase and Bear Stearns) and also TARP bailout programs contribute to the transmission of net upside "fear" in the system because events which may potentially stabilize the financial sector by reducing uncertainty. On the other hand, we find that events, such as, M&A with uncertain results (e.g. Bear Stearns) and speculative trading activity may increase the net downside "fear" transmitted in the system because they may contribute to an increase in the uncertainty in the financial system.

These information and expectations coming from the options trading are balanced out among all the banks when we look at the total sector connectedness. Different information are detected from calls and puts only in correspondence of macro and systematic events which incorporate all the financial sector such as crisis, economic downturns, macroeconomic events and so on, when good or bad news are simultaneously impacting on all the banks. Thus, while in the total connectedness measures, the "fear" connectedness index extracted from calls prevailed for most of the time over the one extracted from puts resulting in having an AFC above 0, in the specific company analysis the two options portfolios appear to be traded in a more homogeneous way.

5.6 Predictive Power of Fear Connectedness Indexes

Motivated by the previous results, we test the predictive power of our asymmetric connectedness measures in forecasting future macroeconomic conditions, as well as the potential increase in uncertainty. Our hypothesis is that forward-looking connectedness measures may result in an *early* warning tool to forecast the declines in the U.S. macroeconomic conditions or increases in financial and economic uncertainty.

We select the following monthly indicators, which reflect the macroeconomic and economic conditions, such as the Aruoba-Diebold-Scotti (ADS) Business Condition Index (Aruoba et al., 2009), the Chicago FED National Activity Index, CFNAI, the Kansas City Financial Stress Index (KCFSI) (see Hakkio et al., 2009), the NBER recession period dummy variable and the U.S. Industrial Production (IP). They are collected according to their available sample. The Aruoba-Diebold-Scotti (ADS) Business Condition Index tracks real business conditions at a high frequency and it is based on economic indicators. It is collected from: `https://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index`. The Chicago FED National Activity Index (CFNAI) is a monthly index that tracks the overall economic activity and the inflationary pressure. It is computed as a weighted average of 85 monthly indicators and it is collected from: `https://www.chicagofed.org/publications/cfnai/index`. The Kansas City Financial Stress Index (KCFSI) is a measure of stress in the U.S. financial system and is based on eleven financial market variables (see Hakkio et al., 2009). It is collected from `https://www.kansascityfed.org/research/indicatorsdata/kcfsi`. The NBER recession period dummy variable for the U.S. tracks recession(1) and expansion (0) periods according to NBER and is available at `https://fred.stlouisfed.org/series/USREC`. The monthly growth rate of the U.S. Industrial Production (IP) measures the real output for all the facilities in the U.S. and is collected from `https://fred.stlouisfed.org/series/INDPRO`.

As uncertainty proxies, we select the Economic Policy Uncertainty (EPU) index (see Baker et al., 2016), the GeoPolitical Risk (GPR) index by Caldara and Iacoviello (2018), the Economic Uncertainty Index (EUI) by Bali et al. (2014), the CBOE implied volatility index (VIX) and the average conditional volatility based on GARCH(1,1) of some U.S. macroeconomic variables (AVGVOL). The EPU index by Baker et al. (2016) is computed from news associated with the ten most important American newspapers, reflecting the concerns and uncertainty around specific economic or political events. It is collected from `http://www.policyuncertainty.com/`. The GeoPolitical Risk index by Caldara and Iacoviello (2018) (GPR) is computed in a similar way to EPU from newspaper articles associated with geopolitical events, wars, terrorist attacks or international conflicts. It is available at `https://www2.bc.edu/matteo-iacoviello/gpr.htm`. The Economic Uncertainty Index (EUI) by Bali et al. (2014) is a measure of economic uncertainty based on the time-varying condi-

tional volatility of macroeconomic and financial variables, such as the default spread, term spread, short-term interest rate, dividend yield, equity market index, inflation, unemployment rate and GDP available at `http://faculty.msb.edu/tgb27/workingpapers.html`. VIX is the CBOE implied volatility index, while AVGVOL is computed, in a similar way as in Allen et al. (2012), as the average time-varying GARCH(1,1) conditional volatility of some macroeconomic variables common in the literature. In this chapter, we select the default spread as difference between the BAA-rated and AAA-rated corporate bonds (DEF), the term spread as the difference between the 10-year T-bond and the three-month T-bill yield (TERM), the relative short-term interest rate, which is computed as a difference between the three-month T-bill rate and its annual moving average (RREL), the industrial production monthly growth rate (IP) and the inflation rate computed by the U.S. consumer price index (INF). All these variables are collected from `https://fred.stlouisfed.org/`.

The first set of equations concerns the macroeconomic indicators (MacroInd), while the second regards the uncertainty indicators (UncertInd). We control for the 1- to 12-month lags of endogenous variables.

$$\text{MacroInd}_{t+h} = \beta_0 + \beta \mathcal{C}_t + \sum_{k=0}^{11} \gamma_k \text{MacroInd}_{t-k} + \epsilon_t \tag{5.16}$$

$$\text{MacroInd}_{t+h} = \beta_0 + \beta^- \mathcal{C}_t^- + \beta^+ \mathcal{C}_t^+ + \sum_{k=0}^{11} \gamma_k \text{MacroInd}_{t-k} + \epsilon_t \tag{5.17}$$

$$\text{MacroInd}_{t+h} = \beta_0 + \beta \frac{\mathcal{C}_t^-}{\mathcal{C}_t^+} + \sum_{k=0}^{11} \gamma_k \text{MacroInd}_{t-k} + \epsilon_t, \tag{5.18}$$

$$\text{UncertInd}_{t+h} = \beta_0 + \beta \mathcal{C}_t + \sum_{k=0}^{11} \gamma_k \text{UncertInd}_{t-k} + \epsilon_t, \tag{5.19}$$

$$\text{UncertInd}_{t+h} = \beta_0 + \beta^- \mathcal{C}_t^- + \beta^+ \mathcal{C}_t^+ + \sum_{k=0}^{11} \gamma_k \text{UncertInd}_{t-k} + \epsilon_t, \tag{5.20}$$

$$\text{UncertInd}_{t+h} = \beta_0 + \beta \frac{\mathcal{C}_t^-}{\mathcal{C}_t^+} + \sum_{k=0}^{11} \gamma_k \text{UncertInd}_{t-k} + \epsilon_t, \tag{5.21}$$

where $\text{MacroInd} \in \{\text{ADS}, \text{CFNAI}, \text{KCSFI}, \text{NBER}, \text{IP}\}$ is one of the macroeconomic indicator variables, and $\text{UncertInd} \in \{\text{EPU}, \text{GPR}, \text{EUI}, \text{VIX}, \text{AVGVOL}\}$ is one of the uncertainty proxies for $h = 1, ..., 12$ horizons up to one year. For the NBER recession dichotomous variable, a probit regression is fitted and the z-statistics are reported in parentheses, while for the other variables, least squares regressions are estimated and Newey t-statistics are reported in parentheses. Equations 5.16 and 5.19 concern the aggregate $\mathcal{C}_t$ index, whereas 5.17 and 5.20 the upside and downside connectedness indexes,

$\mathcal{C}_t^+$ and $\mathcal{C}_t^-$. Equations 5.18 and 5.21 concern the ratio between $\mathcal{C}_t^-$ and $\mathcal{C}_t^+$. Every connectedness index in this exercise is computed as quarterly, end-of-the-quarter, index from forecast error variance decomposition, as in formula (5.7), by aggregating three months of implied volatility observations (60 trading days) with regards to the indexes, VIX , VIX^- and VIX^+ , for every financial institutions The quarterly connectedness measures are rolled every month in order to produce monthly $\mathcal{C}_t$, $\mathcal{C}_t^+$ and $\mathcal{C}_t^-$ observations that reflect the previous quarter. The monthly macroeconomic and uncertainty indicators are taken as the average of the previous quarter, and recession is marked binary as 1 when the average gives values > 0.5 and 0 when the average gives values < 0.5. This process allows us to match the information of the fear connectedness indexes with the macro and uncertainty indicators, thus creating monthly observations that reflect the information in the previous quarter.

5.6.1 Predicting Macroeconomic Conditions and Uncertainty

Tables 5.8 and 5.9 display the results for the predictive power of the fear connectedness indexes for the future macroeconomic conditions and uncertainty indicators, respectively. Table 5.8 reports the results of the predicting regressions estimated through equations (5.16) and (5.17). First, β refers to the effect of the total fear connectedness $\mathcal{C}_t$ on the selected macroeconomic indicators. Second, β^-, and β^+ break the effect into downside and upside parts, respectively. Significant coefficients are highlighted in bold, red and blue for β, β^-, and β^+, respectively. Our main hypothesis is that decomposed connectedness measures $\mathcal{C}_t^-$ and $\mathcal{C}_t^+$ carry additional predictive information compared to the aggregate $\mathcal{C}_t$.

One of the first observations made from Table 5.8 is that $\mathcal{C}_t^-$ and $\mathcal{C}_t^+$ are able to predict the ADS Business condition index from 4 to 12 months and from 4 to 10 months in advance, respectively. Downside and upside information further predicts CFNAI from 3 to 10 months in advance and from 3 to 9 months in advance, respectively. In addition, $\mathcal{C}_t^-$ can signal a recession early, providing an alarm a few months before the aggregate $\mathcal{C}_t$, emphasizing the importance of investors' expectations contained in the put options. $\mathcal{C}_t^-$ is also found to be the only connectedness index that can predict short-mid future levels of KCSFI. In contrast to the decomposed connectedness, the aggregate connectedness $\mathcal{C}_t$ is *unable* to predict the ADS Business condition index, the CFNAI, the KCSFI and the industrial production, while showing only a long horizon predictability power for future recessions.

Table 5.9 shows the results of the predictive regressions estimated through equations (5.19) and (5.20). Both $\mathcal{C}_t$ and $\mathcal{C}_t^+$ contain predictive information for the EPU index, from 4 to 6 months ahead and from 3 to 5 months ahead, respectively. $\mathcal{C}_t^-$ has predictive information for the EPU index, one year ahead. Future geopolitical risk is predicted by all the three $\mathcal{C}_t$ indexes, but at different horizons. $\mathcal{C}_t$ forecasts well the future level of AVGVOL up to one year, while $\mathcal{C}_t^-$ from 8 to 12 months ahead, respectively. The $\mathcal{C}_t$ measure is unable to predict only future economic uncertainty (EUI) and future levels of the VIX index. The latter is only predicted by a mixture of information from $\mathcal{C}_t^+$ and, especially, $\mathcal{C}_t^-$.

$\mathcal{C}_t^-$ is the only measure with predictive power on EUI.

Our results are comparable to findings of Allen et al. (2012), who introduced a Catastrophic Risk in the Financial Sector (CATFIN) measure and found that it is able to predict future macroeconomic conditions. The Catastrophic Risk in the Financial Sector (CATFIN) measure by Allen et al. (2012) is constructed using nonparametric and parametric approaches based on value-at-risk (VaR) and expected shortfall (ES) methods. The parametric distributions used to estimate the 99% VaR and the 1% ES are the generalized Pareto distribution (GPD) and the skewed generalized error distribution (SGED). The nonparametric methods are measured as a cut-off point of the left tail minus one percentile of the monthly excess returns for the VaR and as an average of the extreme financial firms returns beyond the 1% nonparametric VaR. CATFIN is then constructed as an average of the three VaR and ES measures. We include a CATFIN measure in all regressions as a control variable. We find that the results are robust and do not materially change the significance of connectedness measures. This finding leads us to the conclusion that information contained in connectedness indexes carries additional information to CATFIN. Different information content can also be seen from the low correlation of the CATFIN and connectedness indexes.

Overall, we find that in contrast to aggregate connectedness, decomposed indexes carry predictive information for the macroeconomic indicators. This finding is in line with recent literature on the decomposed variance risk premium (e.g. Kilic and Shaliastovich, 2018) assessing how the mixture of information coming from the decomposed premia is more helpful to predict, in their case, future asset returns. We have conducted several robustness checks on the predictive exercise as well; however, our results appear to be robust. We have also changed the construction methodology for the connectedness indexes. We have performed the same predictive exercise by considering $\mathcal{C}_t$ indexes as computed in sections 5.4.2 and 5.5.2, considering a dynamic framework with a rolling window length equal to 200 days. The results are similar to those presented here, with $\mathcal{C}_t^-$ and $\mathcal{C}_t^+$ still playing a major role compared to the total $\mathcal{C}_t$. We have replaced the 200-day window length with 100 days finding that the results still hold; however, they shift a few months. In order to avoid this information mismatch due to the rolling window length, we decided to compute quarterly static $\mathcal{C}_t$ for every quarter and linearly interpolate them in order to obtain monthly measures that match the selected macro and uncertainty indicators. The results were still robust with, in some cases, predictability power spanning from the very short-horizon until month 10. The same major roles for $\mathcal{C}_t^-$ and $\mathcal{C}_t^+$ are found compared with $\mathcal{C}_t$, remaining robust to all the exercises we have tried. However, we decided to discard this methodology due to the interpolation approximation and to present results regarding our $\mathcal{C}_t$ indexes computed quarterly, end-of-the-month, and rolled for every month. We also controlled for CATFIN in all these other cases, finding that results remain robust and provide additional information.

Table 5.8: $\mathcal{C}_t$, $\mathcal{C}_t^-$ **and** $\mathcal{C}_t^+$ **Macroeconomic Activity Prediction**

Forecast		ADS	t-stat	R^2	CFNAI	t-stat	R^2	KCSFI	t-stat	R^2	NBER	t-stat	R^2	IP	t-stat	R^2
1	β	-0.007	(-0.376)	0.981	-0.003	(-0.090)	0.948	-0.001	(-0.991)	0.987	-0.073	(-0.986)	0.776	0.001	(0.292)	0.994
	β^-	0.003	(0.123)		0.001	(0.342)		-0.010	(-2.085)		-0.558	(-0.654)		0.005	(0.859)	
	β^+	-0.001	(-0.602)	0.981	-0.001	(-0.399)	0.942	0.004	(1.600)	0.988	-0.006	(-0.088)	0.774	-0.003	(-0.772)	0.995
2	β	-0.007	(-0.133)	0.889	0.001	(0.061)	0.868	-0.001	(-0.402)	0.940	-0.048	(-0.821)	0.616	0.004	(0.324)	0.991
	β^-	0.005	(0.802)		0.010	(1.231)		-0.021	(-1.696)		-0.050	(-0.783)		0.019	(1.294)	
	β^+	-0.005	(-1.163)	0.890	-0.006	(-1.137)	0.869	0.010	(1.456)	0.943	0.006	(0.111)	0.617	-0.013	(-1.361)	0.991
3	β	0.000	(0.027)	0.731	0.002	(0.234)	0.723	0.000	(0.080)	0.849	-0.039	(-0.767)	0.487	0.013	(0.561)	0.975
	β^-	0.017	(1.629)		0.025	(2.103)		-0.033	(-1.581)		-0.016	(-1.694)		0.041	(1.695)	
	β^+	-0.011	(-1.648)	0.738	-0.013	(-1.667)	0.732	0.015	(1.381)	0.857	0.043	(0.832)	0.505	-0.026	(-1.675)	0.975
4	β	0.000	(0.021)	0.592	-0.002	(-0.244)	0.637	0.001	(0.168)	0.754	-0.002	(-0.722)	0.420	0.013	(0.412)	0.955
	β^-	0.033	(2.376)		0.041	(2.562)		-0.037	(-1.525)		-0.012	(-2.111)		0.070	(2.219)	
	β^+	-0.019	(-2.043)	0.613	-0.024	(-2.372)	0.662	0.017	(1.330)	0.763	0.071	(1.460)	0.410	-0.050	(-2.524)	0.958
5	β	-0.000	(-0.060)	0.492	-0.001	(-0.088)	0.518	0.001	(0.142)	0.660	-0.004	(-0.954)	0.315	0.011	(0.287)	0.931
	β^-	0.045	(2.682)		0.047	(2.502)		-0.041	(-1.670)		-0.079	(-1.586)		0.095	(2.470)	
	β^+	-0.026	(-2.295)	0.531	-0.025	(-2.142)	0.551	0.017	(1.342)	0.671	0.062	(1.410)	0.304	-0.071	(-2.812)	0.935
6	β	0.002	(0.211)	0.392	0.001	(0.012)	0.415	-0.000	(-0.040)	0.561	-0.005	(-0.890)	0.224	0.014	(0.310)	0.898
	β^-	0.054	(2.712)		0.054	(2.471)		-0.042	(-1.727)		-0.116	(-2.309)		0.128	(2.621)	
	β^+	-0.031	(-2.390)	0.446	-0.031	(-2.306)	0.458	0.015	(0.118)	0.573	0.066	(1.525)	0.244	-0.095	(-3.017)	0.905
7	β	0.007	(0.621)	0.299	0.003	(0.256)	0.312	-0.002	(-0.138)	0.468	-0.055	(-1.377)	0.151	0.024	(0.436)	0.855
	β^-	0.057	(2.714)		0.053	(2.547)		-0.043	(-1.687)		-0.130	(-2.630)		0.160	(2.732)	
	β^+	-0.033	(-2.321)	0.358	-0.029	(-2.202)	0.353	0.014	(0.919)	0.481	0.067	(1.588)	0.191	-0.109	(-2.902)	0.865
8	β	0.011	(0.899)	0.218	0.002	(0.191)	0.247	-0.007	(-0.414)	0.381	**-0.072**	**(-1.847)**	0.107	0.038	(0.608)	0.805
	β^-	0.056	(2.840)		0.056	(2.764)		-0.043	(-1.583)		-0.017	(-2.337)		0.197	(2.983)	
	β^+	-0.031	(-2.176)	0.273	-0.034	(-2.412)	0.293	0.012	(0.690)	0.393	0.005	(0.829)	0.112	-0.124	(-2.828)	0.820
9	β	0.009	(0.697)	0.154	0.006	(0.047)	0.193	-0.014	(-0.685)	0.314	**-0.078**	**(-2.030)**	0.089	0.046	(0.647)	0.747
	β^-	0.053	(2.976)		0.049	(2.684)		-0.039	(-1.507)		-0.023	(-2.913)		0.222	(3.051)	
	β^+	-0.028	(-2.010)	0.205	-0.029	(-1.999)	0.229	0.010	(0.502)	0.323	0.005	(0.888)	0.109	-0.133	(-2.663)	0.767
10	β	0.005	(0.375)	0.109	0.001	(0.074)	0.145	-0.017	(-0.756)	0.263	-0.057	(-1.519)	0.058	0.053	(0.686)	0.685
	β^-	0.048	(2.826)		0.043	(2.311)		-0.037	(-1.525)		-0.134	(-3.005)		0.241	(3.033)	
	β^+	-0.027	(-1.737)	0.151	-0.026	(-1.535)	0.175	0.008	(0.423)	0.270	0.051	(1.322)	0.110	-0.145	(-2.534)	0.708
11	β	0.001	(0.110)	0.076	-0.001	(-0.068)	0.104	-0.016	(-0.691)	0.226	-0.057	(-1.533)	0.042	0.052	(0.631)	0.620
	β^-	0.041	(2.322)		0.033	(1.958)		-0.035	(-1.506)		-0.113	(-2.696)		0.241	(3.033)	
	β^+	-0.026	(-1.523)	0.107	-0.022	(-1.238)	0.121	0.012	(0.541)	0.233	0.038	(0.998)	0.079	-0.145	(-2.534)	0.708
12	β	-0.000	(-0.023)	0.054	-0.003	(-0.192)	0.070	-0.018	(-0.747)	0.196	-0.052	(-1.402)	0.030	0.048	(0.549)	0.556
	β^-	0.034	(1.921)		0.035	(1.888)		-0.032	(-1.385)		-0.094	(-2.287)		0.266	(3.109)	
	β^+	-0.025	(-1.372)	0.076	-0.027	(-1.381)	0.091	0.015	(0.612)	0.200	0.029	(0.773)	0.054	-0.164	(-2.351)	0.582

Notes: This table presents the results of the predictive regressions estimated through equation 5.16 and 5.17 between the total $\mathcal{C}_t$ and the decomposed $\mathcal{C}_t^-$ and $\mathcal{C}_t^+$, respectively and some macroeconomic conditions indicators such as the Business Conditions Index (ADS), the Chicago FED National Activity Index (CFNAI), the Kansas City Financial Stress Index (KCFSI), the NBER recession variable (NBER) and the IP Index (IP). For NBER a Probit regression is estimated and the z-statistics are reported in parentheses, while for the other variables OLS regressions are estimated and Newey (1987) t-statistics are reported in parentheses. All the connectedness indexes are computed quarterly and rolled every month. The sample goes from 10-2000 to 12-2017, after 200-days rolling window estimation.

Table 5.9: $\mathcal{C}_t$, $\mathcal{C}_t^-$ and $\mathcal{C}_t^+$ **Uncertainty Indexes Prediction**

Forecast		EPU	t-stat	R^2	GPR	t-stat	R^2	EUI	t-stat	R^2	VIX	t-stat	R^2	AVGVOL	t-stat	R^2
1	β	0.231	(1.281)	0.954	0.436	(0.618)	0.630	-0.007	(-0.222)	0.995	-0.012	(-0.456)	0.960	-0.005	(-0.904)	0.985
	β^-	-0.189	(-1.327)	0.953	-1.491	(-1.311)	0.635	-0.002	(-0.843)	0.995	-0.134	(-2.947)	0.963	-0.005	(-0.654)	0.986
	β^+	0.139	(1.032)		1.162	(0.845)		-0.000	(-0.402)		0.060	(2.124)		-0.003	(-0.443)	
2	β	0.553	(1.506)	0.842	**1.701**	**(1.793)**	0.308	0.000	(0.010)	0.976	0.006	(0.102)	0.834	**-0.002**	**(-2.055)**	0.926
	β^-	-0.237	(-0.716)	0.842	-1.577	(-1.113)	0.312	-0.006	(-1.327)	0.976	-0.279	(-3.714)	0.846	-0.009	(-0.409)	0.926
	β^+	0.461	(1.627)		1.796	(1.061)		-0.002	(-0.551)		0.132	(1.940)		-0.002	(-1.236)	
3	β	0.857	(1.603)	0.684	**2.506**	**(1.706)**	0.211	-0.004	(-0.414)	0.931	-0.046	(0.441)	0.626	**-0.006**	**(-2.662)**	0.802
	β^-	-0.216	(-0.426)	0.686	-0.490	(-0.032)	0.207	-0.018	(-2.057)	0.932	-0.428	(-1.955)	0.652	-0.002	(-0.430)	0.804
	β^+	0.875	(2.172)		1.466	(1.052)		-0.006	(-0.748)		0.181	(1.528)		-0.004	(-1.402)	
4	β	**1.037**	**(1.739)**	0.618	2.818	(1.368)	0.190	-0.010	(-0.727)	0.882	0.095	(0.729)	0.490	**-0.010**	**(-3.282)**	0.684
	β^-	-0.024	(-0.041)	0.625	-0.552	(-0.378)	0.190	-0.036	(-1.939)	0.885	-0.454	(-1.684)	0.519	-0.005	(-0.685)	0.684
	β^+	1.134	(2.582)		2.444	(1.937)		-0.007	(-0.594)		0.175	(1.225)		-0.004	(-1.121)	
5	β	**1.047**	**(1.686)**	0.581	2.989	(1.453)	0.180	-0.019	(-1.033)	0.827	0.103	(0.726)	0.403	**-0.013**	**(-3.530)**	0.589
	β^-	0.030	(0.046)	0.590	-1.048	(-0.848)	0.175	-0.060	(-1.731)	0.835	-0.521	(-1.863)	0.440	-0.008	(-0.989)	0.587
	β^+	1.193	(2.614)		2.135	(1.904)		-0.004	(-0.250)		0.186	(1.316)		-0.003	(-0.645)	
6	β	0.857	(1.310)	0.545	2.423	(1.379)	0.148	-0.020	(-0.951)	0.773	0.100	(0.634)	0.333	**-0.016**	**(-3.682)**	0.522
	β^-	-0.143	(-0.181)	0.548	-1.516	(-1.245)	0.144	-0.083	(-1.656)	0.785	-0.540	(-1.941)	0.374	-0.011	(-1.287)	0.513
	β^+	**0.900**	**(1.660)**		1.458	(1.238)		0.006	(0.283)		0.206	(1.477)		-0.002	(-0.369)	
7	β	0.490	(0.680)	0.505	1.506	(0.958)	0.139	-0.016	(-0.681)	0.713	0.069	(0.399)	0.270	**-0.017**	**(-3.372)**	0.465
	β^-	-0.324	(-0.367)	0.506	-2.461	(-1.795)	0.149	-0.094	(-1.569)	0.731	-0.551	(-1.933)	0.322	-0.011	(-1.485)	0.449
	β^+	0.560	(0.813)		0.054	(0.048)		0.018	(0.273)		0.200	(1.363)		-0.001	(-0.318)	
8	β	0.241	(0.298)	0.485	2.107	(1.610)	0.188	-0.010	(-0.417)	0.661	0.030	(0.176)	0.246	**-0.018**	**(-3.104)**	0.411
	β^-	-0.397	(-0.468)	0.486	-3.044	(-1.794)	0.199	-0.103	(-1.602)	0.677	-0.476	(-1.619)	0.280	-0.011	(-1.712)	0.390
	β^+	0.281	(0.365)		0.936	(0.820		0.030	(0.983)		0.142	(0.885)		-0.001	(-0.341)	
9	β	0.206	(0.233)	0.480	**2.584**	**(2.075)**	0.218	-0.005	(-0.190)	0.600	-0.054	(-0.320)	0.229	**-0.019**	**(-3.046)**	0.361
	β^-	-0.476	(-0.629)	0.483	-2.822	(-1.410)	0.222	-0.103	(-1.577)	0.616	-0.427	(-1.459)	0.258	-0.115	(-1.882)	0.335
	β^+	0.483	(0.621)		1.568	(1.203)		0.037	(1.119)		0.050	(0.282)		-0.001	(-0.340)	
10	β	0.374	(0.408)	0.478	**3.130**	**(2.181)**	0.233	-0.005	(-0.155)	0.536	-0.088	(-0.505)	0.215	**-0.021**	**(-3.356)**	0.323
	β^-	-0.706	(-1.024)	0.483	-2.867	(-1.569)	0.245	-0.109	(-1.660)	0.554	-0.346	(-1.344)	0.237	-0.012	(-2.042)	0.289
	β^+	0.704	(0.986)		3.273	(2.126)		0.040	(1.130)		0.027	(0.014)		-0.000	(-0.116)	
11	β	0.506	(0.538)	0.467	**2.968**	**(1.912)**	0.236	-0.010	(-0.295)	0.468	-0.054	(-0.300)	0.202	**-0.022**	**(-3.730)**	0.300
	β^-	-1.070	(-1.542)	0.477	-1.529	(-1.000)	0.226	-0.116	(-1.738)	0.488	-0.345	(-1.565)	0.223	-0.012	(1.981)	0.253
	β^+	0.967	(1.386)		1.392	(1.145)		0.046	(1.130)		0.003	(0.020)		-0.005	(-0.904)	
12	β	0.526	(0.580)	0.442	1.536	(1.030)	0.228	-0.022	(-0.550)	0.403	-0.028	(-0.155)	0.195	**-0.023**	**(-3.911)**	0.285
	β^-	-1.143	(-1.722)	0.375	-0.014	(-0.011)	0.224	-0.121	(-1.810)	0.424	-0.346	(-1.789)	0.214	-0.011	(-1.915)	0.230
	β^+	1.037	(1.415)		0.401	(1.280)		0.043	(0.970)		0.045	(0.245)		-0.001	(-0.201)	

Notes: This table presents the results of the predictive regressions estimated through equation 5.19 for the total $\mathcal{C}_t$ and 5.20 for the $\mathcal{C}_t^-$ and $\mathcal{C}_t^+$ and some uncertainty proxies such as the Economic and Policy Uncertainty (EPU), the GeoPolitical Risk Index (GPR), the Economic Uncertainty Index (EUI), the CBOE VIX index and the macroeconomic conditional volatility average (AVGVOL). OLS regressions are estimated and Newey (1987) t-statistics are reported in parentheses. All the connectedness indexes are computed quarterly and rolled every month matching the monthly variables we want to predict for the sample from 10-2000 to 12-2017, after 200-days rolling window estimation.

Table 5.10: $\mathcal{C}_t^- / \mathcal{C}_t^+$ **Ratio, Macroeconomic Activity Prediction and Uncertainty Index Prediction**

							Panel A								
Forecast	ADS	t-stat	R^2	CFNAI	t-stat	R^2	KCSFI	t-stat	R^2	NBER	t-stat	R^2	IP	t-stat	R^2
1	0.054	(0.345)	0.981	0.113	(0.413)	0.948	**-0.550**	**(-1.890)**	0.976	-1.652	(-0.312)	0.770	0.342	(0.849)	0.993
2	0.415	(1.018)	0.890	0.634	(1.349)	0.869	**-1.189**	**(-1.714)**	0.942	-2.229	(-0.537)	0.614	1.286	(1.411)	0.990
3	**1.138**	**(1.783)**	0.737	**1.497**	**(2.230)**	0.730	-1.844	(-1.517)	0.854	-5.729	(-1.433)	0.498	**2.622**	**(1.859)**	0.974
4	**2.026**	**(2.462)**	0.609	**2.545**	**(2.782)**	0.658	-2.055	(-1.476)	0.760	**-7.748**	**(-2.032)**	0.406	**4.781**	**(2.614)**	0.951
5	**2.773**	**(2.734)**	0.524	**2.835**	**(2.610)**	0.544	-2.183	(-1.591)	0.667	**-5.992**	**(-1.752)**	0.305	**6.606**	**(2.941)**	0.935
6	**3.292**	**(2.733)**	0.437	**3.278**	**(2.580)**	0.450	-2.129	(-1.540)	0.568	**-7.272**	**(-2.174)**	0.239	**8.834**	**(3.117)**	0.901
7	**3.470**	**(2.645)**	0.348	**3.148**	**(2.586)**	0.345	-2.135	(-1.421)	0.475	**-7.814**	**(-2.395)**	0.181	**10.580**	**(3.132)**	0.865
8	**3.342**	**(2.587)**	0.261	**3.464**	**(2.700)**	0.287	-2.043	(-1.226)	0.387	**-4.925**	**(-1.734)**	0.106	**12.533**	**(3.223)**	0.818
9	**3.142**	**(2.528)**	0.193	**3.064**	**(2.428)**	0.224	-1.808	(-1.075)	0.316	**-6.208**	**(-2.159)**	0.095	**13.835**	**(3.150)**	0.763
10	**2.874**	**(2.273)**	0.143	**2.652**	**(1.949)**	0.171	-1.678	(-1.019)	0.256	**-7.135**	**(-2.493)**	0.088	**14.965**	**(3.018)**	0.705
11	**2.602**	**(1.918)**	0.103	**2.194**	**(1.849)**	0.119	-1.799	(-1.045)	0.230	**-5.918**	**(-2.160)**	0.060	**16.158**	**(2.972)**	0.643
12	**2.357**	**(1.674)**	0.095	**2.530**	**(1.728)**	0.091	-1.850	(-1.014)	0.199	**-4.843**	**(-1.794)**	0.039	**16.670**	**(2.932)**	0.581

							Panel B								
Forecast	EPU	t-stat	R^2	GPR	t-stat	R^2	EUI	t-stat	R^2	VIX	t-stat	R^2	AVGVOL	t-stat	R^2
1	-13.199	(-1.443)	0.953	-104.147	(-1.061)	0.634	-0.027	(-0.154)	0.993	**-7.361**	**(-2.782)**	0.962	-0.005	(-0.086)	0.985
2	-20.923	(-1.519)	0.842	-140.320	(-1.197)	0.388	-0.096	(-0.277)	0.976	**-15.458**	**(-2.151)**	0.843	0.071	(0.459)	0.925
3	**-50.795**	**(-1.763)**	0.683	-75.554	(-0.716)	0.203	-0.325	(-0.546)	0.931	**-22.627**	**(-1.802)**	0.643	0.137	(0.467)	0.798
4	**-56.843**	**(-1.793)**	0.616	-135.436	(-1.394)	0.184	-0.929	(-0.891)	0.882	**-23.408**	**(-1.723)**	0.508	0.081	(0.186)	0.670
5	-58.481	(-1.644)	0.579	**-141.518**	**(-1.692)**	0.173	-1.829	(-0.998)	0.828	**-26.184**	**(-1.687)**	0.425	-0.101	(-0.191)	0.566
6	-51.201	(-1.101)	0.544	**-124.551**	**(-1.661)**	0.145	-3.062	(-1.147)	0.776	**-27.856**	**(-1.852)**	0.359	-0.239	(-0.443)	0.488
7	-41.017	(-0.714)	0.506	-89.873	(-1.247)	0.138	-3.967	(-1.233)	0.722	**-28.002**	**(-1.821)**	0.306	-0.265	(-0.547)	0.425
8	-30.035	(-0.495)	0.487	**-151.071**	**(-1.662)**	0.191	-4.859	(-1.385)	0.669	-22.751	(-1.398)	0.265	-0.261	(-0.598)	0.366
9	-41.205	(-0.720)	0.483	-171.151	(-1.486)	0.219	-5.225	(-1.446)	0.610	-16.777	(-0.995)	0.238	-0.270	(-0.633)	0.312
10	-57.875	(-1.141)	0.483	**-249.011**	**(-2.002)**	0.236	-5.593	(-1.510)	0.547	-10.327	(-0.627)	0.217	-0.353	(-0.817)	0.266
11	-81.023	(-1.637)	0.477	-119.608	(-1.229)	0.226	-6.112	(-1.551)	0.481	-11.443	(-0.743)	0.207	-0.349	(-0.792)	0.232
12	-86.748	(-1.643)	0.453	-19.397	(-0.247)	0.223	-6.173	(-1.508)	0.415	-13.654	(-0.980)	0.202	-0.285	(-0.683)	0.210

Notes: Panel A presents the results of the predictive regressions estimated through equation 5.18 between $\mathcal{C}_t^- / \mathcal{C}_t^+$ and some macroeconomic conditions indicators ,such as the Aruoba-Diebold-Scotti Business Conditions Index (ADS), the Chicago FED National Activity Index (CFNAI), the Kansas City Financial Stress Index (KCFSI), the NBER recession dummy variable (NBER) and the Industrial Production Index (IP). Panel B presents the results of the predictive regressions estimated through equation 5.21 between $\mathcal{C}_t^- / \mathcal{C}_t^+$ and some uncertainty proxies such as the Economic and Policy Uncertainty (EPU), the GeoPolitical Risk Index (GPR), the Economic Uncertainty Index (EUI), the CBOE VIX index and the macroeconomic conditional volatility average (AVGVOL). For NBER, a Probit regression is estimated and the z-statistics are reported in parentheses, while for the other variables, OLS regressions are estimated and Newey (1987) t-statistics are reported in parentheses. Significant relationships are highlighted in bold. All the connectedness indexes are computed quarterly and rolled every month, matching the monthly variables we want to predict for the sample from 10-2000 to 12-2017.

This finding is also confirmed by the fact that, with regard to the 200-day rolling window, for instance, we find that CATFIN is positively but weakly correlated with our connectedness measures, namely, 0.05, 0.24 and 0.23, for $\mathcal{C}_t$, $\mathcal{C}_t^+$ and $\mathcal{C}_t^-$, respectively.

We perform the same predictive exercise for both the macroeconomic and the uncertainty indicators by grouping the information contained in $\mathcal{C}_t^-$ and $\mathcal{C}_t^+$ as a ratio between the two to check whether we can still obtain the same predictability results with a more compact and parsimonious equation. Results for this exercise are reported in Table 5.10. We can observe that the $\mathcal{C}_t^- / \mathcal{C}_t^+$ ratio can predict macroeconomic activity for long horizons.

For instance, the $\mathcal{C}_t^-$ and $\mathcal{C}_t^+$ ratio can predict the ADS Index, from 3 to 12 months in advance, the CFNAI from 3 to 12 months in advance, the NBER recession period from 4 to 12 months in advance and the IP growth rate from 3 up to 12 months in advance. The ratio is found to have short-term predictive power in relation to KCSFI, instead carrying predictive information for only one and two months. From Table 5.10, we infer that the $\mathcal{C}_t^- / \mathcal{C}_t^+$ ratio cannot predict the EUI and AVGVOL, while it can predict the EPU index and the GPR index 3-4 and from 5 to 10 months ahead, respectively. The ratio predicts VIX up to 7 months. Results for the $\mathcal{C}_t^-$ and $\mathcal{C}_t^+$ ratio show that, in some cases, such as for EUI and AVGVOL, the ratio shows no predictive power. Thus, it can be concluded that when information contained in $\mathcal{C}_t^-$ and $\mathcal{C}_t^+$ are kept separate and added to the same regression equation, they are better able to predict future levels of economic activity and, particularly, of uncertainty proxies.

5.7 Asymmetric Connectedness of Implied Skewness

In this last section we extend the asymmetric connectedness analysis to the implied third moment extracted model-free from the selected banks. As already discussed in Chapter 4, during outliers skewness-based measures may better reflect tail risk (e.g. Du and Kapadia, 2014). Instead of defining the fear connectedness index based on the implied volatility measures, in this section we investigate a redefined measure of fear connectedness based on implied skewness decomposition. The methodological framework is discussed in subsection 5.7.1 and some preliminary findings are reported in subsections 5.7.2 and 5.7.3. Further directions of the analysis is drawn in the last paragraph as well as in the conclusive Chapter of the thesis.

5.7.1 Implied Skewness Connectedness: Methodological Framework

We apply the implied skewness formulae as drawn in Chapter 4, namely equation 4.1 to the main ten U.S. banks as described in section 5.2.1 of this Chapter. The set of options is the one we applied in this Chapter, this time, SKEW measures will be at weekly frequency. Moreover, we decompose the measures as illustrated for S&P 500 , this time, for every bank in our sample. We end up with a data set

including three implied skewness index measures for every bank. We label the indexes with the bank ticker followed by the SKEW index or decomposed SKEW indexes. For instance for J.P. Morgan Chase we define the skewness indexes as JPM-SKEW , JPM-SKEW$^+$ and JPM-SKEW$^-$.

We report the descriptive statistics as well as the plots of the SKEW indexes of the main ten banks in the U.S. in the Appendix to Chapter 5. Overall, we observe that U.S. Bancorp shows the highest aggregate SKEW , SKEW$^-$ and SKEW$^+$ values. The aggregate and positive SKEW values (SKEW and SKEW$^+$) are found to be quite similar among the selected ten banks in the sample, while SKEW$^-$ values vary more. This finding is reflected by the lower standard deviation of SKEW and SKEW$^+$ values compared to SKEW$^-$. This echoes the results found with the decomposed implied volatility series in which VIX$^-$ has been found aa the most volatile seris. J.P. Morgan presents the highest maximum values for SKEW (170.15), Bank of America for SKEW$^-$ (271.48) and Citigroup for SKEW$^+$ (115.8).

The following step in this analysis, as done for the VIX series consists in studying the decomposed SKEW indexes for the main ten banks in the U.S. within a Diebold and Yilmaz (2012) framework. We input the decomposed implied SKEW indexes in the methodology as illustrated in section 5.3. We, first, conduct the analysis for the aggregate SKEW , and, second, we investigate the connectedness levels of the decomposed SKEW indexes.

5.7.2 Aggregate Skewness Connectedness: Static and Dynamic Analysis

Table 5.11: **Static Skewness Connectedness in the Financial Sector**

	SKEW Connectedness										
	JPM	BAC	WFC	CITI	GS	MS	USB	AXP	PNC	BK	FROM
JPM	67.44	3.88	4.43	5.48	3.49	2.51	5.67	2.03	2.25	2.78	32.55
BAC	6.77	72.31	2.38	4.46	1.95	6.17	1.43	1.74	2.23	0.52	27.68
WFC	8.14	3.72	59.02	4.54	1.48	3.07	7.61	4.26	2.22	5.84	40.91
CITI	5.60	4.41	2.00	76.62	2.70	0.46	1.53	2.18	2.15	2.30	23.37
GS	2.26	0.14	1.31	3.18	82.05	2.18	1.54	3.55	1.56	2.19	17.94
MS	5.00	3.83	6.67	1.96	4.80	60.47	4.56	8.03	1.39	3.24	39.52
USB	6.70	3.99	4.08	2.94	0.82	4.12	65.36	2.11	2.74	7.09	34.63
AXP	5.02	1.11	4.85	10.22	3.89	2.68	4.41	59.79	2.94	5.04	40.20
PNC	6.04	3.59	2.87	3.40	2.61	1.96	5.98	6.72	58.52	8.25	41.47
BK	4.83	1.95	4.70	6.31	2.04	2.69	11.58	7.93	10.45	47.49	52.50
TO	50.39	26.66	33.33	42.53	23.81	25.87	44.35	38.58	27.96	37.29	TOTAL
NET	17.83	-1.02	-7.57	19.16	5.86	-13.64	9.71	-1.62	-13.50	-15.21	**35.08**

Notes: The table contains a decomposition of forecast error variance computed for the aggregate SKEW indexes for the ten main U.S. financial institutions. Elements in the off-diagonal entries are the pairwise directional connectedness, while the diagonal elements (in grey) are the financial institutions' own variance. The off-diagonal row and column sum to TO and FROM connectedness, respectively. The NET row at the bottom is the difference between TO and FROM. The bottom-right element is the total connectedness index in the considered system. Selected VAR lags = 4 and Forecast Horizon = 12 days. The selected time period spans from 03-01-2000 to 29-12-2017 at weekly frequency.

Table 5.11 reports the static analysis of implied skewness connectedness for the ten main U.S. financial institutions. The diagonal values indicate that the future implied skewness of a stock is impacted by own shocks to expectations, which range from 47.49% to 82.05%. The off-diagonal elements reveal

how the implied skewness spreads from one bank to other banks in the financial sector. The directional FROM connectedness measure ranges from 17.94% for Goldman Sachs to 52.50% for Bank of New York Mellon. The directional FROM contribution accounts to 100% minus the companies' own total forecast error variance in the main diagonal or, in other words, to the sum of the other pairwise directional connectedness elements in the (N- 1) off-diagonal entries for every company. The directional TO connectedness measure in the bottom row of the table ranges from 23.81% for Citigroup to 50.39% for J.P.Morgan.

The highest pairwise connectedness appears to be from Bank of New York Mellon to U.S. Bancorp (11.58%). The second-highest number is from Bank of New York Mellon to PNC (10.45%). The bottom row in the table shows the total directional NET computed as difference between directional TO and directional FROM fear connectedness. A positive difference reveals that the company can be classified as an implied skewness transmitter, while a negative number identifies an implied skewness receiver. The main net aggregate transmitter is found to be Citigroup (19.16%) followed by J.P.Morgan (17.83%). Goldman Sachs and U.S. Bancorp are also net aggregate transmitters. On the other hand, we find that Bank of New York Mellon is the main aggregate implied skewness receivers in the system (15.21%). The total implied skewness connectedness index, bottom-right element, is found to be equal to 35.08%, which means that, on average, more than one-third of the implied skewness for these ten main financial institutions has been generated from spillovers in the financial system.

In this subsection we also report the dynamic analysis of the aggregate connectedness indexes extracted from the U.S. main ten banks SKEW indexes. The first plot shows the trend of the total connectedness index computed by inputting the aggregate SKEW indexes in the Diebold and Yilmaz (2012) and rolling at 200 days.

Figure 5.17: **Total Implied Skewness Connectedness Index**

Notes: This figure shows the total implied skewness connectedness for the ten main financial institutions' aggregate SKEW indexes. Selected VAR lags = 4 and forecast horizon = 12. The rolling window length is equal to 200 days. The selected period spans from 03-01-2000 to 29-12-2017.

Figure 5.17 illustrates how the total SKEW connectedness index spiked in 2004 and 2005 reaching its maximum point at the beginning of 2005 (60.03%). The index remained at high levels, but decreasing, close to 55%, for a few years. Interestingly it decreased right before the financial crisis in 2007 and 2008. This is in line with the findings in Chapter 4 in which we observed a SKEW decreasing in times of crises including the global financial crisis. However, the total SKEW connectedness index rose again in November 2007 anticipating the midst of the global financial crisis, the losses of Merrill Lynch and the collapse of Lehman Brothers in September 2008. After that the index decreased since investors were not expecting similar events again in the aftermaths of the financial crisis. The implied SKEW connectedness index remained at levels between 40% and 50% showing a spike in mid 2012 reflecting the turbulent times of the sovereign debt crisis in the Eurozone. It, then, spiked again in 2016 and 2017 following events such as the Brexit vote or the president Trump election which might have increased the possibility of outliers in the investors' minds. Interestingly the level of the SKEW connectedness are found to be higher in the pre- and post- financial crisis, whereas lower in the midst of it. This plot gives us an overview of the behaviour of the aggregate SKEW connectedness for the main ten financial institutions in the U.S. In the next plot we investigate the asymmetric role of the decomposed SKEW measures in a dynamic framework.

5.7.3 Asymmetric Implied Skewness Connectedness: Static and Dynamic Analysis

Table 5.12 shows the connectedness static analysis performed with the decomposed implied SKEW indexes.

Table 5.12 illustrates the asymmetry of the SKEW connectedness results. The positive implied skewness connectedness and the negative skewness connectedness are reported in the upper and bottom panels, respectively. The overall connectedness from SKEW^{+} (17.97%) accounts for almost half of the connectedness computed using the SKEW^{-} index (32.48%). This confirms the results of Chapter 4 in which we discuss the prevalent role of SKEW^{-} in the stock market compared to SKEW^{+} . However, the on-diagonal elements point to an even stronger role of the own shocks. The positive directional FROM connectedness (right column) is found to span between 9.99% for Bank of America to 23.20% for Morgan Stanley, while the positive directional TO connectedness ranges from 7.46% for U.S. Bancorp to 37.26% for Morgan Stanley.

Morgan Stanley is found to be the main positive implied skewness transmitter in the system (14.06%) followed by Wells Fargo (13.52%). U.S. Bancorp Bank is detected as the main positive SKEW receiver in the system (-13.42%). We also find J.P. Morgan and Citigroup to be positive implied skewness receivers. The highest positive skewness pairwise connectedness is found from J.P. Morgan to Wells Fargo and is equal to 11.16%, and the second from Wells Fargo to Morgan Stanley (7.86%).

Table 5.12: **Asymmetric Implied Skewness Connectedness in the Financial Sector**

	JPM	BAC	WFC	CITI	GS	MS	USB	AXP	PNC	BK	FROM
					SKEW^{+} **Connectedness**						
JPM	80.37	0.40	11.16	1.53	0.62	3.13	0.36	1.23	0.35	0.79	19.62
BAC	1.04	90.00	1.66	0.23	2.75	2.82	0.10	0.74	0.16	0.46	9.99
WFC	5.93	0.37	78.54	0.38	2.25	7.86	0.58	1.27	0.55	2.23	21.45
CITI	1.77	0.37	0.96	88.68	0.61	0.25	0.77	0.65	4.98	0.92	11.31
GS	0.57	4.18	4.11	0.25	80.88	5.25	1.21	2.54	0.71	0.26	19.11
MS	1.72	1.91	7.53	0.28	3.51	76.79	3.05	1.38	0.30	3.48	23.20
USB	1.02	0.76	2.75	1.47	0.77	7.48	79.11	1.15	0.25	5.19	20.88
AXP	0.73	4.01	2.21	1.28	4.37	1.94	0.38	81.51	1.04	2.48	18.40
PNC	0.93	0.64	0.92	2.94	4.33	1.77	0.25	0.24	86.56	1.37	13.43
BK	1.84	1.56	3.62	0.79	2.49	6.73	0.73	3.61	0.80	77.78	22.21
TO	15.58	14.23	34.97	9.19	21.75	37.26	7.46	12.85	9.17	17.21	TOTAL
NET	-4.03	4.24	13.52	-2.12	2.64	14.06	-13.42	-5.62	-4.25	-5.00	**17.97**
					SKEW^{-} **Connectedness**						
	JPM	BAC	WFC	CITI	GS	MS	USB	AXP	PNC	BK	FROM
JPM	57.61	6.69	8.25	7.83	1.70	5.85	3.90	5.09	0.84	2.19	42.38
BAC	6.56	65.08	5.41	6.35	0.59	10.08	2.27	1.50	0.26	1.84	34.91
WFC	4.11	2.55	70.14	5.52	0.54	3.57	6.85	3.87	0.67	2.13	29.85
CITI	3.85	6.86	3.36	74.33	2.38	4.53	1.71	1.06	0.78	1.10	25.66
GS	1.04	0.10	1.10	1.67	86.03	0.93	1.07	4.23	1.75	2.02	13.96
MS	3.81	3.59	5.93	3.26	1.49	72.71	3.40	1.85	1.15	2.76	27.28
USB	5.71	5.45	4.56	1.79	0.46	9.59	65.53	2.98	0.85	3.04	34.46
AXP	7.96	0.93	4.37	6.52	2.63	3.67	6.74	57.56	1.98	7.57	42.43
PNC	2.55	1.18	1.12	1.75	1.05	7.43	2.45	7.06	64.90	10.45	35.09
BK	3.09	1.11	1.47	3.81	1.76	5.71	7.81	6.86	7.05	61.30	38.69
TO	38.73	28.51	35.62	38.54	12.63	51.41	36.24	34.53	15.37	33.14	TOTAL
NET	-3.64	-6.40	5.77	12.88	-1.32	24.12	1.78	-7.89	-19.72	-5.55	**32.48**

Notes: The table contains forecast error variance decomposition computed for the SKEW^{+} andSKEW^{-} indexes for the ten main U.S. financial institutions. Elements in the off-diagonal entries are the pairwise directional connectedness, while the diagonal elements (in grey) are the financial institutions' own variance. The off-diagonal row and column sums to TO and FROM directional connectedness, respectively. The NET row at the bottom is the difference between TO and FROM. The bottom-right element is the total connectedness index in the considered system. Selected VAR lags = 4 and Forecast Horizon = 12 days. The selected time period spans from 03-01-2000 to 29-12-2017 at weekly frequency.

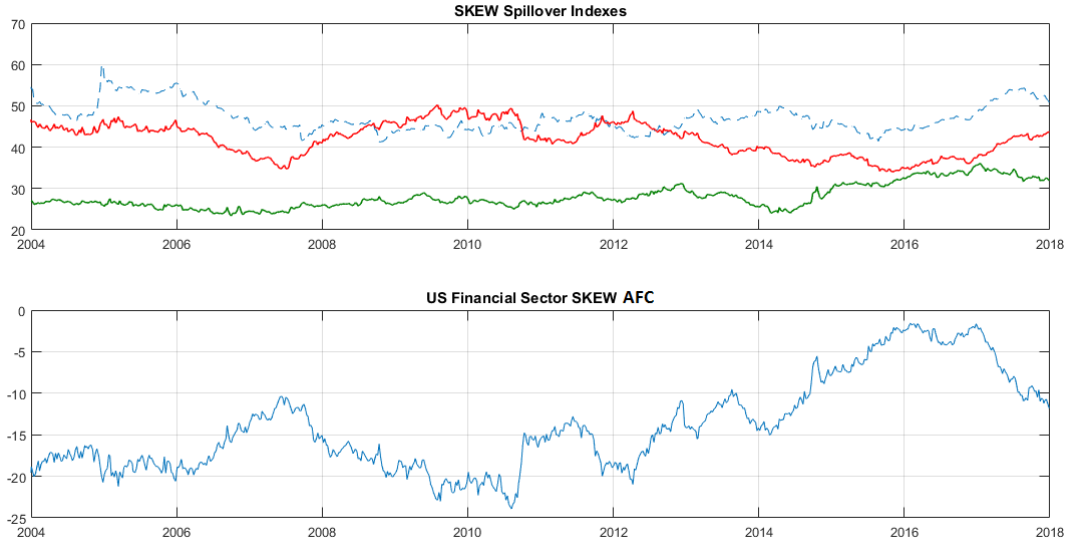
On the bottom panel of Table 5.12, we observe that the negative skewness connectedness is actually higher (32.48%), similar to the total SKEW connectedness, thus representing the main part of it. We thus hypothesize that the SKEW connectedness has a negative asymmetry which we test in the dynamic analysis. The range of the negative skewness directional FROM values ranges between 13.96% of Goldman Sachs to the 42.43% of American Express. The SKEW^{-} directional TO connectedness is quite high, only exceptions being Goldman Sachs and PNC Bank. They are both found to be SKEW^{-} receivers, with the latter found to be the main SKEW^{-} receivers within the system (-19.72%). The main SKEW^{-} transmitter are found to be Morgan Stanley and Citigroup with 24.12% and 12.88%, respectively. The highest SKEW^{-} pairwise connectedness is found to be the one from PNC Bank to Bank of New York Mellon (10.45%), followed by the pair from Bank of America and Morgan Stanley (10.08%).

The static analysis for the decomposed SKEW indexes shows a predominant role of the SKEW^{-} when connectedness measures through variance decomposition are computed. In addition, some of the selected financial institutions change their roles from a net receiver to a net transmitter, or vice versa, when comparing aggregate to positive and negative implied skewness shocks, further confirming asym-

metries in the transmission mechanism of the implied third moment. For instance, J.P. Morgan Chase is found to be an aggregate implied skewness transmitter, whereas a SKEW^- and SKEW^+ receiver. The opposite is found for Wells Fargo which is an aggregate SKEW receiver while a SKEW^- and SKEW^+ transmitter. PNC Bank, American Express and Bank of New York Mellon are, on the other hand, the weakest banks in the system and they are found to receive implied skewness regardless of the skewness measure we consider. The next plot investigate the different roles that positive and negative skewness connectedness have in relation to the different market periods in a dynamic framework.

In Figure 5.18, we depict the implied skewness connectedness indexes and the asymmetric implied skewness connectedness as computed from equation (5.12) over time.

Figure 5.18: **Implied Skewness Connectedness Indexes and AFC**



Notes: The figure shows the comparison between the SKEW , SKEW^+ and SKEW^- connectedness indexes in the upper panel. The bottom panel shows the asymmetric skewness connectedness (AFC). Selected VAR lags = 4 and forecast horizon = 12. The rolling window length is equal to 200 days. The selected period spans from 03-01-2000 to 29-12-2017 at a weekly frequency.

Figure 5.18 confirms our preliminary finding that the connectedness due to negative SKEW (SKEW^-) prevails on the connectedness due to positive SKEW (SKEW^+), thus playing a stronger role in the financial sector for the entire study period. Similar results were detected in Chapter 4. The connectedness index due to SKEW^+ is never overcoming the one due to SKEW^- , thus showing a clear asymmetry towards the negative implied skewness in the U.S. financial sector. Hence, the SKEW^- connectedness is the main index which should be monitored to track the spillovers in skewness in the U.S. financial sector.

5.8 Conclusion

Asymmetric implied volatility connectedness measures were constructed in this chapter to study the transmission of different information on "fears" extracted from the two sides of the stock options market in the U.S. financial sector, as represented by the ten main financial institutions in the U.S. The decomposed connectedness measures computed from these financial institutions' VIX indexes provided forward-looking valuable information reflecting future investors' expectations.

The decomposed $\mathcal{C}_t^-$ and $\mathcal{C}_t^+$ measures are found to play an important and timely role in signaling changes in future macroeconomic activity or uncertainty indicators. Thus, they can be considered forward-looking warning tools that will complement the already-existing toolbox of systemic risk measures. Our empirical analysis points out that the information extracted from $\mathcal{C}_t^-$ and $\mathcal{C}_t^+$ serves as a better and more timely predictive tool than the aggregate $\mathcal{C}_t$, especially for macroeconomic downturns and activity measured by ADS, CFNAI and industrial production. Moreover, $\mathcal{C}_t^-$ is also found to be a early signaling tool with regard to recessions, VIX and EUI since changes in these factors are found to be reflected more strongly in the U.S. put options market.

We highlighted how financial institutions play different roles as upside/downside "fear" transmitters/receivers. From a systemic risk point of view, our new methodology provides a richer and more detailed picture of bank networks. For instance, we identify banks that are predominantly receivers of "fear" , as well banks transmitting "fear" in the financial system, and we identify the role played over time by a top bank like Goldman Sachs. This exercise exacerbates even further the precious role that separate "fear" connectedness indexes play in offering separate information when employed to predict future levels of macroeconomic activity or uncertainty indicators.

Having an ex ante monitoring tool for systemic risk might be particularly useful for financial stability and market supervision. There is significant predictive information in the implied upside and downside connectedness indexes related to future macroeconomic activity or uncertainty. Moreover, being able to identify the more systemically important financial institutions can be helpful for preventing the spread of volatility and risk within the system, preparing the financial institutions and policymakers to implement prudent operations in advance.

Chapter 6

Conclusion

This thesis has shown that important information can still be extracted from the options market when portfolios comprising of calls and puts are taken separately. More specifically, this directional information has been captured when decomposed implied volatility and implied skewness indexes were computed. We have shown how decomposed implied moments can actually enrich the set of information carried by the aggregate indexes. This was found to be true both for the second and also for the third implied moments extracted from the U.S. S&P 500 index. The set of information enclosed in the decomposed implied volatility and implied skewness indexes are not captured by other risk measures and by the aggregate volatility and skewness measures.

We have shown that many areas of finance can benefit from extracting these directional indexes. They provide a new set of tools useful for risk management purposes. We have found that decomposed implied moment indexes improve the predictability ability with regards to future equity risk premium, macroeconomic indicators and uncertainty indicators. Rarely, the aggregate implied volatility index or the aggregate implied skewness index were found to perform better than the decomposed ones in terms of predictability power and asset pricing.

We were the first to study the determinants of decomposed implied volatility indexes placed both among macroeconomic variables, and also among financial market conditions variables. Understanding the determinants of these decomposed risk measures can be beneficial in financial areas such as portfolio allocation, hedging strategies, predictability and forecasting as well as policy makers decisions and regulations. We have shown how macroeconomic variables, such as inflation and GDP, were found to impact mainly on the upside volatility component. On the other hand, variables more linked to the financial markets activity, such as equity, credit and liquidity, were found to impact mainly on the downside volatility component. In other words, macroeconomic variables related to consumption were found to be linked more to the calls activity, whereas financial variables more related to puts activity. Noteworthy was the strong linkage between puts - downside volatility component - and variables such

as economic and policy uncertainty and geopolitical risk index. These variables appeared to share the same set of information enclosed in the puts market, reflecting investors' fears and concerns driven by the uncertain environment and related to stock market downturns.

Furthermore, by focusing on the link between changes in volatility and economic and policy uncertainty, we have attempted to address a field within finance that is currently attracting many macroeconomists and academics intrigued in better disclosing its empirical interpretation. Nowadays political events are more shrouded with uncertainty and unstable consequences compared to the past. This insecurity arising from governments and future political plans is transmitted onto the financial markets and into macroeconomic policies. This chain may have a dangerous leverage effect amplified by all the recent events injecting more instability into the general economic systems of countries with potential implications on the financial markets in the future.

Another main result of this research was a shift in the role of calls and puts from the pre-crisis and post-crisis. The information enclosed in the calls market appeared to be stronger in the pre-crisis period which also encompassed events driven by investors' exuberance such as the dot com bubble - well known to be a high-speculative activity era. In the post-crisis, investors started to increase their demand for hedging portfolios; the trading volume of stock market index increased. Investors were more concerned about financial market losses, thereby began to actively hedge their equity portfolios by trading put options. This shift has been detected both for implied volatility indexes and, also, for implied skewness indexes.

We have also shown how information enclosed in the options market, this being forward looking might be more informative in predicting future levels of macroeconomic and financial variables. This result was found to be even stronger when we looked at upside and downside components of our volatility series. Forward looking implied volatilities are found to predict future levels of future levels of macro variables, economic activity, output growth and inflation rate, whereas volatility risk premia were found to be more informative for predicting future levels of stock return.

The usefulness of directional information extracted from the U.S. equity index options market has also been shown when implied skewness indexes were computed and decomposed. We illustrated how decomposed SKEW indexes represent measures of risk able to support - and improve - the information content of implied volatility indexes, risk premia and other measures of risk already proposed in the financial literature. Indeed, especially when decomposed, SKEW indexes provided, for the first time in the financial literature, new insights spanning several areas of finance. We have shown how market sentiment is perceived and linked differently to call and put based measures.

We detected the positive SKEW index as the one more market sentiment driven and, in turn, as the one more informative in predicting future levels of market sentiment proxies. In general, when the newly computed and decomposed SKEW indexes were linked to equity market premium and asset

pricing, we found a strong predictive ability, especially in the short run. SKEW^{+} was found as the skewness index able to predict future level of S&P 500 as well as individual stocks enclosed in the S&P 500 risk premium the most.

On the other hand, we found that SKEW^{-} was more related to fundamentals. The aggregate SKEW index was found to be, potentially, influenced by optimistic information coming from calls leading to a possible bias in the measurement of the market tail risk. Thus, since extracted from puts, we proposed SKEW^{-} as a new tail risk index. It was identified to react more to extreme tail events and black swans along our time frame. We believed it could foresee the spread of investors' tail risk perceptions and expectations in the U.S. financial markets since it was proposed as a more prudent measure more linked to investors' fear and concern and reflecting the information encapsulated in the puts market. The information content of SKEW^{-} was found useful in predicting future levels of uncertainty indicators, downturns and recessions.

Such findings have also been linked with the possibility of new trading strategies which might be constructed based upon the decomposition of implied volatility and skewness. These strategies might consider trading portfolios comprised only of calls or puts rather than the entire options distributions at certain maturity. New asset pricing insights have been also provided by linking the decomposed implied skewness with the common Fama-French factors in order to better price portfolios based on size and book-to-market and based on size and performance.

In addition, we aimed to initiate of a new strand of literature which could look at the importance of forward looking information extracted from options when it comes to volatility connectedness measurement and monitoring. This could provide a new ex-ante tool helpful in preventing the spread of systemic risk in the financial sector. The decomposed implied connectedness indexes - called Fear Connectedness Indexes - were, also, found to be useful predictors of future financial, economics, macroeconomics downturns as well as uncertainty increases. In this thesis, we applied this new ex-ante connectedness measure to the financial sector in the U.S. using the ten main financial institutions as a proxy. This application had importance in the areas of systemic risk and financial stability. Different information enclosed in single financial stocks' trading in calls and puts were extracted in order to compute single stocks implied volatility indexes.

These decomposed forward looking measures was found to carry ex-ante information on the beliefs and expectations about the future increase or decrease of financial sector stocks' prices. The difference in upside views and negative views generated an asymmetry. This was translated, then, in terms of connectedness. Decomposed $\mathcal{C}_t^-$ and $\mathcal{C}_t^+$ measures were found to signal in advance changes in future macroeconomic activity or uncertainty indicators. These measures could be considered forward-looking warning tools monitoring the spread of systemic risk. The information extracted from $\mathcal{C}_t^-$ and $\mathcal{C}_t^+$ were detected more informative than the one enclosed in the aggregate $\mathcal{C}_t$. This finding has also

been found in the other applications in this thesis mentioned earlier.

We contributed to the systemic risk area by pointing out that forward looking connectedness measures were able to depict a more detailed and directional picture of the bank networks. We were able, not only, to detect financial institutions which can be classified as net receivers of fears or net transmitters of fears in the U.S. financial sector, but our research went a step further. We were able to identify how options traders in the U.S. financial sector weight differently systemic and specific (idiosyncratic) news or events. By focusing on the specific financial institutions connectedness trend, we could detect how calls and puts contain separate information about the single financial institution and the financial sector itself. When separated, implied volatility connectedness - or connectedness of fears - extracted from calls and puts offered a clearer picture concerning how investors' decisions and beliefs were influenced by events. The spread of forward looking connectedness of fears became crucial when systemic risk needs to be closely monitored for banking regulation or supervision. Lastly, by ranking the financial institution by their systemic importance represented a useful tool in preventing the spread of volatility or fears in the financial sector among the other banks. This research aimed to improve financial stability worldwide avoiding ripple effects or systemic impact and other recessions.

Again, $\mathcal{C}_t^-$ extracted from puts was found to be a early signaling tool with regards to recessions, VIX and EUI since changes in these factors were found to be reflected more strongly in the U.S. put options market. Similar results were found with relation to the downside implied volatility index and with relation to our tail risk proxy - SKEW^- . We contributed to the financial stability by suggesting that the forward looking information enclosed in the puts market were highly valuable in predicting and monitoring uncertainty, recessions and downturns. Developing these forward looking and pessimistic-side related monitoring tools and risk measures could be helpful to prepare the markets and investors to sudden increase in volatilities and risk, increase in tail risk and spread of volatility within the considered system of study, crucial for policymakers in order to implement prudent operations in advance as well as for investors to timely hedge their portfolios. A brief additional exercise has also shown how the connectedness of implied skewness of single stocks might evolve over time in an asymmetric way.

There are several areas in which this research could be developed and extended further. First of all, further research should point to a better understanding of the determinants, not only of decomposed implied second moments, but also of decomposed implied third moment. We have studied how, especially the negative implied skewness index, proposed as a proxy of tail risk, could be helpful for predicting future levels of macroeconomic activity and uncertainty indicators. Of interest would be to research where the main drivers of the decomposed implied skewness and, mainly, of the tail risk index, are placed. Is the tail risk index mainly driven by macroeconomic variables, financial variables, economic or political news or investors' beliefs and market sentiment? By definition tracking a tail risk index would be a hard task to do. However, understanding which of these might be the reason for an increase

of tail risk perception in financial markets could have advantages for financial stability purposes as well as precautionary policy makers' decisions.

Different areas in which this thesis might be distilled further is asset pricing and factor modelling. Following recent debates in the literature the market and investment sentiment component should be considered as an additional factor when pricing assets and portfolios. As discussed in Chapter 4, previous studies have found this irrational beliefs factor to over perform the common Fama-French factors or to be a strong additional factor. Our asset pricing exercise in Chapter 4 has shown how implied volatility skewness indexes perform well in these models and should be considered as additional factors. Therefore, further research should investigate the role of ex-ante market sentiment factors when these are extracted from options so as to study how investors' expectations coming from puts or calls might differ in asset pricing models, as well as to shed new light on the role hedgers and speculators might have on the performance of existing asset pricing models.

Another channel in which this research could be directed, encompasses the volatility connectedness and spillovers topic. There are many applications that could be undertaken starting from the pioneering concept we have proposed in this chapter of forward looking volatility connectedness tool. First of all, of interest would be to study how implied volatility propagates among countries, taking into account differences in time zones and trading hours. If the implied volatility series would, also in this case, take into account their separate upside and downside components, these countries can be labelled as upside or downside implied volatility transmitter or receiver according to the nature and shape of volatility they spread. In fact, according to different economic, macroeconomic, financial, political and geopolitical events, the selected economies might spread volatility in a completely different way since positive news and events for one country might have an opposite meaning, thus, bad news for another country in the system. It could represent the first potential study pointing towards the study of countries' stock market indexes implied volatility spillovers in a separate upside-downside framework. In fact, separating the implied volatility indexes for each market into its upside and downside volatility indexes anchors this study to a growing avenue of research which includes different volatilities according to the fact that there are events which impact more on the upside side of volatility, while some others impact more on the downside side generating an asymmetric volatility transmission.

Related to this topic, representing a merger between two of the chapters in this thesis, even more novel would be to investigate which are the macroeconomic and financial variables belonging to the selected economies in the system which are able to drive the total implied volatility connectedness index computed for the whole system as well as the specific country contribution in spreading or receiving volatility. A number of variables might be considered for this exercise; GDP, industrial production, money supply, unemployment rate, term structure, equity premia, dividend yields, etc. in order to encompass both macroeconomic indicator as well as financial market indicators. This further research

may contribute to the areas of financial economics, financial markets, financial stability and macro-prudential policy representing a further and necessary step for a better understanding and monitoring of global financial markets and their volatility. This would be crucial not only from a risk management perspective but also, for policy makers and central bankers. Ultimately, this would have considerable financial stability implications since it will be serving as a useful tool in order to help central banks to react in a prompt manner setting interest rate policies, macro-hedging strategies, and overall, policy interventions and supervision.

In addition, closely related to the aforementioned idea, of interest would be investigating the contagion among other financial assets, taking, firstly, forward looking information and, secondly, decomposing their volatilities in upside and downside components as well. The study of credit market (e.g. CDS, government bonds) volatility connectedness, especially when taken at high-frequency, is in my agenda. Some preliminary results have shown how events that have happened in the Eurozone might spread upside and downside volatility in different ways. Countries more affected by specific credit event might be reacting in different ways. As an example, the sovereign debt crisis has been found as an event contributing to a positive CDS volatility transmission for Germany, while a negative CDS volatility transmission for countries such as Italy, a country more involved in the sovereign debt crisis. In other words, the latter have found to be the one transmitting downside volatility, signs of instability and uncertainty toward the selected system. Germany has been found to be the stabilizer country, transmitting upside volatility. For the first time in the literature, this might be a useful area to research especially given the turbulent and uncertainty period characterising, mainly, the Euro area. Motivated by the fact that the Eurozone has been a fertile ground in the last decades for credit events impacting on credit changes and rating, further research should be conducted on this topic.

Overall, potential implications of the upside or downside linkages in volatility connectedness could be contributive for the financial literature both under a macroeconomic perspective and also under a international portfolios selection perspective. Certain types of volatility connectedness may be desirable, providing comparative advantages in generating international trade, regional and global capital market integration, and enhanced coordination of global financial regulation and accounting standards. I strongly believe that this thesis has been only the first step towards a fast growing financial area looking at improved measures of risk. These risk measures should not only be more timely and forward looking, but take also into account the different investors' expectations and beliefs. The more refined construction of these indexes from the options market should be taken further, extended to different assets, contexts, countries and markets. To recall the discussion in the introduction of this thesis, measuring and tracking risk is not easy at all. However, having more reliable, timely and directional risk monitoring tools can be the first step towards new avenues in areas such as risk management, financial economics, asset pricing, predictability and international finance.

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Appendix A

Additional Material for Chapter 3

A.1 Volatility Modelling: GARCH Comparison

The volatility models we selected for conducting this brief comparison are: GARCH(1,1), GARCH(p,q) where p and q are the best lags choice estimated through maximum likelihood, EGARCH(1,1), GARCH-GJR(1,1) and GARCH-M. The independent variables selected are the most common in the existing literature examining stock market and macroeconomic relationship and well known for having ARCH effects. Applying Engle (1982) test the presence of an ARCH effect at 1% is identified for all variables except for GDP and unemployment Rate at 5%. The estimation of a volatility model for the macro-variables and for the stock market exhibits differences in terms of econometric contribution (see Table A1). The results examining the relationship between stock market volatility and macroeconomic volatility encompasses a degree of subjectivity associated with the analyst's choice for modeling volatility.

Table A1: **Stock Market and Selected Variables Conditional Variances**

Variable	GARCH (1,1)	EGARCH (1,1)	GJR-GARCH (1,1)	GARCH (p,q)	GARCH-M (1,1)
CPI	0.090	0.135^{**}	0.188^{**}	0.058	0.008
IP	-0.005	0.026^{***}	-0.010	0.004	-0.030^{**}
GDP	0.042^{**}	0.005	0.057^{***}	0.067^{***}	0.101^{***}
UR	0.143^{**}	0.430^{***}	0.339^{***}	0.201^{***}	0.366^{*}
OIL	0.267	-0.290^{**}	-0.005	0.345^{*}	0.040^{*}
ER	0.361^{***}	0.098^{***}	0.350^{*}	1.991^{***}	0.041
R^2	0.691	0.849	0.792	0.694	0.724
F-Stat	37.872	92.823	65.551	38.112	43.823
P-value	0.000	0.000	0.000	0.000	0.000

Notes: This table shows the output of OLS regression between our dependent variable, S&P 500 conditional variance, and the conditional variance of six selected macro-variables according to different models and lags used to compute them. Changing the model varies the significance and the sign of the coefficients for some of the macro-variables. Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01. The study period is from 01-2008 to 12-2016, at monthly frequency.

Table A2: **Selected Macro and Financial Variables**

This table shows and describes all the variables that have been used in this chapter for the empirical analysis collected for the U.S. from a relevant data source.

Variable	Notation	Description	Series	Frequency	Data Source
Consumer Price Index	CPI	Measure of the average monthly change in the price for goods and services paid by urban consumers between any two different times. It is commonly used as a proxy for inflation. Significant increases in the CPI within a short time frame might indicate a period of inflation, and significant decreases in CPI within a short time frame might indicate a period of deflation.	$Inflation_t = log(CPI_t) - log(CPI_{t-1})$	M	FRED
Real Gross Domestic Product	GDP	Inflation adjusted GDP. Value of goods and services produced by the nation's economy less the value of the goods and services used in production. Growth rate of real GDP as a variable accounting for changes in real economic activity. We have interpolated the quarterly GDP series into a monthly series.	$GDP = log(GDP_t) - log(GDP_{t-1})$	M	FRED
Industrial Production Index	IP	Economic indicator that measures real output and volume growth for all facilities located in the United States manufacturing, mining and electric, and gas utilities. The index is compiled on a monthly basis.	$IP = log((IP_t) - log(IP_{t-1})$	M	FRED
Unemployment Rate	UR	Number of unemployed as a percentage of the labor force.	$UR = (UR_t) - (UR_{t-1})$	M	FRED
Money Supply	M1	Seasonally adjusted M1 is calculated by summing currency, traveler's checks, demand deposits, and OCDs, each seasonally adjusted separately.	$M1 = log(M1_t) - log(M1_{t-1})$	M	FRED
Term Structure	TS	Difference between a long-run government interest rate proxy 10 years treasury rate and a shorter, 2-years, term government rate.	$TS = 10YTermBonds_t - 2YTermBond_t$	D	FRED
Crude Oil Price	OIL	West Texas Intermediate (WTI) oil with prices expressed in dollars per barrel.	$OIL = log((OIL_t) - log(OIL_{t-1})$	D	FRED
Gold Price	GOLD	Gold Fixing Price 10 : 30 A.M. (London time) in London Bullion Market, based on U.S. Dollars-Sterling.	$GOLD = log(GOLD_t) - log(GOLD_{t-1})$	D	FRED
JPY/US Exchange Rate	ER	Exchange rate prices between the Japanese and U.S. currencies.	$JPY/US = log(JPY/US_t) - log(JPY/US_{t-1})$	D	FRED
Equity Market	SPX	S&P 500 is the stock market index in the U.S. considered a proxy for the U.S. equity market. It includes 500 large cap companies in the U.S. spanning different sectors.	$SPX = log(SPX_t) - log(SPX_{t-1})$	D	FRED
Market Sentiment	SENT	University of Michigan Consumer Sentiment Index. Surveys of consumers collects data on consumer attitudes and expectations summarized in the index in order to determine changes in consumers' willingness to buy and to predict their subsequent discretionary expenditures.	$SENT = log(SENT_t) - log(SENT_{t-1})$	M	FRED
Credit	CRE	Computed as the difference between Moody's seasoned BAA and AAA corporate bond yields which is commonly used as a proxy of credit and default risk in the market.	$CRE = log(CRE_t) - log(CRE_{t-1})$	D	FRED
Liquidity	TED	Calculated as the spread between 3-Month LIBOR based on U.S. dollars and 3-Month T-Bill. It is an indicator of perceived credit risk in the general economy. An increase in the TED spread means lenders believe the risk of default on interbank loans is increasing and they will demand a higher rate of interest. When the risk of bank defaults is decreasing, the TED spread decreases.	$TED = log(TED_t) - log(TED_{t-1})$	D	FRED
Economic Policy Uncertainty	EPU	Computed by Baker et al. (2016), reflects and measures the concerns and uncertainty in the news around specific global politic and economic events for the U.S.	$EPU = log(EPU_t) - log(EPU_{t-1})$	D	http://www.policyuncertainty.com/
GeoPolitical Risk	GPR	Computed by Caldara and Iacoviello (2018), this index measures geopolitical risk and events worldwide.	$GPR = log(GPR_t) - log(GPR_{t-1})$	D	https://www2.bc.edu/matteo-iacoviello/gpr.htm.
Partisan Conflict Index	PCI	Computed by Azzimonti (2017), it reflects the pure political partisan conflicts and political uncertainty in the U.S.	$PCI = log(PCI_t) - log(PCI_{t-1})$	M	www.philadelphiafed.org

A.2 Realized Volatility: Empirical Results

A.2.1 Realized Volatility Stepwise Regression Analysis

In this section we perform a similar empirical analysis for the realized volatility measures. The results in Table A3 indicate that the S&P 500 index plays a relevant role with respect to realized volatilities, impacting negatively on the aggregate RVOL and RVOL^- and positively on the RVOL^+ . Positive S&P 500 returns will command a higher upside realized volatility. The impact of the S&P 500 on the RVOL^- accounts for almost three times its impact on the aggregate measure highlighting the volatility leverage effect. Similar to the implied volatility series, inflation and industrial production are significant for RVOL and RVOL^+ , indicating that the RVOL^+ is related more to changes in consumption and production compared with the downside measure. Variables such as ER, EPU and GPR appear, instead, to be linked more with downside realized volatility, RVOL^- . Gold and oil significantly impact on the realized volatility. Gold impacts only on the aggregate RVOL and it emerges with its first lag and negative sign consistent with the rationale that gold has often been seen as a safe haven for investors whenever the market becomes very volatile. Oil impacts on all three realized volatilities, with higher coefficient on the RVOL^- . Higher R^2 and adjusted R^2 are found with respect to RVOL^+ which appears to be influenced the most by both macro and financial variables.

During the pre-crisis period, we find similarly highly significant results in relation to the S&P 500 . Among the macro variables, we confirm an impact mainly on the upside volatility for inflation, while on the downside component from unemployment rate. Oil is also found to be significant during this period, whereas gold and exchange rate fail to show significance. Credit has effect only on the RVOL^+ at its first lag. The results fail to show any role for the EPU index, whereas GPR index is found to be significant for the downside realized volatility component. The R^2 and adjusted R^2 are found to be highest when corresponding to the RVOL^+ .

During the post-crisis period, we detect a significant role for the S&P 500 , again mainly on the downside volatility component. Inflation and industrial production emerge significant only with their first lag. Liquidity which is found not to be significant during the pre-crisis period shows significance post-crisis. We observe, during this time, a predominant role for the EPU index, especially on the downside realized volatility component. The geopolitical risk index also shows a significant role with respect to RVOL^- . The highest R^2 and adjusted R^2 are now associated with the two volatility components, RVOL^- and RVOL^+ , rather than with the aggregate measure, RVOL .

Table A3: **Stepwise Backward Regression between the U.S. Realized Volatilities and Selected Variables**

	Total Period						Pre-Crisis Period						Post-Crisis Period					
Var	RVOL		RVOL^-		RVOL^+		RVOL		RVOL^-		RVOL^+		RVOL		RVOL^-		RVOL^+	
	t	t-1	t	t-1	t	t-1	t	t-1	t	t-1	t	t-1	t	t-1	t	t-1	t	t-1
CPI	-0.149*	0.174**			-0.233**	0.225***	-0.220**				-0.347***	0.267**		0.514**		0.797**		
	(0.082)	(0.082)			(0.092)	(0.084)	(0.113)				(0.199)	(0.121)		(0.235)		(0.388)		
IP	0.694**				0.738**											-0.238**		
	(0.327)				(0.367)											(0.134)		
GDP																		
UR									-0.488*									
									(0.266)									
M1													-0.714*					
													(0.414)					
TS																		
OIL	0.663**		0.968**		0.686**		0.936***		0.124**		0.940***			-0.188***				-0.175***
	(0.266)		(0.430)		(0.270)		(0.351)		(0.049)		(0.348)			(0.062)				(0.058)
ER			-0.226*										0.289*			-0.563*		
			(0.122)										(0.144)			(0.330)		
GOLD		-0.752**															0.132*	
		(0.411)															(0.074)	
SPX	-0.186***	-0.130***	-0.538***	0.161**	0.093*	-0.364***	-0.198***	-0.177***	-0.585***		0.156***	-0.451***		-0.131***	-0.541***		0.214*	-0.338***
	(0.051)	(0.047)	(0.082)	(0.080)	(0.050)	(0.049)	(0.058)	(0.058)	(0.086)		(0.057)	(0.061)		(0.043)	(0.120)		(0.122)	(0.110)
CRE	0.340*				0.385**							0.104***	0.136***	-0.112**			0.170***	-0.092**
	(0.196)				(0.190)							(0.035)	(0.501)	(0.489)			(0.049)	(0.041)
SENT						-0.747*												
						(0.415)												
TED													0.365**					
													(0.179)					
EPU	0.263**	0.504***	0.557***	0.463**		0.607***							0.494**	0.735***	0.728**	0.794*		
	(0.116)	(0.127)	(0.192)	(0.201)		(0.129)							(0.214)	(0.226)	(0.342)	(0.400)		
GPR	-0.102*		-0.139*						-0.167*							0.351*		
	(0.052)		(0.083)						(0.090)							(0.184)		
R^2	0.318		0.334		0.409		0.324		0.366		0.524		0.487		0.527		0.515	
Adj R^2	0.269		0.279		0.360		0.229		0.299		0.457		0.334		0.377		0.371	

Notes: This table presents the output of the stepwise backward regression analysis between our dependent variables, realized volatilities (RVOL , RVOL^- and RVOL^+) and the 15 selected macroeconomic and financial variables (Inflation (CPI), Industrial Production (IP), Gross Domestic Product (GDP), Unemployment Rate (UR), Money Supply (M1), Term Structure (TS), Oil Price (OIL), JPY-US Exchange Rate (ER), Gold Price (GOLD), S&P 500 Index (SPX), Credit Spread (CRE), Market Sentiment (SENT), TED Spread (TED), Economic and Policy Uncertainty (EPU) Index and GeoPolitical Risk (GPR) Index). The regression as shown in equation (3.9), for realized volatility, $\triangle RV^q_{t,k} = \alpha + \sum_{i=1}^{n-h} \beta_j (\triangle X_{Macro,Fin})_{j,t-h} + \epsilon_{i,j} \quad where \quad q = Tot, +, -$ is run for contemporaneous variables (t) and one period lag (t-1) variables. The table reports the regression coefficients and their respective standard errors in parentheses, only for the variables that passed the stepwise regression test. Selection method is stepwise backwards with stopping threshold p-values higher than 10%. All the variables are taken with difference or log-difference and re-scaled accordingly. Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01. The regression is run over the total time period, from 04-1996 to 09-2016, over the Pre-Crisis period from 01-1996 to 08-2007 and over the Post-Crisis period from 04-2009 to 09-2016, at monthly frequency, for a total of 247, 139 and 90 observations, respectively, after adjustments.

We also test the same model in equation (3.9) though adding an additional second lag with respect to the variables, similar to that undertaken with the implied volatility measures as discussed in Section 3.5.1. However, the results obtained for the realized volatility are very different from the results obtained for the implied volatilities. Some covariates are found to be significantly impacting on RVOL and its components with respect to their second lag, resulting in an increased R^2 and adjusted R^2. The macroeconomic variables second lag increases the performance of the RVOL series in the pre financial crisis period, but it does not in the post financial crisis. This shows how in the post-crisis period the financial conditions variables are the ones driving the realized volatilities the most, with relationships also extending beyond the first lag, showing that these backward looking volatility measures require more time to react and adapt to changes and innovations in macro and financial variables[1].

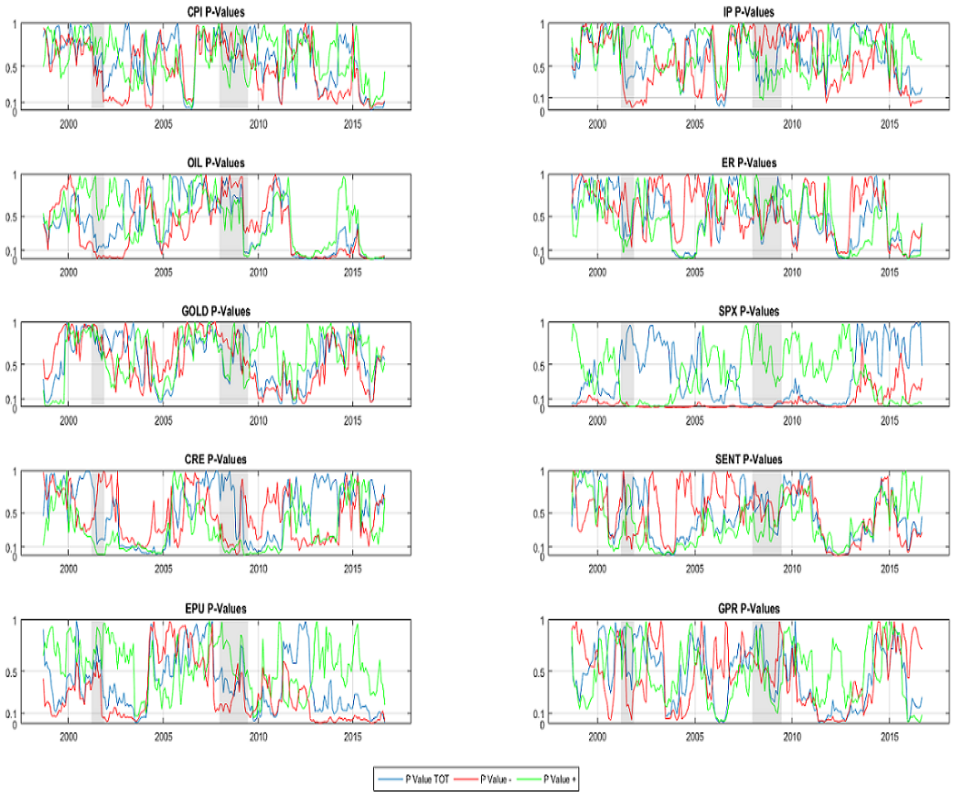
The same exercise to test the reverse signs of the variables coefficients is conducted for the RVOL series as well through equation (3.16). We confirm that the same coefficients of the second difference found for the implied volatility series hold for the realized volatility as well.

Overall, for the U.S. realized volatility, we find an even weaker role for the macroeconomic variables when only contemporaneous and first lag variables are considered. Some of the macro variables are found to be significant only when the second lag is taken (e.g. TS and UR). However, GDP is found not to be significant in any of the time periods nor for any of the realized volatility components. The effect of commodities is stronger in relationship to the backward looking volatility measures. Some of the financial conditions variables emerge significant also when lagged. In addition, some show higher coefficients when increasing the lag. These findings are not evident with respect to the implied volatility series where increasing the lag decreases the variable effect. This is due to the fact that the realized volatility measures are backward looking and will respond with delay to the changes in the independent variables. Higher significance for the model is found in relationship to the upside component, as found for the implied volatility, over the total period and pre-crisis period. Macroeconomic and financial variables appear to show greater significance with regards to the upside volatility component.

For the post-crisis period, we find that the downside volatility component appears to be better explained by the selected variables. This might reflect the fact that after the crisis investors are more concerned about the possibility of negative stock market returns which manifests itself in an increase in Put options trading.

[1]For the total time period, the second lag of S&P 500 and ER is found to be significant in impacting RVOL , increasing the R^2 and the adjusted R^2 to 0.354 and 0.307, respectively. The second lag of S&P 500 , ER, UR and IP significantly influences RVOL^- by increasing the R^2 and the adjusted R^2 to 0.392 and 0.330, respectively. Lastly, for RVOL^+ , only the second lags of S&P 500 and SENT are found to be significant, increasing the R^2 and the adjusted R^2 to 0.435 and to 0.405, respectively. In the pre-crisis period, the second lag of S&P 500 , GOLD, ER and EPU impacts on RVOL , the second lag of S&P 500 , EPU and TS impacts on RVOL^- while the second lag of S&P 500 , CPI, GOLD and TS impacts on the upside component. The R^2 and the adjusted R^2 of these models increase considerably when these variables are added: 0.462 and 0.309 for RVOL , 0.476 and 0.369 for RVOL^- and 0.612 and 0.502 for RVOL^+ . For the post financial crisis period, the role of the second lags of EPU and ER is found significant for RVOL , the second lag of EPU, ER, SENT and GOLD for RVOL^- and the second lag of ER for RVOL^+ . The R^2 and the adjusted R^2 increases also in these cases to 0.607 and 0.406 for RVOL , to 0.687 and 0.523 for RVOL^- and to 0.532 and 0.392 for RVOL^+ , respectively.

Figure A1: **Rolling P Values for the Realized Volatility Regression**



Notes: This figure shows the rolling p-values for the variables selected by the stepwise backward regression in equation (3.9) to explain at least one of the realized volatility components over the total time period (see Table A3): Inflation (CPI), Industrial Production (IP), Oil Price (OIL), JPY-US Exchange Rate (ER), Gold Price (GOLD), S&P 500 Index (SPX), Credit Spread (CRE), Market Sentiment (SENT), Economic and Policy Uncertainty (EPU) Index and GeoPolitical Risk (GPR) Index. Table . The variables selected are the ones found to explain at least one of the realized volatility components over the total time period. The reported rolling p-values are associated to the different volatility series, namely, RVOL (blue line), RVOL^- (red line) and RVOL^+ (green line). 10% significance threshold is shown. Selected window size is 30 months and the regression is rolled every month. NBER recession periods highlighted with a grey shadow. The rolling regression analysis is run over the total time period from 01-1996 to 09-2016, at monthly frequency.

Figure A1 shows the rolling p-values for the variables selected from the stepwise regression analysis for the realized series (RVOL , RVOL^- and RVOL^+) over the total time period. The macroeconomic variables inflation and industrial production are barely significant, while the effect of commodities, gold and oil, appears, overall, more stable. Gold is found to be significant in periods such as the post 2001-2002 recession or during the European sovereign financial crisis in which uncertainty and instability increased the investors' desire to buy gold. S&P 500 is mainly significant for the RVOL^- , confirming the major influence of the negative stock market returns on volatility. Only during calmer periods such as from 2002 to 2004 and from 2015 to 2016 does it impact on RVOL^+ . Market sentiment is mainly related to the RVOL^+ , whereas EPU and GPR indexes are closely related to RVOL^- especially during periods of recession, uncertainty and economic instability[2].

[2]When PCI is used in place of EPU, it emerges as significant (at the 5% level) with a positive sign for the aggregate RVOL and RVOL^- in the pre-crisis period slightly increasing the R^2 and adjusted R^2 to 0.335 and 0.241 for RVOL and to 0.386 and 0.316 for RVOL^- , respectively. A possible explanation for this could be the fact that this time period in the U.S. was characterized by two presidential elections, and there were concerns and tensions among parties especially with regards to the foreign policy of the new administration. PCI is found to be significant (at the 10% level) also in the post-crisis, but only for the RVOL^- . This shows that realized volatilities have reacted a bit more compared to implied volatilities to political events in our

There is evidence that credit was significant during the two recessions and their aftermath on the decomposed RVOL components. It impacts on the RVOL^+ between 2001 and 2005 and between 2009 and 2011, when it was mainly a stimulus for the economic recovery, and it influences the RVOL^- in the middle of the financial crisis. Da Fonseca and Gottschalk (2014) found that during a global crisis there might be a break down between equity volatility measures and credit market (CDS), a problem which may lead to poor hedging performance when equity options are used to hedge credit risk under the theoretical framework of structural credit risk models. Whereas we find similar results both for implied and also for realized aggregate volatility measures, when we examine the two different volatility components a tight relationship between credit and RVOL^- and RVOL^+ holds during the global financial crisis (see Figure A1). A closer relationship between credit and the downside volatility component, VIX^- , is also found (see Figure 3.2). These results further emphasize the different set of information encompassed within the volatility components as compared to the aggregate.

A.2.2 Realized Volatility Granger Causality at Different Frequencies

Here we discuss the results of the Granger causality test for the realized volatility conducted through equations (3.10), (3.11) and (3.15) for low frequency, high frequency and mixed frequency, respectively. The results are summarized in Table A4.

For the aggregate RVOL , the results point to a unilateral feedback effect going from the volatility measure to inflation, industrial production and market sentiment (Δ RVOL $\Rightarrow_{LF}$ Δ CPI, Δ RVOL $\Rightarrow_{LF}$ Δ IP, Δ RVOL $\Rightarrow_{LF}$ Δ SENT), whereas, for low frequency, there is no causality relationship from the macro activity to RV. However, when we perform a MF-VAR we are not only able to confirm the previous low frequency chains, but the interaction between IP and SENT with RVOL becomes bidirectional (Δ RVOL $\Leftrightarrow_{MF}$ Δ IP, Δ RVOL $\Leftrightarrow_{MF}$ Δ SENT) and an unilateral causality relationship from RVOL to the money supply is also detected (Δ RVOL $\Rightarrow_{MF}$ Δ M1).

In relation to the other high frequency variables, when they are temporally aggregated to monthly frequency we are only able to find an unilateral Granger causality from RVOL to credit, TED and EPU index (Δ RVOL $\Rightarrow_{LF}$ Δ CRE, Δ RVOL $\Rightarrow_{LF}$ Δ TED, Δ RVOL $\Rightarrow_{LF}$ Δ EPU) and in the other direction, from JPY-USD and S&P 500 towards RVOL (Δ ER $\Rightarrow_{LF}$ Δ RVOL , Δ S&P 500 $\Rightarrow_{LF}$ Δ RVOL). When daily frequency is considered, bilateral relationships between RVOL and exchange rate, and also between RVOL and EPU index emerge (Δ RVOL $\Leftrightarrow_{HF}$ Δ ER, Δ RVOL $\Leftrightarrow_{HF}$ Δ EPU). Moreover, an unilateral causality link from OIL and TS directed towards the aggregate realized volatility is found (Δ OIL $\Rightarrow_{HF}$ Δ RVOL , Δ TS $\Rightarrow_{HF}$ Δ RVOL) while from RVOL to GPR (Δ RVOL $\Rightarrow_{HF}$ Δ GPR).

In addition, RVOL^- is informative in predicting future changes in inflation, industrial production

time frame.

and market sentiment, whereas no relationship from the macroeconomics to the RVOL^- is found. When we perform the MF-VAR model, we confirm a bilateral relationship between RVOL^- and IP and between RVOL^- and market sentiment (Δ $\mathrm{RVOL}^- \Leftrightarrow_{MF} \Delta$ IP, Δ $\mathrm{RVOL}^- \Leftrightarrow_{MF} \Delta$ SENT) and an unilateral relationship from RVOL^- to the money supply (Δ $\mathrm{RVOL}^- \Rightarrow_{MF} \Delta$ M1). These findings show how the macroeconomic variables, when significant, impact on or are impacted by the volatility market in a similar way, both in the aggregate measure and also in the downside measure.

The same causality relationships are found at low frequency for the other variables, however with a stronger bilateral relationship between the EPU index and RVOL^- both at low frequency (Δ RVOL^- $\Leftrightarrow_{LF} \Delta$ EPU) and also at higher frequency (Δ $\mathrm{RVOL}^- \Leftrightarrow_{HF} \Delta$ EPU). The GPR index appears to be more connected with the downside volatility component in addition to showing a high frequency bilateral causality (Δ $\mathrm{RVOL}^- \Leftrightarrow_{MF} \Delta$ GPR). RVOL^- appears to require more than nine days and more than eighteen days to impact on credit and liquidity, respectively, given that we only find a unilateral causality among these variables at lower frequency. In the other direction, we detect a higher frequency causality relationship between S&P 500 , exchange rate and oil towards RVOL^- (Δ S&P 500 $\Rightarrow_{HF}$ Δ RVOL^- , Δ ER $\Rightarrow_{HF} \Delta$ RVOL^- , Δ OIL $\Rightarrow_{HF} \Delta$ RVOL^-).

For the upside realized volatility, the picture is slightly different. For instance, a bilateral Granger causality between RVOL^+ and inflation is detected at monthly frequency (Δ $\mathrm{RVOL}^+ \Rightarrow_{LF} \Delta$ CPI) and confirmed with MF-VAR model (Δ $\mathrm{RVOL}^+ \Rightarrow_{MF} \Delta$ CPI), indicating how the influence of inflation on volatility is mainly derived from the positive returns component. Unilateral relationship from RVOL^+ and money supply is also found at lower frequency in this case (Δ $\mathrm{RVOL}^+ \Rightarrow_{LF} \Delta$ M1). There is no evidence of Granger causality from RVOL^+ to market sentiment at lower frequency or mixed frequency, whereas when the chain is reverted we uncover market sentiment as a variable impacting on the RVOL^+ (Δ SENT $\Rightarrow_{LF} \Delta$ RVOL^+). A bilateral causality relationship at lower frequency and confirmed at high frequency is found for TED (Δ $\mathrm{RVOL}^+ \Leftrightarrow_{LF} \Delta$ TED, Δ $\mathrm{RVOL}^+ \Leftrightarrow_{HF} \Delta$ TED). RVOL^+ is unable to Granger cause other variables at monthly frequency, whereas it Granger causes gold (Δ $\mathrm{RVOL}^+ \Rightarrow_{HF} \Delta$ GOLD) and it shows a bilateral Granger causality with S&P 500 (Δ $\mathrm{RVOL}^+ \Leftrightarrow_{HF} \Delta$ S&P 500) at daily frequency. Other market variables such as oil, exchange rate and credit Granger cause RVOL^+ at daily frequency (Δ OIL $\Rightarrow_{HF} \Delta$ RVOL^+ , Δ ER $\Rightarrow_{HF} \Delta$ RVOL^+ , Δ CRE $\Rightarrow_{HF} \Delta$ RVOL^+). There is not a causality relationship between RVOL^+ and geopolitical risk index and there is only unilateral causality from the EPU index to RVOL^+ .

Table A4: **Pairwise Granger Causality Test for Mixed Frequencies: From Realized Volatilities to Selected Variables ($\triangle$ RV $\nRightarrow$ $\triangle$ X)**

Aggregate Realized Volatility: RVOL								
	Low Frequency GC		High Frequency GC		Mixed Frequency GC			
HP	l	P-Value	l	P-Value	$h=1$	$h=2$	$h=3$	$h=4$
$\triangle$ RVOL $\nRightarrow$ $\triangle$ CPI	2	0.007			0.855	0.022	0.442	0.000
$\triangle$ RVOL $\nRightarrow$ $\triangle$ GDP	4	0.736			0.005	0.120	0.119	0.000
$\triangle$ RVOL $\nRightarrow$ $\triangle$ IP	4	0.035			0.088	0.005	0.563	0.000
$\triangle$ RVOL $\nRightarrow$ $\triangle$ UR	3	0.653			0.166	0.028	0.114	0.000
$\triangle$ RVOL $\nRightarrow$ $\triangle$ M1	4	0.330			0.000	0.579	0.005	0.011
$\triangle$ RVOL $\nRightarrow$ $\triangle$ SENT	3	0.091			0.097	0.126	0.041	0.000
$\triangle$ RVOL $\nRightarrow$ $\triangle$ TS	3	0.695	8	0.291				
$\triangle$ RVOL $\nRightarrow$ $\triangle$ OIL	3	0.128	9	0.542				
$\triangle$ RVOL $\nRightarrow$ $\triangle$ ER	3	0.243	9	0.024				
$\triangle$ RVOL $\nRightarrow$ $\triangle$ GOLD	2	0.255	8	0.494				
$\triangle$ RVOL $\nRightarrow$ $\triangle$ SPX	2	0.719	16	0.148				
$\triangle$ RVOL $\nRightarrow$ $\triangle$ CRE	2	0.001	9	0.181				
$\triangle$ RVOL $\nRightarrow$ $\triangle$ TED	2	0.000	11	0.045				
$\triangle$ RVOL $\nRightarrow$ $\triangle$ EPU	3	0.055	19	0.006				
$\triangle$ RVOL $\nRightarrow$ $\triangle$ GPR	2	0.317	15	0.075				
Downside Realized Volatility: RVOL^-								
$\triangle$ RVOL^- $\nRightarrow$ $\triangle$ CPI	3	0.017			0.007	0.316	0.058	0.559
$\triangle$ RVOL^- $\nRightarrow$ $\triangle$ GDP	4	0.984			0.015	0.768	0.428	0.018
$\triangle$ RVOL^- $\nRightarrow$ $\triangle$ IP	4	0.019			0.072	0.039	0.410	0.208
$\triangle$ RVOL^- $\nRightarrow$ $\triangle$ UR	3	0.547			0.117	0.348	0.226	0.127
$\triangle$ RVOL^- $\nRightarrow$ $\triangle$ M1	4	0.411			0.039	0.209	0.004	0.004
$\triangle$ RVOL^- $\nRightarrow$ $\triangle$ SENT	2	0.002			0.518	0.063	0.177	0.000
$\triangle$ RVOL^- $\nRightarrow$ $\triangle$ TS	2	0.778	6	0.782				
$\triangle$ RVOL^- $\nRightarrow$ $\triangle$ OIL	2	0.896	7	0.656				
$\triangle$ RVOL^- $\nRightarrow$ $\triangle$ ER	1	0.889	7	0.291				
$\triangle$ RVOL^- $\nRightarrow$ $\triangle$ GOLD	2	0.603	9	0.573				
$\triangle$ RVOL^- $\nRightarrow$ $\triangle$ SPX	2	0.906	16	0.187				
$\triangle$ RVOL^- $\nRightarrow$ $\triangle$ CRE	2	0.000	9	0.453				
$\triangle$ RVOL^- $\nRightarrow$ $\triangle$ TED	2	0.038	18	0.696				
$\triangle$ RVOL^- $\nRightarrow$ $\triangle$ EPU	2	0.002	19	0.013				
$\triangle$ RVOL^- $\nRightarrow$ $\triangle$ GPR	2	0.927	14	0.030				
Upside Realized Volatility: RVOL^+								
$\triangle$ RVOL^+ $\nRightarrow$ $\triangle$ CPI	3	0.089			0.409	0.001	0.029	0.000
$\triangle$ RVOL^+ $\nRightarrow$ $\triangle$ GDP	3	0.179			0.022	0.015	0.079	0.481
$\triangle$ RVOL^+ $\nRightarrow$ $\triangle$ IP	3	0.035			0.832	0.123	0.831	0.001
$\triangle$ RVOL^+ $\nRightarrow$ $\triangle$ UR	2	0.941			0.367	0.996	0.030	0.277
$\triangle$ RVOL^+ $\nRightarrow$ $\triangle$ M1	3	0.081			0.038	0.515	0.000	0.278
$\triangle$ RVOL^+ $\nRightarrow$ $\triangle$ SENT	2	0.696			0.424	0.286	0.021	0.436
$\triangle$ RVOL^+ $\nRightarrow$ $\triangle$ TS	2	0.280	7	0.280				
$\triangle$ RVOL^+ $\nRightarrow$ $\triangle$ OIL	2	0.216	11	0.927				
$\triangle$ RVOL^+ $\nRightarrow$ $\triangle$ ER	2	0.227	10	0.373				
$\triangle$ RVOL^+ $\nRightarrow$ $\triangle$ GOLD	2	0.319	8	0.046				
$\triangle$ RVOL^+ $\nRightarrow$ $\triangle$ SPX	2	0.871	12	0.001				
$\triangle$ RVOL^+ $\nRightarrow$ $\triangle$ CRE	3	0.154	9	0.617				
$\triangle$ RVOL^+ $\nRightarrow$ $\triangle$ TED	2	0.000	12	0.047				
$\triangle$ RVOL^+ $\nRightarrow$ $\triangle$ EPU	3	0.567	16	0.481				
$\triangle$ RVOL^+ $\nRightarrow$ $\triangle$ GPR	2	0.790	14	0.258				

Notes: This table shows the VAR Granger causality tests performed through equation (3.10), (3.11) and (3.15) for low, high and mixed frequency variables, respectively. The direction of the causality chains goes from the realized volatility series, RVOL RVOL^- and RVOL^+ towards the macroeconomic and financial variables ($\triangle$ RV $\nRightarrow$ $\triangle$ X). Lags are selected according to the minimum value between AIC and SIC tests for LF and HF, while fixed to one for MF. MF-VAR controls for forecasting horizon $h = 1, 2, 3, 4$. Null hypotheses: $X \nRightarrow_{LF} Y$, $X \nRightarrow_{HF} Y$ and $X \nRightarrow_{MF} Y$. In bold the Granger Causality relations at 10% level. The total time period is from 04-01-1996 to 29-09-2016. Frequency is according to the model and variables frequency availability.

Table A5: **Pairwise Granger Causality Test for Mixed Frequencies: From Selected Variables to Realized Volatility ($\triangle$ X $\nRightarrow$ $\triangle$ RV)**

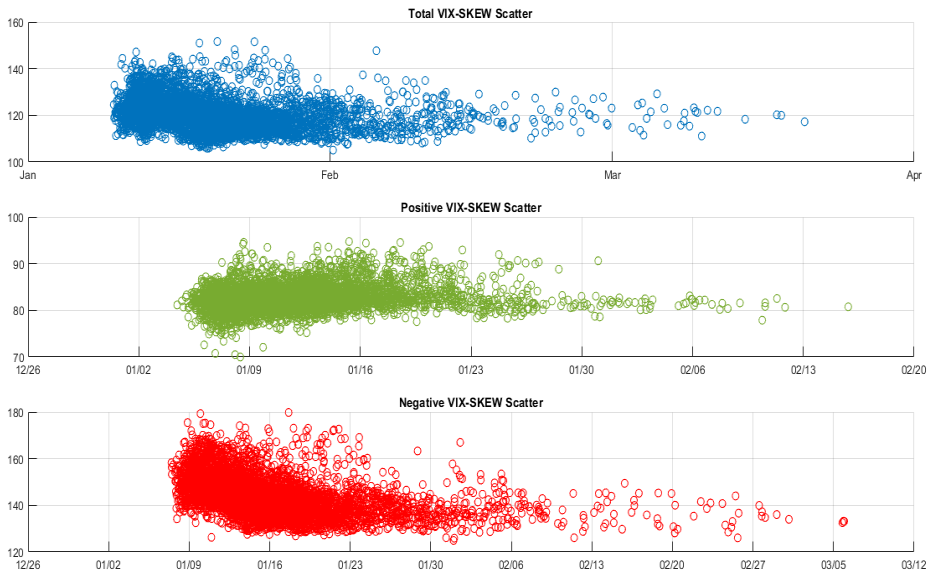
Aggregate Realized Volatility: RVOL								
	Low Frequency GC		High Frequency GC		Mixed Frequency GC			
HP	l	P-Value	l	P-Value	$h=1$	$h=2$	$h=3$	$h=4$
$\triangle$ CPI $\nRightarrow$ $\triangle$ RVOL	2	0.235			0.526	0.679	0.816	0.037
$\triangle$ GDP $\nRightarrow$ $\triangle$ RVOL	4	0.167			0.998	0.305	0.993	0.575
$\triangle$ IP $\nRightarrow$ $\triangle$ RVOL	4	0.777			0.001	0.004	0.127	0.000
$\triangle$ UR $\nRightarrow$ $\triangle$ RVOL	3	0.859			0.154	0.972	0.631	0.000
$\triangle$ M1 $\nRightarrow$ $\triangle$ RVOL	4	0.394			0.512	0.618	0.352	0.000
$\triangle$ SENT $\nRightarrow$ $\triangle$ RVOL	3	0.488			0.000	0.161	0.074	0.000
$\triangle$ TS $\nRightarrow$ $\triangle$ RVOL	3	0.835	8	0.062				
$\triangle$ OIL $\nRightarrow$ $\triangle$ RVOL	3	0.570	9	0.001				
$\triangle$ ER $\nRightarrow$ $\triangle$ RVOL	3	0.062	9	0.048				
$\triangle$ GOLD $\nRightarrow$ $\triangle$ RVOL	2	0.973	8	0.619				
$\triangle$ SPX $\nRightarrow$ $\triangle$ RVOL	2	0.000	16	0.000				
$\triangle$ CRE $\nRightarrow$ $\triangle$ RVOL	2	0.548	9	0.058				
$\triangle$ TED $\nRightarrow$ $\triangle$ RVOL	2	0.232	11	0.415				
$\triangle$ EPU $\nRightarrow$ $\triangle$ RVOL	3	0.356	19	0.000				
$\triangle$ GPR $\nRightarrow$ $\triangle$ RVOL	2	0.684	15	0.143				
Downside Realized Volatility: RVOL^-								
$\triangle$ CPI $\nRightarrow$ $\triangle$ RVOL^-	3	0.431			0.907	0.807	0.178	0.478
$\triangle$ GDP $\nRightarrow$ $\triangle$ RVOL^-	4	0.126			0.963	0.995	0.948	0.556
$\triangle$ IP $\nRightarrow$ $\triangle$ RVOL^-	4	0.917			0.002	0.256	0.068	0.003
$\triangle$ UR $\nRightarrow$ $\triangle$ RVOL^-	3	0.501			0.831	0.700	0.026	0.417
$\triangle$ M1 $\nRightarrow$ $\triangle$ RVOL^-	4	0.799			0.683	0.942	0.825	0.007
$\triangle$ SENT $\nRightarrow$ $\triangle$ RVOL^-	2	0.354			0.007	0.038	0.009	0.000
$\triangle$ TS $\nRightarrow$ $\triangle$ RVOL^-	2	0.724	6	0.871				
$\triangle$ OIL $\nRightarrow$ $\triangle$ RVOL^-	2	0.897	7	0.009				
$\triangle$ ER $\nRightarrow$ $\triangle$ RVOL^-	1	0.002	7	0.000				
$\triangle$ GOLD $\nRightarrow$ $\triangle$ RVOL^-	2	0.586	9	0.939				
$\triangle$ SPX $\nRightarrow$ $\triangle$ RVOL^-	2	0.017	16	0.000				
$\triangle$ CRE $\nRightarrow$ $\triangle$ RVOL^-	2	0.950	9	0.101				
$\triangle$ TED $\nRightarrow$ $\triangle$ RVOL^-	2	0.343	18	0.532				
$\triangle$ EPU $\nRightarrow$ $\triangle$ RVOL^-	2	0.071	19	0.016				
$\triangle$ GPR $\nRightarrow$ $\triangle$ RVOL^-	2	0.557	14	0.099				
Upside Realized Volatility: RVOL^+								
$\triangle$ CPI $\nRightarrow$ $\triangle$ RVOL^+	3	0.070			0.778	0.023	0.446	0.002
$\triangle$ GDP $\nRightarrow$ $\triangle$ RVOL^+	3	0.590			0.992	0.791	0.934	0.870
$\triangle$ IP $\nRightarrow$ $\triangle$ RVOL^+	3	0.822			0.376	0.000	0.026	0.081
$\triangle$ UR $\nRightarrow$ $\triangle$ RVOL^+	2	0.803			0.049	0.336	0.051	0.100
$\triangle$ M1 $\nRightarrow$ $\triangle$ RVOL^+	3	0.303			0.521	0.891	0.287	0.895
$\triangle$ SENT $\nRightarrow$ $\triangle$ RVOL^+	2	0.044			0.000	0.026	0.796	0.185
$\triangle$ TS $\nRightarrow$ $\triangle$ RVOL^+	2	0.853	7	0.183				
$\triangle$ OIL $\nRightarrow$ $\triangle$ RVOL^+	2	0.766	11	0.000				
$\triangle$ ER $\nRightarrow$ $\triangle$ RVOL^+	2	0.535	10	0.010				
$\triangle$ GOLD $\nRightarrow$ $\triangle$ RVOL^+	2	0.363	8	0.178				
$\triangle$ SPX $\nRightarrow$ $\triangle$ RVOL^+	2	0.000	12	0.000				
$\triangle$ CRE $\nRightarrow$ $\triangle$ RVOL^+	3	0.081	9	0.022				
$\triangle$ TED $\nRightarrow$ $\triangle$ RVOL^+	2	0.026	12	0.082				
$\triangle$ EPU $\nRightarrow$ $\triangle$ RVOL^+	3	0.031	16	0.000				
$\triangle$ GPR $\nRightarrow$ $\triangle$ RVOL^+	2	0.641	14	0.710				

Notes: This table shows the VAR Granger causality tests performed through equation (3.10), (3.11) and (3.15) for low, high and mixed frequency variables, respectively. The models are run between the macroeconomic and financial conditions variables and the realized volatility series, RVOL RVOL^- and RVOL^+ . Lags are selected according to the minimum value between AIC and SIC tests for LF and HF, while fixed to one for MF. MF-VAR controls for forecasting horizon $h = 1, 2, 3, 4$. Null hypotheses: $X \nRightarrow_{LF} Y$, $X \nRightarrow_{HF} Y$ and $X \nRightarrow_{MF} Y$. In bold the Granger Causality relations at 10% level. The total time period is from 04-01-1996 to 29-09-2016. Frequency is according to the model and variables frequency availability.

Appendix B

Additional Material for Chapter 4

Figure B1: **Decomposed SKEW and VIX Scatter Plot**



Notes: This graph shows scatter plots between the aggregate and decomposed skewness and volatility indexes, namely between SKEW and VIX , $SKEW^{+}$ and VIX^{+} and $SKEW^{-}$ and VIX^{-} . The selected period is from 04-01-1996 to 29-12-2017, at daily frequency.

B.1 Equity, Implied Volatility and Implied Skewness Indexes

Here we analyze the interconnections among three main groups: equity (S&P 500), volatility (VIX , VIX^{-} and VIX^{+}) and skewness (SKEW , $SKEW^{-}$ and $SKEW^{+}$). Their descriptive statistics are reported in Table B1 The maximum values for all the implied volatility series was reached during the Lehman Brother collapse together with one of the lowest level touched by S&P 500 . The aggregate

VIX presents higher standard deviation compared to its components while SKEW^{-} is the most volatile among the skew indexes as also depicted in Figure 4.1. VIX^{-} and SKEW^{-} result to have higher standard deviation compared to the corresponding upside components, VIX^{+} and SKEW^{+} . The correlation analysis in Table 4.1 in Chapter 4 shows that the S&P 500 index is negatively correlated with all the indexes except that with SKEW and SKEW^{-} , in line with Harvey and Siddique (2000). Conversely, an increase in the SKEW^{+} appears to command lower expected returns. There is a negative relationship between SKEW and SKEW^{-} on one side and the implied volatility indexes on the other side, while a positive relationship is found between SKEW^{+} and the VIX series. VIX is almost perfectly positive correlated with VIX^{-} while slightly less correlated with VIX^{+} . SKEW is positively correlated with SKEW^{-} while negatively correlated with SKEW^{+} . The two skewness components, SKEW^{-} and SKEW^{+} have an almost nil correlation.

Table B1: **Series Descriptive Statistics and Correlation Analysis**

	S&P 500	VIX	VIX^{-}	VIX^{+}	SKEW	SKEW^{-}	SKEW^{+}
Mean	1291.47	20.66	16.56	12.17	120.21	143.85	82.76
Median	1246.32	19.13	15.07	11.46	119.51	142.79	82.56
Max	2190.15	80.74	65.92	46.83	151.63	180.25	94.74
Min	598.48	9.80	7.46	4.42	105.09	124.93	70.01
Std. Dev.	364.78	8.22	6.74	4.87	6.66	8.35	2.64
Skewness	0.66	2.06	2.23	1.71	0.80	0.69	0.57
Kurtosis	3.03	10.22	11.24	8.08	3.89	3.41	4.78

Notes: This table presents the main descriptive statistics for the S&P 500 index, decomposed implied volatility indexes and decomposed implied skewness indexes for the selected period from 04-01-1996 to 30-09-2016, at daily frequency.

We perform a cross-moments and cross-signs comparison within our risk-neutral moments with the aim of understanding whether or not the implied volatility and the implied skewness provide any additional information about investors' behaviors and their risk perception when decomposed. Furthermore, we would like to test if the negative implied skewness, SKEW^{-} is informative and helpful as a tail risk measure. The unit root analysis indicates the presence of non stationarity in levels, but the first differences of all the series are stationary. A study of the Granger causality relationship through a VAR model is performed. In particular, several research hypotheses are tested through Granger causality analysis.

Hypothesis 1: SKEW^{-} *is less Granger causal linked to market sentiment proxies and information coming from Calls compared to* SKEW *and* SKEW^{+} .

Hypothesis 2: *There is a significant relationship between* SKEW *and the S&P 500 equity index.*

Finally, we expect to find differences in SKEW and VIX indexes behaviours when comparing the full sample relationships with the sub-samples'.

Hypothesis 3: *The Granger causality relationships between S&P 500 ,* VIX *and* SKEW *series and their components are different across sub-samples and specific turbulent times.*

The pairwise Granger relationships for each series pair is tested through the following vector autore-

gressive (VAR) model:

$$\triangle Y_{i,t} = c_i + \sum_{j=1}^{n} \alpha_{i,j} \triangle Y_{t-j} + \sum_{j=1}^{n} \theta_{i,j} \triangle X_{t-j} + \epsilon_{i,t} \tag{B.1}$$

where, $i = 1, ...p$ is the indicator for selecting the p variable to test as dependent variables, j is the lag indicator, t is the last day in our sample. The regressors are the lag Y dependent variables and the lag X independent variables and ϵ is distributed as $N(0, \sigma^2)$.

B.1.1 Granger Causality Results

A pairwise cross-moments and cross-signs Granger causality test between the U.S. equity, volatility and skewness indexes is conducted with results reported in Table B2. This analysis is conducted comparatively for the full sample, namely, from January 1996 to September 2016 and, also, for the pre-crisis and post-crisis sub-samples.

From Table B2 we notice a strong unilateral relationship from the stock market to the implied volatility indexes, regardless of the market period, while the opposite directional link holds only in the aggregate 1996-2016 full sample. We find that the S&P 500 is more informative to predict the negative and positive implied skewness components in the full sample and in the pre-crisis (Δ S&P 500 $\Rightarrow \Delta$ SKEW^{-}) and SKEW^{+} in the post-crisis (Δ S&P 500 $\Rightarrow \Delta$ SKEW^{+}), while it does not Granger causes the aggregate SKEW .

Interestingly, only SKEW^{-} is found informative in predicting the stock market (Δ $\mathrm{SKEW}^{-} \Rightarrow \Delta$ S&P 500) even if this is only in the post-crisis period. This might be due to the fact that the increase in the investors' post-crisis concern translated in a more active Put options trading. **Hypothesis 2** is rejected and the negative SKEW^{-} component is more related to equity index, in both directions.

The implied volatility and implied skewness indexes appear to share information over long period of time. For instance, in the full sample period and in the post-crisis we find a bilateral relationship between the aggregate VIX and SKEW (Δ VIX $\Leftrightarrow \Delta$ SKEW) while this relationship is found to be only unilateral in the pre-crisis. In general, this feedback appears to be stronger and directed mainly from the implied skewness indexes towards the implied volatility indexes, with a stronger and more significant role for SKEW^{+} in the pre-crisis. A strong bilateral linkage is found between VIX^{+} and SKEW^{+} through Call portfolios (Δ $\mathrm{VIX}^{+} \Rightarrow \Delta$ SKEW^{+}). In the post-crisis period, on the other hand, we observe a reduced role for the implied skewness in predicting the future volatility changes. In addition, in the post-crisis many of the information the two indexes and sub-indexes share are placed in the Puts side (e.g. Δ $\mathrm{VIX}^{-} \Rightarrow \Delta$ SKEW , Δ $\mathrm{SKEW}^{-} \Rightarrow \Delta$ VIX , Δ $\mathrm{SKEW}^{-} \Rightarrow \Delta$ VIX^{-}).

We observe that, while before the global financial crisis the indexes and their decomposed components did not show a clear difference in their behaviour, the post crisis period is characterised by a

Table B2: **Pairwise Cross-Moments VAR Granger Causality Test**

Full Sample: Jan 1996 - Sept 2016				
Obs	Null Hypothesis	P-Value	Null Hypothesis	P-Value
5206	$\triangle$ **S&P 500** $\nRightarrow$ $\triangle$ VIX	**0.000**	$\triangle$ VIX $\nRightarrow$ $\triangle$ **S&P 500**	**0.023**
5201	$\triangle$ **S&P 500** $\nRightarrow$ $\triangle$ VIX^-	**0.000**	$\triangle$ VIX^- $\nRightarrow$ $\triangle$ **S&P 500**	**0.060**
5206	$\triangle$ **S&P 500** $\nRightarrow$ $\triangle$ VIX^+	**0.000**	$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ **S&P 500**	**0.072**
5203	$\triangle$ S&P 500 $\nRightarrow$ $\triangle$ SKEW	0.650	$\triangle$ SKEW $\nRightarrow$ $\triangle$ S&P 500	0.542
5203	$\triangle$ **S&P 500** $\nRightarrow$ $\triangle$ SKEW^-	**0.000**	$\triangle$ SKEW^- $\nRightarrow$ $\triangle$ S&P 500	0.397
5202	$\triangle$ S&P 500 $\nRightarrow$ $\triangle$ SKEW^+	0.577	$\triangle$ SKEW^+ $\nRightarrow$ $\triangle$ S&P 500	0.778
5203	$\triangle$ VIX $\nRightarrow$ $\triangle$ SKEW	**0.067**	$\triangle$ SKEW $\nRightarrow$ $\triangle$ VIX	**0.026**
5204	$\triangle$ VIX $\nRightarrow$ $\triangle$ SKEW^-	0.209	$\triangle$ SKEW^- $\nRightarrow$ $\triangle$ VIX	**0.072**
5202	$\triangle$ VIX $\nRightarrow$ $\triangle$ SKEW^+	0.771	$\triangle$ SKEW^+ $\nRightarrow$ $\triangle$ VIX	0.709
5204	$\triangle$ VIX^- $\nRightarrow$ $\triangle$ SKEW	**0.022**	$\triangle$ SKEW $\nRightarrow$ $\triangle$ VIX^-	**0.013**
5211	$\triangle$ VIX^- $\nRightarrow$ $\triangle$ SKEW^-	0.733	$\triangle$ SKEW^- $\nRightarrow$ $\triangle$ VIX^-	**0.001**
5202	$\triangle$ VIX^- $\nRightarrow$ $\triangle$ SKEW^+	0.512	$\triangle$ SKEW^+ $\nRightarrow$ $\triangle$ VIX^-	**0.000**
5204	$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ SKEW	0.451	$\triangle$ SKEW $\nRightarrow$ $\triangle$ VIX^+	**0.044**
5204	$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ SKEW^-	0.164	$\triangle$ SKEW^- $\nRightarrow$ $\triangle$ VIX^+	**0.000**
5202	$\triangle$ VIX^+ $\nRightarrow$ $\triangle\text{SKEW}^+$	0.385	$\triangle$ SKEW^+ $\nRightarrow$ $\triangle$ VIX^+	**0.000**
Pre-Crisis Period: Jan 1996 - June 2007				
Obs	Null Hypothesis	P-Value	Null Hypothesis	P-Value
2872	$\triangle$ **S&P 500** $\nRightarrow$ $\triangle$ VIX	**0.000**	$\triangle$ VIX $\nRightarrow$ $\triangle$ S&P 500	0.162
2877	$\triangle$ **S&P 500** $\nRightarrow$ $\triangle$ VIX^-	**0.000**	$\triangle$ VIX^- $\nRightarrow$ $\triangle$ S&P 500	0.401
2877	$\triangle$ **S&P 500** $\nRightarrow$ $\triangle$ VIX^+	**0.000**	$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ S&P 500	0.348
2876	$\triangle$ S&P 500 $\nRightarrow$ $\triangle$ SKEW	0.142	$\triangle$ SKEW $\nRightarrow$ $\triangle$ S&P 500	0.602
2877	$\triangle$ **S&P 500** $\nRightarrow$ $\triangle$ SKEW^-	**0.001**	$\triangle$ SKEW^- $\nRightarrow$ $\triangle$ S&P 500	0.439
2873	$\triangle$ S&P 500 $\nRightarrow$ $\triangle$ SKEW^+	0.596	$\triangle$ SKEW^+ $\nRightarrow$ $\triangle$ S&P 500	0.590
2874	$\triangle$ VIX $\nRightarrow$ $\triangle$ SKEW	**0.012**	$\triangle$ SKEW $\nRightarrow$ $\triangle$ VIX	0.743
2872	$\triangle$ VIX $\nRightarrow$ $\triangle$ SKEW^-	**0.000**	$\triangle$ SKEW^- $\nRightarrow$ $\triangle$ VIX	0.473
2872	$\triangle$ VIX $\nRightarrow$ $\triangle$ SKEW^+	0.241	$\triangle$ SKEW^+ $\nRightarrow$ $\triangle$ VIX	**0.084**
2874	$\triangle$ VIX^- $\nRightarrow$ $\triangle$ SKEW	**0.002**	$\triangle$ SKEW $\nRightarrow$ $\triangle$ VIX^-	**0.029**
2879	$\triangle$ VIX^- $\nRightarrow$ $\triangle$ SKEW^-	0.329	$\triangle$ SKEW^- $\nRightarrow$ $\triangle$ VIX^-	**0.000**
2872	$\triangle$ VIX^- $\nRightarrow$ $\triangle$ SKEW^+	0.474	$\triangle$ SKEW^+ $\nRightarrow$ $\triangle$ VIX^-	**0.000**
2874	$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ SKEW	0.185	$\triangle$ SKEW $\nRightarrow$ $\triangle$ VIX^+	0.523
2879	$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ SKEW^-	**0.000**	$\triangle$ SKEW^- $\nRightarrow$ $\triangle$ VIX^+	**0.000**
2873	$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ SKEW^+	**0.023**	$\triangle$ SKEW^+ $\nRightarrow$ $\triangle$ VIX^+	**0.000**
Post-Crisis Period: Apr 2009 - Sept 2016				
Obs	Null Hypothesis	P-Value	Null Hypothesis	P-Value
1878	$\triangle$ **S&P 500** $\nRightarrow$ $\triangle$ VIX	**0.001**	$\triangle$ VIX $\nRightarrow$ $\triangle$ S&P 500	0.556
1878	$\triangle$ **S&P 500** $\nRightarrow$ $\triangle$ VIX^-	**0.000**	$\triangle$ VIX^- $\nRightarrow$ $\triangle$ S&P 500	0.745
1879	$\triangle$ **S&P 500** $\nRightarrow$ $\triangle$ VIX^+	**0.000**	$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ S&P 500	0.232
1881	$\triangle$ S&P 500 $\nRightarrow$ $\triangle$ SKEW	0.164	$\triangle$ SKEW $\nRightarrow$ $\triangle$ S&P 500	0.239
1883	$\triangle$ S&P 500 $\nRightarrow$ $\triangle$ SKEW^-	0.617	$\triangle$ SKEW^- $\nRightarrow$ $\triangle$ **S&P 500**	**0.084**
1883	$\triangle$ **S&P 500** $\nRightarrow$ $\triangle$ SKEW^+	**0.001**	$\triangle$ SKEW^+ $\nRightarrow$ $\triangle$ S&P 500	0.536
1880	$\triangle$ VIX $\nRightarrow$ $\triangle$ SKEW	**0.084**	$\triangle$ SKEW $\nRightarrow$ $\triangle$ VIX	**0.089**
1879	$\triangle$ VIX $\nRightarrow$ $\triangle$ SKEW^-	0.640	$\triangle$ SKEW^- $\nRightarrow$ $\triangle$ VIX	**0.069**
1874	$\triangle$ VIX $\nRightarrow$ $\triangle$ SKEW^+	**0.009**	$\triangle$ SKEW^+ $\nRightarrow$ $\triangle$ VIX	0.492
1879	$\triangle$ VIX^- $\nRightarrow$ $\triangle$ SKEW	**0.025**	$\triangle$ SKEW $\nRightarrow$ $\triangle$ VIX^-	0.202
1879	$\triangle$ VIX^- $\nRightarrow$ $\triangle$ SKEW^-	0.447	$\triangle$ SKEW^- $\nRightarrow$ $\triangle$ VIX^-	**0.066**
1874	$\triangle$ VIX^- $\nRightarrow$ $\triangle$ SKEW^+	**0.001**	$\triangle$ SKEW^+ $\nRightarrow$ $\triangle$ VIX^-	0.395
1879	$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ SKEW	**0.082**	$\triangle$ SKEW $\nRightarrow$ $\triangle$ VIX^+	0.368
1873	$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ SKEW^-	0.125	$\triangle$ SKEW^- $\nRightarrow$ $\triangle$ VIX^+	0.165
1874	$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ SKEW^+	0.199	$\triangle$ SKEW^+ $\nRightarrow$ $\triangle$ VIX^+	**0.022**

Notes: This table shows the pairwise cross-moments VAR Granger Causality test performed for the equity, implied volatility and implied skewness indexes in the U.S. First difference of the series is considered: S&P 500 , VIX , VIX^- , VIX^+ , SKEW , SKEW^- and SKEW^+ . The null hypothesis is: $\triangle$ X $\nRightarrow$ $\triangle$ Y. In bold the Granger Causality relations are found significant at 10% level. The selected period is the full sample from 04-01-1996 to 30-09-2016 (first panel), the pre-crisis period from 04-01-1996 to 29-06-2007 (mid panel) and the post-crisis period from 01-04-2009 to 30-09-2016 (bottom panel), at daily frequency, for a total of 5221, 2891 and 1888 observations, respectively.

more defined picture. The information contained in the two decomposed SKEW and VIX components appear, now, more detached. In addition, SKEW^- is found to be informative for both the stock market and volatility market (Δ SKEW^- $\Rightarrow$ Δ S&P 500 , Δ SKEW^- $\Rightarrow$ Δ VIX), but it is not Granger caused, in turn, from those. This suggests that nowadays SKEW^- is the index component that is more independent from the implied volatility. For instance, while all the VIX series, VIX , VIX^- and VIX^+ , as proxies for market sentiment, negative and positive investors' expectations, respectively, affect the SKEW index and the SKEW^+ index, the same is not found for the SKEW^- . $\triangle$ S&P 500 and $\triangle$ VIX cause movements in $\triangle$ SKEW^+ reflecting the influence of market sentiment on the Calls side (See Section 4.4). A possible explanation is that investors would like to take a long equity position when VIX is low and S&P 500 looks bullish.

In the post financial crisis, SKEW^- appears more neutral from information coming from Calls,

VIX^{+} and, moreover, there is no evidence of Granger causality between $\triangle$ VIX and $\triangle$ SKEW^{-} implying that the hedgers' trading strategies are more related to fundamentals, neglecting the information carried from the fear index. While VIX is found to Granger cause the aggregate SKEW index both in the full sample and also in the sub-samples, SKEW^{-} remains more detached and independent by market sentiment beliefs carried by VIX . The aggregate SKEW is then found from Table B2 to be more market sentiment contaminated compared to the negative SKEW^{-} which might be a more prudent measure of tail risk. We can conclude that while **Hypothesis 2** is only in part confirmed, **Hypothesis 1** appears to be satisfied at least for the full sample period and, especially, in the post-crisis period.

B.1.2 Zoom in Volatile and Turbulent Times

In this Section B.1.2, we would like to gauge the potential changes in Granger causality relationships across the indexes triggered by specific turbulent events such as the 2007-2009 global financial crisis, the dot-com bubble and the recent UK Brexit vote. Table B3 shows that, for shorter periods, the Granger causality test provides different results. For instance, differences in the relationships among implied volatility and skewness indexes are found especially between the global financial crisis and the dot-com bubble. The Brexit vote, instead, depicts a different picture. In the 2007-2009 financial crisis, the stock market, S&P 500 , presents bidirectional Granger relationships with the VIX and VIX^{-} highlighting the main role Puts play in this bearish time compared to Calls. There is no evidence that the stock market is able to predict the SKEW indexes in this situation, whereas, as already found in Table B2, SKEW^{-} is informative in predicting the future stock market activity (Δ SKEW^{-} $\Rightarrow$ Δ S&P 500). The relationship between VIX and SKEW aggregate indexes and their sub-components is found to be weak. Indeed, there is no Granger causality relationship going from the volatility to the skewness market, while there are few in the opposite direction.

During the dot-com bubble period, well known to be characterized by investors' optimism and exuberance, the results point out to a different story. The stock market shows a strong unilateral relationship going towards the volatility market while the opposite is not detected. Only during this period we find that the S&P 500 is Granger caused by the SKEW Calls component. We also find that measures such as VIX^{+} and SKEW^{+} , that were barely significant in other periods, during the dot-com bubble became highly informative in predicting some of the skew and volatility indexes, respectively. The dot-com bubble was a period of high volatility and also associated with high speculative activity reflected in the Calls measures, VIX^{+} and SKEW^{+} .

Finally, in the short Brexit period we observe that, the stock market and the volatility market are more connected through the aggregate and Puts side, VIX and VIX^{-} . The same holds between the skew indexes and the stock market trough SKEW and SKEW^{-} , while the positive SKEW^{+} is not informative in predicting the stock market future changes. On the other hand, VIX^{-} and SKEW^{-}

Table B3: **Pairwise Cross-Moments VAR Granger Causality Test in Turbulent Times**

2007-2009 Global Financial Crisis				
Obs	Null Hypothesis	P-Value	Null Hypothesis	P-Value
428	$\triangle$ **S&P 500** $\nRightarrow$ $\triangle$ VIX	**0.052**	$\triangle$ VIX $\nRightarrow$ $\triangle$ **S&P 500**	**0.018**
428	$\triangle$ **S&P 500** $\nRightarrow$ $\triangle$ VIX^-	**0.090**	$\triangle$ VIX^- $\nRightarrow$ $\triangle$ **S&P 500**	**0.026**
432	$\triangle$ S&P 500 $\nRightarrow$ $\triangle$ VIX^+	0.624	$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ S&P 500	0.268
435	$\triangle$ S&P 500 $\nRightarrow$ $\triangle$ SKEW	0.857	$\triangle$ SKEW $\nRightarrow$ $\triangle$ S&P 500	0.134
429	$\triangle$ S&P 500 $\nRightarrow$ $\triangle$ SKEW^-	0.787	$\triangle$ SKEW^- $\nRightarrow$ $\triangle$ **S&P 500**	**0.088**
427	$\triangle$ S&P 500 $\nRightarrow$ $\triangle$ SKEW^+	0.348	$\triangle$ SKEW^+ $\nRightarrow$ $\triangle$ S&P 500	0.365
428	$\triangle$ VIX $\nRightarrow$ $\triangle$ SKEW	0.134	$\triangle$ SKEW $\nRightarrow$ $\triangle$ VIX	**0.007**
429	$\triangle$ VIX $\nRightarrow$ $\triangle$ SKEW^-	0.467	$\triangle$ SKEW^- $\nRightarrow$ $\triangle$ VIX	**0.005**
428	$\triangle$ VIX $\nRightarrow$ $\triangle$ SKEW^+	0.570	$\triangle$ SKEW^+ $\nRightarrow$ $\triangle$ VIX	0.464
428	$\triangle$ VIX^- $\nRightarrow$ $\triangle$ SKEW	0.155	$\triangle$ SKEW $\nRightarrow$ $\triangle$ VIX^-	**0.011**
428	$\triangle$ VIX^- $\nRightarrow$ $\triangle$ SKEW^-	0.305	$\triangle$ SKEW^- $\nRightarrow$ $\triangle$ VIX^-	**0.003**
427	$\triangle$ VIX^- $\nRightarrow$ $\triangle$ SKEW^+	0.437	$\triangle$ SKEW^+ $\nRightarrow$ $\triangle$ VIX^-	0.393
429	$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ SKEW	**0.094**	$\triangle$ SKEW $\nRightarrow$ $\triangle$ VIX^+	**0.007**
429	$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ SKEW^-	0.449	$\triangle$ SKEW^- $\nRightarrow$ $\triangle$ VIX^+	**0.015**
427	$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ SKEW^+	0.546	$\triangle$ SKEW^+ $\nRightarrow$ $\triangle$ VIX^+	0.290
Dot-com Bubble				
Obs	Null Hypothesis	P-Value	Null Hypothesis	P-Value
865	$\triangle$ **S&P 500** $\nRightarrow$ $\triangle$ VIX	**0.036**	$\triangle$ VIX $\nRightarrow$ $\triangle$ S&P 500	0.686
873	$\triangle$ **S&P 500** $\nRightarrow$ $\triangle$ VIX^-	**0.000**	$\triangle$ VIX^- $\nRightarrow$ $\triangle$ S&P 500	0.156
869	$\triangle$ **S&P 500** $\nRightarrow$ $\triangle$ VIX^+	**0.000**	$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ S&P 500	0.690
871	$\triangle$ S&P 500 $\nRightarrow$ $\triangle$ SKEW	0.196	$\triangle$ SKEW $\nRightarrow$ $\triangle$ S&P 500	0.562
867	$\triangle$ **S&P 500** $\nRightarrow$ $\triangle$ SKEW^-	**0.026**	$\triangle$ SKEW^- $\nRightarrow$ $\triangle$ S&P 500	0.373
874	$\triangle$ S&P 500 $\nRightarrow$ $\triangle$ SKEW^+	0.465	$\triangle$ SKEW^+ $\nRightarrow$ $\triangle$ **S&P 500**	**0.069**
864	$\triangle$ VIX $\nRightarrow$ $\triangle$ SKEW	**0.000**	$\triangle$ SKEW $\nRightarrow$ $\triangle$ VIX	0.414
867	$\triangle$ VIX $\nRightarrow$ $\triangle$ SKEW^-	**0.001**	$\triangle$ SKEW^- $\nRightarrow$ $\triangle$ VIX	0.729
872	$\triangle$ VIX $\nRightarrow$ $\triangle$ SKEW^+	0.525	$\triangle$ SKEW^+ $\nRightarrow$ $\triangle$ VIX	0.266
865	$\triangle$ VIX^- $\nRightarrow$ $\triangle$ SKEW	**0.000**	$\triangle$ SKEW $\nRightarrow$ $\triangle$ VIX^-	**0.057**
867	$\triangle$ VIX^- $\nRightarrow$ $\triangle$ SKEW^-	**0.098**	$\triangle$ SKEW^- $\nRightarrow$ $\triangle$ VIX^-	**0.001**
872	$\triangle$ VIX^- $\nRightarrow$ $\triangle$ SKEW^+	0.655	$\triangle$ SKEW^+ $\nRightarrow$ $\triangle$ VIX^-	**0.000**
865	$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ SKEW	**0.086**	$\triangle$ SKEW $\nRightarrow$ $\triangle$ VIX^+	0.344
867	$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ SKEW^-	**0.000**	$\triangle$ SKEW^- $\nRightarrow$ $\triangle$ VIX^+	**0.000**
868	$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ SKEW^+	0.307	$\triangle$ SKEW^+ $\nRightarrow$ $\triangle$ VIX^+	**0.000**
Brexit Vote				
Obs	Null Hypothesis	P-Value	Null Hypothesis	P-Value
103	$\triangle$ **S&P 500** $\nRightarrow$ $\triangle$ VIX	**0.005**	$\triangle$ VIX $\nRightarrow$ $\triangle$ **S&P 500**	**0.000**
103	$\triangle$ **S&P 500** $\nRightarrow$ $\triangle$ VIX^-	**0.049**	$\triangle$ VIX^- $\nRightarrow$ $\triangle$ **S&P 500**	**0.000**
103	$\triangle$ S&P 500 $\nRightarrow$ $\triangle$ VIX^+	0.380	$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ S&P 500	0.139
99	$\triangle$ **S&P 500** $\nRightarrow$ $\triangle$ SKEW	**0.015**	$\triangle$ SKEW $\nRightarrow$ $\triangle$ **S&P 500**	**0.000**
102	$\triangle$ **S&P 500** $\nRightarrow$ $\triangle$ SKEW^-	**0.061**	$\triangle$ SKEW^- $\nRightarrow$ $\triangle$ **S&P 500**	**0.000**
102	$\triangle$ S&P 500 $\nRightarrow$ $\triangle$ SKEW^+	0.593	$\triangle$ SKEW^+ $\nRightarrow$ $\triangle$ S&P 500	0.849
92	$\triangle$ VIX $\nRightarrow$ $\triangle$ SKEW	**0.031**	$\triangle$ SKEW $\nRightarrow$ $\triangle$ VIX	0.104
94	$\triangle$ VIX $\nRightarrow$ $\triangle$ SKEW^-	**0.001**	$\triangle$ SKEW^- $\nRightarrow$ $\triangle$ VIX	**0.027**
100	$\triangle$ VIX $\nRightarrow$ $\triangle$ SKEW^+	0.581	$\triangle$ SKEW^+ $\nRightarrow$ $\triangle$ VIX	0.572
100	$\triangle$ VIX^- $\nRightarrow$ $\triangle$ SKEW	**0.000**	$\triangle$ SKEW $\nRightarrow$ $\triangle$ VIX^-	0.178
99	$\triangle$ VIX^- $\nRightarrow$ $\triangle$ SKEW^-	**0.000**	$\triangle$ SKEW^- $\nRightarrow$ $\triangle$ VIX^-	**0.054**
101	$\triangle$ VIX^- $\nRightarrow$ $\triangle$ SKEW^+	0.257	$\triangle$ SKEW^+ $\nRightarrow$ $\triangle$ VIX	0.358
102	$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ SKEW	**0.061**	$\triangle$ SKEW $\nRightarrow$ $\triangle$ VIX^+	**0.008**
101	$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ SKEW^-	0.157	$\triangle$ SKEW^- $\nRightarrow$ $\triangle$ VIX^+	**0.038**
102	$\triangle$ VIX^+ $\nRightarrow$ $\triangle$ SKEW^+	0.560	$\triangle$ SKEW^+ $\nRightarrow$ $\triangle$ VIX^+	0.968

Notes: This table shows the pairwise Cross-Moments (Equity, Volatility, Skewness) VAR Granger Causality Test performed for the U.S. around the global financial crisis (upper panel), dot-com bubble (mid panel) and Brexit vote (bottom panel). First difference of the following series is considered: S&P 500 , VIX , VIX^- , VIX^+ , SKEW , SKEW^- and SKEW^+ . The null hypothesis is: $\triangle$ X $\nRightarrow$ $\triangle$ Y. In bold the Granger Causality relations are found significant at 10% level. The selected period is from 02-07-2007 to 31-03-2009 (441 observations) for the global financial crisis, from 01-07-1998 to 31-12-2001 (879 observations) for the dot-com bubble and from 02-05-2016 to 30-09-2016 (106 observations) for Brexit, at daily frequency.

display a bilateral Granger causality through the Puts portfolios. There is only a unilateral causality from VIX to SKEW and an even weaker relationship emerging from Call options, between VIX^+ and SKEW^+ . Overall, the results in Table B3 suggest that there is less evidence of Granger causality between aggregate VIX and SKEW . This may be explained by the fact that the two indexes do not share the same information during extreme events, as highlighted in Figure 2.3[1]. To conclude, the analysis in Section B.1.2 confirms **Hypothesis 3** and shows that in turbulent times volatility and skewness indexes are mostly linked through the Put options channel. Thus, SKEW^- can be conceptualised as a more prudent tail risk measure, being forward looking and reflecting better the pessimistic investors view during these uncertain market times.

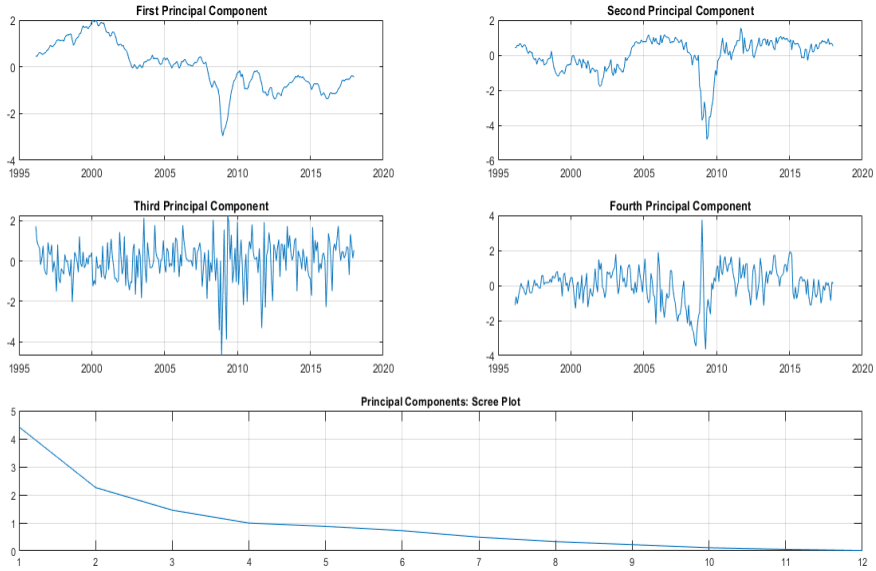
[1]While in the full sample from 1996-2016 or in sub-samples there is more evidence of shared information between the aggregate VIX and SKEW (e.g. low SKEW and low VIX), when extreme events are considered we find mainly high levels of VIX in correspondence of low levels of SKEW . For instance, during the financial crisis in which VIX index reached its highest levels, the SKEW index did not reach levels above 130. This pattern is also confirmed in the Granger analysis showing that the two indexes are less Granger causal linked during outliers.

Table B4: **Predictors Correlation Analysis**

Variable	DP	DY	EP	DE	RVOL	BM	NTIS	TBL	LTY	LTR	TMS	DFY	DFR	INFL	SKEW	$SKEW^+$	$SKEW^-$
DP	1																
DY	0.97	1															
EP	-0.07	-0.01	1														
DE	0.48	0.47	-0.87	1													
RVOL	-0.07	-0.06	-0.65	0.53	1												
BM	0.69	0.67	0.41	-0.02	-0.26	1											
NTIS	-0.49	-0.47	0.08	-0.31	0.16	-0.27	1										
TBL	-0.58	-0.58	-0.01	-0.26	-0.08	-0.69	0.31	1									
LTY	-0.54	-0.54	-0.20	-0.07	0.21	-0.71	0.54	0.81	1								
LTR	0.01	-0.02	0.04	-0.02	0.02	0.04	0.03	0.01	-0.06	1							
TMS	0.37	0.36	-0.20	0.35	0.38	0.34	0.08	-0.75	-0.22	-0.09	1						
DFY	0.58	0.55	-0.50	0.72	0.43	0.33	-0.50	-0.40	-0.26	0.02	0.37	1					
DFR	0.02	0.11	-0.18	0.17	0.11	-0.03	0.01	-0.08	-0.03	-0.47	0.10	0.10	1				
INFL	-0.15	-0.14	0.06	-0.13	-0.08	-0.08	0.04	0.13	0.15	-0.10	-0.05	-0.25	-0.05	1			
SKEW	-0.03	0.03	-0.01	0.01	0.01	-0.01	-0.01	-0.02	-0.02	-0.11	0.03	0.05	0.09	-0.03	1		
$SKEW^+$	0.08	-0.02	0.01	-0.01	0.01	0.05	-0.01	-0.01	-0.01	0.02	-0.01	0.01	-0.02	0.01	-0.05	1	
$SKEW^-$	-0.01	0.04	-0.03	0.02	0.04	-0.03	-0.02	-0.03	-0.01	-0.12	0.04	0.03	0.18	-0.06	0.71	0.25	1

Notes: The table presents the Pearson correlation coefficients for the first difference of the three SKEW indexes, SKEW , $SKEW^+$ and $SKEW^-$ and the 14 predictor variables from Goyal and Welch (2008): the log dividend price ratio (DP), the log dividend yield (DY), the log earnings-price ratio (EP), the log dividend-payout ratio (DE), the excess stock return volatility (RVOL), the book-to-market ratio (BM), the net equity expansion (NTIS), the treasury bill rate (TBL), the long-term yield (LTY), the long-term return (LTR), the term spread (TMS), the default yield spread (DFY), the default return spread (DFR) and the inflation rate (INFL). TBL, LTY, TMS, DFY and INFL are measured in annual percent. The time period is from 1996:01 to 2017:12.

Figure B2: **First Four Principal Components from Goyal and Welch (2008) 14 Predictors**



Notes: This graph shows the first four principal components extracted from the Goyal and Welch (2008) 14 macroeconomic predictors. The last plot shows the scree plot with the eigenvalues from largest to smallest. The selected period is from 01-1996 to 12-2017, at monthly frequency.

Table B5: **U.S. S&P 500 30 Largest and 30 Smallest Stocks: Descriptive Statistics**

Panel A: S&P 500 Largest 30 Stocks: Descriptive Statistics									
Ticker	Stock	Weight (%)	Mean	Std. Dev	Min	Max	Skewness	Kurtosis	Sharpe
AAPL	Apple Inc.	4.37	36.34	45.59	0.46	171.85	1.18	3.30	0.11
ABT	Abbott Lab.	0.52	25.94	10.30	9.09	57.07	0.91	3.19	0.04
ADBE	*Adobe* Inc.	0.52	37.96	33.88	3.28	181.47	1.88	6.83	0.06
AMGN	Amgen Inc.	0.54	72.31	44.43	12	186.45	0.96	3.09	0.06
BA	Boeing Company	0.82	76.78	46.02	25.06	294.91	1.91	7.51	0.04
BAC	Bank of America Corp	1.11	26.88	12.92	3.95	53.87	0.29	1.99	-0.01
C	Citigroup Inc.	0.71	229.91	185.12	15	557	0.29	1.41	-0.04
CMCSA	Comcast Corp. Class A	0.76	14.39	9.29	2.31	41.69	1.22	3.60	0.07
CSCO	Cisco Systems Inc.	0.91	22.72	11.26	4.14	77.31	1.83	8.54	0.04
CVX	Chevron Corp.	0.93	70.72	30.64	25.93	132.53	0.30	1.66	0.02
DIS	Walt Disney Company	0.74	43.47	24.49	14.93	120	1.36	3.41	0.03
DWDP	DowDuPont Inc.	0.54	37.43	10.92	7.16	72.31	0.59	3.79	0.01
HD	Home Depot Inc.	0.87	52.33	37.82	9.61	189.53	1.53	4.55	0.08
INTC	Intel Corp.	0.94	25.97	9.96	6.90	74.87	1.68	8.14	0.02
JNJ	Johnson & Johnson	1.63	65.24	26.08	21.40	139.72	0.86	3.39	0.05
JPM	JPMorgan Chase & Co.	1.59	45.50	15.43	18.99	106.94	1.36	5.62	0.02
KO	Coca-Cola Company	0.79	30.54	7.84	18.56	46.39	0.42	1.86	-0.01
MCD	McDonald's Corp.	0.59	59.11	36.62	13.61	172.12	0.91	3.00	0.05
MDT	Medtronic plc	0.52	47.41	17.01	11.84	88.75	0.31	3.04	0.03
MO	Altria Group Inc	0.53	23.85	18.30	4.64	75.44	1.30	3.63	0.06
MRK	Merck & Co. Inc.	0.85	48.41	13.53	24.20	88.61	0.34	2.48	-0.02
MSFT	Microsoft Corp.	3.57	32.03	14.14	5.48	85.54	1.21	5.12	0.06
PFE	Pfizer Inc.	1.10	28.03	8.71	10.50	48	-0.03	2.25	0.00
PG	Procter & Gamble Company	0.96	57.33	18.20	20.50	92.27	-0.03	2.19	0.08
T	AT&T Inc.	0.97	33.74	8.13	20.06	58	0.67	3.01	-0.04
UNH	UnitedHealth Group Inc.	1.09	48.67	46.33	4.21	228.17	1.66	5.53	0.09
VZ	Verizon Communications Inc.	1.02	39.29	8.81	24.59	60.33	0.21	1.82	-0.03
WFC	Wells Fargo & Company	1.00	30.80	12.53	8.25	60.67	0.55	2.62	0.04
WMT	Walmart Inc.	0.62	53.12	17.78	10.18	98.75	-0.53	3.45	0.06
XOM	Exxon Mobil Corp.	1.47	61.55	23.68	19.87	103.25	-0.09	1.57	0.02
Panel B: S&P 500 Smallest 30 Stocks: Descriptive Statistics									
Ticker	Stock	Weight (%)	Mean	Std. Dev	Min	Max	Skewness	Kurtosis	Sharpe
AIV	Aimco	0.03	28.35	8.42	5.22	46.53	-0.08	3.14	0.02
ALK	Alaska Air Group Inc.	0.03	20.59	24.16	3.83	97.82	1.71	4.52	0.08
AOS	A. O. Smith Corp.	0.02	12.56	14.28	2.09	63.42	1.87	5.51	0.10
AVY	Avery Dennison Corp.	0.03	51.62	15.89	20.15	114.86	0.64	4.47	0.04
BF.B	Brown-Forman Corp.	0.03	16.95	12.01	3.86	54.93	0.97	2.73	0.13
BWA	BorgWarner Inc.	0.03	21.50	17.27	3.62	65.36	0.87	2.54	0.08
CPB	Campbell Soup Company	0.03	37.72	10.08	20.74	66.53	0.68	2.68	-0.01
DISH	DISH Network Corp.	0.03	30.24	18.59	1.46	79.41	0.44	2.59	0.05
FL	Foot Locker Inc.	0.02	25.88	17.42	4.93	77.34	1.32	3.84	0.02
FLIR	FLIR Systems Inc.	0.02	17.70	13.11	0.44	46.82	0.11	1.59	0.09
GPS	Gap Inc.	0.02	23.69	10.00	6.22	50.37	0.72	2.71	0.03
HOG	Harley-Davidson Inc.	0.02	42.07	16.83	7.18	73.94	-0.48	2.24	0.04
HP	Helmerich & Payne Inc.	0.02	34.84	25.44	5.44	116.11	0.82	3.00	0.06
HRB	H&R Block Inc.	0.02	19.72	7.44	6.18	37.26	0.09	2.20	0.02
JEF	Jefferies Financial Group Inc.	0.02	19.76	9.79	6.76	52.82	0.86	3.66	0.02
KIM	Kimco Realty Corp.	0.02	20.93	9.44	7.62	50.26	1.07	3.60	0.01
LB	L Brands Inc.	0.03	31.16	22.54	7.47	96.68	1.29	3.72	0.05
LEG	Leggett & Platt Incorp.	0.02	25.92	9.92	11.43	52.57	1.27	3.77	0.04
MAC	Macerich Company	0.02	46.15	21.85	5.79	89.24	0.16	1.71	0.02
NFX	Newfield Exploration Company	0.01	30.36	15.67	6.68	76.01	0.62	2.85	0.03
NKTR	Nektar Therapeutics	0.02	14.17	9.22	3.35	59.72	2.58	11.03	0.03
PBCT	People's United Financial Inc.	0.02	11.48	5.23	2.68	21.42	-0.16	1.64	0.08
PHM	PulteGroup Inc.	0.02	15.50	9.90	3.10	46.81	0.92	3.19	0.05
RHI	Robert Half International Inc.	0.03	29.28	11.76	6.97	61.96	0.58	2.94	0.06
ROL	Rollins Inc.	0.02	10.61	10.35	1.56	46.53	1.59	5.04	0.13
SCG	SCANA Corp.	0.02	39.32	12.28	21.68	75.66	1.00	3.51	-0.01
UNM	Unum Group	0.03	28.40	11.20	9.80	60.43	0.88	3.11	0.00
WHR	Whirlpool Corp.	0.03	88.00	43.65	22.23	211.95	1.15	3.11	0.02
XRAY	DENTSPLY SIRONA Inc.	0.03	29.87	16.78	6.60	67.01	0.34	2.17	0.11
XRX	Xerox Corp.	0.02	43.51	32.77	11.98	163.34	2.01	6.31	-0.03

Notes: The table shows the main characteristics of the 30 largest and 30 smallest individual stocks in the S&P 500 by market capitalization in Panel A and Panel B, respectively. The first two columns show the companies' ticker and full name. The weight the stock has in the S&P 500 index is shown in percentage. Summary statistics are reported in columns from 5 to 10. The last column shows the Sharpe ratio for each individual stock computed as the mean of the log equity risk premium divided by its standard deviation. Ranking as end of as end of 2017. Time period between 01:1996 and 12:2017.

B.2 SKEW Indexes and Asset Pricing: Robustness

The results reported from Table B6 to Table B9 support the results of Section 4.7 in Chapter 4. From Table B6, with relation to the pre-crisis period, we observe a considerable contribution from SKEW^{-} to the model improvement. When SKEW^{-} is included to the 5-factors model, its significance improves by far compared to the aggregate and positive indexes, SKEW and SKEW^{+} . SKEW^{-} is found to be highly significant (1%) while SKEW^{+} at 10% and the aggregate is not significant. Similar pattern is confirmed in the full 8-factors model in which only SKEW^{-} is found significant. In the post-crisis period the model including SKEW^{-} is still the one performing better. SKEW^{-} is significant at 10% and with negative coefficient while SKEW and SKEW^{+} are not significant in this period. The same occurs for the 8-factors model with SKEW^{-} being the only significant implied skewness index.

In Table B7 we present the analysis conducted on the 100 Size and Operating Profitability portfolios. We observe how, in the full sample, the results are similar between SKEW and SKEW^{-} , improving the regression performance compared to the five-factors model, both significant and with negative coefficients. SKEW^{+} is also improving slightly the regression R^2 and adjusted R^2 compared to the five-factors model. It still appears that having the decomposed implied SKEW indexes in the model is more informative or as well as than the aggregate SKEW . During the pre-crisis period we find similar results, however with stronger role for SKEW^{+} . In the post-crisis period, we observe a more important role for SKEW^{-} being the index with the highest R^2 and adjusted R^2.

Table B8 presents the results for the 100 Size-Operating Profitability sorted portfolios during the turbulent times selected in our study, namely, the global financial crisis (top panel), the dot-com bubble (mid panel) and Brexit (bottom panel).

We observe that the SKEW measures are found *not* significant in predicting the excess portfolios returns during the global financial crisis. This further confirm the results in Chapter 4 in which SKEW indexes appear to be more informative during calmer periods, whereas the SKEW level is found low during the global financial crisis. During the dot-com bubble, adding SKEW indexes to the 5-factors model does increase the performance of the model. However, the aggregate SKEW is found to be significant (1%) and to be the factor increasing the R^2 and adjusted-R^2 the most. Lastly, during Brexit, what appears to be more helpful for asset pricing purposes is the set of information coming from SKEW^{-} reflecting the information enclosed in the tail risk index.

In Table B9 we show the results of the same asset pricing exercise now conducted on 12 Industries portfolios. Once more, in here, we find that the negative SKEW^{-} emerged as significant and the extra information it brings on considerably increases the regression models' R^2 and adjusted R^2. In the post-crisis, we confirm, once more, the more relevant role of Put options; SKEW^{-} is found significant both in the 6-factors and 8-factors models. To conclude, the best model we find in the full sample and in the post-crisis periods are the full 8-factors model containing information embedded in SKEW^{-} .

Table B6: **Sub-Samples Fama-MacBeth Results: 25-Size/Book-to-Market Portfolios**

Pre-Crisis Period: Jan 1996 - Jun 2007						
Coeff	3-Factors	5-Factors	5-Factors & SKEW			Full 8-Factors
	(1)	(2)	(3)	(4)	(5)	(6)
γ_0	0.099^{***}	0.115^{***}	0.113^{***}	0.092^{***}	0.105^{***}	0.115^{***}
	(0.015)	(0.015)	(0.020)	(0.015)	(0.013)	(0.019)
γ_{Mkt-rf}	-0.068^{***}	-0.082^{***}	-0.080^{***}	-0.058^{***}	-0.072^{***}	-0.083^{***}
	(0.016)	(0.014)	(0.020)	(0.014)	(0.012)	(0.018)
γ_{HML}	0.020^{***}	0.022^{***}	0.022^{***}	0.024^{***}	0.023^{***}	0.022^{***}
	(0.004)	(0.004)	(0.005)	(0.003)	(0.004)	(0.003)
γ_{SMB}	0.007	0.009^{**}	0.009^{**}	0.005^{*}	0.007^{***}	0.007^{**}
	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
γ_{RMW}		0.037^{*}	0.035	0.022	0.041^{**}	0.030^{*}
		(0.019)	(0.025)	(0.014)	(0.019)	(0.017)
γ_{CMA}		-0.027	-0.025	-0.025	-0.035	-0.015
		(0.024)	(0.026)	(0.019)	(0.023)	(0.019)
γ_{SKEW}			0.149			0.694
			(0.732)			(0.643)
γ_{SKEW^-}				0.310^{***}		0.345^{***}
				(0.084)		(0.080)
γ_{SKEW^+}					0.137^{*}	0.104
					(0.073)	(0.084)
R^2	0.584	0.678	0.679	0.755	0.718	0.741
Adj R^2	0.524	0.594	0.572	0.673	0.624	0.635
Post-Crisis Period: Apr 2009 - Dec 2017						
Coeff	3-Factors	5-Factors	5-Factors & SKEW			Full 8-Factors
	(1)	(2)	(3)	(4)	(5)	(6)
γ_0	0.101^{***}	0.106^{***}	0.110^{***}	0.112^{***}	0.107^{***}	0.102^{***}
	(0.017)	(0.019)	(0.018)	(0.017)	(0.019)	(0.025)
γ_{Mkt-rf}	-0.023	-0.031	-0.036^{*}	-0.038^{*}	-0.030	-0.028
	(0.016)	(0.019)	(0.018)	(0.018)	(0.018)	(0.021)
γ_{HML}	0.007^{*}	0.007^{**}	0.008^{**}	0.008^{**}	0.009^{*}	0.009
	(0.004)	(0.003)	(0.003)	(0.003)	(0.005)	(0.006)
γ_{SMB}	0.005	0.004	0.005^{*}	0.005	0.002	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
γ_{RMW}		0.008	0.009	0.009	0.007	0.004
		(0.016)	(0.016)	(0.016)	(0.013)	(0.015)
γ_{CMA}		-0.022	-0.014	-0.012	-0.027	-0.016
		(0.022)	(0.025)	(0.023)	(0.025)	(0.039)
γ_{SKEW}			-0.110			-0.077
			(0.069)			(0.057)
γ_{SKEW^-}				-0.203^{*}		-0.179^{*}
				(0.108)		(0.086)
γ_{SKEW^+}					-0.042	-0.041
					(0.073)	(0.070)
R^2	0.288	0.337	0.403	0.428	0.352	0.437
Adj R^2	0.187	0.163	0.205	0.238	0.166	0.349

Notes: This table shows the results of the second stage of the Fama-MacBeth regression approach in which the portfolios' returns, 25 portfolios based on Size and Book-to-Market, are regressed on the β factor loadings computed in the first step and expressing the exposure of each portfolio of assets to that specific factor as in (4.27). γ coefficients measure the risk premium associated with each selected factor. The regressions' outcome we report are for the simple 3-factors model (1) (Equation (4.28)), for the 5-factors model (Equation (4.29)), for the 6-factors model with SKEW indexes (3), (4), and (5) and the full model with all the SKEW indexes (Equation 4.31). Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The selected period are the pre- and post- crisis sub-sample periods from 04-01-1996 to 29-06-2007 (upper panel) and from 01-04-2009 to 29-12-2017 (bottom panel), respectively. Data are taken at daily frequency.

Overall, in many cases from Tables B6 to B9, the empirical results show that the factors models, constructed from the five common factors plus the decomposed implied SKEW indexes can better explain the variations of stock returns confirming the empirical results in Section 4.7.

Table B7: **Fama-MacBeth Results: 100-Size/Profitability Portfolios**

Full Sample: Jan 1996 - Dec 2017						
Coeff	3-Factors	5-Factors	5-Factors & SKEW			Full 8-Factors
	(1)	(2)	(3)	(4)	(5)	(6)
γ_0	0.006^{***}	0.045^{***}	0.044^{***}	0.063^{***}	0.062^{***}	0.061^{***}
γ_{Mkt-rf}	-0.030^{***}	-0.009	-0.010	-0.029^{***}	-0.010	-0.027^{***}
γ_{HML}	0.008	-0.003	-0.008	-0.005	-0.003^{*}	-0.004
γ_{SMB}	0.007^{**}	0.007^{***}	0.009^{***}	0.009^{***}	0.008^{***}	0.008^{***}
γ_{RMW}		0.015^{***}	0.016^{***}	0.016^{***}	0.015^{***}	0.016^{***}
γ_{CMA}		-0.009^{*}	-0.002	-0.002	-0.010^{*}	-0.008
γ_{SKEW}			-0.271^{**}			-0.270^{***}
γ_{SKEW-}				-0.305^{***}		-0.312^{***}
γ_{SKEW+}					-0.048^{*}	-0.052^{**}
R^2	0.294	0.450	0.515	0.516	0.466	0.567
Adj R^2	0.272	0.421	0.484	0.484	0.431	0.539
Pre-Crisis Period: Jan 1996 - Jun 2007						
Coeff	3-Factors	5-Factors	5-Factors & SKEW			Full 8-Factors
	(1)	(2)	(3)	(4)	(5)	(6)
γ_0	0.075^{***}	0.067^{***}	0.068^{***}	0.077^{***}	0.071^{***}	0.080^{***}
γ_{Mkt-rf}	-0.042^{***}	-0.031^{***}	-0.033^{***}	-0.042^{***}	-0.035^{***}	-0.045^{***}
γ_{HML}	0.015^{**}	0.002	-0.003	-0.001	-0.003	-0.004
γ_{SMB}	$0.010***$	0.010^{***}	0.013^{***}	0.012^{***}	0.011^{***}	0.012^{***}
γ_{RMW}		0.017^{***}	0.016^{***}	0.016^{***}	0.016^{***}	0.016^{***}
γ_{CMA}		-0.011	-0.010	-0.009	-0.014	-0.010
γ_{SKEW}			-0.194^{**}			-0.198^{***}
γ_{SKEW-}				-0.182^{**}		-0.180^{**}
γ_{SKEW+}					-0.069^{**}	-0.062^{**}
R^2	0.406	0.478	0.531	0.509	0.502	0.513
Adj R^2	0.387	0.450	0.501	0.477	0.470	0.476
Post-Crisis Period: Apr 2009 - Dec 2017						
Coeff	3-Factors	5-Factors	5-Factors & SKEW			Full 8-Factors
	(1)	(2)	(3)	(4)	(5)	(6)
γ_0	0.068^{***}	0.053^{***}	0.055^{***}	0.061^{***}	0.051^{***}	0.054^{***}
γ_{Mkt-rf}	0.002	0.016	0.014	0.008	0.018	0.015
γ_{HML}	0.002	-0.008	0.009	-0.001	0.001	-0.001
γ_{SMB}	0.006^{**}	0.007^{***}	0.007^{***}	0.008^{***}	0.007^{**}	0.007^{***}
γ_{RMW}		0.004	0.005	0.005^{*}	0.004	0.004^{*}
γ_{CMA}		0.001	0.004	0.005	0.003	0.003
γ_{SKEW}			-0.062			-0.084
γ_{SKEW-}				-0.128^{*}		-0.138^{*}
γ_{SKEW+}					-0.021	-0.014
R^2	0.067	0.141	0.151	0.165	0.152	0.185
Adj R^2	0.038	0.096	0.097	0.117	0.098	0.123

Notes: This table shows the results of the second stage of the Fama-MacBeth regression approach in which the portfolios' returns, 100 portfolios based on Size and Operating Profitability, are regressed on the β factor loadings computed in the first step and expressing the exposure of each portfolio of assets to that specific factor as in (4.27). γ coefficients measure the risk premium associated with each selected factor. The regressions' outcome we report are for the simple 3-factors model (1) (Equation (4.28)), for the 5-factors model (2) (Equation (4.29)), for the 6-factors model with SKEW indexes (3), (4), and (5) (Equation (4.30)) and the full model with all the SKEW indexes (Equation 4.31) (9), (10) and (11) (Equation (**??**)). Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. T-stats are not reported to save space. The selected period is the full sample from 04-01-1996 to 29-12-2017 (upper panel), the pre-crisis period from 04-01-1996 to 29-06-2007 (mid panel) and the post-crisis period from 01-04-2009 to 29-12-2017 (bottom panel), at daily frequency.

Table B8: **Fama-MacBeth Results: 100-Size-Profitability Portfolios Turbulent Events**

Global Financial Crisis 2007 - 2009						
Coeff	3-Factors	5-Factors	5-Factors & SKEW			Full 8-Factors
	(1)	(2)	(3)	(4)	(5)	(6)
γ_0	-0.066^{**}	-0.058^{**}	-0.044	-0.059^{**}	-0.067^{**}	-0.034
γ_{Mkt-rf}	-0.052	-0.053^{*}	-0.067^{**}	-0.053^{*}	-0.044	-0.073^{***}
γ_{HML}	-0.037^{***}	-0.004	0.018	0.005	-0.001	0.007
γ_{SMB}	-0.002	-0.012	-0.013^{*}	-0.012	-0.013^{*}	-0.018^{**}
γ_{RMW}		0.052^{***}	0.052^{***}	0.051^{***}	0.005^{***}	0.052^{***}
γ_{CMA}		-0.013	-0.013	-0.010	-0.011	-0.018
γ_{SKEW}			0.568			0.414
γ_{SKEW-}				0.564		0.614
γ_{SKEW+}					0.092	0.173
R^2	0.075	0.277	0.292	0.289	0.280	0.337
Adj R^2	0.047	0.238	0.246	0.243	0.233	0.283
Dot-com Bubble						
Coeff	3-Factors	5-Factors	5-Factors & SKEW			Full 8-Factors
	(1)	(2)	(3)	(4)	(5)	(6)
γ_0	-0.003	-0.005	-0.006	0.009	0.007	-0.028
γ_{Mkt-rf}	0.009	0.021	0.024	-0.007	0.014	0.044^{*}
γ_{HML}	0.013	-0.011	-0.017	-0.017	-0.013	-0.002
γ_{SMB}	0.021^{***}	0.019^{**}	0.021^{***}	0.020^{***}	0.020^{***}	0.017^{**}
γ_{RMW}		0.011	0.012	0.012	0.010	0.010
γ_{CMA}		0.041^{***}	0.043^{***}	0.041^{***}	-0.037^{**}	0.025
γ_{SKEW}			-0.182^{***}			-0.294^{***}
γ_{SKEW-}				-0.086^{*}		-0.196^{***}
γ_{SKEW+}					-0.064^{**}	-0.057^{*}
R^2	0.106	0.209	0.332	0.248	0.249	0.354
Adj R^2	0.078	0.167	0.289	0.200	0.205	0.325
Brexit						
Coeff	3-Factors	5-Factors	5-Factors & SKEW			Full 8-Factors
	(1)	(2)	(3)	(4)	(5)	(6)
γ_0	0.072^{***}	0.087^{***}	0.099^{***}	0.093^{***}	0.741^{***}	0.067^{***}
γ_{Mkt-rf}	-0.023	-0.036^{**}	-0.051^{**}	-0.046^{**}	-0.022	-0.015
γ_{HML}	-0.022	-0.018	-0.292	-0.033	-0.019	-0.021
γ_{SMB}	0.048^{***}	0.045^{***}	0.049^{***}	0.048^{***}	0.042^{***}	0.042^{***}
γ_{RMW}		-0.015^{*}	-0.013	-0.011	-0.012	-0.011
γ_{CMA}		0.011	0.008	0.008	0.020	0.021
γ_{SKEW}			-0.137^{*}			-0.133^{*}
γ_{SKEW-}				-0.186^{***}		-0.180^{*}
γ_{SKEW+}					0.037^{**}	0.038^{**}
R^2	0.224	0.258	0.300	0.330	0.318	0.357
Adj R^2	0.200	0.219	0.255	0.287	0.274	0.296

Notes: This table shows the results of the second stage of the Fama-MacBeth regression approach in which the portfolios' returns, 100 portfolios based on Size and Operating Profitability, are regressed on the β factor loadings computed in the first step and expressing the exposure of each portfolio of assets to that specific factor as in (4.27). γ coefficients measure the risk premium associated with each selected factor. The regressions' outcome we report are for the simple 3-factors model (1) (Equation (4.28)), for the 5-factors model (2) (Equation (4.29)), for the 6-factors model with SKEW indexes (3), (4), and (5) (Equation (4.30)) and the full model with all the SKEW indexes (Equation 4.31). Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The selected periods are some selected turbulent events, namely, the global financial crisis (upper panel) from 02-07-2007 to 31-03-2009, the dot-com bubble (mid panel) from 01-07-1998 to 31-12-2001 and the Brexit vote (bottom panel) from 02-05-2016 to 30-09-2016, at daily frequency.

Table B9: **Fama-MacBeth Results: 12 Industries Portfolios**

Full Sample: Jan 1996 - Dec 2017						
Coeff	3-Factors	5-Factors	5-Factors & SKEW			Full 8-Factors
	(1)	(2)	(3)	(4)	(5)	(6)
γ_0	0.044^{***}	0.050^{**}	0.054^{**}	0.028	0.046^{*}	0.051^{**}
γ_{Mkt-rf}	-0.008	0.058	-0.027	0.143	0.061	-0.146
γ_{HML}	0.005	0.020	0.013	0.173^{***}	0.140	0.189
γ_{SMB}	-0.446	-0.082	-0.022	-0.351^{**}	-0.102	-0.219^{**}
γ_{RMW}		-0.047	0.041	-0.061	-0.036^{*}	0.001
γ_{CMA}		0.029	0.046	0.047	0.057	0.075
γ_{SKEW}			-0.283			-0.267
γ_{SKEW^-}				0.345^{*}		0.421^{**}
γ_{SKEW^+}					0.091	0.136
R^2	0.065	0.134	0.202	0.337	0.210	0.338
Adj R^2	0.024	0.091	0.089	0.145	0.093	0.135
Pre-Crisis Period: Jan 1996 - Jun 2007						
Coeff	3-Factors	5-Factors	5-Factors & SKEW			Full 8-Factors
	(1)	(2)	(3)	(4)	(5)	(6)
γ_0	0.052^{***}	0.033	0.038	0.006	0.032^{*}	-0.031^{**}
γ_{Mkt-rf}	0.033	0.204	0.016	0.288	0.205	0.105
γ_{HML}	-0.033	0.045	0.032	0.101	0.048	0.004
γ_{SMB}	-0.035	0.005	0.015	-0.168	0.005	-0.561^{***}
γ_{RMW}		-0.202	-0.184	-0.161	-0.203	0.001
γ_{CMA}		0.045	-0.039	0.045	0.043	-0.067
γ_{SKEW}			-0.299			-0.111
γ_{SKEW^-}				-0.394		-0.283
γ_{SKEW^+}					0.223	-0.097
R^2	0.040	0.198	0.200	0.193	0.198	0.210
Adj R^2	0.012	0.084	0.083	0.091	0.078	0.098
Post-Crisis Period: Apr 2009 - Sept 2016						
Coeff	3-Factors	5-Factors	5-Factors & SKEW			Full 8-Factors
	(1)	(2)	(3)	(4)	(5)	(6)
γ_0	0.005^{***}	0.046^{**}	0.061^{***}	0.081^{**}	0.046^{**}	0.064^{**}
γ_{Mkt-rf}	-0.125^{**}	-0.187^{***}	0.141^{**}	-0.113^{*}	-0.191^{**}	-0.148
γ_{HML}	-0.119	-0.180	-0.252	-0.251	-0.029	-0.137
γ_{SMB}	-0.634^{**}	-0.105^{***}	-0.633^{*}	-0.572	-0.953^{***}	-0.644
γ_{RMW}		0.426^{**}	0.347^{*}	0.233	0.469^{**}	0.337
γ_{CMA}		-0.068	-0.082	-0.137	-0.056	-0.094
γ_{SKEW}			-0.255^{*}			-0.272^{*}
γ_{SKEW^-}				-0.259^{*}		-0.343^{*}
γ_{SKEW^+}					-0.085	-0.047
R^2	0.467	0.643	0.815	0.801	0.701	0.853
Adj R^2	0.318	0.435	0.707	0.675	0.473	0.626

Notes: This table shows the results of the second stage of the Fama-MacBeth regression approach in which the portfolios' returns, 12 industries portfolios, are regressed on the β factor loadings computed in the first step and expressing the exposure of each portfolio of assets to that specific factor as in (4.27). γ coefficients measure the risk premium associated with each selected factor. The regressions' outcome we report are for the simple 3-factors model (1) (Equation (4.28)), for the 5-factors model (2) (Equation (4.29)), for the 6-factors model with SKEW indexes (3), (4), and (5) (Equation (4.30)) and the full model with all the SKEW indexes (Equation 4.31). Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The selected period is the full sample from 04-01-1996 to 29-12-2017 (upper panel), the pre-crisis period from 04-01-1996 to 29-06-2007 (mid panel) and the post-crisis period from 01-04-2009 to 30-09-2016 (bottom panel), at daily frequency.

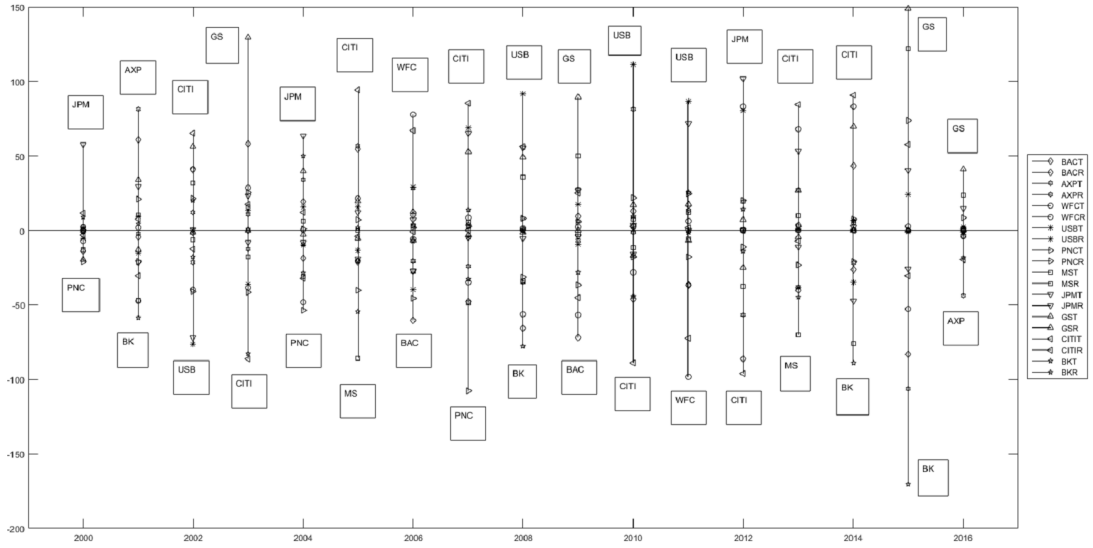
Appendix C

Additional Material for Chapter 5

C.1 Main Ten U.S. Financial Institutions Ranking over Time

The following figures are a graphical representation of Tables 5.4, 5.6 and 5.7 in Chapter 5, more specifically for the 1-year ranking.

Figure C1: **Net Aggregate Fear: 1 Year Ranking**

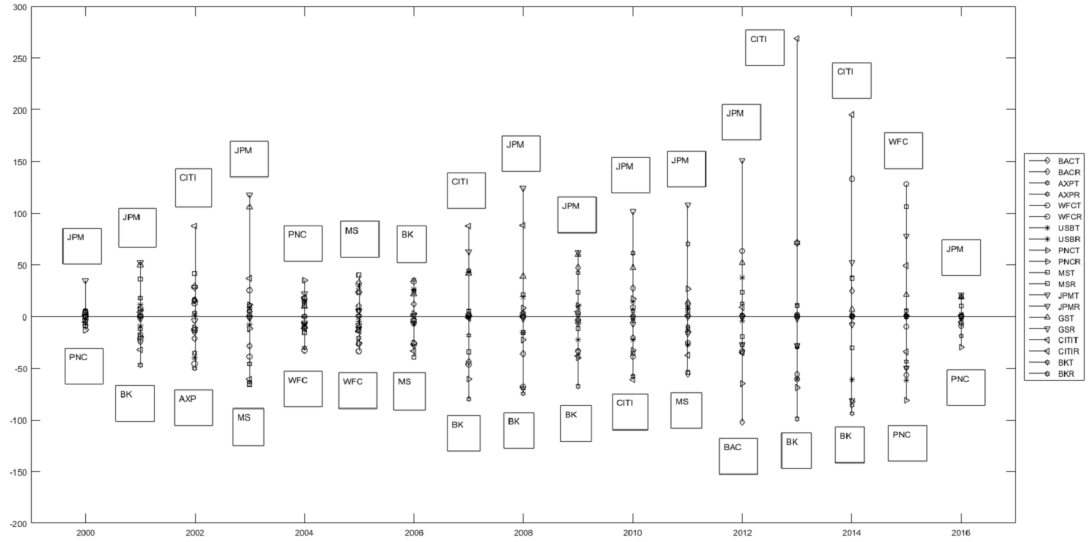


Notes: This figure shows

C.2 Post Financial Crisis and the Role of Berkshire Hathaway

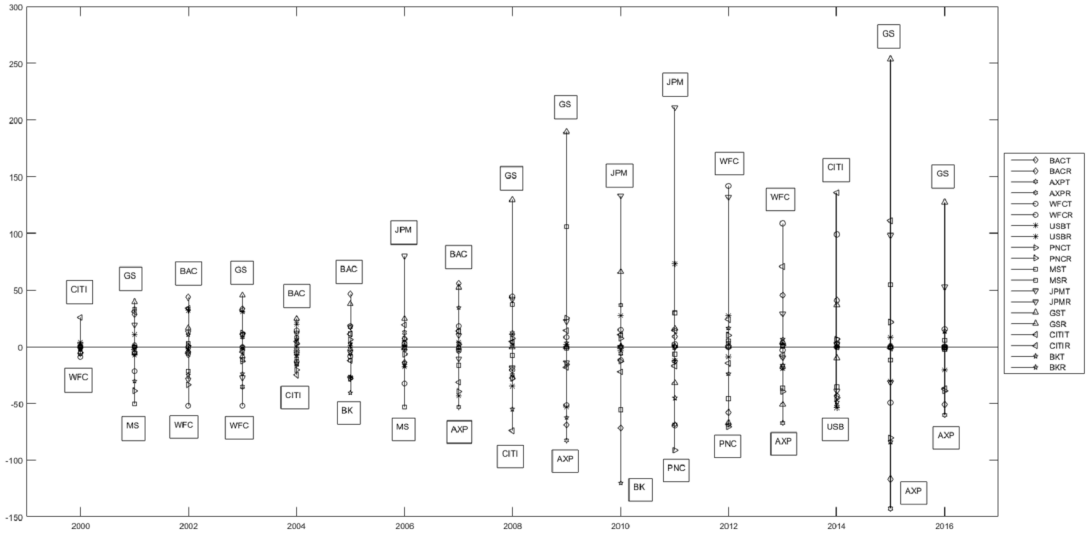
In this section, we extend our financial institutions sample adding other main five banks, namely, Berkshire Hathaway (BRK), MetLife (MET), CME Group (CME), Charles Schwab Corp (SCHW) and BlackRock (BLK) in the post crisis period spanning from July 2009 to December 2017. We report the

Figure C2: **Net Positive Fear: 1 Year Ranking**



Notes: This figure shows

Figure C3: **Net Negative Fear: 1 Year Ranking**



Notes: This figure shows

static analysis as well as the dynamic analysis. The selected VAR lags is 4 and the forecast horizon is equal to 12 days. The rolling window length is kept equal to 200 days. What is interesting to see in here is how, especially, the introduction of Berkshire Hathaway in the sample change the results due to the huge capitalization and role this company plays in the U.S. financial sector nowadays.

Table C1 shows the results of the aggregate financial sector fear connectedness in the post crisis period for the 15 financial institutions. Now the total fear connectedness index is increased to 79.43 for the aggregate measure while to 66.50 and to 52.71 for the upside and downside measures, respectively.

For the aggregate net fear connectedness, we find that J.P. Morgan Chase, Goldman Sachs and, as expected, Berkshire Hathaway are the main net transmitters, whereas CME Group, Charles Schwab Corp and Bank of New York Mellon the main net receivers. With relation to the upside fear connectedness, we find that the main net transmitters are Wells Fargo, Berkshire Hathaway and J.P. Morgan Chase and the main net receivers are PNC, CME Group and Charles Schwab Corp. Lastly, with relation to the downside fear connectedness, the main net transmitters are, again, J.P. Morgan Chase, Wells Fargo and Berkshire Hathaway, whereas the main net receivers are Bank of New York Mellon, American Express and CME Group. From these results, we can observe how some of the roles of the selected financial institutions change when the number in the sample increases. Berkshire Hathaway has been playing a crucial role in the post financial crisis period. It may definitely be considered a systemic important bank also due to its role of main downside implied volatility transmitter.

Table C1: **Aggregate Financial Sector Aggregate Fear Connectedness: Post Crisis**

	Forecast Error Variance Decomposition: Aggregate Fear Connectedness															
	JPM	BAC	WFC	CITI	GS	MS	USB	AXP	PNC	BK	BRK	MET	CME	SCHW	BLK	FROM
JPM	17.53	5.55	7.08	4.10	9.39	7.62	8.53	5.16	8.54	3.85	7.65	5.03	2.55	0.04	7.31	82.46
BAC	8.69	18.59	7.55	4.42	8.50	8.06	7.40	4.66	8.57	3.78	6.52	4.56	1.95	0.08	6.61	81.40
WFC	9.41	5.44	18.51	3.83	8.85	6.14	8.51	5.75	8.71	3.41	7.60	4.77	2.33	0.01	6.64	81.48
CITI	7.83	4.42	6.80	37.85	5.82	5.62	4.87	4.34	4.93	2.16	5.55	3.32	1.76	0.04	4.60	62.14
GS	8.97	5.68	6.96	4.25	16.43	8.38	8.05	4.44	9.49	4.42	8.82	4.60	1.89	0.01	7.54	83.56
MS	9.23	6.27	6.60	4.02	10.67	15.66	7.86	4.70	8.38	4.65	7.61	4.99	1.94	0.03	7.32	84.33
USB	8.76	5.18	7.02	3.57	8.91	7.23	15.56	5.62	9.89	4.49	8.90	5.13	2.52	0.01	7.15	84.43
AXP	8.39	4.37	7.21	3.57	8.72	7.76	8.88	14.35	9.02	5.29	7.14	4.91	2.56	0.07	7.68	85.64
PNC	8.51	5.13	7.37	3.65	9.19	7.18	8.67	4.83	16.98	4.39	7.87	5.08	2.41	0.01	8.65	83.01
BK	8.23	6.07	5.73	3.20	9.05	7.87	8.11	5.81	8.73	13.47	8.09	4.98	2.55	0.01	8.05	86.52
BRK	5.11	4.08	4.81	3.08	7.03	5.76	6.89	5.94	7.33	2.13	31.98	4.16	4.39	0.27	6.97	68.01
MET	7.51	4.95	6.36	3.13	8.78	7.15	8.49	5.26	9.50	5.01	6.61	16.56	3.39	0.01	7.23	83.43
CME	7.22	5.15	5.57	3.48	7.90	6.49	7.61	6.14	7.83	3.77	8.46	4.98	18.76	0.05	6.51	81.23
SCHW	9.59	4.05	5.60	2.09	5.20	3.92	6.44	1.61	4.66	4.47	4.05	3.30	1.26	39.21	4.47	60.78
BLK	8.37	4.55	5.84	3.72	9.24	6.57	7.59	4.37	10.31	5.16	10.06	4.54	2.45	0.04	17.11	82.88
TO	115.87	70.97	90.57	50.17	117.32	95.82	107.97	68.68	115.95	57.02	105.00	64.41	34.02	0.74	96.81	TOTAL
NET	33.41	-10.43	9.09	-11.96	33.75	11.48	23.53	-16.96	32.94	-29.49	36.99	-19.02	-47.21	-60.04	13.92	**79.43**

Notes: This table contains the $N \times (N-1)$ forecast error variance decomposition computed for the aggregate fear connectedness index for the main 15 U.S. financial institutions. d_{ij} elements in the $N \times (N-1)$ off-diagonal entries are the pairwise directional connectedness, while the diagonal elements (in grey) are the financial institutions' own variance. The $2 \times N$ off-diagonal row and column sums, TO and FROM, are the $2 \times N$ total directional spillovers, the NET row at the bottom is the difference between TO and FROM. The bottom-right element is the total spillovers index in the considered system. Selected VAR lags = 4 and Forecast Horizon = 12 days. The selected time period is from 01-07-2009 to 29-12-2017.

Table C2: **Financial Sector Upside and Downside Fear Connectedness: Post Crisis**

Forecast Error Variance Decomposition: Upside Fear Connectedness

	JPM	BAC	WFC	CITI	GS	MS	USB	AXP	PNC	BK	BRK	MET	CME	SCHW	BLK	FROM
JPM	28.51	6.08	9.23	4.90	8.24	8.01	4.22	4.81	4.21	4.21	6.60	4.24	2.50	0.20	3.97	71.48
BAC	7.17	32.73	9.92	4.59	6.03	11.63	3.70	3.39	2.53	5.44	4.36	3.82	1.78	0.54	2.28	67.26
WFC	9.92	6.19	28.14	6.42	5.93	5.88	6.57	5.18	5.99	4.87	4.75	4.60	2.16	0.02	3.31	71.85
CITI	5.04	1.66	7.49	58.15	2.59	3.57	3.35	4.42	2.23	3.38	2.68	1.94	2.06	0.07	1.31	41.84
GS	9.48	6.51	8.69	5.22	27.36	9.42	4.03	3.99	3.82	4.24	6.63	4.32	1.62	0.06	4.53	72.63
MS	8.67	9.26	7.47	4.58	10.42	25.45	3.79	4.20	3.76	6.18	5.56	4.72	1.63	0.56	3.68	74.54
USB	6.88	3.92	11.21	5.58	6.04	5.87	26.09	5.10	6.99	5.06	6.70	4.42	1.99	0.07	4.01	73.90
AXP	6.94	3.11	7.45	4.41	5.09	6.49	4.22	32.08	4.62	5.81	5.51	5.34	3.52	0.05	5.29	67.91
PNC	9.96	3.54	11.90	4.97	5.65	5.79	6.32	4.98	25.42	4.87	5.51	4.91	1.86	0.03	4.21	74.57
BK	8.07	6.37	8.16	3.66	7.32	8.98	4.62	7.29	3.35	21.79	5.17	5.76	2.86	0.40	6.14	78.20
BRK	2.85	2.58	3.97	2.43	4.28	3.13	3.03	4.48	1.40	2.57	54.85	2.10	5.39	0.05	6.82	45.14
MET	5.56	4.60	8.26	3.39	6.55	6.63	3.99	6.29	4.52	6.35	3.40	31.17	4.10	0.01	5.09	68.82
CME	6.83	3.67	6.49	3.59	5.55	6.17	3.68	7.32	3.00	3.62	7.78	3.46	34.53	0.05	4.18	65.46
SCHW	4.59	6.65	3.44	2.59	4.36	8.14	3.51	2.21	1.48	6.39	4.28	2.67	0.72	44.23	4.66	55.76
BLK	7.83	3.27	5.70	3.80	7.19	4.51	4.16	5.52	3.00	6.52	10.21	3.72	2.52	0.06	31.93	68.06
TO	99.85	67.47	109.44	60.20	85.30	94.29	59.22	69.27	50.99	69.57	79.22	56.07	34.77	2.23	59.54	TOTAL
NET	28.37	0.21	37.59	18.36	12.66	19.74	-14.68	1.36	-23.58	-8.63	34.07	-12.75	-30.69	-53.52	-8.52	**66.50**

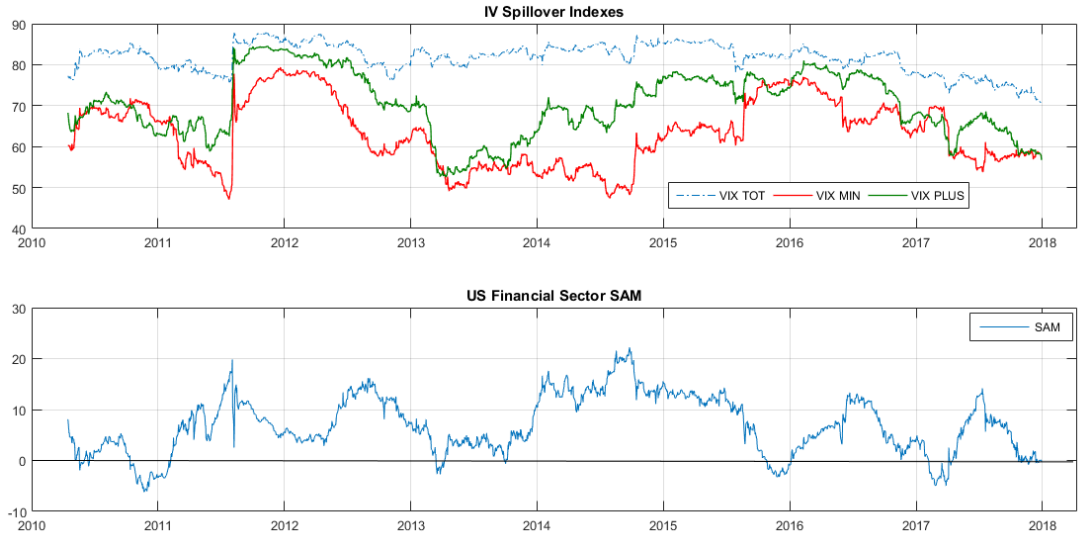
Forecast Error Variance Decomposition: Downside Fear Connectedness

	JPM	BAC	WFC	CITI	GS	MS	USB	AXP	PNC	BK	BRK	MET	CME	SCHW	BLK	FROM
JPM	40.00	2.57	7.10	7.83	4.73	3.92	8.23	2.11	2.18	2.01	8.18	6.16	2.68	0.07	2.17	59.99
BAC	9.96	48.82	6.99	3.60	4.94	4.34	5.99	0.59	3.84	0.92	2.75	3.58	0.45	0.76	2.38	51.17
WFC	11.98	2.50	43.15	4.98	5.72	1.70	6.63	4.68	2.34	1.38	6.86	3.02	1.97	0.01	3.00	56.84
CITI	7.19	2.49	4.69	70.15	0.60	0.93	1.01	2.53	1.41	0.16	3.26	3.18	1.47	0.11	0.74	29.84
GS	8.26	2.72	7.42	3.81	39.54	6.81	5.14	2.60	3.43	2.48	9.22	4.31	0.87	0.09	3.20	60.45
MS	11.16	4.30	6.11	3.14	7.57	39.71	4.32	1.02	1.84	3.33	7.35	6.29	0.92	0.27	2.60	60.28
USB	12.04	3.17	8.16	5.33	4.14	2.84	41.85	3.68	3.23	2.09	6.88	2.88	2.36	0.06	1.21	58.14
AXP	8.41	0.88	11.32	5.15	5.85	3.83	6.10	34.27	3.92	2.38	7.81	3.42	1.87	1.50	3.22	65.72
PNC	8.32	3.15	7.16	2.46	4.88	2.87	5.10	4.39	43.32	1.34	4.86	6.93	1.54	0.24	3.34	56.67
BK	8.42	4.19	3.60	3.02	3.16	5.46	6.12	1.28	1.48	40.56	11.19	4.27	2.34	0.07	4.75	59.43
BRK	4.33	2.06	4.57	3.32	5.50	2.33	4.14	2.94	1.48	1.63	54.97	4.50	4.24	0.57	3.34	45.02
MET	8.13	2.72	4.66	3.91	4.64	5.98	4.14	2.61	3.26	2.72	8.09	42.07	3.68	0.05	3.27	57.92
CME	9.39	2.08	5.37	3.53	2.27	1.60	5.36	2.55	1.72	2.75	8.30	4.28	49.46	0.06	1.20	50.53
SCHW	7.58	1.07	2.43	0.42	0.25	0.80	2.01	0.15	0.13	1.65	2.19	1.15	0.08	79.05	0.99	20.94
BLK	7.88	2.46	4.79	3.53	6.80	3.99	2.62	1.92	3.15	3.97	10.40	4.82	1.08	0.12	42.40	57.59
TO	123.13	36.42	84.42	54.10	61.10	47.47	66.98	33.11	33.47	28.89	97.41	58.87	25.61	4.05	35.47	TOTAL
NET	63.13	-14.74	27.58	24.26	0.65	-12.81	8.84	-32.61	-23.19	-30.53	52.39	0.95	-24.91	-16.88	-22.12	**52.71**

Notes: This table contains the $N \times (N-1)$ forecast error variance decomposition computed for the upside and downside fear connectedness indexes for the main 15 U.S. financial institutions. d_{ij} elements in the $N \times (N-1)$ off-diagonal entries are the pairwise directional connectedness, while the diagonal elements (in grey) are the financial institutions' own variance. The $2 \times N$ off-diagonal row and column sums, TO and FROM, are the $2 \times N$ total directional spillovers, the NET row at the bottom is the difference between TO and FROM. The bottom-right element is the total spillovers index in the considered system. Selected VAR lags = 4 and Forecast Horizon = 12 days. The selected time period is from 01-07-2009 to 29-12-2017.

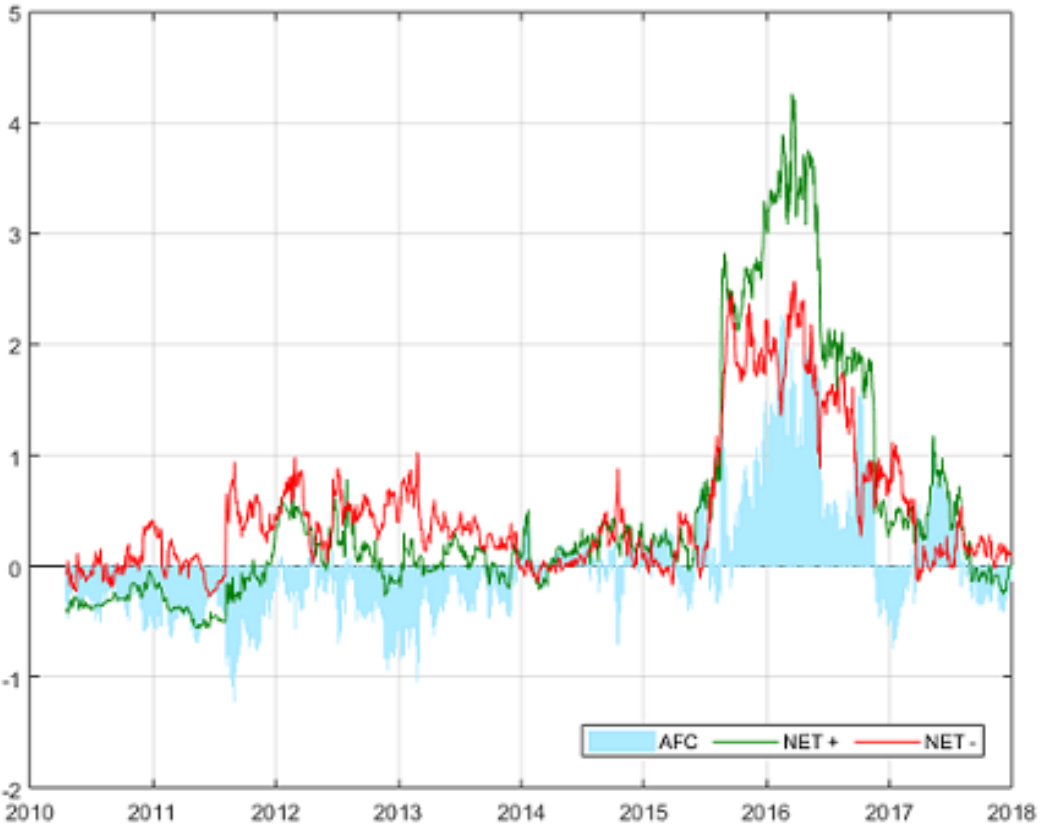
In Figure C4 we show the dynamic analysis for the main 15 financial institutions together with the rolling AFC. We observe how the total connectedness index is found to be more stable in the post global financial crisis however spanning at higher levels from 70 to 88. The upside and downside connectedness for the main 15 financial institutions in the post financial crisis are more volatile than the aggregate and they intertwine more often compared to the all sample for the main ten institutions in Figure 5.8. Thus, the AFC measure is found to be positive most of the time emphasizing also in here the prevalent role of call options. However we find times in which the connectedness measure extracted from puts overcomes the one extracted from calls and the AFC is found to be below zero. It happens, for instance, in response to the two stages of the European sovereign debt crisis, at the end of 2010 and beginning of 2013 and, again, last quarter of 2015 after Grexit and the Chinese Yuan crisis and, ultimately, at the beginning of 2017. Thus, also in this case, with 15 financial institutions in the post crisis era we find evidence of asymmetric implied connectedness among them. Lastly, we focus on the specific role of calls and puts connectedness with regards to Berkshire Hathaway. We, then, compute its upside and downside directional implied volatility connectedness and it is shown in Figure C5). We find that the plot is quite flat with low asymmetry in the volatility connectedness. However, spikes in both the transmitted $\mathcal{C}^{+}_{BRK,\text{NET}}$ and also $\mathcal{C}^{-}_{BRK,\text{NET}}$ are detected, especially during mid 2015 and mid 2016, confirming the important role of Berkshire Hathaway as net transmitter in the financial system.

Figure C4: **Total Implied Volatility Spillovers Indexes and AFC: 15 Banks**



Notes: This figure shows the comparison between the total fear connectedness indexes for the decomposed upside and downside measures (upper panel) for the main 15 financial institutions. The aggregate total connectedness measure is reported (dotted line) for comparative purposes as well. The bottom panel shows the AFC as a difference between the upside connectedness and the downside connectedness indexes. Selected VAR lags = 4 and forecast horizon = 12. The rolling window length is equal to 200 days. The selected period spans between 01-07-2009 to 29-12-2017 at daily frequency.

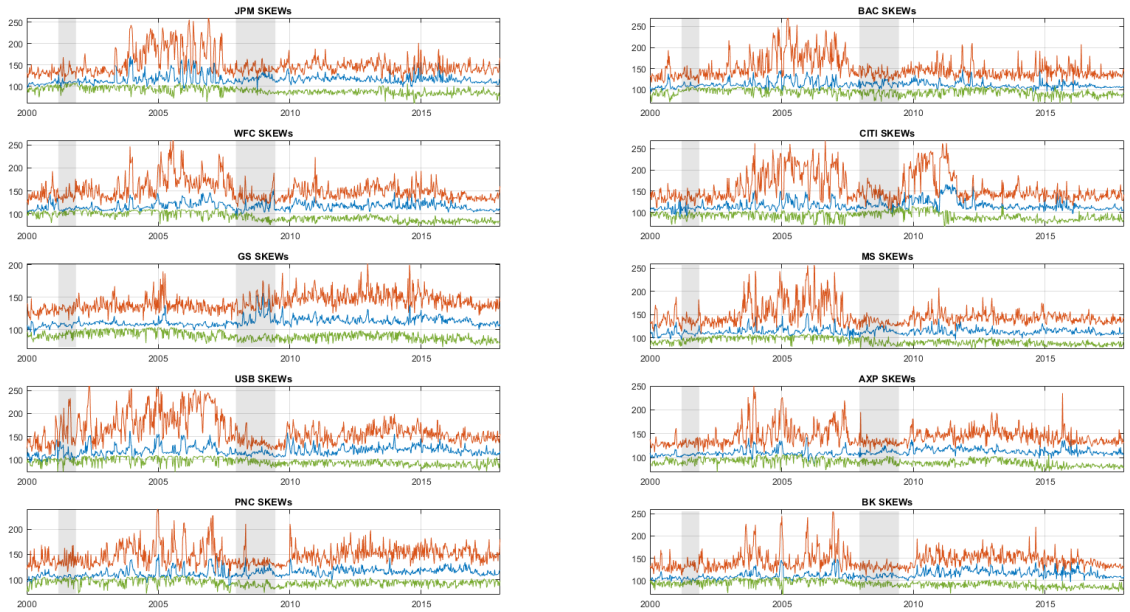
Figure C5: **Net Fear Connectedness and Net BRK - Berkshire Hataway**



Notes: The figure shows the net upside "fear" connectedness, $\mathcal{C}^{+}_{BRK,\text{NET}}$, and net downside "fear" connectedness, $\mathcal{C}^{-}_{BRK,\text{NET}}$ for Berkshire Hataway, together with the AFC, computed as difference between the two. Selected VAR lags = 4 and forecast horizon = 12.The rolling window length is equal to 200 days. The selected period spans from 03-01-2010 to 29-12-2017 at a daily frequency.

C.3 U.S. Financial Sector Implied Skewness Measures

Figure C6: **Implied Skewness Measures in the U.S. Financial Sector**



Notes: The figure shows the aggregate, positive and negative implied skewness indexes for the main ten banks in the U.S. financial sector. The recession periods are highlighted in gray. The selected period spans from 03-01-2010 to 29-12-2017 at a weekly frequency.

Table C3: **Aggregate and Decomposed Implied Skewness Indexes - Descriptive Statistics**

		Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis
JPM	SKEW	116.06	113.52	170.15	91.37	10.83	1.86	7.63
	SKEW^{+}	90.45	89.69	108.42	60.01	8.20	-0.05	2.69
	SKEW^{-}	150.69	142.60	263.29	110.72	26.28	1.76	5.87
BAC	SKEW	111.79	109.74	148.51	94.18	8.34	1.41	5.45
	SKEW^{+}	93.84	94.57	109.24	67.08	8.16	-0.47	2.65
	SKEW^{-}	148.98	141.33	271.48	113.62	25.50	1.75	6.32
WFC	SKEW	116.41	114.54	154.15	95.22	8.55	0.98	4.09
	SKEW^{+}	93.86	93.19	110.66	72.18	9.41	0.05	1.83
	SKEW^{-}	151.01	144.98	269.79	114.67	22.14	1.69	6.84
C	SKEW	115.96	112.27	165.76	85.25	12.05	1.64	6.01
	SKEW^{+}	91.37	91.13	115.80	66.10	9.50	0.04	2.48
	SKEW^{-}	157.61	144.51	269.63	102.57	33.13	1.22	3.52
GS	SKEW	112.20	110.78	156.75	91.01	6.86	1.94	10.31
	SKEW^{+}	90.29	89.96	103.45	73.03	6.49	0.07	2.19
	SKEW^{-}	142.13	139.82	202.23	113.60	12.78	0.91	4.42
MS	SKEW	113.24	111.89	152.81	94.92	6.95	1.44	7.47
	SKEW^{+}	92.81	92.16	107.80	75.52	7.45	0.12	1.98
	SKEW^{-}	146.69	140.88	256.85	108.38	22.07	2.03	7.93
USB	SKEW	118.79	116.71	162.16	91.23	10.51	0.94	4.45
	SKEW^{+}	94.83	94.72	109.01	72.18	7.62	-0.07	2.21
	SKEW^{-}	163.18	155.81	269.42	109.96	30.34	1.12	3.80
AXP	SKEW	111.63	110.07	142.65	88.17	7.10	0.95	4.98
	SKEW^{+}	90.36	90.19	107.33	69.23	7.65	0.03	2.24
	SKEW^{-}	143.77	138.89	250.21	110.61	19.27	1.78	7.46
PNC	SKEW	113.64	112.17	150.66	87.83	8.41	0.91	4.86
	SKEW^{+}	94.06	94.68	107.89	72.22	6.75	-0.35	2.73
	SKEW^{-}	147.73	144.74	240.25	106.21	19.15	1.20	5.41
BK	SKEW	112.75	110.57	148.36	93.82	8.76	1.14	4.50
	SKEW^{+}	92.71	92.77	106.81	68.17	7.37	-0.12	2.46
	SKEW^{-}	144.22	139.65	254.76	110.66	19.84	1.90	8.73

Notes: The table shows the main descriptive statistics for the weekly implied volatility indexes series for the aggregate SKEW and for the positive (SKEW^{+}) and negative (SKEW^{-}) decomposed measures for the selected ten main U.S. financial institutions (tickers in the table) between 03-01-2000 and 29-12-2017.