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MODELING AND TESTING THE EVOLUTION OF SYSTEMIC RISK AND HERDING BEHAVIOR IN FINANCIAL MARKETS

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So it's not about fame, and fortune
It's about believing and believing in yourself
And understanding that this life is life
It's liberty and the pursuit of happiness
And happiness isn't about getting what you want all the time
It's about loving what you have
So get ready it's a new day!

Dedicated to

my beloved family

“Se nun er pa famigl mo aro stav?”

the reason of my happiness

“Tutto questo vale poco
se non hai qualcuno con cui condividerlo.
Io ho dovuto viverlo prima di scriverlo”

Acknowledgment

Growing up, what you see becomes all you know. It doesn't matter if it's good or bad. Right or wrong. It is simply called reality. Normality.
It seems impossible to come out of normality. For someone, it is a betrayal. For others, an utopia. For others still, a dream. But there is something we all have in common. Fear.
Fear of forgetting the memories carried away by the wind. Friends to the airwaves and the airlines. The wisdom of a man who makes you feel the weight of his generations. The eyes of someone who loves you more than herself, but can't tell you. Her smell. Her lips. The ground on the shoes. That crumbs were enough to be rich. It seems to see the details. But, time always adds false memories.
The fear of finding a world that doesn't want us. A world that speaks a different language. Maybe cleaner. It feels almost like small worlds would not allow us to leave. Is it fear? A thin boundary between fear and glory? I don't know.
Growing up, you understand what really matters. When even things you have always believed in realizes that they make no sense. Contradictions. Indecision. With everything I live. But see, dissatisfaction has made me... I know. It's another story. But you don't know how much it hurts knowing that you are up to it, but feeling undervalued. Some things are hard to accept, especially if you are young and had a normal life behind you. Do you understand what I mean? Try taking a goldfish and pouring it into an ocean.
During the last three years, I understood that life is what happens to us while we do other things. We take uprights from those we didn't expect. And, even if they always leave a bitter taste, we continue to grow up as we run. We learn to love even hating. Doing everything. We say goodbye to those who gave us everything. The same everything that we put in our luggage. It weights less if you think it serves to give you a future. I got on the first plane like the last one. And I know you're proud of me even if we don't talk so much. It's never been easy to do it. I still don't know why, but I accepted it.
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depends on his inclination, but also on the luck of meeting a great mentor. Without it, it would be like a house without roof.

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When I was studying in Rome, I've met a great guy who always smiles. With this guy I lived three years. I shared emotions, disappointments, groceries, happiness, laundry, experiences and mutual gestures. Friendship is one of the most beautiful feelings to experience. It gives you wealth and is absolutely free. You can walk next to and grow together while following different paths, even though they will be far apart. I'm sure we will see each other after this. Mattia Bevilacqua, thank you for all.

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Summary

This research investigates: i) the evolution and the information content of market-based systemic risk measures (SRM); ii) the main drivers of herding behavior in equity markets; and, iii) the existing relationship between the market-based risk measures used to estimate systemic risk and herding behavior.

Chapter 2 presents a detailed and extensive literature review on which this thesis is based. It explores the multi-disciplinary approaches to analysing systemic risk and herding behavior, the data requirements and the main measures defined in the existing financial literature.

In Chapter 3, we study the effect of estimation uncertainty of market-based SRMs on selecting and regulating global systemically important banks (G-SIB). Using the three leading SRMs, we test how closely they agree with the list of G-SIBs from the Financial Stability Board (FSB) and how closely the SRMs match the categorization of G-SIBs into the five systemic risk buckets used by the FSB to assign capital surcharges to G-SIBs. Second, using cluster analyses we provide an alternative procedure to identify G-SIBs based on SRMs. This procedure incorporates the SRM confidence intervals of banks and is used to assess the degree of prudence versus conservatism that the FSB applies in compiling their G-SIBs list. Third, our approach integrates the SRM confidence interval in assigning a G-SIB to a systemic risk bucket and in determining the capital surcharge of each bucket. In general, we find that the three SRMs collectively are efficient in discriminating between systemic and non-systemic banks. The systemic risk buckets defined by the FSB are different from those constructed in a full pairwise comparison approach based on the market measures. In addition, we identify banks that were not marked as systemically important by the scoring method of the FSB but that are systemically important based on market-based SRMs. Finally, as the ranking with SRMs is subject to risk estimation uncertainty, we show how the ranking process can be improved by employing confidence intervals. Our methodology is able

to identify as systemically important the banks designated as G-SIBs through supervisory judgment by the financial authority. The results also show that a G-SIBs designation based only on SRM point estimate would assign higher additional capital buffers compared to our new method.

Chapter 4 aims to contribute to the debate on systemic risk by assessing the level of systemic risk of China's financial system over the period from January 2010 to December 2016, a period spanning the deflation of China's property bubble, the banking liquidity crisis, and the stock market crash. We focus on China's financial system because it became a source of risk during the banking liquidity crisis of 2013, and concerns regarding the level of systemic risk of the financial system increased following the popping of the stock market bubble in the summer of 2015. Dividing the financial system into three sectors, namely: banks, insurance and brokerage industries, and real estate, and applying the $\Delta CoVaR$ as the measure for systemic risk; our findings show that the systemic risk level of China's financial system decreased following the deflation of the property bubble in 2012, and successively increased during the banking liquidity crisis in 2013, reaching a major peak during the market crash in 2015. We further show, through the Wilcoxon signed rank test, that the systemic risk level of the financial system and sectors significantly increased after the main systemic events. In order to provide a formal systemic risk ranking of the financial sectors, we apply the bootstrap Kolmogorov-Smirnov test, finding that each financial sector significantly contributes to systemic risk, with the banking sector contributing the most, followed by real estate and subsequently insurance and brokerage industries.

In Chapter 5, we provide new evidence of herding in global markets. Using OLS and quantile regressions and applying daily data for 33 countries from January 2000 to end-January 2019, we find evidence of herding in few Asia Pacific, Latin American and European markets. When, however, we condition on the Eurozone crisis and the China's market crash of 2015-16, we find significant evidence of herding for most countries. We also document important herding behavior evidence related to Brexit. This Chapter pioneers research on the relationship between herding and systemic risk. By conditioning the investigation of herding behavior on different systemic risk levels of the market, the results strongly suggest that herding is more pronounced in case of high systemic risk. Granger causality tests and Johansen's vector error-correction model provide solid evidence of the existence of a strong relationship between herding and systemic risk, suggesting that herding behavior may be an ex-ante aspect of systemic risk.

Lastly, Chapter 6 tests for herding towards the market consensus for the corporates in the United States and the Eurozone equity markets, considering their main financial industries. We find that herding is more likely to be present in the high quantiles, entailing herding effects under turbulent market conditions. This effect appears more pronounced when we condition on the financial crises periods. Our results also support the herding presence in case of asymmetric conditions of volatility, credit deterioration, funding illiquidity and economic policy uncertainty. Furthermore, we provide evidence that the cross-sectional dispersion of returns of the domestic equity market can be partly explained by the corresponding dispersions of the financial sector and its industries, with the latter having influence on the herding of the domestic equity market. In our analysis we cover the last two main global financial crises, revealing new evidence of "spurious" and "intentional" herding corporate activity.

Chapter 7 provides final discussions, concluding the thesis and points towards new directions in which this research might go in order to fill gaps still open in literature, such as: i) cross-country contagion in financial markets due to systemic risk; ii) the use of market-based SRMs as risk measures in risk-budgeting/parity portfolios; iii) the investigation of capital requirements as instrument to assess systemic risk; iv) the examination of the interrelationship between systemic risk and climate-change risks in the insurance sector; and, v) the herding investigation in the option market.

Research Statement and Disclosure

The research illustrated in Chapter 3 of this thesis has benefitted from comments from academics and central bankers from workshop and conference presentations as well as journals' referees comments and suggestions which have, certainly, improved the Chapter. Preliminary results of this Chapter have been presented in the following seminars and conferences: Bucharest Economic Analysis and Research Seminar – Banca Nationala a Romaniei – 29 March 2018, Bucharest (Romania); Systemic Risk and Financial Institutions Seminar – European Central Bank – 12 September 2018, Frankfurt am Main (Germany); Kent Business School PhD Conference – University of Kent – 14 June 2019, Canterbury (England, United Kingdom). Preliminary results of the developed methodology with a different application and story-line can be found in the Bank of Finland Research Discussion Papers: Jokivuolle, Esa and Tunaru, Radu and Vioto, Davide, Testing the Systemic Risk Differences in Banks (June 1, 2018). Bank of Finland Research Discussion Paper No. 13/2018. Available at: https://helda.helsinki.fi/bof/handle/123456789/15525. This Chapter has been submitted (and is under review) to an academic journal with a quality rating of 4 according the Academic Journal Guide 2018 – ABS, the Association of Business School (submission on the 17^{th} of June 2019).

The research illustrated in Chapter 4 of this thesis has been submitted (and is under review) to an academic journal with a quality rating of 3 according the Academic Journal Guide 2018 – ABS, the Association of Business School (submission on the 15^{th} of December 2017).

The research illustrated in Chapter 5 of this thesis has benefitted from comments and suggestions from academics from the Economics and Finance Seminar – Cardiff Business School, Cardiff University – 24 January 2019, Cardiff (Wales, United Kingdom); and, the 12^{th} International Accounting & Finance Doctoral Symposium – Polytechnic University of Milan – 9 - 12 June 2019, Milan (Italy); which have contributed to improve the analysis and the narrative of the Chapter.

The research illustrated in Chapter 6 of this thesis has benefitted from comments from academics and central bankers from the Centre for Advanced Research in Finance and Banking Research Seminar – 15 November 2018, Bucharest (Romania); and, the Financial Decisions in a Changing Global Environment 2018 Chile Conference organized by the International Finance and Banking Society – University of Chile – 13 - 15 December 2018, Santiago de Chile (Chile); as well as journals' referees comments and suggestions which have allowed me to identify and cover gaps in the financial literature related to herding behavior. This Chapter has been submitted (and is under review) to an academic journal with a quality rating of 4 according the Academic Journal Guide 2018 – ABS, the Association of Business School (submission on the 5^{th} of September 2019).

CHAPTER 1

Introduction

This research aims to propose new tools that may enhance the financial risk measures available to track systemic risk and herding behavior.

In the last decade, there has been a significant rise in concerns about the financial and banking stability of national and international systems.[1] These concerns have been reflected in a series of official summits and reports, private initiatives and academic papers by regulators, supervisory authorities, central bankers and academia. Although the increase in theoretical, empirical and policy analyses of financial, banking and economic instability have been substantial, the interest and investigation of regulators, supervisory authorities, central bankers and academia on front-topics such as systemic risk[2] and herding behavior, which may impact

[1]In November 2018, the European Central Bank (ECB) warned that Italy's high spending, the possible end of the U.S. growth cycle and signs of over-valuation in the Eurozone's property market were among its concerns and monitored sources of risk (European Central Bank, November 2018). On the other hand, the Board of Governors of the Federal Reserve System published its first-ever financial stability report, highlighting that the U.S. economy is showing some vulnerabilities as investors increasingly buy up risky corporate debt and businesses rely on "historically high" borrowing levels (Board of Governors of the Federal Reserve System, November 2018). At the global level, some emerging markets (EME) with significant external imbalances have found facing difficulties in adapting to tightening financial conditions. This reinforced the pre-existing vulnerabilities in EMEs like Argentina and Turkey by increasing bond spreads, falling stock prices and boosting large currency depreciations. It has been also argued that a widespread contagion across EMEs could also be triggered by rising trade tensions and/or a failure to rein in the high credit growth in China and it could be amplified due to the interconnected nature of global financial markets.

[2]Silva, Kimura, and Sobreiro (2017) analyzes and classifies 266 articles on systemic risk that were published no later than September 2016.

the resilience of the financial and banking sectors, remains significant. The understanding of these two concepts has become of central importance for maintaining financial stability (Martínez-Jaramillo, Pérez, Embriz, and Dey, 2010). By way of example, financial authorities: i) may impose short-selling bans to moderate the trading activity of informed traders, preventing negative bubble or herding behavior (Diamond and Verrecchia, 1987); and, ii) may intervene to decrease the probability of widespread failures and losses of financial institutions by recapitalising them or applying additional capital surcharges. Berger, Roman, and Sedunov (2019) investigated whether the Troubled Assets Relief Program (TARP) significantly reduced the contribution of banks to systemic risk and hence contributed to stabilising the US economy. As an alternative to recapitalising banks directly as in the TARP, it has been also introduced the notion to increase capital requirements for banks. This has indeed been a route followed by many policymakers after the Global Financial Crisis (GFC). For example, Basel III, the Capital Requirements Directives IV and the Capital Requirements Regulation propose a series of capital requirements for systemically important institutions and a specific systemic risk buffer (SyRB). These additional capital surcharges aim to address systemic risks of a long-term, non-cyclical nature that are not covered by the common capital adequacy ratios. However, they also impact the available capital of firms subject to these buffers. For instance, the Prudential Regulation Authority at the Bank of England estimated that only the SyRB could tie up around £7-8 billion of capital in total across the subject lenders in the United Kingdom.[3]

We divide this thesis into two main parts. The first part attempts to set a starting point for a more comprehensive analysis of the systemic risk of the global systemically important banks (G-SIB) from a market perspective; and, since China's financial system has been recognized as one of the main source that may lead to global financial instability, it also contributes to the debate on systemic risk by assessing the level of systemic risk of

[3] The official document published by the Prudential Regulation Authority at the Bank of England, entitled "Systemic Risk Buffer rates for ring-fenced banks and large building societies," is available at: https://www.bankofengland.co.uk/prudential-regulation/publication/2019/systemic-risk-buffer-rates-for-ring-fenced-banks-and-large-building-societies.

China's financial system and sectors. In the second part, because herding behavior can be considered an ex-ante aspect of systemic risk by affecting the likelihood of joint failure of financial institutions (Acharya and Yorulmazer, 2008), considering 33 countries, we first test for herding trying to identify its main sources; and, then study the relationship between the variables used to measure systemic risk and herding behavior. We conclude by testing for herding in case of asymmetric market conditions in the equity markets and financial sectors of the United States and the Eurozone.

This thesis aims to develop new tools to better understand risk and the main rationale for financial and banking regulation, prudential supervision and crisis management.

The vastness of topics concerning risk and measures of risk is beyond words. Risk may be related to fields 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. Risk is a concept commonly associated with uncertainty, which is interpreted as an unpredictable, and so uncontrollable, status or outcome of any situations or actions. Thus, taking risky actions and decisions implies taking actions and decisions in uncertainty. Knight (2012) established the distinction between risk and uncertainty by highlighting that uncertainty is immeasurable, not possible to calculate, while risk is measurable. Uncertainty makes future outcomes more shady and cloudy. This implies that the lower the accuracy and precision of a risk measure, the larger the uncertainty is. This thesis introduces new tools that may enhance the financial risk measures available to track systemic risk and herding behavior by decreasing uncertainty.

Nowadays, measures and indicators which aim to track uncertainty have spread out. In this context of uncertainty, it becomes of interest to study: i) how to incorporate uncertainty in systemic risk rankings; ii) how uncertainty due to market asymmetries drives herding behavior; and, iii) whether or not a relationship exists between systemic risk and herding behavior. This research mainly focuses on these three points and tries to assess their impacts on banks, financial sectors and equity markets.

A novel set of information that may improve the Basel Committee on Banking Supervision's (BCBS) assessment methodology for G-SIBs is extracted by incorporating systemic risk estimation uncertainty in selecting and regulating G-SIBs. By estimating confidence intervals on the three main market-based systemic risk measures (SRM) – namely, the delta conditional value at risk ($\Delta CoVaR$) developed by Adrian and Brunnermeier (2016), the marginal expected shortfall (MES) of Acharya, Pedersen, Philippon, and Richardson (2017) and the $SRISK$ proposed by Brownlees and Engle (2016) and discussed in more detail in Engle (2018);[4] we show how these SRMs are also able to capture the banks designated as G-SIBs through supervisory judgment by the financial authority. Furthermore, by using the $\Delta CoVaR$ as measure for systemic risk, we assess the systemic risk of China's financial system and find that each financial sector significantly contributes to systemic risk, with the banking sector contributing the most, followed by real estate and subsequently insurance and brokerage industries. Moreover, investigating the relationship between systemic risk and herding behavior, we provide solid evidence of the existence of a strong relationship. Finally, we also confirm the evidence of herding behavior for EMEs and report new ones related to developed markets and aggregates such as the Eurozone.

We anchor the first part of this research to a growing trend in the financial literature which investigate the differences of the systemic risk estimates and rankings generated by the three main SRMs (see Huang, Zhou, and Zhu, 2012; Bernal, Gnabo, and Guilmin, 2014; Castro and Ferrari, 2014; Nucera, Schwaab, Koopman, and Lucas, 2016; Ahnert and Georg, 2018; Kleinow, Moreira, Strobl, and Vähämaa, 2017). More specifically, Chapter 3 results close to Danielsson, James, Valenzuela, and Zer (2016), where the use of two SRMs as "riskometer" for policies targeted at reducing systemic risk is analyzed. By comparison, our aim is to incorporate systemic risk estimation uncertainty in classifying banks as systemically risky and in assigning them to different systemic risk buckets with different capital

[4] A detailed description of these measures can be found in Appendix A.1.

surcharges. As the systemic risk estimation uncertainty is incorporated, our method might also be used to assess the implicit degree of prudence vs conservatism that the regulator has used in selecting the systemically risky banks. As per Bernal, Gnabo, and Guilmin (2014), Chapter 4 analyses the systemic risk level of China's financial system and ranks its financial sectors, by testing the systemic contribution of each sector.

The second segment analysed by this thesis is strictly related to the financial literature investigating herding behavior in equity markets (see e.g. Chang, Cheng, and Khorana, 2000; Philippas, Economou, Babalos, and Kostakis, 2013; Mobarek, Mollah, and Keasey, 2014) and, as per Zhou and Anderson (2013), extends the herding analysis based on quantile regressions. Furthermore, based on the intuition of Acharya and Yorulmazer (2008), who advocate that herding behavior can be considered an ex-ante aspect of systemic risk by affecting the likelihood of joint failure of financial institutions, Chapter 5 pioneers research by conditioning the investigation of herding behavior on different systemic risk levels of the market and analyzes the existing relationship between return clustering of the market – i.e. the measure used to detect herding; and systemic risk increases. Chapter 6 continues the research of Galariotis, Rong, and Spyrou (2015), by conditioning the herding analysis to different market asymmetries. Moreover, we study the difference between "spurious" – i.e. fundamental information driving herding; and "intentional" – i.e. herding due to other reasons not liked to fundamental information; herding, during the GFC and the Eurozone crisis. One main innovation introduced by this Chapter is a robustness check for herding based on the short-selling bans imposed in the United States during the GFC and in the Eurozone during both crises.

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 this thesis and its following Chapters are anchored. As mentioned, Chapter 3 and Chapter 4 contribute to the increasing literature on systemic risk based on market-based SRMs; while, Chapter 5 and Chapter 6 improve the existing framework used to test herding behavior in equity markets. Each of them presents an introduction, the corresponding literature review, the methodology applied to answer the therein research questions and, lastly, the findings of the empirical analysis before concluding. Chapter 7 provides final discussions, concluding the thesis and points towards new directions in which this research might go in order to fill gaps still open in literature. The Appendices at the end of the thesis include further analyses and materials we felt should be separated from the main text.

CHAPTER 2

Literature Review

"Ten years ago, one would have considered the mortgage servicing to be an insignificant and benign component of the financial system. Nowadays, that is not the case."
Fouque and Langsam (2013)

2.1 Introduction

This Chapter presents an 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 each Chapter will be recalled in detail therein. Specifically, Section 2.2 relates to the description of systemic risk and defines it, its causes and channels of propagation. Section 2.3 includes general literature on different measurements of systemic risk. In particular, subsection 2.3.1 describes the market-based systemic risk measures (SRM), subsection 2.3.2 discusses some of the main measures of financial networking, and subsection 2.3.3 illustrates the literature of the main remaining SRMs, which cannot be included into one of the previous categories. Section 2.4 describes the assessment methodology for the global systemically important banks (G-SIB) defined by the Basel Committee on Banking Supervision (Basel Committee on Banking Supervision, 2013; Basel Committee on Banking Supervision, 2014). Lastly, Section 2.5 includes the main literature about herding with application to the equity markets as well as to other asset classes.

2.2 Background on systemic risk

The financial literature has used the term *systemic risk* for many years. Indeed, already in the late 90's and early 2000, the academic sphere agreed on the need to define the main characteristics of this risk.[1] However, only with the Global Financial Crisis (GFC), this risk has manifested in all its intensity, affecting the proper functioning of the financial system in such a way to renew and increase interests in its measurement, management and regulation, as evidenced by the increasing literature on this subject in the decade subsequent to the GFC. Silva, Kimura, and Sobreiro (2017) analyzes and classifies 266 articles on systemic risk that were published no later than September 2016.

Despite the increasing literature on this topic, there is still no widely accepted definition of systemic risk (Lo, 2008; Billio, Getmansky, Lo, and Pelizzon, 2012; Rodríguez-Moreno and Peña, 2013). This remains a challenge also to public policies that explicitly aim to reduce this risk. Billio, Getmansky, Lo, and Pelizzon (2012) define systemic risk as a set of events or circumstances that influence the stability of the financial system. Others like Kaufman (1996) see systemic risk as the probability of cumulative losses originated by a single event, which triggers a series of following losses through a chain of institutions or markets comprising a financial system. According to Kupiec and Nickerson (2004), systemic risk is linked to the possibility that moderate economic shock can provoke significant volatility on share prices, sizable reduction on companies' liquidity, potential bankruptcies and equity losses. For Acharya, Pedersen, Philippon, and Richardson (2017), systemic risk may be seen as a situation of market freezing, which could cause a significant reduction in financial intermediation activities; while, Adrian and Brunnermeier (2016) defines systemic risk as

[1] Sheldon and Maurer (1998) bizarrely likened systemic risk to the monster of Loch Ness: *"Systemic risks are for financial market participants what Nessie, the monster of Loch Ness, is for the Scots (and not only for them). Everyone knows it and is aware of its danger. Everyone can accurately describe the threat. Nessie, like systemic risk, is omnipresent, but nobody knows when and where it might strike. There is no proof that anyone has really encountered it, but there is no doubt that it exists".*

the risk that the entire financial system is impaired, with potential adverse consequences for the real economy.[2]

To better understand such risk, more than focusing on a unique broadly accepted definition, we can identify what systemic risk is not. According to Duffie and Singleton (2012), financial institutions can face five categories of risk:

- *Market risk*: the risk of unexpected changes in market prices;
- *Credit risk*: the risk of default on a debt that may arise from a borrower failing to make required payments;
- *Liquidity risk*: the risk stemming from the lack of marketability of an asset that cannot be bought or sold quickly enough to prevent or minimize a loss;
- *Operational risk*: the risk that frauds, errors or other operational failures lead to loss in value;
- *Systemic risk*: the risk of breakdowns in market wide liquidity or chain-reaction defaults.

Market, credit, liquidity, and operational risk focuses on individual institutions. This entails that these risks are independent from systemic risk. However, each of them also have market wide implications, implying that they can be considered as a part or one of the causes of systemic risk.

Billio, Getmansky, Lo, and Pelizzon (2012) focus on the four *"L"*s – liquidity, losses, leverage and linkages – as main causes that provoke systemic risk. Particular importance is given to the linkages. Indeed, the structure of the financial network can facilitate the spread of losses, illiquidity, insolvencies and defaults, generating and propagating systemic risk. Arnold, Borio, Ellis, and Moshirian (2012) demonstrate how the financial cycle could influence financial stability, and in turn systemic risk; while, De Bandt, Hartmann, and Peydró

[2]Because of the partly different definitions of systemic risk, in Chapter 3 we study the three main market-based SRMs jointly.

(2009) argue that, since different financial institutions tend to hold common exposures in their portfolios, also the assets correlation among banks could destabilize the financial system, leading to systemic risk. Others like Morris and Shin (2016) and Acharya, Gale, and Yorulmazer (2011) advocate that also the "rollover risk" can origin systemic risk. This risk can be defined as the risk that lenders may fail to renew or "rollover" their short-term debt. In this case, systemic risk would spread across the system through the so-called "bank by bank contagion" (Rochet and Tirole, 1996).

2.3 Taxonomy of systemic risk measures

It is important to understand the available measures of systemic risk and their relationships to one another (Rodríguez-Moreno and Peña, 2013). Bisias, Flood, Lo, and Valavanis (2012) undertook a validity study examining the existing systemic risk measures, identifying thirty-one different quantitative measure for this risk, which can be classified according to supervisory, research, and data perspectives. For each of these they present a taxonomy of the area and concise definitions of each risk measure. In this Section, we present an extensive literature review of the SRMs classified as tail dependence measures (subsection 2.3.1) and networking measures (subsection 2.3.2). Subsection 2.3.3 discloses the SRMs that cannot be classified into one of the previous categories.

2.3.1 Tail dependence measures

After the GFC, a strand of the financial literature introduced a series of market-based SRMs which takes into account the entire tail of the loss distribution. Adrian and Brunnermeier (2016) introduce the delta-conditional value at risk ($\Delta CoVaR$). This SRM represents the Value-at-Risk (VaR) of the financial system conditional on an institution being under distress, and captures the contribution of a particular institution, in a non-causal sense, to the overall systemic risk. The methodology proposed by Adrian and Brunnermeier (2016) is based on quantile regressions (Koenker and Bassett Jr, 1978). The main properties of $\Delta CoVaR$ can be summarised as follows:

- The $\Delta CoVaR_q^{j|i}$ is directional. It means that the $\Delta CoVaR_q^{system|i}$ of the financial system conditioned to the distress of an institution i is not equal to $\Delta CoVaR_q^{i|system}$ of institution i conditioned to the financial system being in crisis. We can understand the importance of the direction of the conditioning using a simple example. If the whole financial system is in significant distress, an individual institution is also likely to face difficulties. On the other side, conditioning on this particular institution being in distress does not materially impact the probability that the wider financial system is in distress as well.
- The $\Delta CoVaR$ satisfies the clone property. After splitting one individual institution into n smaller clones, the $\Delta CoVaR$ of the institution is exactly the same of the $\Delta CoVaRs$ of the n clones.
- The clone property is linked to the idea of an institution as a part of a large group of institutions seen as a "herd". The herd is considered as a large number of small financial institutions that hold similar positions, and are funded in a similar way. In other terms, they are exposed to the similar factors. If only one of these institutions falls into distress, this will not cause a systemic crisis because of the size of the institution. However, if the distress is due to a common factor, all the institutions considered are dragged into a crisis. Overall, the institutions are systemic as part of a herd. Each individual institution's co-risk measure should capture this notion of being *systemic as part of a herd*. $\Delta CoVaR$ succeeds in that. Moreover, this property is directly connected to the clone property. Indeed, if an individual institution is split into n clones, the $\Delta CoVaR$ of each clone catches the systemic risk as part of the herd.

Extensions of the $\Delta CoVaR$ estimation method have been proposed in the recent literature. Cao (2013) defines the Multi-CoVaR, where the Multi-$\Delta CoVaR$ is defined as the difference between the VaR of a financial system conditional on a given set of financial institutions being in a tail event and the VaR of the financial system conditional on this set of financial institutions being in a normal state. This measure captures the contribution to systemic risk of a group of financial institutions at the same time. Girardi and Ergün (2013) propose a multivariate GARCH estimation of CoVaR, a method based on a modification of the definition of financial distress, from an institution being exactly at its VaR to being at most at its VaR. This modification allows for the consideration of more severe distress events and improves the CoVaR relationship with the dependence parameter. Reboredo and Ugolini (2015) apply this measure to assess the systemic risk in Europe, adopting a CoVaR extension based on copulas. Lastly, López-Espinosa, Moreno, Rubia, and Valderrama (2012) adopt the CoVaR approach to identify the main factors behind the systemic risk in a number of large international banks. They consider several econometric specifications of increasing complexity, which extends the basic CoVaR model.

Acharya, Pedersen, Philippon, and Richardson (2017) define the systemic expected shortfall (SES) and the marginal expected shortfall (MES). The SES represents the propensity of an institution to be undercapitalized when the entire financial system is undercapitalized; while, the MES indicates the losses of the institution in the tail of the aggregate sector's loss distribution. Brownlees and Engle (2016) argue that: *"it is unclear how SES can be estimated in real time, as it requires observing a systemic crisis to infer the level of systemic risk of an institution"*. Idier, Lamé, and Mésonnier (2014) explore the practical relevance of MES from a supervisory perspective. They find that some standard balance-sheet ratios (like TIER1 ratio) are better able than the MES to predict large equity losses conditionally to a true crisis. Banulescu and Dumitrescu (2015) present as SRM the component expected shortfall, which encompasses the MES. It is a hybrid measure, which, by weighting the MES with market capitalization, combines the "Too-Interconnected-To-Fail" and the "Too-Big-To-Fail" logics.

Brownlees and Engle (2016) introduce the SRISK. This measure aims to identify the systemic risk contribution of each financial firms as the capital shortfall of a firm conditional on a severe market decline. It is a function of size, leverage and risk, which is measured with the long run MES (LRMES). Firms with the highest SRISK are the largest contributors to the undercapitalization of the financial system in case of distress. The systemic risk of the entire financial market can be computed with the sum of each firm's SRISK. This can be interpreted as the total amount of capital that the government would have to provide to bail out the financial system in case of a crisis. The SRISK provides early warning signals of worsening macroeconomic conditions. In particular, an increase of SRISK predicts future declines in industrial production and increases in unemployment, with a more significant predictive power for longer time horizons. Engle, Jondeau, and Rockinger (2015) use the SRISK to investigate the case of the 196 largest European financial firms. Their findings suggest that, for certain countries, the cost for the taxpayer to rescue the riskiest domestic banks is so high that some banks might be considered too big to be saved. Engle (2018) examines the history and application of the SRISK measure on how it compares with other related measures from both academics and regulators.

2.3.2 Networking measures

Networking measures allow to visualize the linkages among financial institutions. Billio, Getmansky, Lo, and Pelizzon (2012) propose several econometric measures of connectedness based on two econometric methods: principal components analysis (PCA) and Granger-causality test. They use these two methodologies to analyse the linkages among hedge funds, banks, brokers/dealers, and insurance companies. While the PCA allows to understand the common characteristics of the four sectors considered, the Granger-causality test is used to measure the degree of connectivity among the sectors considered and the direction of such linkages. Billio, Getmansky, Lo, and Pelizzon (2012) advocate a two-way Granger causality effect may increase the probability of systemic events. The empirical findings show that linkages within and across all four sectors have been highly dynamic over the past decade, and they have a tendency to increase in the future. Moreover, the degree of causality among the four sectors analyzed has increased over time, and the linkages in the system have increased before and during the financial crisis more than non-crisis periods, with the banks as major source of systemic risk.

Chen, Cummins, Viswanathan, and Weiss (2014) define a SRM for the insurance industry based on credit default swap and, using the Granger-causality tests, analyze the linkages between banks and insurers. The methodology used to build the risk measure is based on the distress insurance premium (DIP). This risk measure has been originally proposed by Huang, Zhou, and Zhu (2012). The DIP is defined as the price of an insurance against financial distress and is based on two risk components: i) the probability of default for each insurer and the default correlation. The results of the Granger-causality tests point out a significant relationship between the insurance and banking sectors.

Allen, Babus, and Carletti (2010) develop a simple two-period model, where each bank invests in a risky project and needs external funds as finance. Here, two possible scenarios are analyzed. Investors can provide the funds to banks in exchange for a debt contract that can be long or short-term. Since the project is not risk-free, banks may default at the final date. If this occurs, the investors will recover the project return net of bankruptcy costs, while the bank does not receive anything. If the default does not occur, however, the investors obtain the re-payment specified in the debt contract and the bank retains any surplus. The project returns are independently distributed, so the bank has an incentive to diversify investments by exchanging shares of its own project with other banks. This allows banks to reduce the probability of default and the bankruptcy costs. However, this implies an increase of links among banks. In particular, two networks are analysed. The first considers banks divided in two groups (clustered) of three banks each, while, the second (un-clustered) analyse the banks connected in a circle. In case of long-term debt, the structure of the network is irrelevant in terms of systemic risk or welfare. Instead, if the banks use short-term debt structure, the network is important because banks become exposed to rollover risk.

Diebold and Yilmaz (2008) provide a simple and intuitive measure of interdependence of asset returns and/or volatilities. The formulated measures for return and volatility spillovers is based on vector autoregressive (VAR) models. The spillover index provides an “input - output” decomposition, which allows to account for the direction of the spillover effects. This framework facilitates the study of both non-crisis and crisis episodes, including trends and bursts in spillovers. The empirical findings show evidence of divergent behaviour in the dynamics of return and volatility spillovers. In particular, return spillovers display a smooth increasing trend but no bursts, whereas volatility spillovers are characterized by no trend but clear bursts.

Lastly, Battiston, Gatti, Gallegati, Greenwald, and Stiglitz (2012) focus on the resilience of the financial network. Using a dynamic model, they demonstrate that when the variations in the level of financial robustness of the institutions tend to persist in time or get amplified, the probability of default does not decrease monotonically with diversification. As a result, the financial network is most resilient for an intermediate level of connectivity. Glasserman and Young (2015), however, try to estimate how the interconnections among these institutions will increase expected losses and defaults under a wide range of shock distributions. According to the authors, it is clear that the interconnections influence the transmission of shocks. However, it is less clear whether it significantly increases the likelihood and magnitude of losses compared to a financial system that is not interconnected. The results show that it is difficult to generate contagion only with interbank spillover of losses.

2.3.3 Other measures of systemic risk

Some of the SRMs introduced in the literature cannot be strictly classified as tail dependence or networking measures since they aim to capture other dimensions of systemic risk.

Huang, Zhou, and Zhu (2012) introduce the Distress Insurance Premium (DIP) as systemic risk indicator. It represents a hypothetical insurance premium against the occurrence of a catastrophic loss in the banking system. Within the same framework, the systemic importance of each bank can be properly defined as its marginal contribution to the hypothetical DIP of the whole banking system. The DIP is based on market data and is divided into two components: i) the probability of default of individual banks; and, ii) their equity return correlations. The first component is estimated with CDS spreads, while the second one considering the share's price co-movements. The DIP formula can be implemented with Monte Carlo simulations (Huang, Zhou, and Zhu, 2009). In particular, the authors construct a hypothetical debt portfolio that including the total liabilities (deposits, debts, and others) of all banks. The indicator of systemic risk, effectively weighted by the liability size of each bank, is defined as the insurance premium that protects against the distressed losses of this portfolio. Technically, it is calculated as the risk-neutral expectation of portfolio credit losses that equal or exceed a minimum share of the sector's total liabilities.

Segoviano and Goodhart (2009) develop a framework that aims to monitor banks' distress dependence and estimate the distress risk, which is defined as the impact of large losses and possible default of a specific bank on the whole banking system. Banks' distress dependence depends on the various links among banks, either direct, through inter-bank deposits and loans, or indirect, due to lending to common sectors. This dependence is affected by the economic cycle – indeed, it increases during distress periods, and is captured by the banking system's joint probability of distress (JPoD) – ie, the probability that all the banks in the system experience large losses simultaneously. The banking system is constructed with a portfolio composed by systemically important banks of which the probability of distress is computed; and, from this, the banking system's portfolio multivariate density is estimated. This allows to analyse the stability of the banking system from three different, but complementary, perspectives relate to: i) common distress in the banking system; ii) distress between specific banks; and, iii) distress in the system associated with a single specific bank. Under the first category are analyzed the JPoD and the Banking Stability Index, which represents the expected number of banks becoming distressed because of the distress situation of a single bank. The second category includes the Distress Dependence Matrix, which contains the conditional probabilities of distress between pairs of institutions and groups of banks. The last category includes the probability that at least one bank becomes distressed, given that a specific bank becomes distressed. This allow to measure the cascade effect that occurs in the system from the default of a single institution.

Xu, In, Forbes, and Hwang (2016) use a conditional version of JPoD to investigate the systemic risk of the European sovereign and banking system during the period from 2008 to 2013. The results show that French banks contributed the most to the systemic risk of the banking system during both the GFC and the sovereign debt crisis. However, banks in the larger peripheral sovereigns, such as Italy and Spain, were also perceived by market participants to be systemically risky.

Lehar (2005) develops a framework to measure and monitor the risk in the banking system. This framework is based on the dynamics and correlations between bank's asset portfolios, which are considered fundamental to evaluate banking crises. In particular, when banks hold similar assets, they increase the possibility of simultaneous defaults, which would result in a severe economic crisis. The impact of such banking crisis on the economy may be substantial. To obtain measures for the risk of a regulator's portfolio, the author models the individual liabilities that the regulator has to each bank as contingent claims on the bank's assets. The empirical findings show that correlations, bank asset volatility, and bank capitalization increase for North American and European banks, while Japanese banks face deteriorating capital levels. Moreover, the additional equity capital reduces systemic risk only for banks that are constrained by regulatory capital requirements.

Giglio (2011) defines a SRM that aims to estimate the joint default risk of large financial institutions within a short time period. This SRM is constructed using information in bond and credit default swap (CDS) prices. In particular, while the CDS prices reflect information about the probability of joint default of both the bond issuer and the protection seller; the bond contain information only about the marginal probability of default of the firm that issued the bond. Combining bond and CDS prices allows to construct bounds on the probability of systemic default events.

Duca and Peltonen (2013) propose a model for assessing systemic risk and predicting systemic events, which are defined as periods of extreme financial instability with potential real costs. Using the Financial Distress Index, which measures the level of stress in the financial system in a given country, the authors define a method for identifying the starting date of systemic financial crises. In order to predict systemic crises they combine indicators that capture the building up of vulnerabilities and imbalances, both domestic and global. The empirical analysis covers emerging and developed economies and the results show a good out-of-sample performance of the model in predicting the ongoing financial crisis of 2007-2009. In particular, an early warning signal in the second quarter of 2006 is identified.[3]

Castellacci and Choi (2014) build a multi-agent dynamical system for the global economy to investigate and analyse financial crises. The authors analyse the mechanism of instability contagion for both single and multiple economies. In particular, three different cases are studied: i) a sector-to-sector contagion within a single economy; ii) cross border contagion due to counterparty risk; and, iii) cross-border contagion due to a "fear" factor. They formulate a quantitative definition of instability contagion and study the Eurozone crisis grouping Eurozone countries into two categories:

1. Fiscally weaker economies, which are the countries that have experienced directly the debt crisis – Greece, Ireland, Portugal, Cyprus and possibly Spain, and Italy;
2. Creditor economies, which are the countries heavily exposed to the sovereign debts of the former – such as, for example, France.

In this scenario the contagion manifests itself through the fears that a country in the first group is not able to repay its debt to banks in creditor economies. This may provoke

[3] Duca and Peltonen (2013) identify an early warning signal five quarters before the emergence of the tensions in money markets that started the crisis in August 2007.

bank runs or defaults, leading the creditor economy to financial instability. This, in turn, may affect the rest of the world (outside the Eurozone), which is defined as third category.

Raffestin (2014) analyses the existing relationship between diversification and systemic risk. The developed model relies on the idea that portfolio diversification makes investors individually safer but creates connections between them through common asset holdings. In case of stochastic shocks on investors wealth, they react by buying or selling assets, which further impact asset prices and wealth. This model generates a normal multivariate distribution of investors wealth, which allows to study systemic risk through the probability that a number of investors fall below a given bankruptcy threshold, for different levels of diversification. The author advocates that the number of connections within the system can lead to an increase of systemic risk and, in parallel, the diversification may increase the number of connections, through common asset holdings. The results show that intermediate numbers of financial institution bankruptcies are less likely with high diversification, but the likelihood that many, or even all, fail simultaneously is high. Also Wagner (2010) shows that even though diversification reduces each institution's individual probability of failure, it makes systemic crises more likely.

2.4 BCBS's assessment methodology for global systemically important banks

Following the GFC, there has been renewed scrutiny on the impact that the failure of large financial institutions could have on the broader financial system. The Financial Stability Board (FSB) has been founded with the aim to identify global systemically important banks[4] (G-SIBs) through the assessment methodology developed by the Basel Committee

[4]Systemically important financial institutions (SIFIs) are defined as those institutions "whose disorderly failure, because of their size, complexity and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activity"; while, global SIFIs are identified as "institutions of such size, market importance, and global interconnectedness that their distress or failure would cause significant dislocation in the global financial system and adverse economic consequences across a range of countries"

on Banking Supervision (BCBS) (Basel Committee on Banking Supervision, 2013; Basel Committee on Banking Supervision, 2014).

The BCBS has acknowledged the inability of the existing risk measures to effectively contain the negative externalities that can be caused by G-SIBs (Basel Committee on Banking Supervision, 2013). These banks are recognized as a group of institutions that cannot be made to fail because of their size, global interconnectedness and complexity. For this reason, the main purpose of the BCBS is to improve the ability of the G-SIBs in absorbing losses; this, in turn, would decrease their default probability. The G-SIB methodology is based on twelve bank's activity indicators, which are grouped into five categories of systemic importance, namely:

- *Size*, which is based on the scale of the global activity carried out by the bank – larger is the size of the bank, less replaceable is the same in case of default and the likelihood of triggering a crisis of confidence on the financial markets is greater;
- *Interconnectedness*, which focuses on the existing linkages among banks – higher interconnection means greater systemic risk because of the contagion risk;
- *Substitutability*, which measures the degree of substitutability of the bank, relying on the financial instruments held by the bank – less the bank is replaceable, greater is the risk that its failure has a systemic impact;
- *Complexity*, which refers to the banks' complexity, which is defined as structural, operational and global – higher the complexity of the bank, greater should be the systemic impact as a result of its failure;
- *Cross jurisdictional activity*, which measures the weight of a bank at global level depending on the assets and liabilities held cross-border – greater the weight, higher the risk of contagion in the event of financial distress.

Each of these categories has an equal weight of 20%. The BCBS identified multiple

(Lines, 2010).

indicators (equally weighted within the category) included into each of these categories. Table 2.1 provides the category and weight for each indicator.

Table 2.1: Categories, indicators and weighting used to designate G-SIBs.

Indicator-based measurement approach		
Category (and weighting)	Individual indicator	Indicator weighting
Size (20%)	Total exposures as defined for use in the Basel III leverage Ratio	20%
Cross-jurisdictional activity (20%)	Cross-jurisdictional claims	10%
	Cross-jurisdictional liabilities	10%
Interconnectedness (20%)	Intra-financial system assets	6.67%
	Intra-financial system liabilities	6.67%
	Securities outstanding	6.67%
Substitutability (20%)	Assets under custody	6.67%
	Payments activity	6.67%
	Underwritten transactions in debt and equity markets	6.67%
Complexity (20%)	Notional amount of over-the counter (OTC) derivatives	6.67%
	Level 3 assets	6.67%
	Trading and available-for-sale securities	6.67%

Notes: The table reports the categories with their weight (column 1), the indicators included into each category (column 2) and their weight (column 3).

To calculate the score for a given indicator, the bank's reported value (in Euros) for that indicator is divided by the corresponding sample total, and the resulting value is then expressed in basis points (bps):

$$\frac{\text{Bank Indicators}}{\text{Sample Total}} \times 10.000 = \text{Indicator score (bps)} \tag{2.1}$$

For each category a score is estimated by averaging all the indicators included into the specific category. The final score is calculated as the equally weighted average of the scores obtained with the individual categories. Banks with a score greater than 130bps are designated as G-SIBs. Other banks with a score lower than 130bps can be classified as G-SIB according to supervisory judgment. The final score is translated into a Higher Loss Absorbency (HLA) requirement using the score ranges shown in Table 2.2. The buckets are

Table 2.2: Higher Loss Absorbency (HLA) requirements and score ranges.

End-2013 G-SIBs buckets		
Bucket	Score Range	HLA Requirement
5	530-629	+3.5% CET1
4	430-529	+2.5% CET1
3	330-429	+2.0% CET1
2	230-329	+1.5% CET1
1	130-229	+1.0% CET1

Notes: The table lists the ranges used to allocate G-SIBs into five buckets and the corresponding additional buffers.

Table 2.3: Capital conservation buffer (2.5%) and G-SIB buffer: phase-in period.

Phase-in period	
Year	Applicable Capital Conservation Buffer [a]
n^{th}	25%*[2.5% buffer + G-SIB HLA requirement (based on end-n^{th} data)]
$n^{th}+1$	50%*[2.5% buffer + G-SIB HLA requirement (based on end-n^{th} data)]
$n^{th}+2$	75%*[2.5% buffer + G-SIB HLA requirement (based on end-n^{th} data)]
$n^{th}+3$	100%*[2.5% buffer + G-SIB HLA requirement (based on end-n^{th} data)]

Notes: The table describes the phase-in period for the additional G-SIB buffer.

[a] Note that other buffer components, such as the countercyclical capital buffer, may also apply.

built in such a way to leave the fifth empty. In the case, it should become populated, it would have created a new bucket, in order to encourage banks not to increase their global systemic importance. The FSB announces the G-SIB's list every year in November. Table 2.4 presents the G-SIBs designated by the FSB from its first designation in November 2013 to the last available designation in November 2018.[5]

The implementation of this buffer has been added to that of the capital conservation buffer and is subject to a three-year phase-in period, see Table 2.3.

[5] In November 2011 the FSB published an integrated set of policy measures to address the systemic and moral hazard risks associated with systemically important financial institutions (SIFIs). In that publication, the FSB identified an initial group of G-SIFIs, namely 29 G-SIBs. The designation of G-SIBs become official only in 2013. The FSB and the BCBS used end-2012 data and an updated assessment methodology published by the BCBS in July 2013 to identify the G-SIBs.

Table 2.4: List of G-SIBs as of the FSB announcements in November 2013 to November 2018

Bucket	G-SIBs in alphabetical order within each bucket					
	2013	2014	2015	2016	2017	2018
5^{th} (3.5%)	(Empty)	(Empty)	(Empty)	(Empty)	(Empty)	(Empty)
4^{th} (2.5%)	HSBC Holdings JPMorgan Chase & Co	HSBC Holdings JPMorgan Chase & Co	HSBC Holdings JPMorgan Chase & Co	Citigroup JPMorgan Chase & Co	JPMorgan Chase & Co	JPMorgan Chase & Co
3^{rd} (2.0%)	Barclays BNP Paribas Citigroup Deutsche Bank	Barclays BNP Paribas Citigroup Deutsche Bank	Barclays BNP Paribas Citigroup Deutsche Bank	Bank of America BNP Paribas Deutsche Bank HSBC Holdings	Bank of America Citigroup Deutsche Bank HSBC Holdings	Citigroup Deutsche Bank HSBC Holdings
2^{nd} (1.5%)	Bank of America Credit Suisse Group Goldman Sachs Group/The Groupe Crédit Agricole Mitsubishi UFJ Financial Group Morgan Stanley Royal Bank of Scotland Group UBS Group	Bank of America Credit Suisse Group Goldman Sachs Group/The Mitsubishi UFJ Financial Group Morgan Stanley Royal Bank of Scotland Group	Bank of America Credit Suisse Group Goldman Sachs Group/The Mitsubishi UFJ Financial Group Morgan Stanley	Barclays Credit Suisse Group Goldman Sachs Group/The Industrial & Com. Bank of China Mitsubishi UFJ Financial Group Wells Fargo & Co	Bank of China Barclays BNP Paribas China Construction Bank Goldman Sachs Group/The Industrial & Com. Bank of China Mitsubishi UFJ Financial Group Wells Fargo & Co	Bank of America Bank of China Barclays BNP Paribas Goldman Sachs Group/The Industrial & Com. Bank of China Mitsubishi UFJ Financial Group Wells Fargo & Co
1^{st} (1.0%)	Banco Santander Bank of China Bank of New York Mellon/The BBVA Groupe BPCE Industrial & Com. Bank of China ING Groep Mizuho Financial Group Nordea Bank Société Générale Standard Chartered State Street Corporation Sumitomo Mitsui Financial Group UniCredit Group Wells Fargo & Co	Agricultural Bank of China Banco Santander Bank of China Bank of New York Mellon/The BBVA Groupe BPCE Groupe Crédit Agricole Industrial & Com. Bank of China ING Groep Mizuho Financial Group Nordea Bank Société Générale Standard Chartered State Street Corporation Sumitomo Mitsui Financial Group UBS Group Unicredit Group Wells Fargo & Co	Agricultural Bank of China Banco Santander Bank of China Bank of New York Mellon/The China Construction Bank Groupe BPCE Groupe Crédit Agricole Industrial & Com. Bank of China ING Groep Mizuho Financial Group Nordea Bank Royal Bank of Scotland Group Société Générale Standard Chartered State Street Corporation Sumitomo Mitsui Financial Group UBS Group UniCredit Group Wells Fargo & Co	Agricultural Bank of China Banco Santander Bank of China Bank of New York Mellon/The China Construction Bank Groupe BPCE Groupe Crédit Agricole ING Groep Mizuho Financial Group Morgan Stanley Nordea Bank Royal Bank of Scotland Group Société Générale Standard Chartered State Street Corporation Sumitomo Mitsui Financial Group UBS Group UniCredit Group	Agricultural Bank of China Banco Santander Bank of New York Mellon/The Credit Suisse Group Groupe Crédit Agricole ING Groep Mizuho Financial Group Morgan Stanley Nordea Bank Royal Bank of Canada Royal Bank of Scotland Group Société Générale Standard Chartered State Street Corporation Sumitomo Mitsui Financial Group UBS Group UniCredit Group	Agricultural Bank of China Banco Santander Bank of New York Mellon/The China Construction Bank Credit Suisse Group Groupe BPCE Groupe Crédit Agricole ING Groep Mizuho Financial Group Morgan Stanley Royal Bank of Canada Société Générale Standard Chartered State Street Corporation Sumitomo Mitsui Financial Group UBS Group UniCredit Group

Notes: The list contains the G-SIBs as of the FSB announcements in November 2013 to 2018. The G-SIBs are allocated to buckets corresponding to required levels of additional capital buffers. The G-SIBs are designated using end-2012, end-2013, end-2014, end-2015, end-2016, and end-2017 data, respectively.

2.5 Herding behavior in financial markets

Stock prices may deviate from their fundamentals due to waves of irrational market sentiment. This may lead to herding, which could undermine financial stability and could pose unhedgeable systemic risk to market participants and financial institutions. Herding is commonly described as a behavioral tendency for investors to suppress their own beliefs and mimic collective actions in the market, leading to a convergence or a correlated patterns of actions (see Nofsinger and Sias, 1999; Welch, 2000; Hwang and Salmon, 2004).

Previous literature identifies several reasons that justify this behavior. According to Avery and Zemsky (1998), in the case of tail events of the market, herding is due to a mistaken belief that some investors may have more accurate information. Others like Devenow and Welch (1996) argue that investors may herd because of an intrinsic preference for conformity with the market consensus; while, Bernile and Jarrell (2009) and Carow, Heron, Lie, and Neal (2009) argue that, particularly after the arrival of public information, there are systematic patterns in institutional activities that may destabilize market prices, causing herding by private investors. Lastly, Bikhchandani and Sharma (2000) advocate that money managers may herd because of the incentives provided by the compensation scheme and terms of employment.

Hott (2009) developed a model for herding formation that shows how a price bubble is generated by herding behavior without assuming any speculative motivations. Also Dass, Massa, and Patgiri (2008) find that bubbles are caused by herding among traders and that traders herd when the incentives for herding are strong. Herding may trigger important informational inefficiencies in the market, contributing, on average, to 4% of the asset's expected value Cipriani and Guarino (2014). In corporate bond markets, institutional investors' herding is higher than the reported level observed in equities, and impact of herding is highly asymmetric (Cai, Han, Li, and Li, 2019). However, Bernile, Sulaeman, and Wang (2015) find that the anticipated trades by institutional investors ahead of other firms is more likely to reflect their superior ability to process publicly available information, rather than their access to private information.

Herding behavior may pose also significant liquidity constrains to financial firms. In particular, according to Oh (2018), firms facing a severe liquidity constrain may be forced to sell a large part of their assets to avoid bankruptcy, causing a fire sale effect that could impact the entire industry, entailing correlated patterns of actions. Park and Sabourian (2011) find that people may herd if their information is sufficiently dispersed so that they consider extreme outcomes more likely than moderate ones. In turn, herding generates more volatile prices and lower liquidity. Also Avramov, Chordia, and Goyal (2006), by decomposing sell trades into "contrarian" and "herding" trades,[6] find that while contrarian trades decrease volatility, herding trades tend to increase volatility.

A large body of research covered herding effects in several stock markets. Christie and Huang (1995) examined twelve US industries, while Chang, Cheng, and Khorana (2000) analyzed the investment behavior of market participants within five markets, namely US, Hong Kong, Japan, South Korea, and Taiwan. There is a comprehensive analysis of herding that focuses on the Chinese stock markets (see, among others, Demirer and Kutan, 2006; Tan, Chiang, Mason, and Nelling, 2008; Chiang, Li, and Tan, 2010). Guney, Kallinterakis, and Komba (2017) investigate herding in eight African markets. Gleason, Mathur, and Peterson (2004) use intra-day data to examine herding on nine S&P500 sectors of Exchange Traded Funds during periods of market's extreme movements. Recent studies of herding behavior provide evidence of cross-country herding effects. In particular, Chiang and Zheng (2010), first, examine herding within eighteen countries, which are then grouped into advanced markets (seven), Latin American markets (four) and Asian markets (seven), and then, focus on the presence of cross-country herding effects from the US market to the others. Economou, Kostakis, and Philippas (2011) provide evidence of cross-country herding for four South European markets, while Mobarek, Mollah, and Keasey (2014) enlarged the sample under

[6] Avramov, Chordia, and Goyal (2006) define contrarian trades as sell trades when returns are positive; while, herding trades as sell trades when returns are negative.

analysis to eleven developed European markets. The US REIT market is examined by Philippas, Economou, Babalos, and Kostakis (2013), who find that the herding is more prevalent during days of extreme negative returns. This finding is confirmed by Zhou and Anderson (2013), over a larger sample period (1980 – 2010) and using quantile regressions in order to study herding in high quantiles (ie, turbulent states of the market). During earlier financial crises, Galariotis, Rong, and Spyrou (2015) report evidence[7] of herding for US investors when fundamental macroeconomic announcements are released and spillover herding effects from the US to the UK markets. Moreover, they examine the presence of "spurious" and "intentional" herding in these two markets. In a follow up study, Galariotis, Krokida, and Spyrou (2016) provide new evidence on the relation between herding behavior and equity market's liquidity for the G5 markets – namely US, France, Germany, UK and Japan. Overall, emerging markets are more likely to herd than developed markets; and, as empirically demonstrated by Drehmann, Oechssler, and Roider (2005), the presence of a flexible market price prevents herding.

In Chapters 5 and 6 more details on the herding behavior literature and measures will be provided with an application to equity markets as well as more insights on the linkage with the systemic risk literature.

[7] A more recent analysis of "spurious" and "intentional" herding of the US financial industries is done by Humayun Kabir (2018).

CHAPTER 3

Incorporating systemic risk estimation uncertainty in selecting and regulating G-SIBs

"The need for economic foundations for a systemic risk measure is more than an academic concern since regulators around the world consider how to reduce the risks and costs of systemic crises."

Acharya, Pedersen, Philippon, and Richardson (2017)

3.1 Introduction

The Basel Committee on Banking Supervision (BCBS) defined a systemic-risk scoring methodology (Basel Committee on Banking Supervision, 2013; Basel Committee on Banking Supervision, 2014) that aggregates information about five categories of systemic importance: size, interconnectedness, substitutability, complexity, and cross-jurisdictional activity; see Section 2.4 for a description of the process. Based on this assessment methodology, the Financial Stability Board (FSB) annually decides the list of global systemically important banks (G-SIB), which are allocated into four populated buckets. The designation of a bank as G-SIB and the allocation within a specific bucket is important, because firms coming out from the list or reallocated in different buckets trigger substantial changes in their regulatory capital for those entities.

In this Chapter we are interested in the effect of estimation uncertainty on selecting and assigning capital surcharges to G-SIBs, generated by the three leading market-based systemic risk measures (SRM)[1] – namely, the delta conditional value at risk ($\Delta CoVaR$) developed by Adrian and Brunnermeier (2016), the marginal expected shortfall (MES) of Acharya, Pedersen, Philippon, and Richardson (2017) and the $SRISK$ proposed by Brownlees and Engle (2016) and discussed in more detail in Engle (2018);[2] and, how these compare with the list of G-SIBs published annually by the FSB. First, we test how closely the SRMs agree with the classification of G-SIBs and with their assignment to risk buckets as designated by the FSB. Second, using confidence intervals and cluster analyses we provide an alternative procedure to identify G-SIBs based on SRMs. As this procedure incorporates the SRM confidence intervals of banks, it provides a way to assess the degree of prudence versus conservatism that the FSB applies in compiling its list of G-SIBs. We find that compared to the method employing only the SRM point estimates and hence not accounting for SRM estimation uncertainty, when using our method, the ranking based on confidence intervals is more prudent. Moreover, our improved methodology is able to capture banks that have been designated by the financial authority as systemically important based on supervisory judgement.

The importance of reliably measuring the systemic risk of banks can be motivated on several grounds. Crockett (2000) argues that macroprudential policy should target only financial firms proved to be systemically risky and only those firms should be required to increase their capital ratios. On the other hand, companies may start litigations against the

[1] Silva, Kimura, and Sobreiro (2017) analyze and classify 266 articles on systemic risk that were published no later than September 2016. The increasing number of studies has resulted in a large number of SRMs. Bisias, Flood, Lo, and Valavanis (2012) carries-out a meta-analysis on the measures of systemic risk, surveying 31 quantitative measures for systemic risk, which can be classified according to data requirements, supervisory perspective and research perspective.

[2] A detailed description of these measures can be found in Appendix A.1.

regulator for being given a systemic risk status that will imply operating under more stringent capital requirements than their commercial competitors.[3] In this Chapter, we focus only on banks. According to Elsinger, Lehar, and Summer (2006) the financial stability is often put forth as the main reason for enacting bank regulation in the first place. However, proving with high confidence that a company is posing systemic risk to a financial system is not straightforward and, at least in the case of the most used SRMs, the estimation uncertainty may cloud the results, as demonstrated by Danielsson, James, Valenzuela, and Zer (2016).

Benoit, Hurlin, and Pérignon (2019) identified two major shortcomings in this systemic-risk scoring methodology: the first is linked to the categories that, as defined by the official methodology, are quite volatile in the cross section; and, the second is related to the reference currency (EUR) used to aggregate bank data across currency zones. They empirically demonstrate that these two shortcomings may affect the final ranking. Benoit, Colliard, Hurlin, and Pérignon (2017) provided an excellent review of systemic risk literature and concluded that there are two main family of SRMs. They highlighted that one branch focuses on low-frequency regulatory data that are not always public; while, the other line of investigation often encountered in recent studies on systemic risk employs higher-frequency market data to derive measures that could be replicated and allow a more transparent computation, which may contribute to a more efficient regulation and supports also the view of Liang (2013), who argues that large and complex financial firms should be monitored with measures of expected financial conditions and tail risks, such as the SRMs we use in our study. Moreover, as these three measures capture the co-movements among financial

[3]See for instance, the case of MetLife suing Financial Stability Oversight Council (FSOC) – "MetLife to mount legal challenge to systemic risk label," Financial Times, January 13, 2015. On March 30, 2016, the US District Court ruled against the MetLife's SIFI designation on the basis that the Financial Stability Oversight Council (FSOC) did not weigh the economic cost of the financial regulation on MetLife against the benefits of increased financial stability. Naubert and Tesar (2019) estimated that the lifting of the SIFI designation created $1.4 billion in corporate wealth for MetLife, suggesting that MetLife would be 3.4% more profitable as a non-SIFI. Moreover, in September 2017 FSOC voted to remove a similar designation for American International Group Inc., GE Capital was able to reverse the labelling in 2016 after overhauling its business. The House Financial Services Committee released a staff report highlighting pitfalls on the FSOC methodology for the systemically important financial institutions (SIFI) designation; see e.g. "Does 'Too Big to Fail' Mean Too Big for the Rule of Law?", The Wall Street Journal, March 31 - April 2, 2017.

institutions and the possibility that the distress of one financial institution propagates to others, thus leading ultimately to a systemic crisis, our line of investigation may be of interest to central banks, which use the risk of contagion to justify intervention when a financial institution in distress occupies a key position in particular financial or banking system Allen and Carletti (2013).

Using regulatory and market data for banks included in the G-SIBs assessment sample between end-2014 and end-2017, we estimate the SRMs conditioned on the respective domestic index (for each bank in the sample) and also on the global index and find empirical evidence that conditioning the analysis on the global index allows a more meaningful comparison between the market-based SRMs and the BCBS' assessment methodology. Employing the bootstrap Kolmogorov-Smirnov (KS) test, we demonstrate that the three SRMs collectively produce a relatively similar classification of banks into systemic and non-systemic as the FSB's G-SIBs list.[4] However, the systemic risk buckets defined by the FSB are generally different from those constructed in a full pairwise comparison approach based on the market-based SRMs. We show that the systemic risk assessments based on different SRMs may lead to different[5] conclusions, so categorizing a financial firm as systemically risky may be SRM dependent.[6] However, since the FSB classification of G-SIBs has been proven controversial, we believe that market-based SRMs provide an useful and transparent tool to test whether G-SIBs assigned by the FSB do contribute more than the other banks to the overall systemic risk. We show that our proposed approach based on confidence intervals and cluster analyses classifies as systemically important Nordea Bank in 2015, 2016 and 2017, and Royal Bank of Scotland Group in 2017, which have been designated as G-SIBs "only" thorough

[4]Considering the SRMs stressed at 5% level over the entire year, our approach differs from Hurlin, Laurent, Quaedvlieg, and Smeekes (2017) who introduce a bootstrap-based test of the null hypothesis of equality of two firms' conditional risk measures at a single point in time. Moreover, considering the end-year data, it comes closest to the FSB approach.

[5]Drehmann and Tarashev (2013) also found out that other measures of systemic risk can disagree substantially about the systemic importance of individual banks.

[6]Löffler and Raupach (2018), considering as SRM the $\Delta CoVaR$ and the MES, found that changes in the company's systematic risk, idiosyncratic risk, size or contagiousness, affect the systemic risk rankings. Ignoring SRMs selection uncertainty, banks may be estimating a lower systemic contribution and then regulators may ask them to take actions that could increase the risk of the system rather than reduce it.

supervisory judgment. Moreover, comparing the additional capital buffers generated by our methodology, we show that they are more stable year on year compared to the methodology based on SRM point estimate; which, would find G-SIBs over-capitalized, assigning them higher additional capital buffers than our new method.

This Chapter is inspired by the research of Danielsson, James, Valenzuela, and Zer (2016) who analyze the use of two SRMs as "riskometer" for policies targeted at reducing systemic risk. They compare the MES and the $\Delta CoVaR$ and evaluate the reliability of the riskometers built on these two measures. The riskometer reliability is estimated as the proportion of risky banks. They find that while the bank with the highest estimated systemic risk score is generally susceptible of creating systemic risk, the probability of false judgement for banks with next highest systemic risk scores increases rapidly. In comparison, our aim is to incorporate systemic risk estimation uncertainty in classifying banks as systemically risky and in assigning them to different systemic risk buckets with different capital surcharges. As the systemic risk estimation uncertainty is incorporated, our method might also be used to assess the implicit degree of prudence vs conservatism that the regulator has used in selecting the systemically risky banks.[7] Finally, our results support the view of Angelini, Neri, and Panetta (2014), who suggest that time-varying capital requirements can improve macroeconomic stability.

The remainder of this Chapter is organized as follows. In Section 3.2 we discuss the statistical tests to be used in comparing banks' systemic risk rankings, the methodology to build non-parametric confidence intervals for SRMs, and the proposed new systemic risk ranking method that takes the estimation uncertainty into account. Section 3.3 summarizes the characteristics of the data used in this study. The empirical results linked to the G-SIB classification lists published by the financial authority are presented in Section 3.4.

[7] Other main related studies are: Huang, Zhou, and Zhu (2012), Benoit, Colletaz, Hurlin, and Pérignon (2013), Rodríguez-Moreno and Peña (2013), Bernal, Gnabo, and Guilmin (2014), Castro and Ferrari (2014), Nucera, Schwaab, Koopman, and Lucas (2016), Ahnert and Georg (2018), Kleinow, Moreira, Strobl, and Vähämaa (2017), van de Leur, Lucas, and Seeger (2017), which investigate the differences of the systemic risk estimates and rankings generated by the three main SRMs.

Section 3.5 concludes the discussion.

3.2 Methodologies for testing and ranking systemic risk contribution

In this Section, we first present the statistical tests employed to compare the classification and ranking of FSB's G-SIBs with that based on the three SRMs. Second, in subsection 3.2.1 we describe a method to compute non-parametric confidence intervals for the SRMs. We then propose an alternative method based on cluster analyses that incorporates systemic risk estimation uncertainty, using the confidence intervals, to designate systemically important risky banks and assign them capital surcharges.

We start by testing the systemic contribution of the G-SIBs, as identified by the FSB in each November 2015 to 2018 – see Table 3.1, compared to the systemic contribution of the banks not designated as G-SIB (non G-SIBs). In particular, considering the G-SIBs' lists of November 2015 to November 2018, we test whether or not the systemic contribution of these banks is greater than the systemic contribution of the non G-SIBs. We test if the G-SIBs as identified by the FSB are effectively the systemically riskier banks in the light of the SRMs that we use. We also run an additional test that aims to determine whether or not the systemic contribution of the G-SIBs is greater than the "mean" systemic contribution of the global banking sector. This test arises from the cut-off value of 130bps used for the designation of G-SIBs under the BCBS' assessment methodology. In particular, according to this methodology, the G-SIB indicators (x) associated with each category (k) are normalized (to 10,000) by their sums. The G-SIB score is computed as an equally weighted sum of these k categories. As highlighted by Benoit, Hurlin, and Pérignon (2019), by definition, all k have an equal mean (of 132bps) $10.000/n$ – where n is the number (76) of banks that contribute to the global denominators and are part of this scoring exercise. This entails that the cut-off value of 130bps used for the designation of G-SIBs is very close to the G-SIB score of the "mean" bank. Finally, we employ a dominance test to contrast the systemic ranking of the G-SIBs identified by the FSB to those provided by the three SRMs. For testing these hypotheses we use the bootstrap KS test[8] because it compares the cumulative distribution functions (CDFs) instead of considering only the means that could be sensitive to outliers. Moreover, its nonparametric nature does not require any assumptions about the distribution of the SRMs. The two sample KS test statistic is given by:

$$D_{mn} = \sqrt{\left(\frac{mn}{m+n}\right)} sup_x |S_m(x) - T_n(x)| \tag{3.1}$$

where $S_m(x)$ and $T_n(x)$ are the CDFs of the SRM related to two different populations, and, m and n represent the size of the two samples, respectively.

We test if the estimates of the three SRMs for the G-SIBs resonate with their systemic importance under the FSB ranking. In order to test this hypothesis, we compare the stressed 5% systemic risk contribution $SRM_{5\%}^{G-SIB_i}$ of each market-based SRM with the stressed 5% systemic risk contribution $SRM_{5\%}^{non\ G-SIBs}$ of all the non G-SIBs for the period from end-2014 to end-2017.[9] The systemic risk contribution of the G-SIBs during a systemic event (measure stressed 5%) should be greater than the non G-SIBs. We test the following hypothesis:

$$H_0 : SRM_{5\%}^{G-SIB_i} \leq SRM_{5\%}^{non\ G-SIBs} \tag{3.2}$$

$$H_1 : SRM_{5\%}^{G-SIB_i} > SRM_{5\%}^{non\ G-SIBs} \tag{3.3}$$

[8] Bernal, Gnabo, and Guilmin (2014) apply the bootstrap KS test developed by Abadie (2002) for testing the systemic contribution of different financial sectors during the period from 2004 to 2012. Castro and Ferrari (2014) use the same test to determine whether or not a financial institution can be identified as systemically important. The resampling method introduced by Abadie (2002) is superior to the standard KS test because of the Durbin problem (see Durbin, 1973). On the other hand, Ahnert and Georg (2018) use the Wilcoxon signed rank sum test for paired data to test whether information contagion due to counterparty risk increases systemic risk.

[9] In all our tests related to the comparison of the market-based SRMs and the BCBS' assessment methodology for G-SIBs, in order to have a full pairwise comparison, we employ the market-based SRMs over the same time horizon used by the FSB for the designation of G-SIBs. In particular, because the FSB designates the G-SIBs with end-year (n-1) data for the next year (n), we measure the systemic relevance of G-SIBs in year *"n"* as the SRM for year *"n - 1"*.

Table 3.1: List of G-SIBs as of the FSB announcements in November 2015 to November 2018

Bucket	G-SIBs in alphabetical order within each bucket			
	2015	2016	2017	2018
5^{th} (3.5%)	(Empty)	(Empty)	(Empty)	(Empty)
4^{th} (2.5%)	HSBC Holdings	Citigroup	JPMorgan Chase & Co	JPMorgan Chase & Co
	JPMorgan Chase & Co	JPMorgan Chase & Co		
3^{rd} (2.0%)	Barclays	Bank of America	Bank of America	Citigroup
	BNP Paribas	BNP Paribas	Citigroup	Deutsche Bank
	Citigroup	Deutsche Bank	Deutsche Bank	HSBC Holdings
	Deutsche Bank	HSBC Holdings	HSBC Holdings	
2^{nd} (1.5%)	Bank of America	Barclays	Bank of China	Bank of America
	Credit Suisse Group	Credit Suisse Group	Barclays	Bank of China
	Goldman Sachs Group/The	Goldman Sachs Group/The	BNP Paribas	Barclays
	Mitsubishi UFJ Financial Group	Industrial & Com. Bank of China	China Construction Bank	BNP Paribas
	Morgan Stanley	Mitsubishi UFJ Financial Group	Goldman Sachs Group/The	Goldman Sachs Group/The
		Wells Fargo & Co	Industrial & Com. Bank of China	Industrial & Com. Bank of China
			Mitsubishi UFJ Financial Group	Mitsubishi UFJ Financial Group
			Wells Fargo & Co	Wells Fargo & Co
1^{st} (1.0%)	Agricultural Bank of China	Agricultural Bank of China	Agricultural Bank of China	Agricultural Bank of China
	Banco Santander	Banco Santander	Banco Santander	Banco Santander
	Bank of China	Bank of China	Bank of New York Mellon/The	Bank of New York Mellon/The
	Bank of New York Mellon/The	Bank of New York Mellon/The	Credit Suisse Group	China Construction Bank
	China Construction Bank	China Construction Bank	Groupe Crédit Agricole	Credit Suisse Group
	Groupe BPCE	Groupe BPCE	ING Groep	Groupe BPCE
	Groupe Crédit Agricole	Groupe Crédit Agricole	Mizuho Financial Group	Groupe Crédit Agricole
	Industrial & Com. Bank of China	ING Groep	Morgan Stanley	ING Groep
	ING Groep	Mizuho Financial Group	Nordea Bank	Mizuho Financial Group
	Mizuho Financial Group	Morgan Stanley	Royal Bank of Canada	Morgan Stanley
	Nordea Bank	Nordea Bank	Royal Bank of Scotland Group	Royal Bank of Canada
	Royal Bank of Scotland Group	Royal Bank of Scotland Group	Société Générale	Société Générale
	Société Générale	Société Générale	Standard Chartered	Standard Chartered
	Standard Chartered	Standard Chartered	State Street Corporation	State Street Corporation
	State Street Corporation	State Street Corporation	Sumitomo Mitsui Financial Group	Sumitomo Mitsui Financial Group
	Sumitomo Mitsui Financial Group	Sumitomo Mitsui Financial Group	UBS Group	UBS Group
	UBS Group	UBS Group	UniCredit Group	UniCredit Group
	UniCredit Group	UniCredit Group		
	Wells Fargo & Co			

Notes: The list contains the G-SIBs as of the FSB announcements in November 2015 to 2018. The G-SIBs are allocated to buckets corresponding to required levels of additional capital buffers. The G-SIBs are designated using end-2014, end-2015, end-2016, and end-2017 data, respectively.

The failure to reject the null (3.2) implies that the SRM disagrees with FSB's view of bank i's systemic risk.[10]

Our second test aims to determine whether or not the three SRMs for the G-SIBs are greater than the systemic importance of the mean-bank in the global banking sector. The systemic risk associated with the mean-bank is computed as the cross-sectional average of the SRM estimates stressed at 5% within each year for the period from end-2014 to end-2017 ($SRM_{5\%}^{mean-bank}$). $SRM_{5\%}^{G-SIB_i}$ is also stressed at 5%. We test the following hypothesis:

$$H_0 : SRM_{5\%}^{G-SIB_i} \leq SRM_{5\%}^{mean-bank} \tag{3.4}$$

$$H_1 : SRM_{5\%}^{G-SIB_i} > SRM_{5\%}^{mean-bank} \tag{3.5}$$

The failure to reject the null (3.4) implies that the $G-SIB_i$ is not systemically riskier than the mean-bank included in the G-SIB assessment sample.

The FSB allocates the G-SIBs to five systemic risk buckets corresponding with different capital surcharges. Banks contained in the n^{th}-bucket are systemically riskier than the banks contained in the $(n-1)^{th}$-bucket. These buckets were built in such a way as to leave the highest (5^{th}) empty as a deterrent for banks not to increase their global systemic importance.

As our third test, we test whether or not higher ranked buckets as defined by the FSB are effectively systemically riskier than the lower buckets in the light of the SRMs. To test this hypothesis, we consider all the G-SIBs classified in each risk-bucket and with the bootstrap KS test we compare the CDFs of the systemic risk contribution of each bucket. The null and alternative hypotheses are defined as follows:

$$H_0 : SRM^{i^{th}-Bucket} \leq SRM^{j^{th}-Bucket} \quad \text{with} \quad i > j \in \{1, 2, 3, 4\} \tag{3.6}$$

[10]We run the bootstrap KS dominance test with hypotheses (3.2) and (3.3) also for the banks not classified as G-SIBs, included in our sample, to investigate whether or not these banks present systemically importance. In this case, the systemic risk of the non G-SIBs is measured by the panel distribution of the measure without the bank under the analysis.

$$H_1 : SRM^{i^{th}-Bucket} > SRM^{j^{th}-Bucket} \quad \text{with} \quad i > j \in \{1, 2, 3, 4\} \tag{3.7}$$

where $SRM^{i^{th}-Bucket}$ and $SRM^{j^{th}-Bucket}$ are the SRM for the i^{th} and the j^{th} buckets. The failure to reject the null hypothesis (3.6) implies that the SRM disagrees with the FSB's systemic risk allocation of G-SIBs into buckets.

Fourthly, in order to test and rank the individual G-SIBs according to their systemic risk, we use the bootstrap KS test to investigate whether or not G-SIBs included in higher buckets are systemically riskier than the ones in lower buckets. This pairwise dominance test defines the following null and alternative hypotheses:

$$H_0 : SRM^i_{5\%} \leq SRM^j_{5\%} \quad \text{with} \quad i > j \quad i = 1, 2, ..., n \quad \text{and} \quad j = 1, 2, ..., n-1 \tag{3.8}$$

$$H_1 : SRM^i_{5\%} > SRM^j_{5\%} \quad \text{with} \quad i > j \quad i = 1, 2, ..., n \quad \text{and} \quad j = 1, 2, ..., n-1 \tag{3.9}$$

where SRM is the risk measure considered stressed at 5%, i and j indicate the G-SIB entities that are tested. The failure to reject the null hypothesis (3.8) means that bank j is systemically riskier than bank i, entailing a higher[11] ranking position of j. Using the results from the KS dominance test, we rank the G-SIBs at 99% confidence level. We use this test to rank the G-SIBs and then to investigate the rankings produced by different SRMs from 2015 to 2018.[9]

As an additional test, we investigate the contribution of the G-SIBs during the main high volatility events of 2015, 2016 and 2018. In particular, we investigate whether or not the contribution of the G-SIBs h-days after the volatile events is greater than h-days before. We consider the horizon h as one month (22 days). As main volatile events, we examine the Chinese market crash on August 24^{th} 2015, the Brexit vote on June 23^{th} 2016, the presidential election in US of 2016 (November 8^{th}), and the tech crash on September 21^{st}

[11] For the dominance test we carry out two tests, first with a null hypothesis that the SRM are identical for the two entities, and if this is rejected then we take one direction as the null hypothesis. Thus, in the end the testing results will indicate either equality or a strict inequality indicating dominance of systemic risk in one direction.

2018. The Wilcoxon signed rank sum test is applied to the following hypotheses:

$$H_0 : SRM^i_{t:t+h-1} \leq SRM^i_{t-h-1:t-1} \tag{3.10}$$

$$H_1 : SRM^i_{t:t+h-1} > SRM^i_{t-h-1:t-1} \tag{3.11}$$

where SRM is the risk measure considered and i indicates the particular G-SIB under study. The failure to reject the null hypothesis (3.10) means that the systemic risk level of the bank under the analysis did not increase during the high volatility events previously described.

3.2.1 Systemic risk ranking with confidence intervals

The FSB publishes the list of the G-SIBs annually in November. Banks within the same systemic risk category should carry a similar systemic risk. However, the riskier banks in a given category could carry similar systemic risk to the less riskier banks in the upper next category. Hence, we propose a systemic risk ranking methodology based on confidence intervals, that should improve on the pointwise ranking previously used in literature.

In this Section, we construct nonparametric confidence intervals based on bootstrapping. In particular, we build confidence intervals based on the mean applying the non-overlapping block bootstrap as described in Carlstein et al. (1986)[12] with a re-sampling of (n=) 1000 and considering a block with a length of 1-year.[13] If $\overline{x}$ is the sample average, we estimate the bootstrapped mean $\overline{x}^*$ with a (n=) 1000 resampling. The bootstrap differences are given by $\delta^* = \overline{x}^* - \overline{x}$. Repeating this exercise for 1000 times, we can estimate the critical values at 0.975 and 0.025 ($\delta^*_{0.975}$ and $\delta^*_{0.025}$) leading to the bootstrap confidence interval at 95%

[12] See also Lahiri (1999) for a comprehensive comparison of block bootstrap method.

[13] In order to have a full pairwise comparison with the FSB list of G-SIBs and the BCBS' assessment methodology of G-SIBs, we estimate the confidence intervals each year in December, considering a sample length of 3 years. The same sample length is used by the Bank of England and the European Systemic Risk Board to identify and monitor the systemic risk and the key financial stability risks. The estimates of end-2014, end-2015, end-2016, and end-2017 are used to designate the G-SIBs (from a market-based perspective) of 2015, 2016, 2017, and 2018, respectively.

confidence level as:

$$[\overline{x} + \delta^*_{0.025}, \quad \overline{x} + \delta^*_{0.975}] \tag{3.12}$$

In this Chapter, we built confidence intervals associated with $\Delta CoVaR_{95^{th}}$, MES and $SRISK\%$.[14]

By definition, a G-SIB's systemic loss given default (sLGD) is higher than that of a non G-SIB. Considering as measure of sLGD the three SRMs, we implement a methodology that relies on four different cluster analyses, which are used to define the threshold between G-SIBs and non G-SIBs.[15] In particular, considering the G-SIB assessment sample, we employ: i) a k-means clustering that allows to partition the n banks into five different clusters such that each bank belongs to the cluster with the nearest mean; ii) a "top-down" hierarchical cluster analysis, which considering an initial unique cluster, recursively splits the banks into five different clusters as the first bank moves down the hierarchy; iii) a Jenk's natural breaks optimization that aims to reduce variance within the cluster and maximise variance between clusters; and, iv) a Fisher's natural breaks classification that classifies the banks into five classes such that the sum of the squared deviations from the class means is minimized. All the different clustering methodologies assume five populated clusters to have a pairwise comparison with the FSB's list of G-SIBs. By selecting four clusters representing the populated buckets of G-SIBs and one cluster for the non G-SIBs, the same number of populated buckets as specified by the FSB for their list is obtained.[16]

We perform these cluster analyses every year from 2008 to 2018. The systemic threshold is defined considering a two steps methodology. First, for each cluster methodology implemented and each SRMs, we consider the average between the score of the bank classified as lowest in the fourth G-SIBs cluster, which corresponds to the lowest risky cluster, and the bank classified as highest in the non G-SIBs cluster. We repeat this exercise every year

[14]The same methodology may be used for other market-based SRMs.

[15]The European Central Bank uses a similar methodology for assessing the buffer calibration of the Other-Systemically Important Institutions. The methodology is described in the Macroprudential Bulletin, Issue 3, June 2017.

[16]Note that the FSB leaves the highes bucket (5^{th}) empty.

with an iterative process of 1000 repetitions. Second, we define the G-SIBs (market-based) threshold "η" associated to each year by averaging the four clusters' thresholds from a 3-year moving window.

To complete our ranking exercise, we classify a bank as systemically important if the upped bound of the SRM of such bank is greater than the defined systemic threshold. We believe that from a macro-prudential perspective, which we follow in this Chapter, the upper bound of the confidence interval should be used, because it represents, on average, the worst systemic loss given default of the banks with 95% confidence level. As an additional exercise, we do a sensitivity analysis to show how the designation of systemically important banks could be affected by the use of the midpoint or the lower bound, instead of the upper bound, of the confidence interval. The results are shown in Table 3.17 (Section 3.4.2). The midpoint, lower bound, and upper bound used are estimated as the three-year horizon average of results of the non-overlapping block bootstrap. We then account for size[17] and normalize the confidence intervals to built five categories associated with different additional capital requirements. Denoting by $maxU$ the maximum upper bound cross-sectionally across all companies and by $minU$ the minimum upper bound again cross-sectionally, for each company i we consider x_i as the upper bound of the confidence interval of its SRM. We then calculate a normalized systemic risk score for each company i, using the following formula:

$$Score_i = \frac{x_i - minU}{maxU - minU} \times 100 \tag{3.13}$$

All the normalized systemic risk scores will fall onto a 0 to 100% scale. We define the systemic risk categories by dividing the scale into five equally spaced buckets that cover this

[17]By weighting the SRM with size, we combine the "Too-Interconnected-To-Fail" and the "Too-Big-To-Fail" logics (Banulescu and Dumitrescu, 2015). Since the $SRISK$ already incorporates these logic, we do not weight (again) the $SRISK\%$ for the size.

scale. Hence:

$$\begin{array}{llll} 5^{th} & category, & if & 80\% < Score_i \leq 100\% \\ 4^{th} & category, & if & 60\% < Score_i \leq 80\% \\ 3^{rd} & category, & if & 40\% < Score_i \leq 60\% \\ 2^{nd} & category, & if & 20\% < Score_i \leq 40\% \\ 1^{st} & category, & if & 0\% < Score_i \leq 20\% \end{array}$$

The additional capital requirements are computed using the expected impact approach as described in Basel Committee on Banking Supervision (2013). This approach assumes that the failure of a G-SIB would harm the financial stability more than a non G-SIB. Thus, if all the banks would be subject to the same capital requirements and have similar probabilities of default, a G-SIB will impose far greater systemic risks than a non G-SIB. In particular, if the impact on the system of the failure of a G-SIB is x times greater than the one of a non G-SIB, the capital requirement of the G-SIB has to increase to reduce its probability of default until its expected impact is equal to the expected impact of a (reference) non G-SIB. More formally, with EL denoting the expected loss:

$$EL_{G-SIB} = EL_{\text{non G-SIB}} \tag{3.14}$$

To implement the expected impact approach, we also need a function that relates capital ratio increases to reductions in probability of default. As described[18] in Board of Governors of the Federal Reserve System (2015), this function can be calibrated using a standard panel data regression. Denoting $p_{RORWA} \doteq Prob(\tilde{R} \leq RORWA)$ the empirical cumulative distribution function of the $RORWA$, where $RORWA$ stands for returns on risk-weighted

[18] A comprehensive description of this methodology is provided in Basel Committee on Banking Supervision (2013).

assets, we fit the regression:

$$RORWA = \alpha + \beta \ln(p_{RORWA}) + \varepsilon \tag{3.15}$$

We implement (3.15) using quarterly data from 2007 to 2018. The inverse of Eq. (3.15), gives:

$$p_{RORWA} = \exp\left(\frac{RORWA - \alpha}{\beta}\right) \tag{3.16}$$

Because $EL = sLGD \times PD$, we can rewrite (3.14) as:

$$sLGD_{G-SIB} * p(\kappa_{\text{non G-SIB}} + \kappa_{G-SIB}) = sLGD_{\text{non G-SIB}} * p(\kappa_{\text{non G-SIB}}) \tag{3.17}$$

where $\kappa_{\text{non G-SIB}}$ is the capital held by the reference non G-SIBs and κ_{G-SIB} is the capital surcharge that the given G-SIB is required to hold on top of $\kappa_{\text{non G-SIB}}$.

We would like to estimate the probability that a bank with capital $\kappa_{\text{non G-SIB}}$ will suffer sufficiently severe losses to bring its capital ratio down to the failure point ϕ. More specifically, we are looking for the probability that $\kappa_{\text{non G-SIB}} + \text{RORWA} = \phi$. Replacing $RORWA = \phi - \kappa_{\text{nonG}-\text{SIB}}$ in (3.16), gives:

$$p_{RORWA} = \exp\left(\frac{\phi - \kappa_{\text{non G-SIB}} - \alpha}{\beta}\right) \tag{3.18}$$

Combining (3.18) with (3.17) and solving for κ_{G-SIB}, we obtain:

$$\kappa_{G-SIB} = -\beta * \ln\left(\frac{sLGD_{nonG-SIB}}{sLGD_{G-SIB}}\right) \tag{3.19}$$

Formula (3.19) allows us to define a range of additional capital requirements for each of the five buckets defined. In particular, given that $sLGD_{nonG-SIB}$ is the systemic threshold found through the cluster analyses previously described and $sLGD_{G-SIB}$ is the upper bound of each systemically important bank, we define the additional capital requirement associated with the highest bucket defined by (3.20), lowest bucket defined by (3.21) and the i^{th} categories defined by (3.22), respectively.[19] In each bucket i we have $j \in \{1, 2, ..., n_i\}$ with n_i the number of banks included in the i^{th} category. The capital requirements are computed from the formulae:

$$\kappa_{G-SIB,5^{th}} = max\{\kappa_{G-SIB,j} : j = 1, 2, ..., n_5\} \tag{3.20}$$

$$\kappa_{G-SIB,1^{th}} = max(max\{\kappa_{G-SIB,j} : j = 1, 2, ..., n_1\}, 0.25\%) \tag{3.21}$$

$$\kappa_{G-SIB,i^{th}} = \kappa_{G-SIB,(i^{th}-1)} + \frac{(\kappa_{G-SIB,5^{th}} - \kappa_{G-SIB,1^{th}})}{4} \tag{3.22}$$

where $i = 2, 3, 4$ such that in total we have five categories in order to have a one-to-one comparison with the FSB classification of G-SIBs.

3.3 Data

The BCBS requires a sample of banks to report a set of indicators to national supervisory authorities. The main G-SIBs assessment sample includes the largest 76 banks in the world as determined by the Basel III leverage ratio exposure measure, along with any banks that were designated as G-SIBs in the previous year (unless supervisors agree that there is a valid reason to exclude them). This large sample of banks is used as proxy for the global banking sector. Moreover, an additional sample composed by all banks with a leverage ratio exposure in excess of EUR 200 billion is considered. However, these banks do not contribute to the global denominators and are not part of the scoring exercise. Because of this reason, we also exclude these banks from our analysis. Table 3.2 lists the banks included in the G-SIBs assessment sample of end-2014, end-2015, end-2016, and end-2017. These banks compose our sample[20] and have been used by the FSB to designate the G-SIBs of 2015, 2016, 2017,

[19] We round the capital requirements $\kappa_{G-SIB,i^{th}}$ to the nearest $x.00$, $x.25$, $x.50$, $x.75$. Moreover, we apply Eq. (3.22) to equally distribute the additional capital requirements along the distance between the 5^{th} and the 1^{st} category.

[20] Being the SRMs used in this study based on public market data, we do not consider banks: (i) which are not publicly listed or have become de-listed; (ii) for which market data is not available; (iii) with not enough available observations (at least 1-year of daily observations). In particular, we exclude Caixa (Brazil),

Table 3.2: Countries, bank names and tickers.

Country	Bank name	Ticker
Australia	Australia and New Zealand Banking Group	ANZ
	Commonwealth Bank of Australia	CBA
	National Australia Bank	NAB
	Westpac Banking Corporation	WBC
Brazil	Banco Bradesco †† ‡‡	BBDC
	Banco do Brasil	BBAS
	Ita Unibanco	ITUB
Canada	Bank of Montreal	BMO
	Bank of Nova Scotia/The	BNS
	Canadian Imperial Bank of Commerce	CM
	Royal Bank of Canada	RY
	Toronto-Dominion Bank/The	TD
China	Agricultural Bank of China	ABC
	Bank of Beijing †	BoB
	Bank of China	BoC
	Bank of Communications	BC
	CITIC Securities	CITIC
	China Construction Bank	CCB
	China Everbright Bank	CEB
	China Merchants Bank	CMB
	China Minsheng Bank	CM
	Huaxia Bank	HX
	Industrial & Commercial Bank of China	ICBC
	Industrial Bank	IB
	Ping An Bank	PAB
	Shanghai Pudong Development Bank	SPDB
Denmark	Danske Bank	DANSKE
France	BNP Paribas	BNP
	Groupe BPCE[22]	BPCE
	Groupe Crédit Agricole	ACA
	Société Générale	GLE
Germany	Commerzbank	CBK
	Deutsche Bank	DBK
India	State Bank of India	SBIN
Italy	Intesa Sanpaolo	ISP
	UniCredit Group	UCG
Japan	Mitsubishi UFJ Financial Group	MUFJ
	Mizuho Financial Group	MFG
	Nomura Holdings	NOM
	Sumitomo Mitsui Financial Group	SMFG
	Sumitomo Mitsui Trust Holdings	SMTH
Korea	Hana Financial Group	HFG
	Kookmin Bank †	KB
	Shinhan Financial Group	S
Netherlands	ABN AMRO Group	ABN
	ING Groep	INGA
Norway	DNB Bank †† ‡ ‡‡	DNB
Russia	Sberbank of Russia	SBER
Singapore	DBS Group Holdings	DBS
Spain	Banco Bilbao Vizcaya Argentaria	BBVA
	CaixaBank	CABK
	Banco Santander	SAN
Sweden	Svenska Handelsbanken †† ‡	SHBA
	Nordea Bank	NDA
	Skandinaviska Enskilda Banken ‡ ‡‡	SEBA
Switzerland	Credit Suisse Group	CSGN
	UBS Group	UBSG
United Kingdom	Barclays	BARC
	HSBC Holdings	HSBC
	Lloyds Banking Group	LLOY
	Royal Bank of Scotland Group	RBS
	Standard Chartered	STAN
United States	Bank of America	BAC
	Bank of New York Mellon/The	BK
	Capital One Financial Corporation †	COF
	Citigroup	C
	Goldman Sachs Group/The	GS
	JPMorgan Chase & Co	JPM
	Morgan Stanley	MS
	PNC Financial Services Group	PNC
	State Street Corporation	STT
	US Bancorp	USB
	Wells Fargo & Co	WFC

Notes: The table reports the list of bank and tickers names included in the G-SIBs assessment sample and used in our analysis. The list is sorted by country. †, ††, ‡ and ‡‡ indicate that the bank was not included into the G-SIBs assessment sample of end-2014, end-2015, end-2016, and end-2017, respectively.

and 2018, respectively.

We collect the data disclosed by each bank included in the G-SIBs assessment sample from their regulatory reporting on the G-SIB indicators disclosure, and the global denominators from the Bank for International Settlements web-site in order to replicate the G-SIB scores used to designate G-SIBs over the period from 2015 to 2018.[21] The daily stock prices and balance sheet data are retrieved from Bloomberg over the period 01/01/2006 - 31/12/2018 in order to have robust estimations of the SRMs between January 2007 and December 2018, covering the two main crises (2007-2009 and 2009-2012). All the series are in EUR to have a full pairwise comparison with the BCBS' assessment methodology.

3.4 Systemic risk measurement under estimation uncertainty

In this Section we present five sets of empirical results, contrasting banks systemic risk based on the three SRMs with the G-SIBs classification and ranking under the BCBS' assessment methodology. In Section 3.4.1, we test first using individual SRM whether each G-SIB has a significantly higher systemic risk than the non G-SIBs, and higher than the "average" bank in the global sector. Second, we test whether the G-SIBs in a given systemic risk bucket as defined by the FSB have a significantly higher systemic risk measured by the SRMs than G-SIBs in the next lower bucket. Third, we form alternative G-SIB rankings using the point estimates of each SRM for each G-SIB. In addition, we also consider how the SRM based systemic risk measurement is affected in particularly turbulent or uncertain periods in the financial markets. Finally, in Section 3.4.2 we apply the method introduced in

Groupe Crédit Mutuel (France), DZ Bank (Germany), Norinchukin Bank (Japan), Rabobank (Netherlands).

[21] The BCBS publishes the data disclosed by banks and used in the G-SIBs calculations at: https://www.bis.org/bcbs/gsib/.

[22] Being Gropue BPCE not listed, we consider Natixis, which is the corporate and investment banking, asset management, insurance and financial services arm of Groupe BPCE. Groupe BPCE owns more than 70% of Natixis.

Section 3.2.1 to incorporate systemic risk estimation uncertainty in classifying and ranking G-SIBs and provide a preliminary discussion of the prudence vs conservatism implicit in the FSB listing in the light of our proposed method. We estimate the systemic risk by conditioning the analysis to the respective domestic index of the bank (Panel A) and to the global index (Panel B).[23]

Additional results presented in the Supplement Appendix A.5 cover the similarities between the three SRMs. We find that the $\Delta^{\$}CoVaR_{95^{th}}$ and the $MES^{\$}$ measures have a relatively high and stable correlation over time while both of them have a relatively low and somewhat unstable correlation with the $SRISK$ measure. Moreover, the SRMs estimated conditioning the analysis to the global index (Panel B) point out a higher comparability with BCBS' assessment methodology for G-SIBs.

3.4.1 Testing the contribution of the G-SIBs

Idier, Lamé, and Mésonnier (2014) argue that, as a financial crisis unfolds, regulators have to identify quickly the most endangered institutions. The FSB imposes higher capital levels for banks defined as G-SIBs to make sure they could cope with the risk that a future stress event could cause. The FSB publishes the list of G-SIBs, every year in November. We use the $\Delta^{\$}CoVaR_{95^{th}}$, the $MES^{\$}$ and the $SRISK$ to test if these measures are able to capture the G-SIBs as designated by the FSB as systemically riskier than the non G-SIBs.

Tables 3.3 and 3.4 report the results of the bootstrap KS dominance test for Panel A and Panel B of the banks classified as G-SIBs as of November 2015 to 2018, respectively. Excepting few cases, we always reject the null hypothesis at 1% critical level, implying that G-SIBs are individually systemically riskier than the pool of non G-SIBs. For most of the banks considered, this is consistent for all three SRMs.

[23] The domestic indexes considered are: S&P 500 Index for the United States; STOXX Europe 600 Index for Denmark, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, Switzerland and United Kingdom; MSCI AC Asia Pacific Index for Australia, China, India, Japan, Korea and Singapore; MSCI North America Index for Canada; MSCI Emerging Markets Latin America Index for Brazil; and, MSCI Russia Index for Russia. The global index considered is the MSCI World Index.

Table 3.3: Dominance test results for the G-SIBs (Panel A).

Panel A: Domestic Index

H_0: $SRM_{5\%}^{G-SIB_i} \leq SRM_{5\%}^{nonG-SIBs}$

	2015			2016			2017			2018		
	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$
Agricultural Bank of China	1.000***	1.000***	1.000***	1.000***	0.766***	1.000***	5E-17	5E-17	1.000***	0.158	0.293*	1.000***
Banco Santander	0.987***	0.994***	0.621***	1.000***	1.000***	0.473***	1.000***	0.969***	0.610***	0.503***	6E-07	0.549***
Bank of America	1.000***	1.000***	1.000***	1.000***	1.000***	0.803***	1.000***	1.000***	1.000***	1.000***	1.000***	9E-17
Bank of China	1.000***	1.000***	1.000***	0.748***	0.064	1.000***	5E-17	5E-17	1.000***	9E-17	6E-07	1.000***
Bank of New York Mellon/The	5E-17	5E-17	5E-17	3E-17	3E-17	3E-17	5E-17	5E-17	5E-17	9E-17	6E-07	9E-17
Barclays	5E-17	5E-17	1.000***	0.966***	0.798***	0.557***	0.734***	0.344**	1.000***	9E-17	6E-07	0.847***
BNP Paribas	5E-17	0.355**	1.000***	1.000***	1.000***	1.000***	0.764***	0.669***	1.000***	9E-17	6E-07	1.000***
China Construction Bank	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	5E-17	5E-17	1.000***	1.000***	1.000***	1.000***
Citigroup	1.000***	1.000***	0.991***	1.000***	1.000***	0.537***	1.000***	1.000***	1.000***	0.894***	1.000***	0.868***
Credit Suisse Group	5E-17	5E-17	0.061	3E-17	3E-17	3E-17	5E-17	5E-17	5E-17	9E-17	6E-07	9E-17
Deutsche Bank	5E-17	5E-17	1.000***	3E-17	3E-17	0.901***	0.0644	5E-17	1.000***	9E-17	6E-07	1.000***
Goldman Sachs Group/The	5E-17	0.971***	5E-17	0.527***	0.862***	3E-17	0.485***	5E-17	5E-17	0.205	0.399**	9E-17
Groupe BPCE	5E-17	5E-17	5E-17	3E-17	3E-17	3E-17				9E-17	6E-07	9E-17
Groupe Crédit Agricole	5E-17	5E-17	1.000***	3E-17	3E-17	0.558***	5E-17	5E-17	1.000***	9E-17	6E-07	1.000***
HSBC Holdings	0.996***	1.000***	0.913***	1.000***	1.000***	0.537***	0.898****	1.000***	0.339*	0.271	0.722***	9E-17
Industrial & Commercial Bank of China	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	5E-17	5E-17	1.000***	0.971***	1.000***	1.000***
ING Groep	5E-17	5E-17	0.581***	3E-17	3E-17	3E-17	5E-17	5E-17	5E-17	9E-17	6E-07	9E-17
JPMorgan Chase & Co	1.000***	1.000***	1.000***	1.000***	1.000***	0.537***	1.000***	1.000***	0.998***	1.000***	1.000***	9E-17
Mitsubishi UFJ Financial Group	5E-17	0.965***	1.000***	1.000***	0.298*	1.000***	1.000***	0.367**	1.000***	9E-17	6E-07	1.000***
Mizuho Financial Group	5E-17	5E-17	1.000***	3E-17	3E-17	1.000***	5E-17	5E-17	1.000***	9E-17	6E-07	1.000***
Morgan Stanley	5E-17	0.180	0.292*	0.908***	0.841***	3E-17	0.621***	5E-17	5E-17	0.343**	0.453***	9E-17
Nordea Bank	5E-17	5E-17	5E-17	3E-17	3E-17	3E-17	5E-17	5E-17	5E-17			
Royal Bank of Canada							5E-17	5E-17	5E-17	9E-17	6E-07	9E-17
Royal Bank of Scotland Group	5E-17	5E-17	0.998***	3E-17	3E-17	0.457***	0.535***	5E-17	0.551***			
Société Générale	5E-17	5E-17	1.000***	3E-17	3E-17	0.537***	0.193	5E-17	1.000***	9E-17	6E-07	0.944***
Standard Chartered	5E-17	5E-17	5E-17	3E-17	3E-17	3E-17	0.433***	5E-17	5E-17	9E-17	6E-07	9E-17
State Street Corporation	5E-17	5E-17	5E-17	3E-17	3E-17	3E-17	5E-17	5E-17	5E-17	9E-17	6E-07	9E-17
Sumitomo Mitsui Financial Group	5E-17	5E-17	1.000***	3E-17	3E-17	1.000***	0.149	5E-17	1.000***	9E-17	6E-07	1.000***
UBS Group	5E-17	5E-17	5E-17	0.154	3E-17	3E-17	5E-17	5E-17	5E-17	9E-17	6E-07	9E-17
UniCredit Group	5E-17	5E-17	0.590***	3E-17	3E-17	0.207	1.000***	5E-17	0.577***	9E-17	6E-07	9E-17
Wells Fargo & Co	1.000***	1.000***	5E-17	1.000***	1.000***	3E-17	1.000***	1.000***	5E-17	1.000***	1.000***	9E-17

Notes: The results, for the G-SIBs (as of the FSB announcements in November 2015 to 2018), of the bootstrap Kolmogorov-Smirnov tests, which aims to determine whether or not the systemic risk of the G-SIBs is greater than the systemic risk of the banks not designed as G-SIB (non G-SIBs). The hypothesis tested is H_0: $SRM_{5\%}^{G-SIB_i} \leq SRM_{5\%}^{nonG-SIBs}$. The failure to reject this hypothesis means that the FSB identified incorrectly bank i as systemically riskier. The systemic risk is measured with $\Delta^{\$}CoVaR_{95^{th}}$, $MES^{\$}$ and $SRISK$, conditioned to the respective domestic index (Panel A). The columns contain the test statistic. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 3.4: Dominance test results for the G-SIBs (Panel B).

Panel B: Global Index

H_0: $SRM_{5\%}^{G-SIB_i} \leq SRM_{5\%}^{nonG-SIBs}$

	2015			2016			2017			2018		
	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$
Agricultural Bank of China	1.000***	1.000***	1.000***	0.899***	0.968***	1.000***	5E-17	5E-17	1.000***	9E-17	0.953***	1.000***
Banco Santander	0.993***	0.774***	0.550***	1.000***	1.000***	0.537***	1.000***	1.000***	0.899***	0.355***	0.271	0.323*
Bank of America	1.000***	1.000***	1.000***	1.000***	1.000***	0.825***	1.000***	1.000***	1.000***	1.000***	1.000***	0.816***
Bank of China	1.000***	1.000***	1.000***	0.644***	0.162	1.000***	5E-17	0.558***	1.000***	9E-17	0.205	1.000***
Bank of New York Mellon/The	5E-17	5E-17	5E-17	3E-17	3E-17	3E-17	5E-17	6E-17	5E-17	0.256	0.179	9E-17
Barclays	5E-17	5E-17	1.000***	0.968***	0.700***	0.597***	0.857***	0.850***	1.000***	9E-17	9E-17	0.786***
BNP Paribas	5E-17	0.315*	1.000***	1.000***	1.000***	1.000***	0.998***	1.000***	1.000***	9E-17	9E-17	1.000***
China Construction Bank	1.000***	1.000***	1.000***	0.977***	1.000***	1.000***	5E-17	5E-17	1.000***	0.976***	1.000***	1.000***
Citigroup	1.000***	1.000***	1.000***	1.000***	1.000***	0.553***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Credit Suisse Group	5E-17	5E-17	2E-01	3E-17	3E-17	3E-17	0.135957066	5E-17	5E-17	9E-17	9E-17	9E-17
Deutsche Bank	5E-17	5E-17	1.000***	3E-17	3E-17	0.917***	0.483***	5E-17	1.000***	9E-17	9E-17	1.000***
Goldman Sachs Group/The	0.519***	1.000***	5E-17	0.755***	0.969***	3E-17	0.567***	0.764***	6E-02	1.000***	1.000***	0.395**
Groupe BPCE	5E-17	5E-17	6E-02	3E-17	3E-17	3E-17				9E-17	9E-17	9E-17
Groupe Crédit Agricole	5E-17	5E-17	1.000***	3E-17	3E-17	0.603***	5E-17	5E-17	1.000***	9E-17	9E-17	1.000***
HSBC Holdings	1.000***	1.000***	0.922***	1.000***	1.000***	0.537***	1.000***	1.000***	0.993***	0.192919255	1.000***	9E-17
Industrial & Commercial Bank of China	1.000***	1.000***	1.000***	0.989***	1.000***	1.000***	5E-17	0.528***	1.000***	0.901***	1.000***	1.000***
ING Groep	5E-17	5E-17	0.696***	0.276595745	3E-17	3E-17	0.361**	0.725***	5E-17	9E-17	9E-17	9E-17
JPMorgan Chase & Co	1.000***	1.000***	1.000***	1.000***	1.000***	0.543***	1.000***	1.000***	1.000***	1.000***	1.000***	9E-17
Mitsubishi UFJ Financial Group	5E-17	0.973***	1.000***	3E-17	3E-17	1.000***	5E-17	0.324*	1.000***	9E-17	9E-17	1.000***
Mizuho Financial Group	5E-17	5E-17	1.000***	3E-17	3E-17	1.000***	5E-17	5E-17	1.000***	9E-17	9E-17	1.000***
Morgan Stanley	5E-17	0.889***	0.481***	0.934***	0.968***	3E-17	0.762***	0.723***	3E-01	1.000***	1.000***	9E-17
Nordea Bank	5E-17	5E-17	5E-17	3E-17	3E-17	3E-17	5E-17	5E-17	5E-17			
Royal Bank of Canada							5E-17	0.363**	5E-17	9E-17	0.826***	9E-17
Royal Bank of Scotland Group	5E-17	5E-17	1.000***	0.291*	3E-17	0.498***	0.528***	0.404**	0.585***			
Société Générale	5E-17	5E-17	1.000***	0.518***	3E-17	0.544***	0.544***	0.644***	1.000***	9E-17	9E-17	0.927***
Standard Chartered	5E-17	5E-17	5E-17	0.636***	3E-17	3E-17	0.662***	5E-17	5E-17	9E-17	9E-17	9E-17
State Street Corporation	5E-17	5E-17	5E-17	3E-17	3E-17	3E-17	5E-17	5E-17	5E-17	9E-17	9E-17	9E-17
Sumitomo Mitsui Financial Group	5E-17	1E-17	1.000***	3E-17	3E-17	1.000***	5E-17	5E-17	1.000***	9E-17	9E-17	1.000***
UBS Group	5E-17	5E-17	5E-17	0.859***	3E-17	3E-17	0.524***	0.637***	5E-17	9E-17	9E-17	9E-17
UniCredit Group	5E-17	5E-17	0.677***	3E-17	3E-17	0.268	1.000***	0.698***	0.632***	9E-17	9E-17	9E-17
Wells Fargo & Co	1.000***	1.000***	5E-17	1.000***	1.000***	3E-17	1.000***	1.000***	2E-01	1.000***	1.000***	9E-17

Notes: The results, for the G-SIBs (as of the FSB announcements in November 2015 to 2018), of the bootstrap Kolmogorov-Smirnov tests, which aims to determine whether or not the systemic risk of the G-SIBs is greater than the systemic risk of the banks not designed as G-SIB (non G-SIBs). The hypothesis tested is H_0: $SRM_{5\%}^{G-SIB_i} \leq SRM_{5\%}^{nonG-SIBs}$. The failure to reject this hypothesis means that the FSB identified incorrectly bank i as systemically riskier. The systemic risk is measured with $\Delta^{\$}CoVaR_{95^{th}}$, $MES^{\$}$ and $SRISK$, conditioned to the global index (Panel B). The columns contain the test statistic. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 3.5: Dominance test results for the G-SIBs (Panel A) compared to the mean-bank.

Panel A: Domestic Index

H_0: $SRM_{5\%}^{G-SIB_i} \leq SRM_{5\%}^{mean-bank}$

	2015			2016			2017			2018		
	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$
Agricultural Bank of China	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	8E-07	1.3437E-12	1.000***	1.000***	1.000***	1.000***
Banco Santander	1.000***	1.000***	1.000***	1.000***	1.000***	0.473***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Bank of America	1.000***	1.000***	1.000***	1.000***	1.000***	0.803***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Bank of China	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	8E-07	0.692***	1.000***	1.000***	1.000***	1.000***
Bank of New York Mellon/The	8E-07	1E-12	8E-07	2E-06	8E-07	3E-17	8E-07	1E-12	2E-06	1.000***	0.857***	4E-18
Barclays	1.000***	1.000***	1.000***	1.000***	1.000***	0.557***	1.000***	1.000***	1.000***	6E-07	5E-08	1.000***
BNP Paribas	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	5E-08	1.000***
China Construction Bank	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	8E-07	0.154	1.000***	1.000***	1.000***	1.000***
Citigroup	1.000***	1.000***	1.000***	1.000***	1.000***	0.537***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Credit Suisse Group	8E-07	1E-12	8E-07	2E-06	8E-07	3E-17	0.615***	1E-12	2E-06	6E-07	5E-08	4E-18
Deutsche Bank	8E-07	1E-12	1.000***	2E-06	8E-07	0.901***	1.000***	1E-12	1.000***	0.286	5E-08	1.000***
Goldman Sachs Group/The	1.000***	1.000***	8E-07	1.000***	1.000***	3E-17	1.000***	1.000***	2E-06	1.000***	1.000***	0.643***
Groupe BPCE	8E-07	1E-12	8E-07	2E-06	8E-07	3E-17				6E-07	5E-08	4E-18
Groupe Crédit Agricole	8E-07	1E-12	1.000***	2E-06	8E-07	0.558***	8E-07	0.154	1.000***	6E-07	5E-08	1.000***
HSBC Holdings	1.000***	1.000***	1.000***	1.000***	1.000***	0.537***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Industrial & Commercial Bank of China	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	8E-07	0.615***	1.000***	1.000***	1.000***	1.000***
ING Groep	1.000***	1.000***	1.000***	1.000***	1.000***	3E-17	1.000***	1.000***	2E-06	6E-07	5E-08	4E-18
JPMorgan Chase & Co	1.000***	1.000***	1.000***	1.000***	1.000***	0.537***	1.000***	1.000***	1.000***	1.000***	1.000***	4E-18
Mitsubishi UFJ Financial Group	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Mizuho Financial Group	8E-07	1E-12	1.000***	2E-06	8E-07	1.000***	8E-07	1E-12	1.000***	6E-07	5E-08	1.000***
Morgan Stanley	1.000***	1.000***	8E-07	1.000***	1.000***	3E-17	1.000***	1.000***	1.000***	1.000***	1.000***	4E-18
Nordea Bank	8E-07	1E-12	8E-07	2E-06	8E-07	3E-17	8E-07	1E-12	2E-06			
Royal Bank of Canada							0.159	0.615***	2E-06	6E-07	1.000***	4E-18
Royal Bank of Scotland Group	8E-07	1E-12	1.000***	1.000***	1.000***	0.457***	1.000***	1.000***	1.000***			
Société Générale	8E-07	1E-12	1.000***	1.000***	1.000***	0.537***	1.000***	1.000***	1.000***	1.000***	5E-08	1.000***
Standard Chartered	8E-07	1E-12	8E-07	1.000***	8E-07	3E-17	1.000***	1E-12	2E-06	6E-07	5E-08	4E-18
State Street Corporation	8E-07	1E-12	8E-07	2E-06	8E-07	3E-17	8E-07	1E-12	2E-06	6E-07	5E-08	4E-18
Sumitomo Mitsui Financial Group	8E-07	1E-12	1.000***	1.000***	8E-07	1.000***	1.000***	1.000***	1.000***	6E-07	5E-08	1.000***
UBS Group	8E-07	1E-12	8E-07	1.000***	1.000***	3E-17	1.000***	1.000***	2E-06	1.000***	5E-08	4E-18
UniCredit Group	1.000***	1E-12	1.000***	0.500**	8E-07	0.207	1.000***	1.000***	1.000***	1.000***	5E-08	1.000***
Wells Fargo & Co	1.000***	1.000***	4E-18	1.000***	1.000***	3E-17	1.000***	1.000***	2E-06	1.000***	1.000***	4E-18

Notes: The results, for the G-SIBs (as of the FSB announcements in November 2015 to 2018), of the bootstrap Kolmogorov-Smirnov tests, which aims to determine whether or not the systemic risk of the G-SIBs is greater than the systemic risk of the mean-bank. The hypothesis tested is H_0: $SRM_{5\%}^{G-SIB_i} \leq SRM_{5\%}^{mean-bank}$. The failure to reject this hypothesis means that the G-SIB i is not systemically riskier than the mean-bank included in the G-SIB assessment sample. The systemic risk is measured with $\Delta^{\$}CoVaR_{95^{th}}$, $MES^{\$}$ and $SRISK$, conditioned to the respective domestic index (Panel A). The columns contain the test statistic. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 3.6: Dominance test results for the G-SIBs (Panel B) compared to the mean-bank.

Panel B: Global Index

H_0: $SRM_{5\%}^{G-SIB_i} \leq SRM_{5\%}^{mean-bank}$

	2015			2016			2017			2018		
	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$
Agricultural Bank of China	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	2E-06	1E-16	1.000***	8E-07	1.000***	1.000***
Banco Santander	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Bank of America	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Bank of China	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	2E-06	1.000***	1.000***	8E-07	1.000***	1.000***
Bank of New York Mellon/The	8E-07	4E-17	9E-09	8E-07	6E-17	8E-07	2E-06	1E-16	2E-06	1.000***	1.000***	8E-07
Barclays	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	8E-07	6E-17	1.000***
BNP Paribas	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	6E-17	1.000***
China Construction Bank	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	2E-06	0.769***	1.000***	1.000***	1.000***	1.000***
Citigroup	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Credit Suisse Group	8E-07	4E-17	9E-09	1.000***	6E-17	8E-07	1.000***	1E-16	1.000***	8E-07	6E-17	8E-07
Deutsche Bank	8E-07	4E-17	1.000***	1.000***	6E-17	1.000***	1.000***	0.231	1.000***	8E-07	6E-17	1.000***
Goldman Sachs Group/The	1.000***	1.000***	9E-09	1.000***	1.000***	8E-07	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Groupe BPCE	8E-07	4E-17	9E-09	8E-07	6E-17	8E-07				8E-07	6E-17	8E-07
Groupe Crédit Agricole	8E-07	4E-17	1.000***	8E-07	6E-17	1.000***	0.923***	0.615***	1.000***	8E-07	6E-17	1.000***
HSBC Holdings	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	8E-07
Industrial & Commercial Bank of China	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	2E-05	1.000***	1.000***	1.000***	1.000***	1.000***
ING Groep	1.000***	4E-17	1.000***	1.000***	1.000***	8E-07	1.000***	1.000***	2E-06	8E-07	6E-17	8E-07
JPMorgan Chase & Co	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	0.286
Mitsubishi UFJ Financial Group	1.000***	1.000***	1.000***	0.643***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	6E-17	1.000***
Mizuho Financial Group	8E-07	4E-17	1.000***	8E-07	6E-17	1.000***	2E-06	1E-16	1.000***	8E-07	6E-17	1.000***
Morgan Stanley	1.000***	1.000***	0.429*	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
Nordea Bank	8E-07	4E-17	9E-09	8E-07	6E-17	8E-07	2E-06	1E-16	2E-06			
Royal Bank of Canada							4E-01	1.000***	2E-06	1.000***	1.000***	8E-07
Royal Bank of Scotland Group	1.000***	4E-17	1.000***	1.000***	0.143	1.000***	1.000***	1.000***	1.000***			
Société Générale	8E-07	4E-17	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	8E-07	6E-17	1.000***
Standard Chartered	8E-07	4E-17	9E-09	1.000***	6E-17	8E-07	1.000***	1E-16	2E-06	8E-07	6E-17	8E-07
State Street Corporation	8E-07	4E-17	9E-09	8E-07	6E-17	8E-07	2E-06	1E-16	2E-06	0.500**	6E-17	8E-07
Sumitomo Mitsui Financial Group	8E-07	4E-17	1.000***	8E-07	6E-17	1.000***	2E-06	1E-16	1.000***	8E-07	6E-17	1.000***
UBS Group	8E-07	4E-17	9E-09	1.000***	1.000***	8E-07	1.000***	1.000***	2E-06	8E-07	6E-17	8E-07
UniCredit Group	1.000***	4E-17	1.000***	1.000***	6E-17	1.000***	1.000***	1.000***	1.000***	8E-07	6E-17	0.143
Wells Fargo & Co	1.000***	1.000***	4E-18	1.000***	1.000***	8E-07	1.000***	1.000***	1.000***	1.000***	1.000***	0.214

Notes: The results, for the G-SIBs (as of the FSB announcements in November 2015 to 2018), of the bootstrap Kolmogorov-Smirnov tests, which aims to determine whether or not the systemic risk of the G-SIBs is greater than the systemic risk of the mean-bank. The hypothesis tested is H_0: $SRM_{5\%}^{G-SIB_i} \leq SRM_{5\%}^{mean-bank}$. The failure to reject this hypothesis means that the G-SIB i is not systemically riskier than the mean-bank included in the G-SIB assessment sample. The systemic risk is measured with $\Delta^{\$}CoVaR_{95^{th}}$, $MES^{\$}$ and $SRISK$, conditioned to the global index (Panel B). The columns contain the test statistic. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Tables 3.5 and 3.6 contain the results of the bootstrap KS dominance test that aims to determine whether or not the systemic risk of the G-SIBs is greater than the systemic risk of the mean-bank, for Panel A and Panel B, respectively. In this case also, we reject the null hypothesis at 1% critical level for most of the cases analysed. This entails that the G-SIBs are individually systemically riskier than the mean-bank in the G-SIBs assessment sample. This result, for most of the banks considered, is consistent for all three SRMs.

Table 3.7 shows that the success ratios at 1% critical level of each measure, for our first (i) and second (ii) null hypothesis, are greater for Panel B. In particular, this ratio reaches a maximum value of 70% for the $SRISK$ in 2015 and of 77% for the $\Delta^{\$}CoVaR_{95^{th}}$ in 2016 and the $SRIKS$ in 2017, respectively. While the results of (i) suggest that the G-SIBs as designated by the FSB are not always systemically riskier than the non G-SIBs; overall, the evidence of (ii) points out that the SRMs agree quite well with the FSB's listed G-SIBs as riskier than the mean-bank in the G-SIBs assessment sample.

Table 3.8 contains the results of the bootstrap KS dominance test for the systemic buckets identified by the FSB as of November 2015 to 2018. The results highlight a difference in the risk of different buckets. In most of the cases analysed, the null hypothesis is rejected for nonadjacent buckets at the 1% critical level. However, the same is not true in the case of adjacent buckets. In particular, we fail to reject the null hypothesis when testing the difference between 3^{rd} and 2^{nd} buckets in 2015 and 2018 for all the SRMs in both panels, and, always, between the 4^{th} and 3^{rd} buckets for the $SRISK$ in both panels.

The results of the Wilcoxon signed rank sum test for the G-SIBs during the Chinese market crash in 2015, the Brexit vote in 2016, the US presidential election of 2016, and the tech crash in 2018 are illustrated in Tables 3.9 and 3.10 for Panel A and Panel B, respectively. We run this test to inspect whether or not the systemic risk of the G-SIBs significantly increases after a volatile event or a period of financial instability. The null hypothesis is rejected at 1% critical level in most of the cases, excluding the tech crash of 2018, which seems to have affected mainly the domestic systemic risk (Panel A). Overall, during high

Table 3.7: Success ratios of the market-based SRMs.

	Panel A: Domestic Index			Panel B: Global Index		
i) H_0: $SRM_{5\%}^{G-SIB_i} \leq SRM_{5\%}^{nonG-SIBs}$						
	$\Delta^{\$}CoVaR_{95^{th}}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95^{th}}$	$MES^{\$}$	$SRISK$
2015	33.33%	43.33%	70.00%	36.67%	46.67%	70.00%
2016	50.00%	46.67%	60.00%	60.00%	43.33%	60.00%
2017	46.67%	30.00%	63.33%	56.67%	63.33%	63.33%
2018	27.59%	34.48%	48.28%	31.03%	37.93%	55.17%
ii) H_0: $SRM_{5\%}^{G-SIB_i} \leq SRM_{5\%}^{mean-bank}$						
	$\Delta^{\$}CoVaR_{95^{th}}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95^{th}}$	$MES^{\$}$	$SRISK$
2015	56.67%	53.33%	66.67%	60.00%	50.00%	70.00%
2016	73.33%	63.33%	60.00%	76.66%	60.00%	66.66%
2017	66.67%	66.67%	66.67%	66.67%	70.00%	76.67%
2018	62.07%	51.72%	62.07%	51.72%	48.28%	58.62%

Notes: The success ratio for the G-SIBs identified riskier than (i) the non G-SIBs and (ii) the mean-bank – according to $\Delta^{\$}CoVaR_{95^{th}}$, $MES^{\$}$ and $SRISK$, conditioned to the domestic index (Panel A) and the global index (Panel B) – over the number of G-SIBs as of the FSB announcements in November 2015 to 2018. The test used is the Kolmogorov-Smirnov bootstrap test.

volatile periods the systemic risk of the G-SIBs is significantly increased according to all three SRMs. These results may further motivate the supervisory authority to carefully monitor and keep under control these banks during such periods.

The results related to the presidential election of 2016 in the US show an asymmetric increase in the systemic risk of the G-SIBs. Considering the $\Delta^{\$}CoVaR_{95^{th}}$, the null hypothesis is rejected at 1% for all but six (Panel A) and four (Panel B). The $MES^{\$}$ produces similar results. However, when using the $SRISK$, we fail to reject the null hypothesis for all but nineteen (eighteen) of the G-SIBs in Panel B (Panel A). Thus, the $\Delta^{\$}CoVaR_{95^{th}}$ and the $MES^{\$}$ seem to be more sensitive to changes in market conditions. Thus, in relation to this election event, the $SRISK$ does not capture a significant increase in the risk of the G-SIBs,

Table 3.8: Dominance test results for the buckets as defined by the FSB.

	Panel A: Domestic Index			Panel B: Global Index		
	$\Delta^{\$}CoVaR_{95^{th}}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95^{th}}$	$MES^{\$}$	$SRISK$
2015						
$SRM^{4^{th}-Bucket} \leq SRM^{3^{th}-Bucket}$	1.000***	1.000***	2E-17	1.000***	1.000***	2E-17
$SRM^{4^{th}-Bucket} \leq SRM^{2^{th}-Bucket}$	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
$SRM^{4^{th}-Bucket} \leq SRM^{1^{th}-Bucket}$	1.000***	0.794***	1.000***	1.000***	0.783***	1.000***
$SRM^{3^{th}-Bucket} \leq SRM^{2^{th}-Bucket}$	7E-17	0.186	7E-17	7E-17	7E-17	7E-17
$SRM^{3^{th}-Bucket} \leq SRM^{1^{th}-Bucket}$	1.000***	1.000***	1.000***	1.000***	1.000***	0.961***
$SRM^{2^{th}-Bucket} \leq SRM^{1^{th}-Bucket}$	6E-17	6E-17	0.961***	6E-17	0.351***	0.911***
2016						
$SRM^{4^{th}-Bucket} \leq SRM^{3^{th}-Bucket}$	0.125	1.000***	1E-16	0.125	1.000***	1E-16
$SRM^{4^{th}-Bucket} \leq SRM^{2^{th}-Bucket}$	1.000***	0.772***	1.000***	1.000***	0.949***	1.000***
$SRM^{4^{th}-Bucket} \leq SRM^{1^{th}-Bucket}$	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
$SRM^{3^{th}-Bucket} \leq SRM^{2^{th}-Bucket}$	1.000***	7E-17	7E-17	1.000***	7E-17	7E-17
$SRM^{3^{th}-Bucket} \leq SRM^{1^{th}-Bucket}$	1.000***	1.000***	4E-17	1.000***	1.000***	1.000***
$SRM^{2^{th}-Bucket} \leq SRM^{1^{th}-Bucket}$	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
2017						
$SRM^{4^{th}-Bucket} \leq SRM^{3^{th}-Bucket}$	0.113	0.846***	0.124	0.134	0.789***	0.087
$SRM^{4^{th}-Bucket} \leq SRM^{2^{th}-Bucket}$	1.000***	0.981***	1.000***	1.000***	0.991***	1.000***
$SRM^{4^{th}-Bucket} \leq SRM^{1^{th}-Bucket}$	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
$SRM^{3^{th}-Bucket} \leq SRM^{2^{th}-Bucket}$	1.000***	0.846***	0.012	1.000***	0.981***	0.009
$SRM^{3^{th}-Bucket} \leq SRM^{1^{th}-Bucket}$	1.000***	1.000***	3E-17	1.000***	1.000***	3E-17
$SRM^{2^{th}-Bucket} \leq SRM^{1^{th}-Bucket}$	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
2018						
$SRM^{4^{th}-Bucket} \leq SRM^{3^{th}-Bucket}$	1.000***	1.000***	1.1E-16	1.000***	1.000***	1E-16
$SRM^{4^{th}-Bucket} \leq SRM^{2^{th}-Bucket}$	1E-16	1.000***	1.000***	1E-16	1.000***	1.000***
$SRM^{4^{th}-Bucket} \leq SRM^{1^{th}-Bucket}$	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
$SRM^{3^{th}-Bucket} \leq SRM^{2^{th}-Bucket}$	3E-17	3E-17	3.5E-17	3E-17	3E-17	3E-17
$SRM^{3^{th}-Bucket} \leq SRM^{1^{th}-Bucket}$	0.554***	0.914***	1.000***	1.000***	1.000***	1.000***
$SRM^{2^{th}-Bucket} \leq SRM^{1^{th}-Bucket}$	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***

Notes: The results of the bootstrap Kolmogorov-Smirnov tests, which aims to determine whether or not the systemic risk of the G-SIBs (as of the FSB announcements in November 2015 to 2018) classified in a higher bucket is greater than the systemic risk of the G-SIBs classified in a lower bucket. The hypothesis tested is H_0: $SRM^{n^{th}-Bucket} \leq SRM^{(n-j)^{th}-Bucket}$, with $j = 1, 2, ..., n-1$. The failure to reject this hypothesis means that the FSB identified incorrectly the systemic buckets. The systemic risk of the buckets is measured with $\Delta^{\$}CoVaR_{95^{th}}$, $MES^{\$}$ and $SRISK$, conditioned to the respective domestic index (Panel A) and to the global index (Panel B). The columns contain the test statistic. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

contrary to the results estimated for the Chinese market crash in 2015 and the Brexit vote result in 2016. Laeven, Ratnovski, and Tong (2016) argue that the $SRISK$, contrary to the $\Delta CoVaR$ that captures the contagion risk, is sensitive only to the exposure to common shocks that affect the entire financial market.

The bootstrap KS dominance test is run for each pair of G-SIBs using the SRMs stressed at 5% with a one-year moving window. Then, the G-SIBs are ranked as of end-2014 to end-2017 for the period from 2015 to 2018 with a significance level of 1%.

Tables 3.11 and 3.12 report the rankings resulting from the dominance test at 1% critical level. The results indicate that the G-SIBs that are classified in the higher buckets by the FSB are not always riskier than the G-SIBs classified in the lower buckets, from a market perspective. Moreover, the ranking slightly changes by conditioning the analysis to the respective domestic index (Panel A) or the global index (Panel B). These results suggest that a systemic risk rating process that is replicable using market data allowing companies to self-check their status on a regular basis might have merit as an alternative ranking process.

3.4.2 Systemic risk rankings incorporating confidence intervals

In this Section, we present an alternative systemic risk ranking method for all three major SRMs that incorporates its nonparametric confidence intervals. As described in Section 3.2.1, we build nonparametric confidence intervals for the $\Delta CoVaR_{95^{th}}$, MES and $SRISK\%$ of the banks included in the G-SIBs assessment sample through non-overlapping block bootstrap. In order to estimate confidence intervals for the each SRM, we use resampling of (n=) 1000 simulations, considering a one-year moving window (block). Figures 3.1 and 3.2 show the confidence intervals at 95% of the $\Delta CoVaR_{95^{th}}$, MES and $SRISK\%$ for Panel A and Panel B, respectively. The horizontal line represents the G-SIBs (market-based) threshold (η) computed through the cluster analyses described in 3.2.1.

Figures 3.1 and 3.2 indicate that the confidence intervals of the SRMs estimated condi-

Table 3.9: Wilcoxon signed rank sum test for the G-SIBs during the main volatile events of 2015, 2016 and 2018 (Panel A).

Panel A: Domestic Index

H_0: $SRM^i_{t:t+h-1} \leq SRM^i_{t-h-1:t-1}$

	Chinese Market Crash 2015			Brexit 2016			US Presidential Election 2016			Tech Crash 2018		
	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$
Agricultural Bank of China	-3.577***	-5.166***	-5.166***	0.000	-8.964	-0.091	0.000	-5.166***	0.000	-5.166***	-5.166***	-1.649*
Banco Santander	0.000	-5.976	-5.166***	-3.340***	-3.577***	-5.035***	-4.011***	-2.463**	-0.117	-2.660***	-0.559	-0.714
Bank of America	-5.035***	-5.166***	-5.166***	-5.166***	-2.694***	-4.717***	-5.166***	-5.166***	-4.717***	0.000	0.000	-4.648***
Bank of China	-4.585***	-4.249***	-5.166***	-1.430	-4.957***	-5.166***	0.000	-4.717***	-4.717***	-5.166***	-5.166***	-3.577***
Bank of New York Mellon/The	-5.166***	-5.166***	-5.166***	-1.222	-0.000	-5.035***	-5.166***	-4.585***	-4.717***	-6.185	-0.735	0.000
Barclays	-1.324	-5.166***	-5.166***	-5.166***	-5.166***	-5.035***	-5.166***	-5.166***	0.000	-0.192	-0.008	-5.166***
BNP Paribas	0.000	-2.971***	-1.593	-4.648***	-5.166***	-5.166***	-5.166***	-5.166***	-4.717***	-0.017	-1.538	-0.053
China Construction Bank	-3.577***	-5.166***	-5.166***	0.000	-8.964	-0.000	-5.976	-2.971***	0.000	-5.166***	-4.468***	-5.166***
Citigroup	-5.976	-5.166***	-5.166***	-0.798	-2.240**	-5.166***	-5.166***	-5.166***	-4.717***	0.000	-3.264***	-0.307
Credit Suisse Group	-2.762***	-5.166***	-5.166***	-3.340***	-5.166***	-5.035***	-5.166***	-4.717***	-0.117	-2.398**	-0.014	-1.377
Deutsche Bank	0.000	-0.348	-5.035***	-3.340***	-0.578	-5.035***	-5.166***	-5.166***	0.000	-0.182	-3.496***	0.000
Goldman Sachs Group/The	-4.648***	-5.166***	-5.166***	-2.594***	-3.226***	-4.856***	-5.166***	-5.166***	-4.717***	-1.643	-0.003	-2.528**
Groupe BPCE	-5.677	-0.009	-5.166***	-3.340***	-3.659***	-5.166***	-5.035***	-5.166***	-2.091	-2.660***	-0.173	-3.286
Groupe Crédit Agricole	0.000	0.000	-5.035***	-3.340***	-5.166***	-4.105***	-5.166***	-5.166***	0.000	-4.527***	-1.849*	-0.015
HSBC Holdings	-5.035***	-5.166***	-5.166***	-5.166***	-5.166***	-3.496***	-5.166***	-5.166***	0.000	-1.146	-3.152***	-2.561**
Industrial & Commercial Bank of China	-3.577***	-5.166***	-5.166***	-5.976	-8.964	-1.762*	-1.247	-5.166***	0.000	-5.166***	-5.166***	-4.203***
ING Groep	-1.511	-2.594***	-5.166***	-3.340***	-5.166***	-5.035***	-5.166***	-5.166***	0.000	-5.166***	-5.976	-5.166***
JPMorgan Chase & Co	-3.226***	-5.166***	-5.166***	-1.457	-2.272**	-5.166***	-5.166***	-5.166***	-4.717***	-2.988	-2.935***	0.000
Mitsubishi UFJ Financial Group	-3.042***	-4.254***	-5.166***	-0.075	-9.173	-5.166***	-5.166***	-5.166***	-2.091	-0.026	-5.166***	-2.988
Mizuho Financial Group	-5.166***	-5.166***	-5.166***	0.000	-0.000	-5.166***	-5.166***	-5.166***	-7.470	-2.398**	-1.762*	0.000
Morgan Stanley	0.000	-5.166***	-5.166***	-2.796***	-2.971***	-5.035***	-5.166***	-5.166***	-4.717***	-0.007	-0.006	-3.340***
Nordea Bank	0.000	-5.166***	-4.717***	0.000	-0.004	-3.379***	-4.957***	-4.527***	-2.988			
Royal Bank of Canada										-1.073	-4.411***	0.000
Royal Bank of Scotland Group	-0.269	-5.166***	-5.166***	-2.117**	-5.035***	-5.035***	-5.035***	-5.166***	-1.494			
Société Générale	-2.988	-5.035***	-4.411***	-3.340***	-3.920***	-5.035***	-5.166***	-5.166***	0.000	-0.362	-0.192	-0.022
Standard Chartered	-2.831***	-4.585***	-5.166***	-1.733*	-5.166***	-1.565	-2.026**	-0.033	-3.042***	0.000	-0.008	-3.701***
State Street Corporation	-5.166***	-5.166***	-5.166***	-0.004	-2.629	-5.166***	-5.166***	-3.152***	-4.717***	-5.049	-1.073	-0.005
Sumitomo Mitsui Financial Group	-2.762***	-5.166***	-5.166***	-0.018	-0.000	-5.166***	-5.166***	-5.166***	-2.988	-2.398**	-3.659***	-0.182
UBS Group	-3.920***	-5.166***	-5.166***	-3.340***	-5.166***	-5.035***	-5.166***	-5.166***	0.000	-2.660***	-2.528**	-2.303**
UniCredit Group	0.000	-0.423	-0.024	-3.340***	-1.565	-5.166***	-0.257	-0.028	-2.935***	-2.660***	-0.777	-2.762***
Wells Fargo & Co	-3.302***	-5.166***	0.000	-1.073	-0.028	-5.166***	-5.166***	-5.166***	-4.717***	0.000	-2.629	0.000

Notes: The results, for the G-SIBs (as of the FSB announcements in November 2015 to 2018), of the Wilcoxon signed rank sum test, which aims to determine whether or not the systemic risk of the G-SIBs h-days after a volatile event is greater than the systemic risk of the same h-days before. The hypothesis tested is H_0: $SRM^i_{t:t+h-1} \leq SRM^i_{t-h-1:t-1}$, with h=22-days. The failure to reject this hypothesis means that the systemic risk level of the bank i did not increase during the high volatility event considered. This test consider the main volatile events of 2015, 2016 and 2018. The systemic risk is measured with $\Delta^{\$}CoVaR_{95^{th}}$, $MES^{\$}$ and $SRISK$, conditioned to the respective domestic index (Panel A). The columns contain the test statistic. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 3.10: Wilcoxon signed rank sum test for the G-SIBs during the main volatile events of 2015, 2016 and 2018 (Panel B).

Panel B: Global Index

H_0: $SRM^i_{t:t+h-1} \leq SRM^i_{t-h-1:t-1}$

	Chinese Market Crash 2015			Brexit 2016			US Presidential Election 2016			Tech Crash 2018		
	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$
Agricultural Bank of China	-5.166***	-5.166***	-5.166***	0.000	0.000	-0.017	-1.937*	-4.411***	-1.643	-5.166***	-2.561**	-0.212
Banco Santander	0.000	-4.011***	-5.166***	-1.762*	-5.035***	-5.035***	-4.957***	-1.907*	-0.559	0.000	-2.303**	-0.011
Bank of America	-5.035***	-5.166***	-5.166***	-5.166***	-1.298	-4.527***	-5.166***	-5.166***	-4.717***	0.000	0.000	-4.203***
Bank of China	-5.166***	-5.166***	-5.166***	-1.273	-5.035***	-5.166***	-6.185	-4.585***	-4.717***	-5.166***	-0.798	-1.849*
Bank of New York Mellon/The	-5.166***	-5.166***	-5.166***	-1.196	-1.677*	-5.166***	-5.166***	-5.166***	-5.166***	-3.286	-2.495**	-2.398**
Barclays	-0.455	-5.166***	-5.166***	-5.035***	-4.254***	-5.035***	-5.166***	-5.166***	-2.430**	-4.183	-2.988	-4.358***
BNP Paribas	0.000	-5.166***	-2.430**	-4.648***	-5.166***	-2.430**	-5.166***	-5.166***	-2.430**	0.000	-3.577***	0.000
China Construction Bank	-5.166***	-5.035***	-5.166***	-2.988	-8.964	-0.010	-1.049	-2.561**	-0.124	-5.166***	0.000	-5.166***
Citigroup	-1.494	-5.166***	-5.166***	-0.777	-2.463**	-5.166***	-5.166***	-4.957***	0.000	0.000	-5.166***	-0.117
Credit Suisse Group	-0.033	-5.166***	-5.166***	-5.035***	-5.166***	-5.166***	-5.166***	-3.577***	-2.209**	-2.988	-1.222	-0.578
Deutsche Bank	0.000	-5.166***	-5.166***	-5.035***	-1.705*	-5.035***	-5.166***	-5.166***	-9.860	-5.677	-0.086	0.000
Goldman Sachs Group/The	-5.166***	-5.166***	-5.166***	-2.240**	-3.457***	-4.856***	-5.166***	-5.166***	0.000	-2.988	-0.392	-1.621
Groupe BPCE	-2.988	-5.166***	-5.166***	-5.035***	-5.035***	-5.166***	-5.166***	-5.166***	-0.281	-8.964	-2.728***	0.000
Groupe Crédit Agricole	0.000	-3.701***	-5.166***	-5.035***	-5.166***	-4.648***	-5.166***	-5.166***	-2.091	-2.988	-4.358***	-2.091
HSBC Holdings	-5.035***	-5.166***	-5.166***	-5.166***	-5.166***	-4.789***	-5.166***	-5.166***	-9.860	-9.173	-2.463**	-1.705*
Industrial & Commercial Bank of China	-5.166***	-5.166***	-5.166***	-1.494	-8.964	-1.377	-3.577***	-4.154***	-3.577***	-5.166***	-0.164	-1.849*
ING Groep	-0.001	-5.166***	-5.166***	-5.035***	-5.166***	-5.035***	-5.166***	-5.166***	-0.000	-1.565	0.000	-3.079***
JPMorgan Chase & Co	-3.042***	-5.166***	-5.166***	-1.001	-2.303**	-5.166***	-5.166***	-5.166***	-3.577***	0.000	-2.971***	-1.403
Mitsubishi UFJ Financial Group	-5.166***	-5.166***	-5.166***	0.000	0.000	-5.166***	-5.035***	-4.058***	-8.964	-2.117**	-5.166***	0.000
Mizuho Financial Group	-5.166***	-5.166***	-5.166***	0.000	0.000	-5.166***	-5.035***	-1.791*	-8.964	-0.110	-3.226***	-2.988
Morgan Stanley	-0.001	-5.166***	-5.166***	-2.971***	-4.527***	-5.166***	-5.166***	-5.166***	-3.577***	-0.003	-0.155	-2.087**
Nordea Bank	-1.494	-4.203***	-4.203***	-0.006	0.000	-5.166***	-5.166***	-5.035***	-3.577***			
Royal Bank of Canada										-0.439	-4.411***	-0.909
Royal Bank of Scotland Group	-0.039	-5.166***	-5.166***	-2.831***	-2.831***	-5.035***	-5.035***	-5.166***	-9.860			
Société Générale	0.000	-5.166***	-4.358***	-3.340***	-5.166***	-5.035***	-5.166***	-5.166***	-2.988	0.000	-1.073	0.000
Standard Chartered	-2.178**	-5.166***	-5.166***	-3.875***	-4.957***	-3.744***	-3.417***	-0.269	-4.305***	0.000	-1.643	-2.430**
State Street Corporation	-5.166***	-5.166***	-5.166***	-0.005	-0.026	-5.166***	-5.166***	-5.035***	-3.577***	-8.964	-0.777	0.000
Sumitomo Mitsui Financial Group	-5.166***	-5.166***	-5.166***	0.000	0.000	-5.166***	-5.035***	-0.864	-8.964	-3.701***	-5.166***	-1.049
UBS Group	-0.654	-5.166***	-5.166***	-4.585***	-5.166***	-5.035***	-5.166***	-5.166***	-2.988	0.000	-2.627***	-1.733*
UniCredit Group	0.000	-5.166***	-0.407	-0.020	-2.865***	-5.166***	-0.842	-0.015	-3.920***	-2.988	-1.705*	-1.122
Wells Fargo & Co	-3.152***	-5.166***	0.000	-0.423	-0.026	-4.648***	-5.166***	-5.166***	-5.166***	0.000	0.000	-4.305***

Notes: The results, for the G-SIBs (as of the FSB announcements in November 2015 to 2018), of the Wilcoxon signed rank sum test, which aims to determine whether or not the systemic risk of the G-SIBs h-days after a volatile event is greater than the systemic risk of the same h-days before. The hypothesis tested is H_0: $SRM^i_{t:t+h-1} \leq SRM^i_{t-h-1:t-1}$, with h=22-days. The failure to reject this hypothesis means that the systemic risk level of the bank i did not increase during the high volatility event considered. This test consider the main volatile events of 2015, 2016 and 2018. The systemic risk is measured with $\Delta^{\$}CoVaR_{95^{th}}$, $MES^{\$}$ and $SRISK$, conditioned to the global index (Panel B). The columns contain the test statistic. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 3.11: Ranking of the G-SIBs for the period from 2015 to 2018 (Panel A).

Panel A: Domestic Index

H_0: $SRM^i_{5\%} \leq SRM^j_{5\%}$, with $i > j$, i=1,2,...,n and j=1,2,...,n-1

2015			2016			2017			2018		
$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$
1. ICBC	1. WFC	1. ICBC	1. BAC	1. JPM	1. MUFJ	1. BAC	1. JPM	1. MUFJ	1. BAC	1. JPM	1. MUFJ
CCB	2. JPM	MUFJ	2. JPM	WFC	2. MFG	2. JPM	2. BAC	2. MFG	2. JPM	2. BAC	2. CCB
2. JPM	3. ICBC	2. ABC	3. C	2. BAC	3. ICBC	3. C	3. WFC	3. SMFG	3. WFC	3. WFC	3. ABC
3. WFC	4. BAC	CCB	4. WFC	3. C	CCB	WFC	4. C	4. ABC	4. CCB	4. ICBC	ICBC
4. ABC	5. C	3. BNP	5. HSBC	4. HSBC	4. ABC	4. SAN	HSBC	5. BoC	5. ICBC	5. CCB	4. BoC
BoC	CCB	4. BoC	6. SAN	5. ICBC	5. SMFG	5. MUFJ	5. SAN	6. CCB	6. C	6. C	5. MFG
5. BAC	6. HSBC	MFG	ICBC	6. SAN	6. BoC	6. UCG	6. BNP	7. BNP	7. SAN	7. HSBC	6. SMFG
6. C	7. ABC	5. DBK	CCB	CCB	7. BNP	7. HSBC	7. BARC	8. ICBC	8. MS	8. MS	7. BNP
7. HSBC	8. BoC	SMFG	7. MUFJ	7. BNP	8. DBK	8. BARC	MUFJ	9. DBK	9. HSBC	ABC	8. ACA
8. SAN	9. SAN	6. BARC	8. ABC	8. GS	9. BAC	BNP	8. GS	10. BAC	10. GS	9. GS	9. DBK
9. BNP	10. GS	7. ACA	9. BARC	9. MS	10. ACA	9. MS	INGA	11. ACA	11. ABC	10. BoC	10. C
10. MUFJ	11. MUFJ	JPM	10. BNP	10. BARC	BARC	10. GS	9. GLE	12. BARC	12. BNP	11. MUFJ	GLE
11. GS	12. BNP	8. BAC	MS	ABC	11. GLE	RBS	MS	13. C	13. MUFJ	12. SAN	11. BARC
12. INGA	13. MS	9. GLE	BoC	11. MUFJ	12. C	11. STAN	UBSG	GLE	14. UCG	13. RY	12. SAN
13. UCG	14. BARC	10. RBS	11. GS	12. INGA	13. JPM	12. GLE	10. RBS	14. JPM	15. BoC	14. BK	13. BAC
14. BARC	15. INGA	11. C	12. UBSG	13. UBSG	14. HSBC	SMFG	11. UCG	15. SAN	16. BK	15. BNP	14. HSBC
15. MS	16. RBS	12. HSBC	13. RBS	14. GLE	15. RBS	13. DBK	12. SMFG	16. UCG	GLE	16. UBSG	15. UCG
16. RBS	17. UBSG	13. SAN	14. STAN	BoC	SAN	INGA	13. RY	17. RBS	17. DBK	17. STT	16. GS
17. SMFG	SMFG	14. INGA	15. GLE	15. RBS	16. UCG	UBSG	ICBC	18. HSBC	UBSG	18. CSGN	17. INGA
18. UBSG	18. MFG	UCG	16. SMFG	16. SMFG	17. MS	14. CSGN	BoC	19. MS	18. ACA	19. INGA	18. MS
19. GLE	19. BK	15. MS	17. INGA	17. BK	18. INGA	15. ACA	14. ACA	20. CSGN	BARC	20. SMFG	19. CSGN
20. ACA	20. UCG	16. CSGN	18. UCG	18. ACA	19. GS	16. ICBC	CCB	GS	19. INGA	21. ACA	20. UBSG
21. BK	21. GLE	17. BPCE	19. CSGN	MFG	20. CSGN	17. RY	15. CSGN	21. INGA	20. RY	BARC	21. BPCE
NDA	22. DBK	18. STAN	20. DBK	19. CSGN	21. UBSG	MFG	DBK	WFC	21. CSGN	UCG	22. STAN
22. DBK	23. NDA	19. GS	21. MFG	20. NDA	22. BPCE	18. BK	16. NDA	22. STAN	22. STT	22. DBK	23. WFC
23. STAN	24. ACA	20. NDA	22. ACA	21. STAN	23. STAN	19. CCB	STAN	23. UBSG	23. SMFG	GLE	24. JPM
MFG	CSGN	UBSG	23. BK	22. DBK	WFC	20. NDA	17. MFG	24. NDA	24. STAN	23. STAN	RY
24. STT	25. STAN	21. STT	24. NDA	23. STT	24. NDA	21. STT	18. BK	25. RY	25. BPCE	24. BPCE	25. STT
25. CSGN	STT	22. BK	STT	UCG	25. BK	BoC	ABC	26. STT	26. MFG	MFG	26. BK
26. BPCE	26. BPCE	WFC	25. BPCE	24. BPCE	STT	22. ABC	19. STT	27. BK			

Notes: The ranking of the G-SIBs as of the FSB announcements in November 2015 to 2018. The ranking results from the bootstrap Kolmogorov-Smirnov test with 0.01 significance level. The hypothesis tested is H_0: $SRM^i_{5\%} \leq SRM^j_{5\%}$, with $i > j$, i=1,2,...,n and j=1,2,...,n-1. The failure to reject this hypothesis means that bank j is systemically risker than bank i, entailing an higher ranking position of j. The systemic risk is measured with $\Delta^{\$}CoVaR_{95^{th}}$, $MES^{\$}$ and $SRISK$, conditioned to the respective domestic index (Panel A). All the systemic risk measures are stressed at 5%. G-SIB's full names are in Table 3.2.

Table 3.12: Ranking of the G-SIBs for the period from 2015 to 2018 (Panel B).

Panel B: Global Index

H_0: $SRM^i_{5\%} \leq SRM^j_{5\%}$, with $i > j$, i=1,2,...,n and j=1,2,...,n-1

2015			2016			2017			2018		
$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$	$\Delta^{\$}CoVaR_{95th}$	$MES^{\$}$	$SRISK$
1. JPM	1. WFC	1. ICBC	1. BAC	1. JPM	1. MUFJ	1. BAC	1. BAC	1. MUFJ	1. BAC	1. JPM	1. MUFJ
2. WFC	2. JPM	MUFJ	2. C	2. WFC	2. MFG	2. JPM	JPM	2. ABC	2. JPM	2. BAC	2. BoC
3. ICBC	3. BAC	2. ABC	JPM	3. BAC	3. ICBC	3. C	2. WFC	MFG	3. WFC	3. WFC	MFG
CCB	4. ICBC	CCB	3. WFC	4. C	CCB	4. WFC	3. C	3. SMFG	4. C	4. C	3. SMFG
4. BAC	5. C	3. BNP	4. HSBC	5. HSBC	4. ABC	5. SAN	HSBC	4. BoC	5. MS	5. ICBC	4. ABC
5. C	CCB	4. DBK	5. SAN	6. ICBC	5. SMFG	6. HSBC	4. SAN	5. BNP	6. GS	6. CCB	ICBC
6. ABC	6. HSBC	5. MFG	6. ICBC	7. CCB	6. BoC	UCG	5. BNP	6. CCB	7. CCB	7. MS	CCB
7. BoC	7. ABC	6. JPM	7. BNP	8. SAN	7. BNP	7. BNP	6. BARC	7. BAC	8. ICBC	8. GS	5. BNP
8. HSBC	8. BoC	BoC	CCB	9. BNP	8. DBK	8. BARC	7. GS	8. DBK	9. SAN	9. HSBC	6. DBK
9. SAN	9. GS	7. SMFG	8. BARC	ABC	9. BAC	9. MS	8. INGA	ICBC	10. HSBC	10. ABC	7. ACA
10. GS	10. MUFJ	8. BARC	9. MS	10. GS	10. ACA	STAN	MS	9. ACA	11. BK	11. RY	C
11. BNP	11. MS	9. ACA	10. ABC	MS	11. BARC	10. GS	9. GLE	10. C	12. BNP	12. SAN	8. GLE
12. INGA	12. SAN	BAC	11. UBSG	11. BARC	12. C	11. GLE	UCG	11. BARC	13. RY	13. BK	9. BAC
13. MS	13. BNP	10. GLE	12. GS	12. UBSG	13. GLE	RBS	10. UBSG	12. GLE	MUFJ	BoC	10. BARC
UCG	14. BARC	11. C	BoC	BoC	JPM	UBSG	ICBC	13. JPM	14. STT	14. UBSG	11. GS
14. BARC	15. UBSG	12. RBS	13. STAN	13. INGA	14. HSBC	12. DBK	BoC	14. HSBC	15. ABC	15. STT	12. SAN
15. RBS	16. BK	13. HSBC	14. GLE	14. GLE	15. SAN	INGA	11. RBS	15. SAN	16. DBK	MUFJ	13. MS
16. MUFJ	INGA	14. INGA	15. RBS	15. MUFJ	16. RBS	13. CSGN	RY	16. UCG	UBSG	16. BNP	14. JPM
17. UBSG	17. RBS	15. UCG	16. INGA	16. BK	17. UCG	14. MUFJ	12. CCB	17. RBS	17. CSGN	17. DBK	UCG
18. BK	18. SMFG	16. SAN	17. CSGN	RBS	18. MS	15. ACA	MUFJ	18. MS	18. UCG	18. CSGN	WFC
DBK	19. MFG	17. MS	UCG	17. ACA	19. GS	RY	13. ACA	WFC	19. GLE	19. INGA	15. CSGN
19. GLE	20. DBK	18. CSGN	18. DBK	18. CSGN	INGA	16. ICBC	14. DBK	19. GS	BoC	20. STAN	INGA
20. ACA	21. GLE	19. BPCE	19. MUFJ	19. STAN	20. CSGN	BK	15. CSGN	20. CSGN	20. STAN	SMFG	16. BPCE
NDA	NDA	20. GS	20. ACA	SMFG	21. UBSG	17. NDA	STAN	21. INGA	21. BARC	21. ACA	17. UBSG
STAN	UCG	21. STAN	21. BK	20. MFG	WFC	18. SMFG	16. ABC	22. STAN	22. ACA	22. BARC	18. HSBC
21. SMFG	22. CSGN	22. NDA	22. NDA	21. DBK	22. BPCE	19. STT	17. BK	23. UBSG	23. INGA	UCG	STAN
22. STT	STT	UBSG	23. STT	NDA	23. STAN	CCB	NDA	24. RY	24. SMFG	23. MFG	19. RY
23. MFG	23. STAN	23. STT	24. BPCE	22. STT	24. NDA	20. BoC	18. SMFG	25. NDA	25. BPCE	24. BPCE	20. STT
24. CSGN	24. ACA	24. BK	25. SMFG	23. UCG	25. BK	21. MFG	19. STT	26. STT	26. MFG	25. GLE	21. BK
25. BPCE	25. BPCE	25. WFC	26. MFG	24. BPCE	26. STT	22. ABC	20. MFG	27. BK			

Notes: The ranking of the G-SIBs as of the FSB announcements in November 2015 to 2018. The ranking results from the bootstrap Kolmogorov-Smirnov test with 0.01 significance level. The hypothesis tested is H_0: $SRM^i_{5\%} \leq SRM^j_{5\%}$, with $i > j$, i=1,2,...,n and j=1,2,...,n-1. The failure to reject this hypothesis means that bank j is systemically risker than bank i, entailing an higher ranking position of j. The systemic risk is measured with $\Delta^{\$}CoVaR_{95^{th}}$, $MES^{\$}$ and $SRISK$, conditioned to the global index (Panel B). All the systemic risk measures are stressed at 5%. G-SIB's full names are in Table 3.2.

Table 3.13: Number of overlapping confidence intervals over the period from 2015 to 2018.

Panel A: Domestic Index

	$\Delta CoVaR_{95^{th}}$		MES		$SRISK\%$	
Year	n	N	n	N	n	N
2015	52	72	52	72	33	72
2016	48	73	50	73	36	73
2017	49	73	50	73	30	73
2018	54	73	55	73	38	73

Panel B: Global Index

	$\Delta CoVaR_{95^{th}}$		MES		$SRISK\%$	
Year	n	N	n	N	n	N
2015	56	72	59	72	35	72
2016	54	73	59	73	37	73
2017	55	73	62	73	32	73
2018	51	73	54	73	35	73

Notes: The table presents the number (N) of banks, in the G-SIBs assessment sample, the number (n) of cases in which the confidence intervals overlap. The systemic risk is measured with $\Delta CoVaR_{95^{th}}$, MES and $SRISK\%$, conditioned to the respective domestic index (Panel A) and to the global index (Panel B).

tioning the analysis to the global index (Panel B) are wider, especially for $\Delta CoVaR_{95^{th}}$ and MES. The most important feature coming out is that, considering both panels, the confidence intervals frequently overlap. Thus, while the overlapping is expected for the banks in the middle of the ranking, finding this feature in the top positions of the rankings entails that banks ranked lower may have similar systemic risk contribution with higher ranked banks. Secondly, because the size of the confidence intervals becomes wider in case of financial threats and there are more overlapping of confidence intervals, it implies that there is more uncertainty about the real level of systemic risk during turmoil periods.

Table 3.13 presents the number of cases in which we encountered a confidence intervals

Panel A: Domestic Index

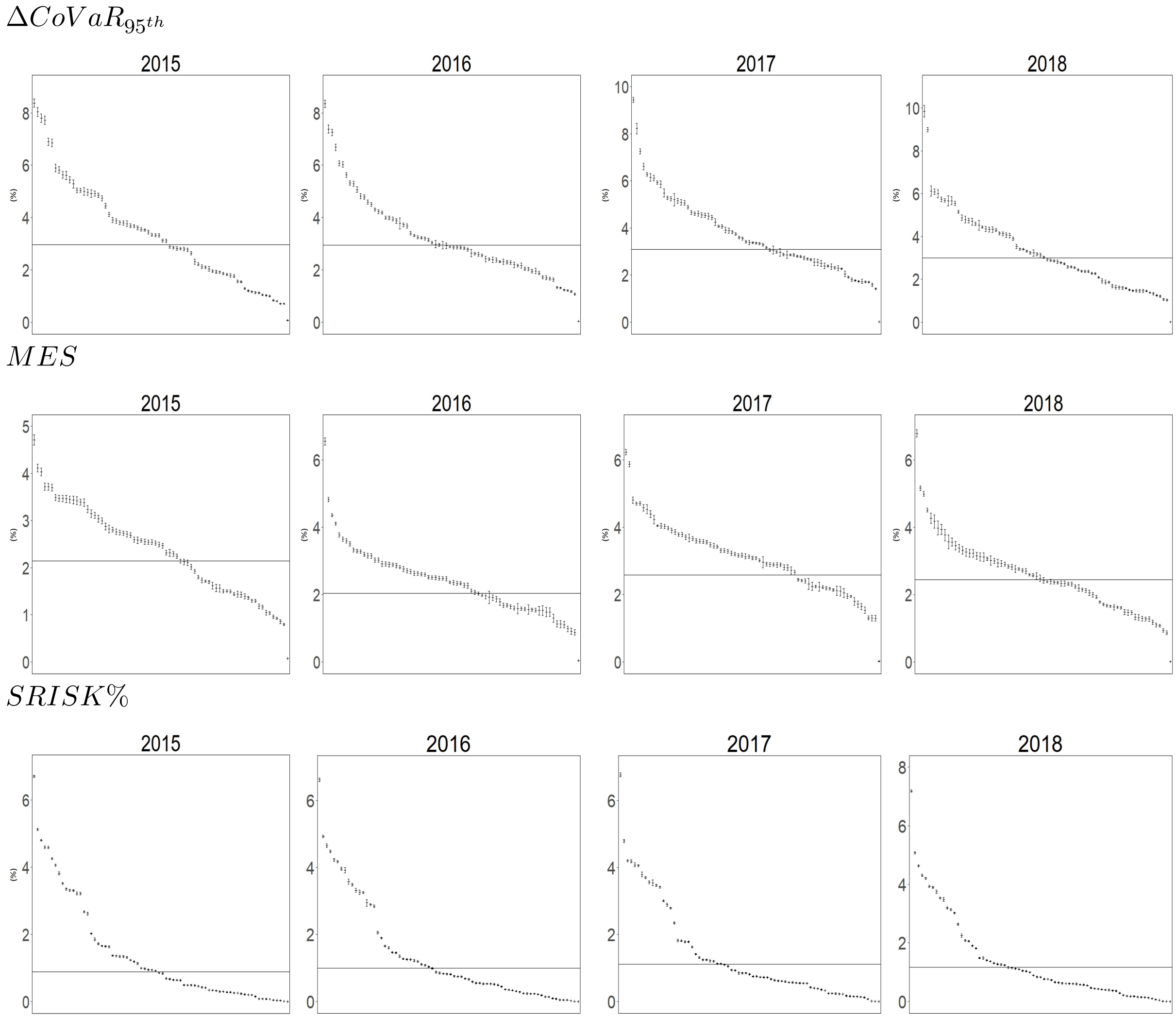
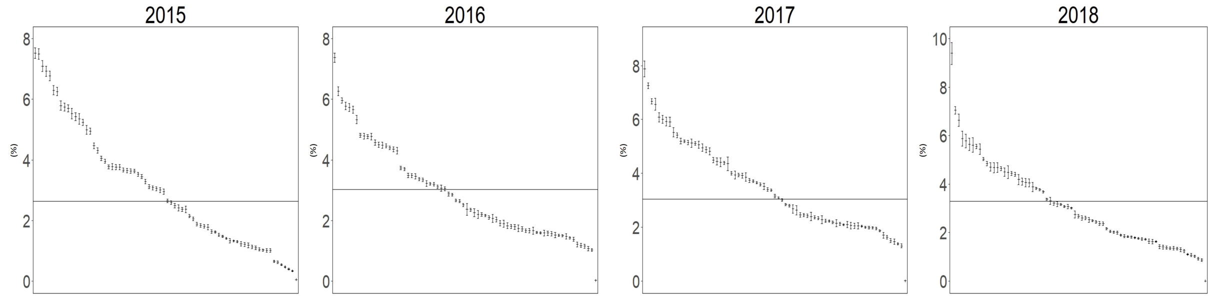


Figure 3.1: Confidence intervals 95% of the systemic risk measures with G-SIBs threshold (Panel A).

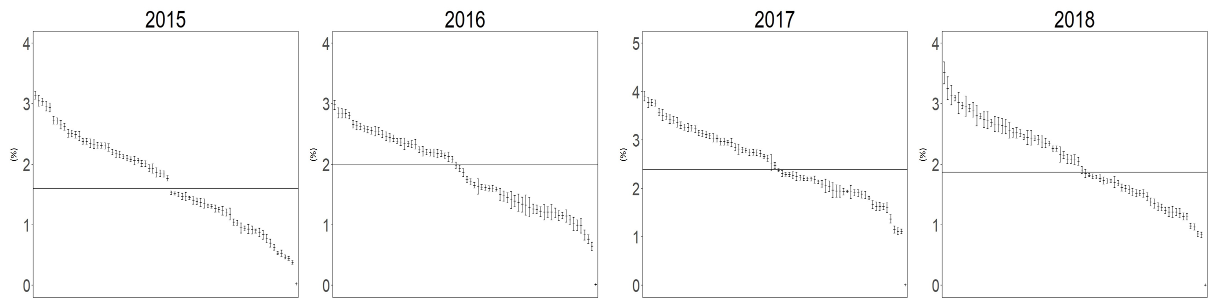
Notes: The estimated confidence intervals at 95% of the systemic risk measures (SRM) – $\Delta CoVaR_{95^{th}}$, MES and $SRISK\%$, for the banks included in the G-SIBs assessment sample of end-2014, end-2015, end-2016, and end-2017, respectively. The systemic risk is measured conditioned to the respective domestic index (Panel A). The horizontal line indicates the G-SIBs (market-based) threshold – "η". The vertical axis reports the value of the SRMs in percentage points. The title of each sub-chart refers to the specific year over the period from 2015 to 2018.

Panel B: Global Index

$\Delta CoVaR_{95th}$



MES



$SRISK\%$

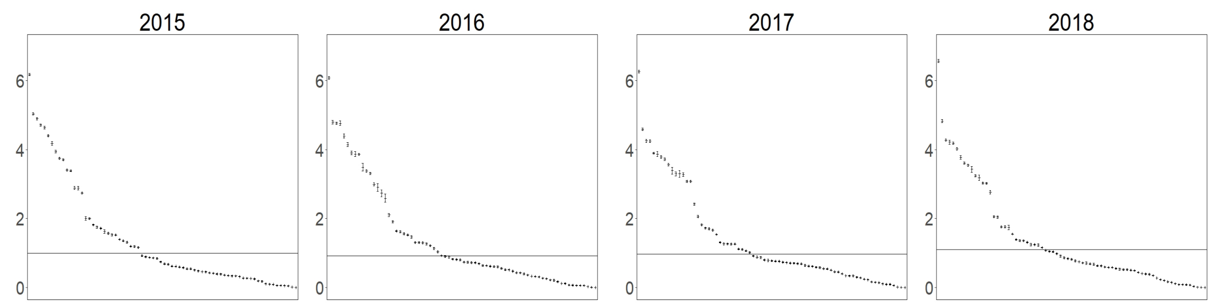


Figure 3.2: Confidence intervals 95% of the systemic risk measures with G-SIBs threshold (Panel B).

Notes: The estimated confidence intervals at 95% of the systemic risk measures (SRM) – $\Delta CoVaR_{95th}$, MES and $SRISK\%$, for the banks included in the G-SIBs assessment sample of end-2014, end-2015, end-2016, and end-2017, respectively. The systemic risk is measured conditioned to the global index (Panel B). The horizontal line indicates the G-SIBs (market-based) threshold – "η". The vertical axis reports the value of the SRMs in percentage points. The title of each sub-chart refers to the specific year over the period from 2015 to 2018.

overlap. We consider only substantial overlap of confidence intervals. In particular, we define two confidence intervals to be overlapped only when the upper bound of the SRM for the bank rated less risky is above the midpoint of the bank rated as riskier.[24] There are some interesting insights in Table 3.13. Analyzing both panels, we can see that the number of overlapping intervals is persistent for any given SRM.

Tables 3.14 to 3.16 report the classification of the G-SIBs as designated by each market-based SRM,[25] the corresponding G-SIBs (market-based) threshold (η) and additional capital requirements, over the period from 2015 to 2018 for Panel A and Panel B, respectively. Further, because $\Delta CoVaR_{95^{th}}$ and MES do not take into account bank size; as described in Section 3.2.1, after computing η, which allows to designate a bank as systemically important, we account for size in order to face the issue already reported by Castro and Ferrari (2014).[26] In particular, not accounting for size would position some banks in high systemic risk categories because of only their high degree of interconnectedness. The banks are allocated in five normalized categories, as considered by the FSB. First of all, in the cases of $\Delta^{\$}CoVaR_{95^{th}}$ and $MES^{\$}$, compared to $SRISK\%$, a higher number of banks are designated as systemically important but only few banks fill the higher categories. For $SRISK\%$ there is a quasi-uniform allocation of banks over for the 3^{rd} and the 2^{th} category. All the market-based SRMs have a major concentration into the 1^{st} category. This result gives support with the G-SIBs classification made by the FSB, which allocates most banks in the lowest risky bucket (see Table 3.1). Another important finding is that a given bank is not necessarily ranked in the same category according different SRMs and different indexes. In particular, the same bank can be ranked in different categories under the $\Delta^{\$}CoVaR_{95^{th}}$, $MES^{\$}$ and $SRISK\%$ rankings in Panel A and Panel B. This points out that the systemic risk contri-

[24] We do not consider an overlap of confidence intervals when the upper bound of the SRM for the bank rated less risky is above the lower bound of the bank rated as riskier.

[25] Tables 3.14 to 3.16 allow also a comparison with the FSB's designation of G-SIBs. Banks in cyan are the G-SIBs designated by the FSB – see Table 3.1.

[26] Castro and Ferrari (2014) showed that scaling the $\Delta CoVaR$ by the bank size could lead to changes into the classification of the financial firms, being the rank mainly influenced by the bank size. In our methodology to rank G-SIBs, we built confidence intervals associated with $\Delta CoVaR$ and MES, then we account for bank size to built the final ranking.

bution of the same bank may be also measure specific, confirming the criticism detailed in Danielsson, James, Valenzuela, and Zer (2016) that it would be difficult for the regulator to select a single SRM for a targeted macro-prudential approach, and that banks may be subject to a global and domestic systemic assessment because some could be more correlated to the respective domestic index rather than the global.[27] Overall, our approach results are close to the FSB designation of G-SIBs and could support their designation through supervisory judgment. Banks designated as G-SIBs with the supervisory judgment, such as Nordea Bank (NDA) in 2015, 2016 and 2017, and Royal Bank of Scotland Group (RBS) in 2017, in most of the cases, are identified as G-SIBs with our methodology.[28]

Finally, as an additional exercise, we perform a sensitivity analysis[29] based on the underlying role used to designate systemically important banks. In particular, we show that the usage of the midpoint or the lower bound of the confidence interval changes the number of banks designed as systemically important and their allocation into the five categories. Table 3.17 presents the results of such analysis.

As explained in Section 3.2.1, we have followed a macro-prudential perspective in this Chapter, taking the upper bound of the confidence interval to designate systemically important banks, as it represents, on average, the worst historical systemic loss given default of the banks with 95% confidence level. The G-SIBs identified by the FSB were always 30 from 2015 to 2017 and 29 in 2018. With our approach, the "total designated systemic important banks" of Panel B (Panel A) is on average 35 (39), 37 (45), and 31 (32) according to $\Delta^{\$}CoVaR_{95^{th}}$, $MES^{\$}$ and $SRISK\%$, respectively. Our calculations come close to FSB.[30] Moreover, our results in Panel B are putting more emphasis on the macroprudential

[27] In the European Union, the Article 131(3) of Directive 2013/36/EU (CRD) defines the criteria used by the European Banking Authority for the assessment of Other Systemically Important Institutions, which are the domestic systemically important institutions of the EU countries (European Banking Authority, 2014).

[28] In Panel A, NDA is designated as G-SIB in 2015 ($\Delta^{\$}CoVaR_{95^{th}}$, $MES^{\$}$, $SRISK\%$), 2016 and 2017 ($\Delta^{\$}CoVaR_{95^{th}}$, $MES^{\$}$); while, RBS in 2017 ($\Delta CoVaR_{95^{th}}$, MES, $SRISK\%$). In Panel B, Nordea Bank (NDA) is designated as G-SIB in 2015, 2016 and 2017 ($\Delta^{\$}CoVaR_{95^{th}}$ and $MES^{\$}$); while, Royal Bank of Scotland Group (RBS) in 2017 ($\Delta CoVaR_{95^{th}}$, MES, $SRISK\%$).

[29] Some additional analysis focused on measuring and testing the similarity between different rankings schemes is provided in the Supplement Appendix C.

[30] The calculations are merely an illustration of our method and they are not to be taken literally.

Table 3.14: List of G-SIBs allocated in categories according to the $\Delta^{\$}CoVaR_{95^{th}}$–ranking based on confidence intervals.

Category	$\Delta^{\$}CoVaR_{95^{th}}$ – G-SIBs in alphabetical order within each category															
	Panel A: Domestic Index								Panel B: Global Index							
	2015	$\eta = 2.96\%$	2016	$\eta = 2.94\%$	2017	$\eta = 3.10\%$	2018	$\eta = 3.01\%$	2015	$\eta = 2.64\%$	2016	$\eta = 3.03\%$	2017	$\eta = 3.05\%$	2018	$\eta = 3.29\%$
5^{th}	GS MUFJ	(2.00%)	C MS	(2.00%)	ABN NOM	(2.00%)	SMTH		JPM SAN WFC	(2.00%)	DBK SAN	(1.75%)	STT	(2.00%)	BAC	(2.00%)
4^{th}	BK COF	(1.75%)	(Empty)		UBSG	(1.75%)	STT		BARC UBSG	(1.75%)	(Empty)		SEBA	(1.75%)	UBSG	(1.50%)
3^{rd}	BARC CBK SBER STAN	(1.50%)	ISP	(1.75%)	DNB	(1.50%)	BBAS CABK RBS		C MS SBER	(1.50%)	INGA RBS	(1.25%)	ABN	(1.50%)	DBK STT	(1.25%)
2^{nd}	ACA BAC BBAS BBVA BNP BPCE DBK DNB GLE INGA ISP NDA RBS	(1.25%)	ACA BARC BBAS CITIC GLE INGA ITUB NDA SAN SBER SMTH STT	(1.50%)	ACA BAC BARC BBAS BBVA CBK CITIC CSGN SAN SMTH STAN	(1.25%)	BPCE HFG SAN SBER STAN UCG		ACA BBAS BBVA BK BNP BPCE CABK CBK DNB INGA ISP ITUB RBS UCG	(1.25%)	BBDC C GLE ISP SBIN STAN STT	(1.00%)	BBVA BNP BPCE C CABK CBK CITIC GLE LLOY RBS UCG	(1.25%)	BBAS CBK CSGN MS SBER UCG	(1.00%)
1^{st}	BBDC C CABK CSGN HFG ITUB JPM LLOY MS NOM S SAN SEBA SMFG SMTH STT UBSG UCG	(0.75%)	BAC BBDC BBVA BNP BPCE CABK CBK DBK DNB HFG IB JPM LLOY MUFJ NOM PAB RBS SEBA SMFG STAN UCG	(0.75%)	BBDC BK BNP BPCE C CABK COF DBK GLE GS HX INGA ISP ITUB JPM LLOY MFG MS MUFJ NDA PAB RBS SBER SBIN SEBA SMFG STT UCG	(1.00%)	ACA BAC BARC BBDC BBVA BK BNP C CBK CITIC COF CSGN DBK DNB GLE GS INGA ISP ITUB LLOY MS MUFJ NOM SBIN SMFG UBSG		BAC BBDC COF CSGN DBK GLE GS LLOY NDA PNC SBIN SEBA SHBA STAN STT	(0.75%)	ACA BAC BARC BBAS BBVA BK BNP BPCE CABK CBK COF DNB GS ITUB JPM LLOY MS NDA SBER UCG	(0.75%)	ACA BAC BARC BBAS BBDC BK COF CSGN DBK DNB GS HSBC INGA ISP ITUB JPM MS NDA PNC SAN SBER SBIN STAN UBSG WFC	(1.00%)	ACA BARC BBDC BBVA BK BNP BPCE C CABK COF GLE GS INGA ISP ITUB LLOY RBS SAN SBIN STAN	(0.75%)

Notes: The list contains the bank designated as G-SIBs allocated in categories according to the ranking based on confidence intervals introduced in Section 3.2.1. The required levels of additional capital buffer associated with each category (in parentheses) have been computed with the expected impact approach as described in Section 3.2.1. "η" indicate the G-SIBs (market-based) threshold computed through the cluster analyses described in 3.2.1. The systemic risk is measured with $\Delta^{\$}CoVaR_{95^{th}}$ conditioned to the respective domestic index (Panel A) and to the global index (Panel B). Banks in cyan are the G-SIBs designated by the FSB – see Table 3.1. Bank's full names are in Table 3.2.

Table 3.15: List of G-SIBs allocated in categories according to the $MES^{\$}$ –ranking based on confidence intervals.

$MES^{\$}$ – G-SIBs in alphabetical order within each category

Panel A: Domestic Index

Category	2015	$\eta = 2.14\%$	2016	$\eta = 2.04\%$	2017	$\eta = 2.58\%$	2018	$\eta = 2.44\%$
5^{th}	PNC	(1.75%)	SAN USB	(2.00%)	CABK CITIC STT	(1.75%)	BNP JPM	(2.00%)
4^{th}	BBVA GS UBSG	(1.50%)	DBK	(1.50%)	(Empty)		UBSG	(1.50%)
3^{rd}	SHBA USB	(1.25%)	WFC	(1.25%)	DNB	(1.25%)	C ITUB WBC	(1.25%)
2^{nd}	ACA BAC BBDC BNP BPCE C CABK S SAN STAN UCG	(1.00%)	BBVA GLE GS INGA ISP ITUB LLOY MFG MS SBER SMTH	(1.00%)	BAC BBVA BK C CBK NOM SAN	(1.00%)	BBAS BBDC BK GLE LLOY SAN STAN	(1.00%)
1^{st}	BARC BBAS BK CBK COF CSGN DBK DNB GLE HFG INGA ISP ITUB JPM LLOY MFG MS MUFJ NDA NOM RBS SBER SEBA SMFG SMTH STT WFC	(0.75%)	ACA BAC BARC BBAS BBDC BK BNP BPCE C CABK CBK CITIC COF CSGN DANSKE DNB HSBC JPM MUFJ NDA NOM PNC RBS SEBA SHBA SMFG STAN STT UBSG UCG	(0.75%)	ABN ACA ANZ BARC BBAS BBDC BNP BPCE COF CSGN DBK GLE GS HSBC INGA ISP ITUB JPM LLOY MFG MS MUFJ NDA PNC RBS SBER SEBA SHBA SMFG SMTH STAN UBSG UCG USB WBC WFC	(0.75%)	ABN ACA BAC BARC BBVA BPCE CABK CBK COF CSGN DBK DNB GS HSBC INGA ISP MFG MS MUFJ NDA NOM PNC RBS SBER SEBA SHBA SMFG SMTH STT UCG USB WFC	(0.75%)

Panel B: Global Index

Category	2015	$\eta = 1.60\%$	2016	$\eta = 1.99\%$	2017	$\eta = 2.31\%$	2018	$\eta = 1.88\%$
5^{th}	HSBC UBSG	(1.50%)	BBDC	(1.50%)	ACA BBAS	(1.50%)	INGA SEBA	(1.50%)
4^{th}	BBDC SAN	(1.25%)	GS	(1.25%)	USB	(1.25%)	SBER	(1.25%)
3^{rd}	DBK	(1.00%)	SEBA	(1.00%)	GS	(1.00%)	JPM	(1.00%)
2^{nd}	BK C CBK DNB GS ITUB PNC RBS STT	(0.75%)	BBVA BK DBK DNB GLE INGA ISP PNC STAN UCG	(0.75%)	ABN BBVA BNP DNB HSBC LLOY SAN	(0.75%)	BARC C GLE ITUB LLOY STAN STT	(0.75%)
1^{st}	ACA BAC BARC BBAS BBVA BNP BPCE COF CSGN GLE INGA ISP JPM LLOY MS NDA SBER SEBA SHBA STAN UCG USB WFC	(0.50%)	ACA BAC BARC BBAS BNP BPCE C CBK COF CSGN ITUB JPM LLOY MS NDA RBS SAN SBER STT USB WFC	(0.50%)	BAC BARC BBDC BK BPCE C CBK CITIC COF CSGN DBK GLE INGA ISP JPM MS NDA PNC RBS SBER SBIN SEBA STAN STT UBSG UCG WFC	(0.50%)	ABN ACA BAC BBAS BBDC BBVA BK BNP BPCE CABK CBK COF CSGN DBK DNB GS HFG HSBC ISP MS NDA PNC RBS SAN SBIN UBSG UCG USB WFC	(0.50%)

Notes: The list contains the bank designated as G-SIBs allocated in categories according to the ranking based on confidence intervals introduced in Section 3.2.1. The required levels of additional capital buffer associated with each category (in parentheses) have been computed with the expected impact approach as described in Section 3.2.1. "η" indicate the G-SIBs (market-based) threshold computed through the cluster analyses described in 3.2.1. The systemic risk is measured with $MES^{\$}$ conditioned to the respective domestic index (Panel A) and to the global index (Panel B). Banks in cyan are the G-SIBs designated by the FSB – see Table 3.1. Bank's full names are in Table 3.2.

Table 3.16: List of G-SIBs allocated in categories according to the $SRISK\%$–ranking based on confidence intervals.

Category	$SRISK$ – G-SIBs in alphabetical order within each category															
	Panel A: Domestic Index								Panel B: Global Index							
	2015	$\eta = 0.94\%$	2016	$\eta = 0.95\%$	2017	$\eta = 0.97\%$	2018	$\eta = 1.15\%$	2015	$\eta = 0.83\%$	2016	$\eta = 0.92\%$	2017	$\eta = 0.97\%$	2018	$\eta = 1.03\%$
5^{th}	BBAS ICBC SMFG	(3.50%)	RBS SAN	(3.50%)	MS	(3.50%)	BAC SMFG	(3.50%)	BARC GS SMFG	(3.75%)	BC RBS	(3.75%)	GS	(3.50%)	BC	(3.50%)
4^{th}	BAC BNP GLE INGA NDA	(3.00%)	BNP	(3.00%)	C MUFJ	(3.00%)	MFG	(2.75%)	BNP BoC JPM	(3.50%)	DBK	(3.25%)	C MUFJ	(3.00%)	SMFG	(3.00%)
3^{rd}	ACA C DBK IB MFG SAN SMFG UCG	(2.50%)	ABC ACA C DBK GLE	(2.75%)	ABC ACA BNP BoC GLE SMFG	(2.50%)	DBK ICBC MUFJ	(2.50%)	ABC ACA BAC C DBK	(3.00%)	ABC BAC GLE JPM SMFG	(3.00%)	ABC ACA BNP DBK GLE HSBC SPDB	(2.75%)	MFG	(2.75%)
2^{nd}	ABC BoC BPCE CCB ICBC ISP MUFJ	(1.50%)	BAC BoC BPCE CCB ICBC MFG MS MUFJ	(1.75%)	BAC BC CBK CCB DBK HSBC IB INGA MFG SMTH UCG	(2.25%)	ABC ACA BoC C GLE INGA UCG	(2.25%)	BBAS INGA MFG MS RBS UCG	(2.50%)	ACA BARC BBAS CCB ICBC MFG MS MUFJ	(2.75%)	BAC BoC CBK IB ICBC MFG MS RBS SAN SMFG SMTH	(2.50%)	ACA BAC BARC BPCE CSGN ICBC MUFJ	(2.50%)
1^{st}	BBAS CBK CSGN GS HSBC LLOY MS NOM RBS SMTH SPDB UBSG	(1.00%)	BARC BBAS BC CBK CSGN GS HSBC IB INGA JPM LLOY SMFG SMTH SPDB UCG	(1.25%)	BARC CM CSGN GS ICBC JPM LLOY RBS SAN	(1.25%)	BARC BC BNP CCB CM CSGN GS HSBC IB JPM MS RBS SAN SMTH SPDB	(1.75%)	BC BPCE CBK CCB CSGN GLE HSBC IB ICBC LLOY MUFJ SAN SPDB	(1.50%)	BNP BoC BPCE C CBK CSGN GS HSBC IB INGA LLOY SAN SMTH SPDB UCG	(1.50%)	BARC BBAS BC BPCE CCB CM CSGN INGA JPM LLOY UCG	(1.50%)	ABC BNP BoC C CBK CCB CEB CM DBK GLE GS HSBC IB JPM MS RBS SAN SMTH SPDB UCG	(1.50%)

Notes: The list contains the bank designated as G-SIBs allocated in categories according to the ranking based on confidence intervals introduced in Section 3.2.1. The required levels of additional capital buffer associated with each category (in parentheses) have been computed with the expected impact approach as described in Section 3.2.1. "η" indicate the G-SIBs (market-based) threshold computed through the cluster analyses described in 3.2.1. The systemic risk is measured with $SRISK\%$ conditioned to the respective domestic index (Panel A) and to the global index (Panel B). Banks in cyan are the G-SIBs designated by the FSB – see Table 3.1. Bank's full names are in Table 3.2.

view by designating a higher number of G-SIBs for each SRM. Comparing the designation of systemically important banks based on confidence intervals with the SRM point estimate, which has been computed as the last estimate of the SRMs for each year (n-1) in December for the designation of G-SIBs the year after (n),[31] we find that the ranking using confidence intervals, especially in the cases of $\Delta^{\$}CoVaR_{95^{th}}$ and $MES^{\$}$, is more prudent so it is especially interesting that the confidence interval method gives much more stable total number of G-SIBs, year on year – see, Table 3.17.

Our analysis concludes by comparing our methodology with the SRM point estimate, and the FSB framework, for the additional capital buffers assigned to each category. Table 3.18 reports the results of this analysis. The greater similarity between the $SRISK\%$ and the FSB framework is also confirmed by the additional capital buffers, which take almost the same distribution from a minimum of 1.00% to a maximum of 3.75%; while, $\Delta^{\$}CoVaR_{95^{th}}$ and $MES^{\$}$ seem to assess, again, differently the systemic risk of G-SIBs, with capital surcharges spanning values from a minimum of 0.50% to a maximum of 2.50%. Overall, our methodology, under all three SRMs, assigns more stable year on year capital surcharges to each category. This may be due to the fluctuation of a marked-based SRM based solely on a pointwise estimate. Taking into account confidence intervals, we are able to decrease the uncertainty related to this issue. In particular, considering only the G-SIBs designated by the FSB,[32] Figure 3.3 shows the difference between the additional capital buffers estimated under the confidence intervals methodology and the SRM point estimate. In the majority of the cases, the implementation of additional capital buffers under a SRM point estimate would find at least 50% of the G-SIBs over-capitalized by imposing them higher capital requirements compared to the confidence intervals methodology. This result appears even clearer in

[31] In this case we use the SRM point estimates only to compute, through the cluster analyses described in Section 3.2.1, the G-SIBs (market-based) threshold – denoted as the point estimate systemic threshold in Table 3.17.

[32] The ranking similarity, estimated with τ_b and τ_x, between the classification of only the G-SIBs designed by the FSB under the confidence intervals methodology and the SRM point estimate range from 0.09 to 0.41 (-0.31 to 0.70) for the $\Delta^{\$}CoVaR_{95^{th}}$; -0.64 to 0.22 (-0.54 to 0.24) for the $MES^{\$}$; and, -0.64 to 0.56 (-0.19 to 0.39) for the $SRISK\%$, in Panel B (Panel A). The results suggest a strong dissimilarity between the two methodologies.

Table 3.17: Sensitivity analysis for the designation of G-SIBs over the period from 2015 to 2018.

i) Upper bound $\geq \eta$

Panel A: Domestic Index

	$\Delta^{\$}CoVaR_{95^{th}}$					MES^{th}					$SRISK\%$				
	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$
5^{th}	2	2	2	1	2	1	2	3	2	2	3	2	1	2	2
4^{th}	2	0	1	1	1	3	1	0	1	1	5	1	2	1	2
3^{rd}	4	1	1	3	2	2	1	1	3	2	8	5	6	3	6
2^{nd}	13	12	11	6	11	11	11	7	7	9	7	8	11	7	8
1^{st}	18	21	28	26	23	27	30	36	32	31	12	15	9	15	13
Tot. designated systemically important banks	39	36	43	37	39	44	45	47	45	45	35	31	29	28	31

Panel B: Global Index

	$\Delta^{\$}CoVaR_{95^{th}}$					MES^{th}					$SRISK\%$				
	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$
5^{th}	3	2	1	1	2	2	1	2	2	2	3	2	1	1	2
4^{th}	2	0	1	1	1	2	1	1	1	1	3	1	2	1	2
3^{rd}	3	2	1	2	2	1	1	1	1	1	5	5	7	1	5
2^{nd}	14	7	11	6	10	9	10	7	7	8	6	8	11	7	8
1^{st}	15	20	25	20	20	23	21	27	29	25	13	15	11	20	15
Tot. designated systemically important banks	37	31	39	30	35	37	34	38	40	37	30	31	32	30	32

ii) Midpoint $\geq \eta$

Panel A: Domestic Index

	$\Delta^{\$}CoVaR_{95^{th}}$					MES^{th}					$SRISK\%$				
	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$
5^{th}	2	2	2	1	2	1	2	3	1	2	3	2	1	2	2
4^{th}	2	0	1	1	1	3	1	0	1	1	5	1	2	1	2
3^{rd}	3	1	1	3	2	1	1	1	2	1	8	5	6	3	6
2^{nd}	13	12	11	6	11	9	11	7	7	9	7	8	11	7	8
1^{st}	18	19	25	25	22	27	28	36	28	30	12	15	9	15	13
Tot. designated systemically important banks	38	34	40	36	38	41	43	47	39	43	35	31	29	28	31

Panel B: Global Index

	$\Delta^{\$}CoVaR_{95^{th}}$					MES^{th}					$SRISK\%$				
	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$
5^{th}	3	2	1	1	2	2	1	2	2	2	3	2	2	1	2
4^{th}	2	0	1	1	1	2	1	0	1	1	3	1	1	1	2
3^{rd}	3	0	1	2	2	0	0	1	1	1	5	5	8	1	5
2^{nd}	14	9	11	6	10	10	11	8	7	9	6	8	10	7	8
1^{st}	15	20	24	19	20	23	20	27	28	25	13	15	10	20	15
Tot. designated systemically important banks	37	31	38	29	35	37	33	38	39	38	30	31	31	30	32

iii) Lower bound $\geq \eta$

Panel A: Domestic Index

	$\Delta^{\$}CoVaR_{95^{th}}$					MES^{th}					$SRISK\%$				
	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$
5^{th}	2	1	2	1	2	1	2	3	1	2	3	2	1	2	2
4^{th}	2	1	1	1	1	3	1	0	1	1	5	1	2	1	2
3^{rd}	3	1	1	3	2	1	1	1	2	1	8	5	6	3	6
2^{nd}	13	9	11	6	10	9	11	7	7	9	7	8	10	7	8
1^{st}	18	19	25	24	22	27	27	36	28	30	12	15	9	15	13
Tot. designated systemically important banks	38	31	40	35	37	41	42	47	39	43	35	31	28	28	31

Panel B: Global Index

	$\Delta^{\$}CoVaR_{95^{th}}$					MES^{th}					$SRISK\%$				
	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$
5^{th}	2	2	1	1	2	2	1	2	2	2	3	2	2	1	2
4^{th}	2	0	1	0	1	2	1	0	1	1	3	1	1	1	2
3^{rd}	3	0	1	2	2	0	0	1	1	1	5	5	8	1	5
2^{nd}	14	8	11	6	10	10	11	8	7	9	6	8	10	7	8
1^{st}	15	19	23	19	19	23	20	27	27	24	12	13	10	18	13
Tot. designated systemically important banks	36	29	37	28	34	37	33	38	38	37	29	29	31	28	30

iv) SRM point estimate $\geq$ Point estimate systemic threshold

Panel A: Domestic Index

	$\Delta^{\$}CoVaR_{95^{th}}$					MES^{th}					$SRISK\%$				
	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$
5^{th}	2	3	2	3	3	3	3	3	2	3	3	3	2	3	3
4^{th}	1	1	2	3	2	1	1	1	1	1	4	2	2	1	2
3^{rd}	4	1	2	2	2	2	2	1	1	2	6	6	3	3	5
2^{nd}	10	13	13	1	9	14	15	12	9	13	6	7	11	3	7
1^{st}	10	27	22	5	16	16	31	35	13	24	12	10	7	13	11
Tot. designated systemically important banks	27	45	41	14	32	36	52	52	26	43	31	28	25	23	28

Panel B: Global Index

	$\Delta^{\$}CoVaR_{95^{th}}$					MES^{th}					$SRISK\%$				
	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$
5^{th}	2	3	1	2	2	2	3	2	2	2	5	3	2	2	3
4^{th}	1	1	2	0	1	2	1	1	3	2	4	2	2	1	2
3^{rd}	5	2	2	1	3	3	2	2	1	2	7	4	4	1	4
2^{nd}	11	16	14	6	12	11	13	10	5	10	6	8	12	5	8
1^{st}	15	30	33	8	22	17	33	37	9	24	14	9	6	16	11
Tot. designated systemically important banks	34	52	52	17	40	35	52	52	20	40	36	26	26	25	28

Notes: The table presents the number of banks allocated in each category and the total designated systemically important banks over the period from 2015 to 2018. The systemically important banks are designed using: i) the upper bound; ii) the midpoint; iii) the lower bound of the confidence intervals; and, iv) the cluster analyses applied to the SRM point estimate. The systemic risk is measured with $\Delta^{\$}CoVaR_{95^{th}}$, $MES^{\$}$ and $SRISK\%$, conditioned to the respective domestic index (Panel A) and to the global index (Panel B).

Table 3.18: SRM under the confidence intervals methodology vs. SRM point estimate: additional capital buffer over the period from 2015 to 2018.

	Panel A: Domestic Index										Panel B: Global Index									
	SRM confidence intervals – (%)					SRM point estimate – (%)					SRM confidence intervals – (%)					SRM point estimate – (%)				
	$\Delta^{\$}CoVaR_{95^{th}}$																			
	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$
5^{th}	2.00	2.00	2.00	2.25	2.06	2.25	2.25	2.50	1.75	2.19	2.00	1.75	2.00	2.00	1.94	2.50	2.75	3.50	1.25	2.50
4^{th}	1.75		1.75	2.00	1.83	1.75	2.00	2.25	1.00	1.75	1.75		1.75	1.50	1.67	2.25	2.00	3.25		2.50
3^{rd}	1.50	1.75	1.50	1.75	1.63	1.50	1.50	2.00	0.75	1.44	1.50	1.25	1.50	1.25	1.38	2.00	1.74	2.75	1.00	1.87
2^{nd}	1.25	1.50	1.25	1.25	1.31	1.00	1.25	1.75	0.50	1.13	1.25	1.00	1.25	1.00	1.13	1.50	1.50	2.50	0.75	1.56
1^{st}	0.75	0.75	1.00	1.00	0.88	0.25	0.75	1.25	0.25	0.63	0.75	0.75	1.00	0.75	0.81	1.00	1.00	2.00	0.50	1.13
	$MES^{\$}$																			
	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$
5^{th}	1.75	2.00	1.75	2.00	1.88	2.00	2.75	2.25	1.75	2.19	1.50	1.50	1.50	1.50	1.50	1.75	2.00	2.25	1.50	1.88
4^{th}	1.50	1.50		1.50	1.50	1.75	1.75	2.00	1.50	1.75	1.25	1.25	1.25	1.25	1.25	1.50	1.75	2.00	1.25	1.63
3^{rd}	1.25	1.25	1.25	1.25	1.25	1.50	1.50	1.75	1.25	1.50	1.00	1.00	1.00	1.00	1.00	1.25	1.50	1.75	0.75	1.31
2^{nd}	1.00	1.00	1.00	1.00	1.00	1.00	1.25	1.50	1.00	1.19	0.75	0.75	0.75	0.75	0.75	0.75	1.25	1.50	0.50	1.00
1^{st}	0.75	0.75	0.75	0.75	0.75	0.50	1.00	1.25	0.50	0.81	0.50	0.50	0.50	0.50	0.50	0.50	1.00	1.00	0.25	0.69
	$SRISK\%$																			
	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$
5^{th}	3.50	3.50	3.50	3.50	3.50	3.50	3.25	3.50	3.50	3.44	3.75	3.75	3.50	3.50	3.63	3.50	3.00	3.25	3.25	3.25
4^{th}	3.00	3.00	3.00	2.75	2.94	2.75	3.00	2.75	2.75	2.81	3.50	3.25	3.00	3.00	3.19	3.00	2.75	2.50	2.75	2.75
3^{rd}	2.50	2.75	2.50	2.50	2.56	2.50	2.50	2.50	2.50	2.50	3.00	3.00	2.75	2.75	2.88	2.75	2.50	2.25	2.50	2.50
2^{nd}	1.50	1.75	2.25	2.25	1.94	2.00	2.00	2.25	2.25	2.13	2.50	2.75	2.50	2.50	2.56	2.00	2.00	2.00	2.25	2.06
1^{st}	1.00	1.25	1.25	1.75	1.31	0.75	1.00	1.00	1.75	1.13	1.50	1.50	1.50	1.50	1.50	1.00	1.00	0.75	2.00	1.19

Notes: The table presents the vis-a-vis comparison of the additional capital buffer associated with each category between the SRM under the confidence intervals methodology – designation based on the upped bound, and the SRM point estimate, over the period from 2015 to 2018. The required levels of additional capital buffer associated with each category have been computed with the expected impact approach as described in Section 3.2.1. The systemic risk is measured with $\Delta^{\$}CoVaR_{95^{th}}$, $MES^{\$}$ and $SRISK\%$, conditioned to the respective domestic index (Panel A) and to the global index (Panel B).

Table 3.19, which shows that on average 19, 16, 10 (16, 19, 15) FSB's G-SIBs would receive greater; 6, 9, 8 (5, 7, 10) lower; and, 1, 3, 0 (3, 4, 4) equal additional capital surcharges under the SRM point estimate for $\Delta^{\$}CoVaR_{95^{th}}$, $MES^{\$}$, and, $SRISK\%$, respectively, for Panel B (Panel A).[33] This is, again, due to the fluctuation of the systemic threshold "η", which, is almost stable year over year under our method – see, Tables 3.14 to 3.16; while, it rises and falls under the SRM point estimate, entailing a less stable designation and regulation of G-SIBs – see, Table 3.17 and 3.18.

The classification of financial institutions according to their systemic risk level and the application of confidence intervals can provide valuable support for regulators and supervisory authorities in order to develop, choose and employ their plan to monitor the systemic risk level of banks. The usage of confidence intervals supports the estimation of the effective difference among the banks by degree of systemic risk contribution to the whole system. In addition, our methodology offers an objective and transparent approach in deciding the classification categories for the G-SIBs based on the current market data information and taking into consideration the uncertainty surrounding rank estimates. Hence, the classification of banks as systemically risky inherits a dynamic feature in our approach.

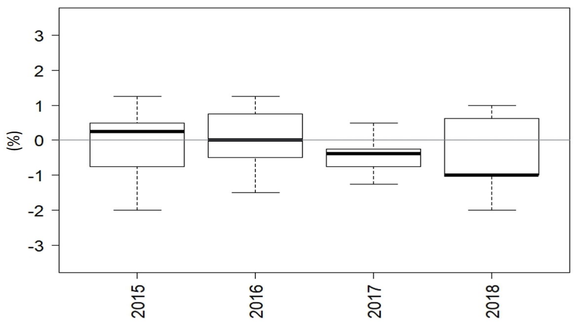
Table 3.19 reports the structural differences when ranking using different ranking systems. In Panel B (Panel A) changing from a pointwise ranking system to a confidence upper boundary system incorporating estimation uncertainty may lead to both over-charging, between 0.24% (0.44%) under $MES^{\$}$ ($\Delta^{\$}CoVaR_{95^{th}}$) in 2015 (2016) and 1.38% (1.06%) for $SRISK\%$ ($\Delta^{\$}CoVaR_{95^{th}}$) in 2016 (2018) and under-charging, between 0.13% (0.08%) for $SRISK\%$ ($\Delta^{\$}CoVaR_{95^{th}}$) in 2016 (2018) and 1.12% (0.79) for $MES^{\$}$ in 2016, with a relative predominance for overcharging.

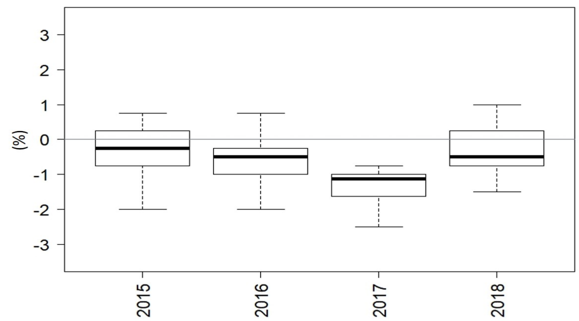
[33] In particular, we find that: i) the $\Delta^{\$}CoVaR_{95^{th}}$ would assign additional capital buffers greater for 14, 27, 24, 12 (11, 16, 23, 13); lower for 14, 1, 1, 7 (12, 5, 1, 3); equal for 1, 0, 0, 1 (2, 0, 4, 6) G-SIBs. ii) The $MES^{\$}$ for 15, 17, 18, 15 (16, 20, 18, 20); lower for 13, 7, 8, 8 (14, 6, 6, 1); equal for 1, 5, 4, 3 (0, 1, 5, 8) G-SIBs. iii) The $SRISK\%$ for 8, 12, 14, 16 (14, 19, 11, 16); lower for 9, 6, 12, 6 (10, 8, 13, 10); equal for 0, 0, 0, 0 (6, 4, 2, 4) G-SIBs, in 2015, 2016, 2017 and 2018, respectively, for Panel B (Panel A).

(a) Panel A: Domestic Index

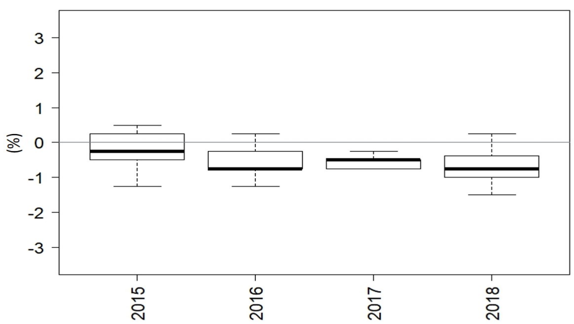
(b) Panel B: Global Index

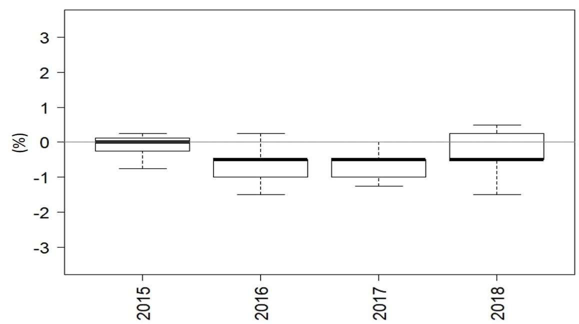
$\Delta^{\$}CoVaR_{95^{th}}$



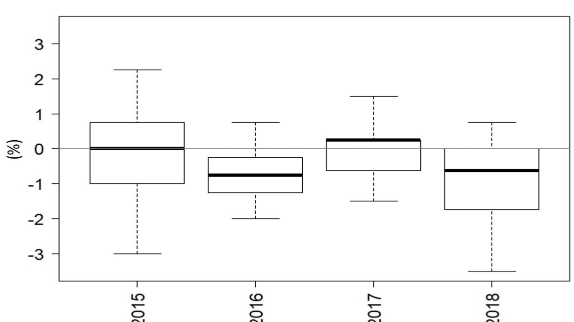


$MES^{\$}$





$SRISK\%$



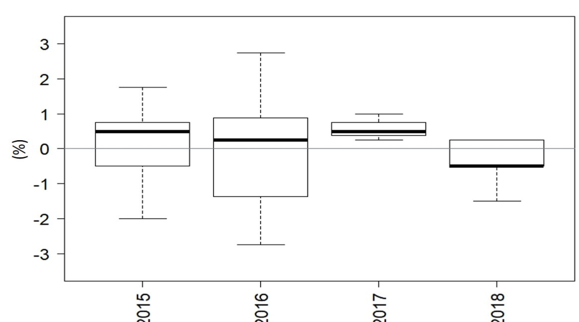


Figure 3.3: Difference of the additional capital buffers for the SRM under the confidence intervals methodology vs. SRM point estimate.

Notes: The box-plots show the difference between the additional capital buffers estimated under the confidence intervals methodology and the SRM point estimate for (only) the G-SIBs designated by the FSB in 2015, 2016, 2017, and 2018. The systemic risk is measured with $\Delta^{\$}CoVaR_{95^{th}}$, $MES^{\$}$ and $SRISK\%$, conditioned to the domestic index (Panel A) and the global index (Panel B). The vertical-axis indicates the difference in percentage points. The horizontal-axis indicates the years.

Table 3.19: SRM under the confidence intervals methodology vs. SRM point estimate: changes of the additional capital buffers for FSB's G-SIBs.

Panel A: Domestic Index

		Number of G-SIBs					Average change				
		2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$
$\Delta^{\$}CoVaR_{95^{th}}$	"+"	11	16	23	13	16	-1.02	-0.44	-0.62	-1.06	-0.78
	"-"	12	5	1	3	5	0.27	0.30	0.50	0.08	0.29
	"="	2	0	4	6	3					
		2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$
$MES^{\$}$	"+"	16	20	18	20	19	-0.45	-0.71	-0.64	-0.80	-0.65
	"-"	14	6	6	1	7	0.68	0.79	0.42	0.19	0.52
	"="	0	1	5	8	4					
		2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$
$SRISK\%$	"+"	14	18	11	16	15	-0.89	-1.04	-0.86	-0.94	-0.93
	"-"	10	8	13	10	10	0.38	0.50	0.13	0.15	0.29
	"="	6	4	2	4	4					

Panel B: Global Index

		Number of G-SIBs					Average change				
		2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$
$\Delta^{\$}CoVaR_{95^{th}}$	"+"	14	27	24	12	19	-0.68	-0.78	-1.34	-0.67	-0.87
	"-"	14	1	1	7	6	0.23	0.25	0.15	0.32	0.24
	"="	1	0	0	1	1					
		2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$
$MES^{\$}$	"+"	15	17	18	15	16	-0.24	-0.72	-0.68	-0.60	-0.56
	"-"	13	7	8	8	9	0.83	1.12	0.80	0.38	0.78
	"="	1	5	4	3	3					
		2015	2016	2017	2018	$\overline{x}$	2015	2016	2017	2018	$\overline{x}$
$SRISK\%$	"+"	8	12	4	16	10	-0.88	-1.38	-1.06	-0.78	-1.02
	"-"	9	6	12	6	8	0.36	0.13	0.15	0.21	0.21
	"="	0	0	0	0	0					

Notes: The table presents the number of G-SIBs designated by the FSB with different additional capital buffer (and the average changes of the difference between the additional capital buffers) under the confidence intervals methodology and the SRM point estimate in 2015, 2016, 2017, and 2018. *"+"*, *"-"*, and *"="* indicate that the additional capital buffers under the SRM point estimate are greater, lower, and equal than the ones estimated under the confidence intervals methodology. The systemic risk is measured with $\Delta^{\$}CoVaR_{95^{th}}$, $MES^{\$}$ and $SRISK\%$, conditioned to the domestic index (Panel A) and the global index (Panel B).

3.5 Concluding remarks

Our tests suggest that the group of G-SIBs as identified by the FSB belong to the group of banks that do contribute more than other banks in the global banking sector to the overall systemic risk. However, our tests also indicate that the more nuanced systemic risk rankings within the group of G-SIBs obtained by the SRMs may be less tuned with the FSB ranking.

Using nonparametric confidence intervals we further demonstrated that institutions with different pointwise systemic risk estimates may have similar systemic risk confidence intervals. We proposed a simple method to account for estimation uncertainty in the systemic risk ranking of banks and we demonstrated how our method may be employed to gauge the implicit degree of macroprudential concerns vs conservatism that FSB applies in identifying the G-SIBs. This new approach offers an objective and transparent approach that may help regulators and supervisory authorities in identifying G-SIBs through robust analysis.

Comparing additional capital buffers determined with our new method to similar calculations based on the main three SRMs we observed a more stable year on year capital surcharges to each G-SIB category. A G-SIBs designation methodology based only on SRM point estimate would find banks over-capitalized. The SRISK measure produces on its own results closest to our calculations accounting for estimation uncertainty and it seems the most robust SRM out of the main three, from this perspective.

CHAPTER 4

Measuring and assessing systemic risk: Empirical evidence from China's financial system

"In China, inadequate coordination among regulators has hampered effective systemic risk oversight and active use of macroprudential measures, and there are important gaps in functional supervision. Regular systemic risk analysis should be undertaken on a collaborative, cross-agency basis between relevant experts of the People's Bank of China and regulatory agencies."

International Monetary Fund (2017)

4.1 Introduction

During 2015, with the popping of the stock market bubble, China's financial system appeared to be on the brink of a financial crisis, a crisis which would have had dramatic consequences for the major world economies given the financial linkages that many global companies have with China's markets. As contagion fears spread across the world's financial markets, one of the greatest concerns related to the size of the systemic risk of China's financial system. Given that China has experienced a very rapid and stable economic growth since the start of its reforms in 1978, the consequence of a period of financial instability could be disastrous.

Over the years China has partially opened its domestic stock markets to international capital, becoming an emerging market characterized by high returns and high volatility (Tunaru, Fabozzi, and Wu, 2006). Glick and Hutchison (2013) showed that the size and dynamism of China's economic activity and trading relationship have played a dominant role in linking equity markets across the Asian region, with a modest growth in the interrelationship between the mainland stock markets and the Hong Kong stock market following the Asian financial crisis (Hatemi-J and Roca, 2004). Moreover, Shu, He, Dong, and Wang (2018) using a structural vector autoregression model highlighted a growing influence, close to that of the United States, of China's financial market to the rest of Asia-Pacific, with the South China Growth Triangular markets, namely Hong Kong, Taiwan, Shanghai and Shenzhen contemporaneously correlated with the return volatility of the US market (Hu, Chen, Fok, and Huang, 1997). Furthermore, Bekiros (2014) empirically demonstrated that the BRIC economies have become more internationally integrated following the US financial crisis, substantiating the contagion effects across the US, EU and the BRIC stock markets. Therefore, assessing the systemic risk of China's financial system and sectors is particularly critical not only for Asia but also global markets given the potential for systemic spillovers.

The International Monetary Fund (2017) stated that there are critical gaps in the functional supervision of China's financial system, recommending that regular systemic risk analyses should be undertaken by the People's Bank of China (PBoC) and China's regulatory agencies. Furthermore, using the spillover index of Diebold and Yılmaz (2014) as a measure of systemic risk, Wang, Xie, Zhao, and Jiang (2018) found that China's publicly-traded commercial banks are highly interconnected in terms of volatility shocks. Motivated by this our study aims to investigate the main systemic risk contributors to China's financial system fragility, especially given the inevitable role they play in the quest for an effective regulatory framework. Addressing this issue requires the need to measure, not only the level of systemic risk in China's financial system, but also the contribution played by financial sectors and the individual institutions within these sectors in order to gain a better understanding of the overall systemic risk of the financial system. As discussed by Bernal, Gnabo, and Guilmin (2014), companies other than banks can also have a critical impact on the whole economy. For this reason, we focus on a broad range of Chinese banks, insurance and brokerage industries, and real estate companies. By comparing the systemic risk contributions of each financial sector should provide interesting insights into the existing link between systemic risk and the standards that financial institutions and sectors are expected to meet.

The empirical strategy developed in this Chapter examines the magnitude of the systemic risk in China's financial system over the period from the 1^{st} of January 2010 to the 31^{st} of December 2016. We apply the $\Delta CoVaR$ developed by Adrian and Brunnermeier (2016), estimated with the use of quantile regressions (Koenker and Bassett Jr, 1978), to estimate the systemic risk of a broad range of Chinese banks, insurance and brokerage industries, and real estate companies. The contribution of individual institutions and of the respective sectors to the overall systemic risk is examined. We analyse the period after the global financial crisis, an event which may have affected China's economy differently from what one observes in mature market economies (Bo, Driver, and Lin, 2014). Indeed, the intensive state ownership of Chinese companies mitigates financial constraints during times of financial crisis (Liu, Uchida, and Yang, 2012). The period under analysis is divided into three subperiod, characterised by the deflating of China's property bubble with the stimulus program (January 1^{st}, 2010 – December 31^{st}, 2012); the banking liquidity crisis (January 1^{st}, 2013 – December 31^{st}, 2014); and the stock market crash (January 1^{st}, 2015 – December 31^{st}, 2016). Having analysed the systemic risk level of the financial system, the Wilcoxon signed rank test is applied to test the increases in the systemic risk level of the financial system and sectors during the main systemic events covered by our sample period. Moreover, the financial sectors are ranked, as per Bernal, Gnabo, and Guilmin (2014), by testing the systemic contribution of each sector adopting the bootstrap Kolmogorov-Smirnov (KS) test as developed by Abadie (2002).

Our study is motivated by the fear that new systemic events at national level could trigger a new global crisis. The analysis builds on the recent literature that attempts to empirically measure systemic risk during the main systemic or high volatility episodes of the last decade (see e.g. Acharya, Pedersen, Philippon, and Richardson, 2017; Adrian and Brunnermeier, 2016; Bernal, Gnabo, and Guilmin, 2014; Black, Correa, Huang, and Zhou, 2016; Brownlees and Engle, 2016; Derbali and Hallara, 2016). However, most of the existing literature is focused only on the Subprime and/or the Sovereign Debt crisis, and does not consider other episodes, such as China's recent stock market turbulence, which could have a severe systemic impact on the major global financial markets.

This Chapter contributes to the existing literature by attempting to estimate and assess systemic risk. Silva, Kimura, and Sobreiro (2017) present an analysis of the literature on systemic risk analyzing a total of 266 articles that were published no later than September 2016. The need to monitor systemic risk is largely explained by the effect that this risk could have on the real economy. The Bank for International Settlements defines systemic risk as: *"a risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and has the potential to have serious negative consequences on the real economy"* (Caruana, 2010). Billio, Getmansky, Lo, and Pelizzon (2012) defined systemic risk as whatever set of events or circumstances which influence the stability of the financial system. Moreover, our study further contributes to the growing literature adopting the $\Delta CoVaR$ as a measure of assessing the marginal contribution to the overall systemic risk. Our analysis applies the methodology proposed by Adrian and Brunnermeier (2016), which is based on quantile regressions (Koenker and Bassett Jr, 1978).

Extensions of the $\Delta CoVaR$ estimation method have been proposed in the recent literature. Girardi and Ergün (2013) proposed a multivariate GARCH estimation of $CoVaR$, a method based on a modification of the definition of financial distress, from an institution being exactly at its VaR to being at most at its VaR. This modification allows for the consideration of more severe distress events and improves the $CoVaR$ relationship with the dependence parameter. Cao (2013) introduced the $Multi - CoVaR$, where the $Multi - \Delta CoVaR$ is defined as the difference between the VaR of a financial system conditional on a given set of financial institutions being in a tail event and the VaR of the financial system conditional on this set of financial institutions being in a normal state. Reboredo and Ugolini (2015) applied this measure to assess the systemic risk in Europe, adopting a $CoVaR$ extension based on copulas. López-Espinosa, Moreno, Rubia, and Valderrama (2012) adopted the $CoVaR$ approach to identify the main factors behind the systemic risk in a number of large international banks, considering several econometric specifications of increasing complexity, thereby extending the basic $CoVaR$ model. Sedunov (2016) modified the $\Delta CoVaR$ to allow for forecasting, and compared the ability of this measure to forecast the performance of financial institutions with the systemic expected shortfall introduced by Acharya, Pedersen, Philippon, and Richardson (2017), and the Granger causality of Billio, Getmansky, Lo, and Pelizzon (2012). His findings shows that the $\Delta CoVaR$ forecasts the within-crisis performance of financial institutions, providing useful forecasts of future systemic risk exposures.

Other systemic risk measures have also been proposed. Bisias, Flood, Lo, and Valavanis (2012) undertook a validity study examining the existing systemic risk measures, identifying thirty-one different quantitative measure for this risk.[1]

Our study applies the $\Delta CoVaR$ to measure systemic risk given that over the last decade this measure has become one of the most widely accepted measures for systemic risk. Furthermore, this measure is strongly positively correlated with interconnectedness, and such a positive correlation mainly arises from an elevated effect of interconnectedness on systemic risk during recessions (Cai, Eidam, Saunders, and Steffen, 2018).

Our empirical results show that the systemic risk of China's financial system decreased

[1] Bisias, Flood, Lo, and Valavanis (2012) argue that systemic risk measures can be classified according to supervisory, research, and data perspectives. For each of these they present a taxonomy of the area and concise definitions of each risk measure.

after the deflating of the property bubble, reaching the minimum value in the second half of 2012. The banking liquidity crisis of 2013 vortically increased the systemic risk level, reaching its absolute peak with the stock market crash in the summer of 2015. This level decreased only after the restrictions upon investors introduced by the Chinese government and supervisory authorities were imposed. The statistical tests show an increase in the systemic risk level of the financial system and sectors during the major dates that characterized the Standard & Poor's (S&P) downgrade of China's developers in 2011, the banking liquidity crisis in 2013, and the China's market crash in 2015, and 2016. Moreover, our findings show that each of the financial sectors significantly contribute to systemic risk over the total and subperiods analysed. The banking sector is found to contribute the most to systemic risk, followed by real estate and subsequently insurance and brokerage industries. Such results emphasize the need for the Chinese supervisory authorities to monitor the systemic risk of the different financial sectors, as opposed to solely focusing on the regulation of the banking sector. Different financial sectors contribute differently to systemic risk, and supervisory authorities could potentially develop different courses of action depending upon the characteristics of the sectors. These results are particularly important in a country characterized by a strong government's role in banking (Jiang, Liu, and Molyneux, 2019).

The remainder of the Chapter is organized as follows. Section 4.2 outlines the systemic risk model focusing on the estimation of the $\Delta CoVaR$ and the methodology by which the financial sectors and individual companies are ranked. Section 4.3 describes the data used for the empirical analysis. The empirical results are presented in Section 4.4 while Section 4.5 concludes the discussion.

4.2 Systemic risk model

Financial markets are in constant motion. Ten years ago, one would have considered mortgage servicing to be an insignificant and benign component of the financial system.

Clearly, that is not the case today (Fouque and Langsam, 2013). For this reason it is important that the empirical analysis is not constrained solely to the banking sector.

In this Section, we present the methodology used in order to estimate the systemic risk of the banking, insurance and brokerage, and real estate sectors. Such a structured network is able to represent more accurately the financial system, expressing its main characteristics thereby increasing the robustness of the results. The proposed methodology relies on the estimation of the $\Delta CoVaR$ as proposed by Adrian and Brunnermeier (2016), which is based on quantile regressions (Koenker and Bassett Jr, 1978).[2] Moreover, as in the study of Bernal, Gnabo, and Guilmin (2014), we perform a formal test of significance and dominance in order to rank the sectors according to their contribution to systemic risk.

4.2.1 Constructing the $\Delta CoVaR$

As a measure for systemic risk, Adrian and Brunnermeier (2016) introduced the $\Delta CoVaR$. This measure is based on the most common measure of risk used by financial institutions, namely the Value-at-Risk (VaR). However, the VaR focuses on the risk of an individual institution in isolation, which does not necessarily represent its contribution to the overall systemic risk. In order to emphasize the systemic nature of this risk measure, Adrian and Brunnermeier (2016) added the prefix "Co", representing conditional, to the existing risk measure.

The $CoVaR_q^{j|i}$ is defined as institution j's VaR conditional on some event $\mathbb{C}(X^i)$ of another institution i. This event $\mathbb{C}$ is considered as institution i's equity loss being at or above its VaR_q^i level. $CoVaR_q^{j|i}$ is implicitly defined by the q% quantile of the conditional probability distribution:

$$Pr(X^j|\mathbb{C}(X^i) \leq CoVaR_q^{j|\mathbb{C}(X^i)}) = q\% \tag{4.1}$$

[2]The methodology employed in this Chapter differs from the one used in Chapter 3 and Chapter 5. In particular, as described in Section 4.2.1, the $\Delta CoVaR$ has been estimated using a set of state variables M_{t-1}, which allow to consider the main characteristics of China's financial system.

The $\Delta CoVaR$ is defined as the difference between the CoVaR of the institution j (or financial system) conditional on institution i being in distress - i.e. the 95^{th} or 99^{th} quantile, and the CoVaR of the same conditional on the normal state of institution i - i.e. the median state identified with the 50^{th} quantile:

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i=VaR_q^i} - CoVaR_q^{j|X^i=VaR_{50th}^i} \tag{4.2}$$

This risk measure provides the marginal contribution of the institution to the overall systemic risk.

Following the approach of Adrian and Brunnermeier (2016), we use quantile regressions (Koenker and Bassett Jr, 1978) to estimate the VaR_q^i and the related $CoVaR_q^{j|i}$. In particular, to capture time-variation in the joint distribution of X^{system} and X^i, both $VaRs$ and $CoVaRs$ are estimated as a function of the state variables. The time-varying $CoVaR_{q,t}^i$ and $VaR_{q,t}^i$ depend on time t and estimate the time variation conditional on a vector of lagged state variable M_{t-1}.

We estimate the following quantile regressions at the 50^{th}, 75^{th}, 95^{th} and 99^{th} quantile:

$$X_t^i = \alpha_q^i + \beta_q^i M_{t-1} + \varepsilon_{q,t}^i \tag{4.3}$$

$$X_t^{system|i} = \alpha_q^{system|i} + \beta_q^{system|i} M_{t-1} + \gamma_q^{system|i} X_t^i + \varepsilon_{q,t}^{system|i} \tag{4.4}$$

where α_q^i represents the constant, and $\varepsilon_{q,t}^i$ the error term, which is assumed to be i.i.d. with zero mean and unit variance and independent of the state variables M_{t-1}.

We compute the predicted VaR, for each quantile, using the estimation of α_q^i and β_q^i from Eq. (4.3):

$$VaR_{q,t}^i = \hat{\alpha}_q^i + \hat{\beta}_q^i M_{t-1} \tag{4.5}$$

In the same way, we compute the predicted CoVaR, for each quantile, using the estimation of $\alpha_q^{system|i}$, $\beta_q^{system|i}$ and $\gamma_q^{system|i}$ from Eq. (4.4), and the estimates of the $VaR_{q,t}^i$ from Eq. (4.5):

$$CoVaR_{q,t}^i = \hat{\alpha}_q^{system|i} + \hat{\beta}_q^{system|i} M_{t-1} + \hat{\gamma}_q^{system|i} VaR_{q,t}^i \tag{4.6}$$

The $\Delta CoVaR_{q,t}^i$ is estimated by taking the difference between the predicted CoVaR at 99^{th}, 95^{th} or 75^{th} quantile and the one at the 50^{th} quantile. The $\Delta CoVaR_{q,t}^i$ represents the marginal contribution of the institution, or financial sector,[3] to systemic risk:

$$\Delta CoVaR_{q,t}^i = CoVaR_{q,t}^i - CoVaR_{50^{th},t}^i \tag{4.7}$$

Our study considers an equity loss with positive values. For this reason, in the empirical results, we consider only positive values for $VaR_{q,t}^i$ and $CoVaR_{q,t}^i$, because the contribution of negative capital shortfall indicates a capital surplus.[4]

4.2.2 Testing the systemic contribution

As in Bernal, Gnabo, and Guilmin (2014), in order to rank the financial sectors considered in this study, we test the contribution of each sector to the systemic risk using the bootstrap KS test developed by Abadie (2002). The resampling method developed by Abadie (2002) is better suited than the standard KS test because of the so-called Durbin problem[5] (Durbin, 1973). The bootstrap KS test compares the cumulative distribution functions instead of the means, which are sensitive to outliers. Moreover, this test does not require any assumptions regarding the underlying distribution. This becomes fundamental in order to minimize the risk of errors based on assumptions. We run the hypothesis test considering

[3]In this case, we considered X^i computed as the average market equity-valued returns of the 18 financial institutions, within the sector, weighted by their (lagged) market value of equity.

[4]We estimate positive values for $VaR_{q,t}^i$ and $CoVaR_{q,t}^i$ only at the 50^{th} quantile, which represents the median state, so the absence of a distress for institution i.

[5]The distribution-free nature of the standard KS test could be jeopardized by the estimated distributions we use in the test. In particular, they could introduce an unknown nuisance parameter into the null hypothesis, which is known as the Durbin problem.

the entire sample and the subperiods described in Section 4.3.

For the significance test, we test whether or not the cumulative distribution functions of $\Delta CoVaRs$ of each sector are systemically risky. This is determined by testing if the conditional contribution to systemic risk of each sector is statistically equal (or different) to 0. The two-sample KS statistics is defined as:

$$D_{mn} = \sqrt{\left(\frac{mn}{m+n}\right)} sup_x |F_m(x) - Gn(x)| \tag{4.8}$$

where $F_m(x)$ and $G_n(x)$ represent the cumulative distribution functions of the $CoVaRs$ at the 95^{th} and 50^{th} quantiles, and, m and n represent the size of the two samples, respectively. The null hypothesis is defined as follow:

$$H_0 = \Delta CoVaR^{system|i}_{95^{th}} = CoVaR^{system|i}_{95^{th}} - CoVaR^{system|i}_{50^{th}} = 0 \tag{4.9}$$

For the dominance test, we test if sector i contributes more than sector j to systemic risk. The two-sample KS statistics is defined as:

$$D_{mn} = \sqrt{\left(\frac{mn}{m+n}\right)} sup_x |S_m(x) - Tn(x)| \tag{4.10}$$

where $S_m(x)$ and $T_n(x)$ are the cumulative distribution functions of the $\Delta CoVaRs$ at the 95^{th} related to the two sectors, and, m and n represent the size of their samples. The null hypothesis is defined as follow:

$$H_0 = \Delta CoVaR^{system|i}_{95^{th}} \leq \Delta CoVaR^{system|j}_{95^{th}} \tag{4.11}$$

$$H_1 = \Delta CoVaR^{system|i}_{95^{th}} > \Delta CoVaR^{system|j}_{95^{th}} \tag{4.12}$$

Contrary to Bernal, Gnabo, and Guilmin (2014), we consider the systemic contribution with a positive value only, thereby allowing us to ignore the absolute values of $\Delta CoVaR$.

As an additional test, we investigate the contribution of the financial system and sectors during the main systemic events covered by our sample period. In particular, as with Ahnert and Georg (2018) who use the Wilcoxon signed rank sum test for paired data to test whether information contagion due to counterparty risk increases systemic risk, we investigate whether or not the level of systemic risk for China's financial system and sectors h-days after a systemic event, or a period of financial instability, is greater than h-days before. We consider the horizon h as one month (22 days). As main systemic events, we examine the S&P downgrade of China's developers on June 15^{th} 2011; the banking liquidity crisis that starts on June 20^{th} 2013, with a credit crunch affecting China's banks due to a rise in the Shanghai interbank overnight lending rates to a high of 30% from its usual rate of close to 3%; and finally China's stock market crash, in which three main dates are examined, namely, July 27^{th} 2015, a day in which the Shanghai Stock Exchange fell of 8.5%; August 24^{th} 2015, a day referred to as "Black Monday" because of losses of around 8% in all the Chinese main stock indexes; and, January 4^{th} 2016, which represents the first day of the period ending the 15^{th} of January, a period in which China's stock market fell 18%. This final event also affected global markets with the Dow Jones Industrial Average falling by 8.2%.[6] The Wilcoxon signed rank sum test is applied to the following hypotheses:

$$H_0 : \Delta CoVaR^i_{t:t+h-1} \leq \Delta CoVaR^i_{t-h-1:t-1} \tag{4.13}$$

$$H_1 : \Delta CoVaR^i_{t:t+h-1} > \Delta CoVaR^i_{t-h-1:t-1} \tag{4.14}$$

where i indicates the financial system or sector studied. The failure to reject the null hypothesis (4.13) implies that the systemic risk level of the financial system or sector under analysis did not increase during the systemic events previously described.

[6] *"Why This Market Meltdown Isn't a Repeat of 2008: U.S. economy and financial system are in a very different place now"*, The Wall Street Journal, January 15, 2016.

4.3 Data

Our data consist of daily observations. We collect daily stock prices of 54 Chinese institutions classified as financials in the four sub-sectors of the Hong Kong Stock Exchange Index (SEHK) and all allocated within three financial sectors, namely banks, insurance and brokerage and real estate. The SEHK includes the largest and most frequently traded companies – ie, most liquid stocks, listed on the Hong Kong exchange.[7] We have retained only Chinese institutions that exist in the financial market during the study period, with at least 253 daily observations (1-year) prior to January 2010. The panel is balanced in that all companies have been trading continuously during the sample period. Each of the three sectors consists of 18 companies. We only consider companies listed in the SEHK because of the restrictions to foreign investors in the Chinese equity markets.[8] In particular, the shares listed on the SEHK, which take the name of H-shares, can be traded freely by non-Chinese investors without obtaining the Qualified Foreign Institutional Investor license and are denominated only in Hong Kong dollars. They are the only type of shares traded on the SEHK, contrary to the shares listed on the Shanghai and Shenzhen Stock Exchanges. The list of companies within the three sectors adopted in this study is presented in Table 4.1.

The empirical analysis spans the period from the 1^{st} of January 2010 to the 31^{st} of December 2016, with a total of 1712 estimates for each financial sector and firm included in our sample. We divide this period into three subperiods: the period in between the property bubble and the economic stimulus package (January 1^{st}, 2010 – December 31^{st}, 2012); the period in between the banking liquidity crisis and the pre-stock market crash (January 1^{st}, 2013 – December 31^{st}, 2014); the stock market crash (January 1^{st}, 2015 – December 31^{st}, 2016).

The variables used in the quantile regressions are: the equity losses of the individual

[7] A comprehensive description of the SEHK is available at: `https://www.hsi.com.hk/eng/indexes/all-indexes/hsi`.

[8] See Alford and Lau (2015) for a comprehensive analysis of the accessibility to the Chinese equity markets for foreign investors.

Table 4.1: Tickers, company names and financial sectors.

Banks (18)		Insurance and Brokerage (18)		Real Estate (18)	
0005:HK	HSBC Holdings PLC	0218:HK	Shenwan Hongyuan HK Ltd	0119:HK	Poly Property Group Co Ltd
0011:HK	Hang Seng Bank Ltd	0227:HK	First Shanghai Investments Ltd	0123:HK	Yuexiu Property Co Ltd
0023:HK	Bank of East Asia Ltd/The	0231:HK	Ping An Securities Group Holdings Ltd	0173:HK	K Wah International Holdings Ltd
0626:HK	Public Financial Holdings Ltd	0662:HK	Asia Financial Holdings Ltd	0272:HK	Shui On Land Ltd
0939:HK	China Construction Bank Corp	0665:HK	Haitong International Securities Group Ltd	0410:HK	SOHO China Ltd
0998:HK	China CITIC Bank Corp Ltd	0945:HK	Manulife Financial Corp	0688:HK	China Overseas Land & Investment Ltd
1062:HK	China Development Bank International Investment Ltd	0966:HK	China Taiping Insurance Holdings Co Ltd	0754:HK	Hopson Development Holdings Ltd
1111:HK	Chong Hing Bank Ltd	1049:HK	Celestial Asia Securities Holdings	0813:HK	Shimao Property Holdings Ltd
1288:HK	Agricultural Bank of China Ltd	1299:HK	AIA Group Ltd	0978:HK	China Merchants Land Ltd
1398:HK	Industrial & Commercial Bank of China Ltd	1336:HK	New China Life Insurance Co Ltd	1109:HK	China Resources Land Ltd
1988:HK	China Minsheng Banking Corp Ltd	1339:HK	People's Insurance Co Group of China Ltd/The	1813:HK	KWG Property Holding Ltd
2356:HK	Dah Sing Banking Group Ltd	2318:HK	Ping An Insurance Group Co of China Ltd	1838:HK	China Properties Group Ltd
2388:HK	BOC Hong Kong Holdings Ltd	2328:HK	PICC Property & Casualty Co Ltd	2007:HK	Country Garden Holdings Co Ltd
2888:HK	Standard Chartered PLC	2601:HK	China Pacific Insurance Group Co Ltd	2777:HK	Guangzhou R&F Properties Co Ltd
3328:HK	Bank of Communications Co Ltd	2628:HK	China Life Insurance Co Ltd	3377:HK	Sino-Ocean Group Holding Ltd
3618:HK	Chongqing Rural Commercial Bank Co Ltd	6030:HK	ZhongAn Online P&C Insurance Co Ltd	3383:HK	Agile Group Holdings Ltd
3968:HK	China Merchants Bank Co Ltd	6837:HK	Haitong Securities Co Ltd	3883:HK	China Aoyuan Property Group Ltd
3988:HK	Bank of China Ltd	6881:HK	China Galaxy Securities Co Ltd	3900:HK	Greentown China Holdings Ltd

Notes: The Table reports the list of tickers (from Bloomberg) and company names used in the $\Delta CoVaR$ analysis grouped by financial sector.

Table 4.2: List of the state variables used in the quantile regressions.

State Variable	**Definition**	**Source**
3-month Government bond spread variation	Difference between the Generic Hong Kong 3-month Government Bond rate in time t and $t-1$	Bloomberg
Yield spread change	Difference between the Generic Hong Kong 10 Year Government Bond rate and the Generic Hong Kong 3-month Government Bond rate	Bloomberg
Liquidity spread	Difference between the 3-month HIBOR rate and the Generic Hong Kong 3-month Government Bond rate	Bloomberg
Credit spread change	Difference between the S&P Hong Kong BBB Investment Grade Corporate Bond Rate Index and the Generic Hong Kong 10 Year Government Bond rate	Bloomberg and S&P Dow Jones Indices
Equity return	Hong Kong Hang Seng Index returns	Bloomberg
Real estate and Financial sector spread	Difference between the Hong Kong Hang Seng Real Estate Index returns and the Hong Kong Hang Finance Index returns	Bloomberg
Equity Volatility	22-day rolling standard deviation of the daily Hong Kong Hang Seng Index	Bloomberg

Notes: The Table lists the state variables (M_{t-1}) used to estimate the CoVaR for the quantiles considered.

company (X^i), computed as the negative logarithmic returns of the daily prices in order to consider an equity loss with a positive value; the equity losses of the financial system portfolio (X^{system}), computed as the average market equity-valued returns of the 54 financial institutions weighted by their (lagged) market value of equity; the (lagged) state variables (M_{t-1}) reported in Table 4.2, which represent the same variables considered by Adrian and Brunnermeier (2016). All the data used in this study is obtained from Bloomberg, except the S&P Hong Kong BBB Investment Grade Corporate Bond Rate Index, which is obtained from the S&P Dow Jones Indices.[9]

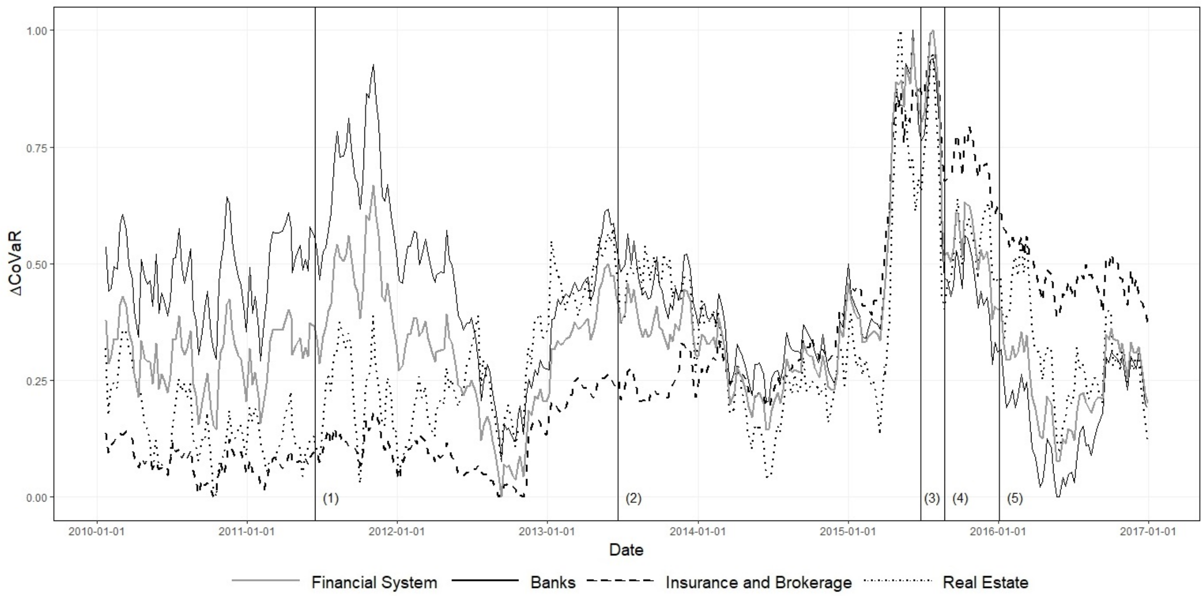
Table 4.3 provides summary statistics of the financial system and sectors returns, and the state variables. The 1 percent stress represents the realization of each variable in the worst 1 percent realization of the financial system returns. The worst realization for the banking and real estate sectors coincides with the worst 1 percent realization of the financial system returns. Similarly, the 1 percent stress level corresponds also to the worst realization of the SEHK equity return, a high level of liquidity and credit spreads, and equity volatility.

4.4 Empirical results

This Section presents the $\Delta CoVaR$ estimates with an analysis of the systemic risk in China's financial system (Section 4.4.1), along with the systemic contribution of each financial sector and individual institution to the overall risk, reporting the results of the bootstrap KS tests (Section 4.4.2).

[9] The S&P Hong Kong BBB Investment Grade Corporate Bond Rate Index consists of bonds in the S&P Hong Kong Investment Grade Corporate Bond Index with a rating of BBB from Standard & Poor's Ratings Services and is available, with daily frequency, at: http://us.spindices.com/indices/fixed-income/sp-hong-kong-bbb-investment-grade-corporate-bond-index.

Figure 4.1: $\Delta CoVaR_{95^{th}}$ of China's financial system.



Notes: The Figure plots the $\Delta CoVaR_{95^{th}}$ of China's financial system. The series are normalized by their value as of December 2016. The normalized value is reported on the left vertical axis. The solid vertical lines mark: (1) the S&P downgrade of China developers in 2011; (2) the banking liquidity crisis in 2013; (3) the 27^{th} of July 2015; (4) the 24^{th} of August 2015, *("Black Monday")*; and, (5) the 4^{th} of January 2016.

4.4.1 China's systemic risk

Figure 4.1 plots the systemic risk measured with the $\Delta CoVaR_{95^{th}}$ of China's financial system[10] from the 1^{st} of January 2010 to the 31^{st} of December 2016. Figure 4.1 also includes the three sectors that compose the financial system. The time period spans three different subperiods, namely, the period in between the property bubble and the economic stimulus package (January 1^{st}, 2010 – December 31^{st}, 2012); the period in between the banking liquidity crisis and the pre-stock market crash (January 1^{st}, 2013 – December 31^{st}, 2014); and finally the period of the stock market crash. Some major dates are included in order to label the three subperiods (January 1^{st}, 2015 – December 31^{st}, 2016). As shown in Figure 4.1, the systemic risk level of China's financial system peaks during the stock market turbulence in 2015. Prior to this event the systemic risk was restrained. The first subperiod

[10] The $\Delta CoVaR_{95^{th}}$ of the financial system has been approximated with the average value, similar to Adrian and Brunnermeier (2016), who adopted this to compare forward and contemporaneous $\Delta CoVaR$ estimates.

Table 4.3: Summary statistics of financial system, sectors and state variables.

	Mean	Std. dev.	Skewness	Min	Max	1 percent Stress	Obs.
Returns							
Financial System	0.0040	1.7797	-0.1084	-14.1806	12.9789	12.9789	2219
Banks	0.0077	1.7754	-0.2627	-16.7531	13.2618	13.2618	2219
Insurance and Brokerage	0.0002	1.9430	0.2029	-14.7156	12.2162	11.1154	2219
Real Estate	0.0077	2.4931	-0.2347	-12.3168	13.4513	13.4513	2219
State variables							
3-month Government bond spread variation	-0.0591	4.1488	-1.7398	-0.5800	0.4800	-0.0500	2219
Yield spread change	1.6533	0.6346	-0.0545	0.2250	3.3130	2.1010	2219
Liquidity spread	0.3295	0.5134	3.8100	-0.2907	4.3721	2.9386	2219
Credit spread change	4.0723	1.4151	2.0811	2.4500	9.2100	8.2100	2219
Equity return	-0.0106	1.6534	0.0643	-13.5820	13.4068	13.4068	2219
Real estate and Financial sector spread	-0.0005	1.1097	0.3417	-6.9037	8.1645	2.7357	2219
Equity Volatility	1.4177	0.8675	2.9117	0.4497	7.0043	5.2138	2219

Notes: The Table reports summary statistics for the financial system and sectors returns and state variables. The 1 percent stress in the last column corresponds to the financial sector return and state variable realizations in the worst 1 percent of financial system returns. Note that, as stated in Section 4.2.1, our study considers an equity loss with positive values.

is characterized by the stimulus program of $586-billion issued by the State Council of the People's Republic of China in order to minimize the effect of the U.S. Subprime Crisis and the property bubble, which began to deflate in 2011. One of the main problems of this huge stimulus program was that the creation of new money caused the devaluation of the existing money, which in turn lead to inflation. As with many stimulus programmes, the Chinese stimulus program created some form of immediate economic growth, though this was short lived. During this subperiod, the systemic risk level reached a first peak in the second half of 2011 due to the effect of the real estate bubble and China's declining economic growth. The peak is evident for the banking sector, underlining the importance of this sector in the financial system as a systemic risk source. The difficult situation faced by China's financial system is underlined by the Standard & Poor's downgrade of the Chinese real estate development from stable to negative in August 2011. At the beginning of 2012, the Chinese real estate bubble completely deflated, stabilizing the financial system until the credit crunch of the Chinese commercial banks in 2013. As a consequence of market stability experienced after the deflating of the real estate bubble, low levels of systemic risk characterize 2012, in particular during the second half of the year.

During the second subperiod, China's financial system was hit by the banking liquidity crisis, which began with a dramatic surge in short-term borrowing costs in June 2013. Nomura Research Institute, which is the largest Japanese consulting and IT consulting firm, argued that the credit crunch was a consequence of the People's Bank of China (PBoC) refusing to inject liquidity into the system. Moreover, they found that China was displaying the same three symptoms shown by the U.S. prior to suffering their financial crises, namely, a rapid build-up of leverage, elevated property prices, and a decline in potential growth. As shown in Figure 4.1, the systemic risk does not reach any remarkable peak during the period from the 1^{st} of January 2013 to the 31^{st} of December 2014, however, this period can be looked upon as the build-up to the subsequent market turbulence in 2015–16. It is interesting to notice that during this subperiod the contribution of the real estate sector is similar to the banking sector. This highlights the increasing systemic importance of the real estate sector prior to the market crash.

The dramatic increase in the systemic risk level commences early in 2015. The systemic risk of China's financial system increased dramatically after the popping of the stock market bubble on the 12^{th} June, 2015. A third of the value of Chinese shares was lost within one month of this date. By the beginning of July the stock market had fallen by 30% despite the efforts of the Chinese government to reduce the losses. In an attempt to restart the economy, the PBoC devalued the Chinese yuan on several different occasions during August 2015. As an unexpected consequence, the Chinese main stock indexes lost around 8% of their value on the 24^{th} August, a day referred to as "Black Monday". Similar events occurred in the days following. Billions were lost on international markets causing severe difficulties for the companies reliant on the Chinese market. The Nikkei index in Japan slipped by 4.6%, European markets were down 4-5% and the Dow Jones opened down more than 1,000 basis points. Figure 4.1 indicates that the peak across the entire time series of the $\Delta CoVaRs$ occurs with Black Monday. However, it is clear to see that the systemic risk reacted with an increase experienced by all three sectors between June and July due to the popping of the stock market bubble.

By the end of 2015 the Chinese systemic risk decreased due to the response of the Chinese government and the supervisory authorities, introducing restrictions, such as, limits to short selling and prohibiting shareholders with holdings of in access of 5% of a company's stock from selling shares for six months. Such measures were successful in halting the fall in stock prices which were causing disturbance to global financial markets.

The results of the Wilcoxon signed rank sum test for China's financial system and sectors during the S&P downgrade of China's developers in 2011, the banking liquidity crisis in 2013, and China's stock market crash in 2015, and 2016, are illustrated in Table 4.4. We run this test to inspect whether or not the systemic risk level of China's financial system and sectors significantly increases after a systemic event or a period of financial instability covered by our

Table 4.4: Wilcoxon signed rank sum test during the main systemic events of 2011, 2013, 2015 and 2016.

H_0: $\Delta CoVaR^i_{t:t+h-1} \leq \Delta CoVaR^i_{t-h-1:t-1}$

	Financial System	Banks	Insurance and Brokerage	Real Estate
S&P downgrade of China's developers				
June 15^{th}, 2011	-0.3011	-0.7623	-0.0021	-1.5155*
Banking liquidity crisis				
June 20^{th}, 2013	-3.1488***	-3.3527***	-0.3598	-3.3527***
Stock market crash				
July 27^{th}, 2015	-2.9156***	-2.9156***	-2.9536***	-3.1888***
August 24^{th}, 2015	-2.9156***	-3.1888***	-2.5143**	-1.9147**
January 4^{th}, 2016	-4.9010***	-5.0354***	-3.2699***	-3.3527***

Notes: The results report for China's financial system and sectors the Wilcoxon signed rank sum test, which aims to determine whether or not the level of systemic risk h-days after a systemic event, or a period of financial instability, is greater than the same h-days before. The hypothesis tested is H_0: $\Delta CoVaR^i_{t:t+h-1} \leq \Delta CoVaR^i_{t-h-1:t-1}$, with $h = 22$–days. The failure to reject this hypothesis implies that the systemic risk level of the financial system (or sector) i did not increase during the systemic event considered. The columns contain the test statistic. ***, **, and * indicate significance at 1%, 5%, and 10% levels respectively.

sample period. The null hypothesis is rejected at 1% significance level in most of the cases, with the exception of the S&P downgrade of China's developers in 2011, which seems to affect only the real estate sector with an estimate statistically significant at 10% level. The banking liquidity crisis did not affect the systemic risk level of the insurance and brokerage companies, while, all the dates tested during the stock market crash between 2015 and 2016 show a statistically significant increase in the systemic risk level of the financial system and sectors. This result is in line with our previous analysis, which shows a major peak of the systemic risk level during China's stock market crash.

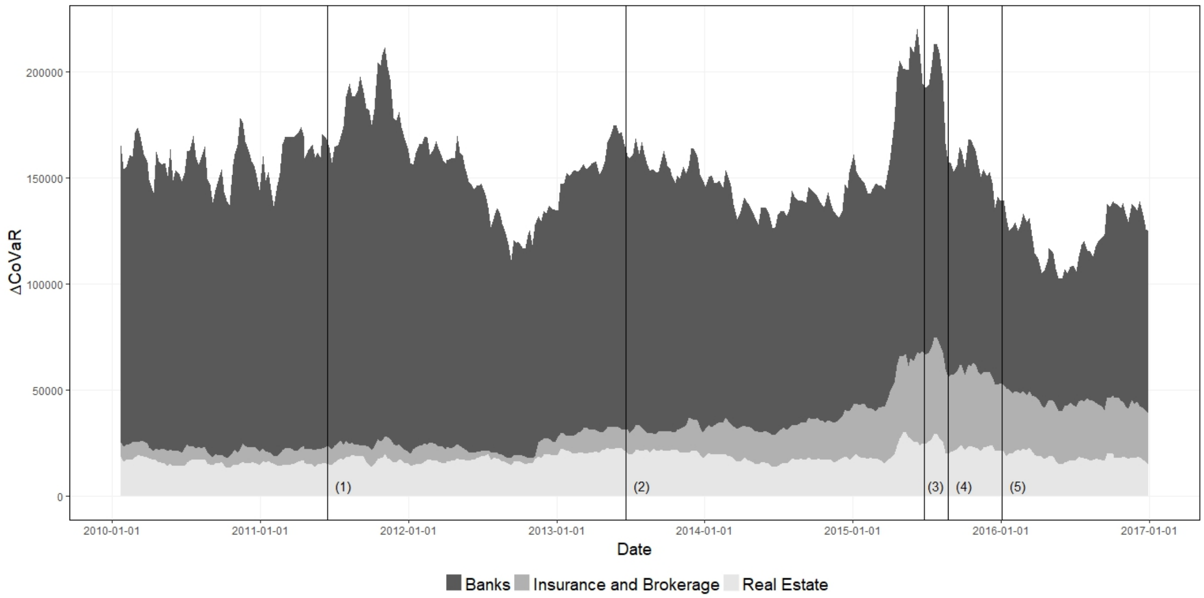
4.4.2 The contribution of sectors and individual companies to systemic risk

As in the case of the Subprime crisis, the increase in systemic risk is not solely due to the banking sector. This explains our decision to examine the systemic risk of sectors outside the banking sector, namely, the insurance and brokerage, and real estate sectors. In this Section, we analyse the estimated values of the $\Delta CoVaR$ of the three sectors,[11] ranking the systemically important institutions during the stock market crash, and finally, undertaking a statistical significance and dominance test to determine the contributions to systemic risk of the different sectors.

Figure 4.2 plots the $\Delta^{\$}CoVaR_{95^{th}}$ of the three financial sectors over the period analysed. The systemic contribution is weighted by the market equity of the companies included in the particular sector. Figure 4.2 clearly shows a dominance of the equity weighted marginal contribution of the banking sector for the entire period. However, what is not clear to see is the difference between the contribution of the insurance and brokerage sector and the real estate sector. For this reason, the results from the statistical tests are fundamental. Figure 4.2 highlights an interesting feature, namely that even though the banking sector contributes

[11] In this case, we considered X^i computed as the average market equity-valued returns of the 18 financial institutions, within the sector, weighted by their (lagged) market value of equity.

Figure 4.2: $\Delta^{\$}CoVaR_{95^{th}}$ of China's financial sectors.



Notes: The Figure plots the $\Delta^{\$}CoVaR_{95^{th}}$ of China's financial sectors: (i) Banks; (ii) Insurance and Brokerage Industries; and, (iii) Real Estate. The solid vertical lines mark: (1) the S&P downgrade of China developers in 2011; (2) the banking liquidity crisis in 2013; (3) the 27^{th} of July 2015; (4) the 24^{th} of August 2015 *("Black Monday")*; and, (5) the 4^{th} of January 2016.

more to systemic risk, the contribution of the other two financial sectors increased after 2014. In particular, the first two subperiods analysed are characterized by a banking systemic contribution, while the systemic risk level of the market turbulence of 2015–16 is higher due to a greater contribution from the other two financial sectors. Such findings confirm the fact that studies of systemic risk should no longer be undertaken considering the banking sector in isolation, given that systemic risk threatens the functioning of the entire financial system (Martínez-Jaramillo, Pérez, Embriz, and Dey, 2010).

Table 4.5 shows the descriptive statistics of the systemic contribution of the banking, insurance and brokerage, and real estate sectors, respectively. Considering the absolute value of the $\Delta CoVaR$, the banking sector, on average, has a higher contribution at the 95^{th} quantile over the entire time period of the study, moreover, the systemic contribution is less volatile compared to the other two financial sectors. However, the insurance and brokerage, and the real estate sectors reach a higher maximum peak. It is interesting to

Table 4.5: $\Delta CoVaRs$ of China's financial sectors.

	Banks				**Insurance and Brokerage**				**Real Estate**				
	Mean	Std. dev.	Max	Min	Mean	Std. dev.	Max	Min	Mean	Std. dev.	Max	Min	No. obs.
<u>2010-2016</u>													
$\Delta CoVaR_{75^{th}}$	1.1373	0.1590	1.7117	0.8054	1.0884	0.1791	1.7307	0.6766	1.1504	0.1576	1.7471	0.7046	1,712
$\Delta CoVaR_{95^{th}}$	3.1470	0.4734	5.2793	2.3604	2.9440	0.5268	5.7509	1.8390	3.0678	0.4940	5.6336	1.8403	1,712
$\Delta CoVaR_{99^{th}}$	4.8073	0.7944	8.6386	3.3889	4.6788	0.9064	9.2327	2.9071	4.7345	0.9473	9.9318	2.8983	1,712
<u>2010-2012</u>													
$\Delta CoVaR_{75^{th}}$	1.2173	0.1701	1.7117	0.8054	1.1765	0.1827	1.7307	0.7525	1.2012	0.1672	1.7471	0.7216	729
$\Delta CoVaR_{95^{th}}$	3.3614	0.5493	5.2793	2.3604	3.1504	0.6005	5.7509	1.8390	3.1826	0.5722	5.6336	1.8403	729
$\Delta CoVaR_{99^{th}}$	5.0739	0.9155	8.6386	3.4140	4.9249	0.9877	9.2327	2.9071	4.9562	1.0970	9.9318	2.8983	729
<u>2013-2014</u>													
$\Delta CoVaR_{75^{th}}$	1.0464	0.0973	1.3436	0.8446	0.9881	0.0958	1.2944	0.7845	1.0879	0.0986	1.4127	0.8392	491
$\Delta CoVaR_{95^{th}}$	2.8784	0.2296	3.6020	2.3676	2.6502	0.2675	3.5768	2.0872	2.8447	0.2692	3.7008	2.0978	491
$\Delta CoVaR_{99^{th}}$	4.3337	0.4027	5.7173	3.3889	4.1032	0.4947	5.9320	3.1381	4.2162	0.5262	5.8963	2.9608	491
<u>2015-2016</u>													
$\Delta CoVaR_{75^{th}}$	1.1096	0.1314	1.4853	0.8613	1.0577	0.1751	1.5053	0.6766	1.1374	0.1658	1.6078	0.7046	492
$\Delta CoVaR_{95^{th}}$	3.0975	0.3715	4.3394	2.5089	2.9313	0.4597	4.6083	2.0851	3.1204	0.4695	4.7820	2.1268	492
$\Delta CoVaR_{99^{th}}$	4.8850	0.6770	7.5578	3.6324	4.8886	0.8408	7.8740	3.0016	4.9234	0.8304	8.1573	2.9844	492

Notes: The Table shows the descriptive statistics of the $\Delta CoVaR$ related to the different quantiles for China's financial sectors. The whole sample period 2010-2016 includes three periods: the period after the Global crisis (2010-2012), the pre-Chinese market stock crash (2013-2014), the Chinese market stock crash (2015-2016). All the figures are expressed as a percentage.

see that, whereas prior to 2014, specifically during the first two subperiods analysed, the contribution of the banking sector is greater than the other two financial sectors, in the last subperiod (2015–2016) the contributions of the three sectors are similar, with the prevalence of the real estate sector, in absolute value. The finding that the systemic contribution of the banking sector remains less volatile, highlights a greater consistency over time. Overall, we can confirm that all three financial sectors represent a valid source of risk for the real economy.

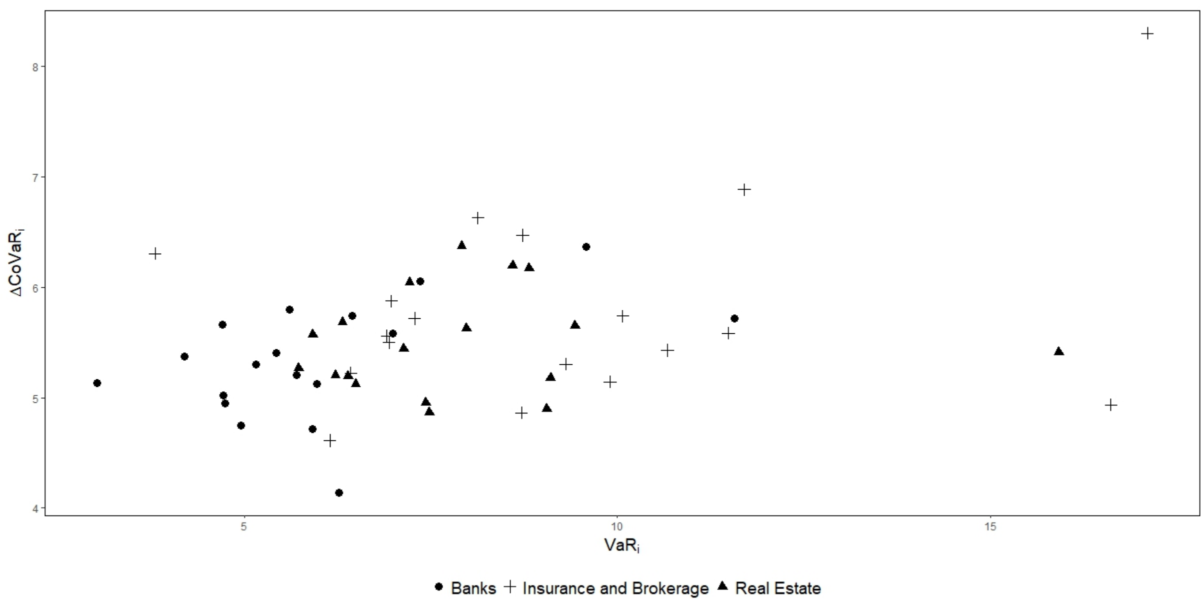
Table 4.6 shows the ranking, per sector, of the Chinese financial institutions as of August 24^{th}, 2015. Even in this case, it can be confirmed that the marginal contributions of the individual banks are not superior to the insurance and brokerage companies and the real estate companies. In particular, the company that experienced the highest contribution to systemic risk, namely China Galaxy Securities Co Ltd, is within the insurance and brokerage sector.

Figure 4.3 shows the relation between the VaR and the $\Delta CoVaR$ of the institutions within the three financial sector as of the 24^{th} of August. Figure 4.3 clearly shows that across institutions there exists a very loose link between VaR_i and $\Delta CoVaR_i$, consistent with the argument put forward by Adrian and Brunnermeier (2016). Such a finding implies that the supervisory authorities cannot rely on regulation based upon individual risk measures that do not consider the systemic risk.

The results above are based on average values. By using average values it is not possible to identify the sector that had the greatest risk during the entire period and subperiods analysed. Similar to Bernal, Gnabo, and Guilmin (2014), we implement two statistical tests: (i) a significance test to determine whether or not a sector is statistically significantly risky for the financial system; and, (ii) a dominance test in order to determine which sector has been more systemically risky. As described in Section 4.2.2, the bootstrap KS test is employed to test our hypothesis.

Table 4.7 presents the results for the significance test. We apply this test to verify

Figure 4.3: VaR and ΔCoVaR of the China's financial sectors.



Notes: The scatter plot shows the weak correlation between the VaR (x-axis) and the $\Delta CoVaR$ (y-axis) of the Chinese financial institutions as of the 24^{th} August 2015 (*"Black Monday"*). The VaR_i measures the the risk of the institution in isolation, while the $\Delta CoVaR_i$ measures the systemic risk of the same institution.

Table 4.6: Systemic risk ranking of the Chinese financial institutions as of August 24^{th}, 2015.

Rank	Banks		Insurance and Brokerage		Real Estate	
1.	Chongqing Rural Commercial Bank Co Ltd	6.37	China Galaxy Securities Co Ltd	8.30	Shimao Property Holdings Ltd	6.38
2.	China Minsheng Banking Corp Ltd	6.06	New China Life Insurance Co Ltd	6.88	Guangzhou R&F Properties Co Ltd	6.20
3.	Agricultural Bank of China Ltd	5.80	Haitong Securities Co Ltd	6.63	Sino-Ocean Group Holding Ltd	6.17
4.	BOC Hong Kong Holdings Ltd	5.74	People's Insurance Co Group of China Ltd/The	6.47	Country Garden Holdings Co Ltd	6.05
5.	China Development Bank International Investment Ltd	5.72	Manulife Financial Corp	6.31	China Resources Land Ltd	5.69
6.	HSBC Holdings PLC	5.66	China Pacific Insurance Group Co Ltd	5.88	Greentown China Holdings Ltd	5.65
7.	Dah Sing Banking Group Ltd	5.58	ZhongAn Online P&C Insurance Co Ltd	5.74	Agile Group Holdings Ltd	5.63
8.	Standard Chartered PLC	5.41	PICC Property & Casualty Co Ltd	5.72	SOHO China Ltd	5.57
9.	Public Financial Holdings Ltd	5.38	Shenwan Hongyuan HK Ltd	5.59	KWG Property Holding Ltd	5.44
10.	Bank of East Asia Ltd/The	5.30	Asia Financial Holdings Ltd	5.56	China Merchants Land Ltd	5.41
11.	Bank of China Ltd	5.20	China Life Insurance Co Ltd	5.50	China Overseas Land & Investment Ltd	5.27
12.	Hang Seng Bank Ltd	5.13	Haitong International Securities Group Ltd	5.43	Shui On Land Ltd	5.20
13.	Bank of Communications Co Ltd	5.13	First Shanghai Investments Ltd	5.30	China Properties Group Ltd	5.20
14.	Chong Hing Bank Ltd	5.02	Ping An Insurance Group Co of China Ltd	5.22	Hopson Development Holdings Ltd	5.18
15.	China CITIC Bank Corp Ltd	4.95	Ping An Securities Group Holdings Ltd	5.14	China Aoyuan Property Group Ltd	5.12
16.	China Construction Bank Corp	4.74	Celestial Asia Securities Holdings	4.94	K Wah International Holdings Ltd	4.96
17.	Industrial & Commercial Bank of China Ltd	4.72	China Taiping Insurance Holdings Co Ltd	4.86	Poly Property Group Co Ltd	4.90
18.	China Merchants Bank Co Ltd	4.14	AIA Group Ltd	4.61	Yuexiu Property Co Ltd	4.86

Notes: The companies are grouped by financial sectors and listed in descending order according to the $\Delta CoVaR_{95^{th}}$. The value of the $\Delta CoVaR$ is expressed as a percentage.

Table 4.7: Significance test results.

	2010–2016	2010–2012	2012–2014	2014–2016
H_0: $\Delta CoVaR$ *Banks = 0*	1.000***	1.000***	1.000***	1.000***
H_0: $\Delta CoVaR$ *Ins. and Brkg. = 0*	1.000***	1.000***	1.000***	1.000***
H_0: $\Delta CoVaR$ *RE = 0*	1.000***	1.000***	1.000***	1.000***

Notes: The Table reports the results of the significance test based on the two-sample Kolmogorov-Smirnov test. The null hypothesis *"$\Delta CoVaR$ Banks = 0"* determines whether or not the cumulative distribution function (CDFs) of the $CoVaRs$ at a 95^{th} quantile and at a 50^{th} quantile are different from each other. Therefore, the null hypothesis signifies that there is equality between the CDFs of the $CoVaRs$ related to the 95^{th} and 50^{th} quantile. The columns contain the test statistic. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 4.8: Dominance test results.

	2010–2016	2010–2012	2012–2014	2014–2016
H_0: *Banks* $\leq$ *Ins. and Brkg.*	0.2377***	0.2058***	0.3646***	0.2480***
H_0: *Banks* $\leq$ *RE*	0.0993***	0.1742***	0.1018***	0.0691***
H_0: *RE* $\leq$ *Ins. and Brkg.*	0.1589***	0.0549	0.2974***	0.2033***

Notes: The Table reports the results of the dominance test based on the two-sample Kolmogorov-Smirnov test. The null hypothesis *"Banks $\leq$ Ins. and Brkg."* means that the $\Delta CoVaRs_{95^{th}}$ related to the banking sector are lower (or equal to), in absolute value, than the $\Delta CoVaRs_{95^{th}}$ related to the insurance and brokerage sector. Therefore, the null hypothesis signifies that the banking sector is less (or equal) systemically risky than the insurance and brokerage sector. The columns contain the test statistic. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

whether there is no difference between the CoVaR measured at the 50^{th} and the 95^{th} quantiles. A finding of no difference between these values, namely that the $\Delta CoVaR$ is equal to zero, would imply that the sector has no contribution to the overall systemic risk. For each of the financial sectors considered, over all the time periods, the null hypothesis is rejected at 1% significance level, indicating that each financial sector is systemically relevant, significantly contributing to the systemic risk in China's financial system.

Table 4.8 presents the results for the dominance test. In this case, the dominance test is used to compare the cumulative distribution functions of the $\Delta CoVaRs$ of two distinct financial sectors, in order to determine which of them contributes most to systemic risk. In particular, we test the null hypothesis to determine whether a sector is less (or equally) risky compared to another sector, over all the time periods. The first row of Table 4.8 compares the banking sector with the insurance and brokerage sector. Our results show that the null hypothesis is rejected at 1% significance level, implying that the banking sector is systemically riskier than the insurance and brokerage sector. Such a finding is consistent across all time periods tested. The second row shows that banks are also systemically riskier than real estate companies. An interesting feature is reported in the third row, where it is found that real estate companies turn out to be systemically riskier than insurance and brokerage companies. Such a finding can be explained by the various property bubbles in China, which have made the real estate sector highly risky and volatile. The results do show that the finding that real estate companies are riskier than insurance and brokerage companies is not the case during the subperiod from the 1^{st} of January 2010 to the 31^{st} December 2012. This can be easily explained by the fact that, as already argued in Section 4.4.1, during this period the Chinese government introduced the economic stimulus program, which in turn deflated the property bubble. This probably decreased the systemic contribution of the real estate sector, stabilizing it.

Our results are consistent with previous literature examining systemic risk. In particular, our findings showing that the banking sector is systemically riskier than the insurance and brokerage sector is consistent with Bernal, Gnabo, and Guilmin (2014) for the Eurozone, and Girardi and Ergün (2013) for the US, where both adopted the $\Delta CoVaR$ to analyse systemic risk. Such findings are consistent with the argument put forward by Billio, Getmansky, Lo, and Pelizzon (2012), namely the banks plays a much more important role in transmitting systemic instability than other financial institutions. Furthermore, our finding that following the financial crisis of 2007 the real estate sector has become one of the main source of systemic risk, is consistent with Li, Pan, and He (2016) who found that, in China, the real estate sector has become systemically relevant to the point that affects bank returns.

4.5 Conclusion

Systemic risk can be looked upon as the risk associated with the collapse of a financial system. Given that a county's financial system is essential for its economy, the need not only to accurately measure systemic risk but also attempt to determine the contribution that individual sectors within the financial system play is important. As China balances on the edge of a financial crisis, with the global implications of such an event, concerns have been raised with respect to the size of systemic risk in China's financial system. This study contributes to the literature examining systemic risk by measuring the level of systemic risk of China's financial system, and assessing the contribution that key financial sectors play, namely banks, insurance and brokerage industries, and real estate, and specifically the role of individual institutions within these sectors. The analysis is undertaken during the period form January 2010 to December 2016, a period spanned by the deflating property bubble, the liquidity banking crisis, and the stock market crash. The systemic contribution of each of these sectors, and the level of systemic risk of the financial system, is measured by the systemic risk measure $\Delta CoVaR$ as proposed by Adrian and Brunnermeier (2016).

We find that the systemic risk level of China's financial system is linked to key financial events that occurred during the period analysed. In particular, systemic risk decreased after the property bubble deflated, only to increase again after the minimum value was reached in the second half of 2012 as a result of the bank liquidity crisis. The systemic risk drastically intensified after the stock market bubble burst in the summer of 2015. The restrictions imposed on investors by the Chinese government and supervisory authorities played a fundamental role in containing the implications of the stock market crash.

During the main systemic and financial instability dates covered by our sample period, the systemic risk level of the financial system and sectors significantly increased. Moreover, with respect to determining the systemic contribution of each of the sectors analysed, the significance test shows that the contribution of each sector is significantly important. The dominance test indicates that the banking sector contributes most to the overall systemic risk, this is the case in all the periods analysed. The real estate sector significantly exceeds the insurance and brokerage industry in the risk contribution. Such findings suggest the need to introduce an ad-hoc systemic regulation for each sector in order to monitor and contain the systemic contribution of the key companies identified within the sectors.

CHAPTER 5

Herding behavior and systemic risk in global stock markets

> *"However, focusing only on size fails to acknowledge that many small institutions can be systemic as a herd."*
>
> Adrian and Brunnermeier (2016)

5.1 Introduction

In the aftermath of the last two main crises, namely the Global Financial Crisis (GFC) and the Eurozone Crisis (EZC), herding behavior and systemic risk have become a relatively popular topic in the financial literature because of their potential impact on financial stability. Both concepts represent a pivotal issue for policymakers and supervisory authorities. Herding can be considered an ex-ante aspect of systemic risk. In particular, it affects the likelihood of joint failure of financial institutions, creating systemic risk, while information contagion, which is affected and affects herding, can be considered as the ex-post aspect of systemic risk (Acharya and Yorulmazer, 2008). Moreover, Demirer, Kutan, and Chen (2010) argue that correlated patterns of trades may aggravate returns' volatility, destabilizing the financial stability. This may undermine the goal of a financial stability authority, which is to identify vulnerabilities and the potential amplification channels, such as herding, and to preemptively address these vulnerabilities in order to reduce the frequency and severity of crises in the future (Liang, 2013).

This study investigates a large data-set containing 33 stock exchange markets categorized into Asia Pacific; Latin and North America; Western, Northern and Souther European markets.[1] This allows to analyze different investing behavior related to different countries. We analyze a sample period that fully capture the main market drops in the last decade, permitting to examine the different investing behavior related to different sub-periods. In particular, despite the prior literature, which offers a comprehensive analysis of herding behavior during the GFC (see, among others, Chiang and Zheng, 2010; Galariotis, Rong, and Spyrou, 2015; Mobarek, Mollah, and Keasey, 2014), the studies that attempt to investigate herding during the last main market turbulences are limited. We fill this gap, analyzing herding behavior during the last two main market drops, namely the EZC and the China's market crash of 2015-16, and investigating the herding patterns due to UK's Brexit tensions. Finally, this study opens a new research pattern by conditioning the investigation of herding behavior on different systemic risk levels of the market and analyzes the existing relationship between the return clustering of the market – i.e. the measure used to detect herding, and systemic risk.

Herding is commonly defined as a behavioral tendency of market participants that suppress their own beliefs in order to emulate collective actions in the market, leading to a convergence or a correlated patterns of actions among all or most of the market participants (see, among others, Nofsinger and Sias, 1999; Welch, 2000; Hwang and Salmon, 2004). The previous literature identifies several reasons that justify this behavior. According to Avery and Zemsky (1998), in the case of tail events of the market, herding is due to a mistaken belief that some investors may have more accurate information. Others like Devenow and

[1] We divide Europe in regions according to the EuroVoc classification. The EuroVoc is a multilingual thesaurus maintained by the Publications Office of the European Union. It is used by the European Parliament, the Publications Office of the European Union, the national and regional parliaments in Europe, some national government departments, and other European organisations.

Welch (1996) argue that investors may herd because of an intrinsic preference for conformity with the market consensus, while, Bernile and Jarrell (2009) and Carow, Heron, Lie, and Neal (2009) argue that, particularly after the arrival of public information, there are systematic patterns in institutional activities that may destabilize market prices, causing herding by private investors. Lastly, Bikhchandani and Sharma (2000) advocate that money managers may herd because of the incentives provided by the compensation scheme and terms of employment.

Hott (2009) developed a model for herding formation that shows how a price bubble is generated by herding behavior without assuming any speculative motivations. Also Dass, Massa, and Patgiri (2008) find that bubbles are caused by herding among traders and that traders herd when the incentives for herding are strong. Herding may trigger important informational inefficiencies in the market, contributing to, on average, to 4% of the asset's expected value (Cipriani and Guarino, 2014). In corporate bond markets institutional investors' herding is higher than the reported level observed in equities, and impact of herding is highly asymmetric (Cai, Han, Li, and Li, 2019). However, Bernile, Sulaeman, and Wang (2015) find that the anticipated trades by institutional investors ahead of other firms is more likely to reflect their superior ability to process publicly available information, rather than their access to private information.

Herding behavior may pose significant liquidity constrains to financial firms. In particular, according to Oh (2018), firms facing a severe liquidity constrain may be forced to sell a large part of their assets to avoid bankruptcy, causing a fire sale effect that could impact the entire industry, entailing correlated patterns of actions. Park and Sabourian (2011) find that people may herd if their information is sufficiently dispersed so that they consider extreme outcomes more likely than moderate ones. In turn, herding generates more volatile prices and lower liquidity. Also Avramov, Chordia, and Goyal (2006), by decomposing sell trades into "contrarian" and "herding" trades,[2] find that while contrarian trades decrease volatility,

[2] Avramov, Chordia, and Goyal (2006) define contrarian trades as sell trades when returns are positive; while, herding trades as sell trades when returns are negative.

herding trades tend to increase volatility. According to Drehmann, Oechssler, and Roider (2005) only the presence of a flexible market price prevents herding.

Several studies attempted to detect herding behavior in emerging and developed markets. Christie and Huang (1995), examining 12 US industries, were the first to try to detect herding during periods of large price movements. However, their results, based on daily and monthly data, are inconsistent with the presence of herding in all the 12 US industries. Chang, Cheng, and Khorana (2000) analyzed herding behavior within US and four Asian markets, namely Hong Kong, Japan, South Korea and Taiwan. They found evidence of herding only for South Korea and Taiwan. Since herding is more likely for emerging markets, it is well-researched in these markets (Mobarek, Mollah, and Keasey, 2014), with a particular focus to the Asian ones. Hence, there is a large body of research of herding in the Chinese stock markets. Demirer and Kutan (2006) investigate the presence of herding in the Shanghai and Shenzhen stock exchanges at the sector-level without finding evidence of it. Tan, Chiang, Mason, and Nelling (2008) examine herding behavior within the same stock exchanges. Considering the differences between A-share and B-share stocks, they found evidence of herding within both types of shares in rising and falling market conditions. Finally, Chiang, Li, and Tan (2010) use the quantile regression in order to resolve the mixed findings of herding behavior in China, highlighting a more pronounced herding within the A-share of both markets. Demirer, Kutan, and Chen (2010) study the Taiwanese market, within they find consistent results indicating strong evidence of herd formation in all sectors. The US REIT market is analyzed by Philippas, Economou, Babalos, and Kostakis (2013), who evidenced herding behavior during days of extreme negative returns; and by Zhou and Anderson (2013), who employing a larger sample period (1980-2010) find that herding is more pronounced in high quantiles. Their findings underline that investors tend to herd more likely under distressed market conditions. Gleason, Mathur, and Peterson (2004) analyze nine sectors of Exchange Traded Funds (ETF) using intra-day data. Their results support the conclusion that herding is absent in the ETFs.

A recent body of literature investigates the cross-country herding effects. Chiang and Zheng (2010) were the first to introduce this concept. They examine herding within eighteen markets, divided into advanced, Latin American and Asian markets, and, then, the presence of cross-country herding effects from the US market to the others. Their results support the presence of herding in all the markets except US and Latin American ones, in which they find herding only during crisis periods. Moreover, the US market seems to play a significant role in all the other markets in terms of cross-country herding effects. Economou, Kostakis, and Philippas (2011) study the presence of cross-country herding effects from the US market to four South European markets. Mobarek, Mollah, and Keasey (2014) expand this study to 11 developed European markets, adding evidences of cross-country herding effects from Germany. The last two studies highlight the presence of herding also in several asymmetric market conditions, such as conditions of rising and declining markets, high and low volatility and high and low trading volume. Galariotis, Rong, and Spyrou (2015) find evidence of herding for US investors when fundamental macroeconomic announcements are released and evidence of spill over herding effects from the US to the UK. Moreover, the authors study the difference between "spurious" – i.e. fundamental information driving herding, and "intentional" – i.e. herding due to other reasons not liked to fundamental information, herding. They report the presence of both types of herding in US during different crises, but the presence of only spurious herding in UK during the Dot-com bubble burst. Focusing only on the GFC period, Humayun Kabir (2018) studies herding in the US financial industries by introducing a new equation[3] that takes into account downward (upward) markets and the volatility. Moreover, the author enriches the finding of Galariotis, Rong, and Spyrou (2015), highlighting a more pronounce spurious herding for commercial and investment banks. Finally, Galariotis, Krokida, and Spyrou (2016) provides new evidence on the relationship between herding and equity market's liquidity for the US, France, Germany, UK and Japan.

[3] Humayun Kabir (2018) introduces the following augmented equation in order to detect herding: $CSAD_t = \alpha + \gamma_0|R_{m,t}| + \gamma_1 R_{m,t}^2 + \gamma_2 R_{m,t}^3 + \gamma_3 \sigma_t^2 R_{m,t}^2 + \varepsilon_t$, where a positive (negative) and significant value of γ_2 indicates that herding increases in a downward (upward) market, and, a positive (negative) and significant value of γ_3 indicates that herding decreases (increases) as the volatility (σ_t^2) increases (decreases).

Overall, the existing literature provides controversial evidences of herding behavior, stressing that emerging markets tend to herd more likely than the developed ones, and that herding is more pronounced in case of adverse market conditions, such as high volatility or days of negative market returns (falling market), and during market distressed periods. Because of these reasons, we are motivated to condition the study of herding behavior on systemic risk. Allen and Carletti (2013) argue that if financial markets are incomplete, banks cannot hedge completely against shocks and the financial system would stop providing an efficient level of liquidity. This could generate mispricing of assets, with prices that may fall below their fundamental values, leading to herding. Moreover, systemic risk typically builds in times of low market volatility, and materializes during crises (Adrian and Brunnermeier, 2016), which are characterized by falling markets with high volatility and illiquidity.

Economou, Kostakis, and Philippas (2011) argue that the financial stability is threatened by herding, which exposes market participants and financial institutions to unhedgeable systemic risk. According to Bikhchandani and Sharma (2000) intentional herding may intensify the impact of a crisis, leading to fragile markets, excess volatility and systemic risk. For instance, Galariotis, Rong, and Spyrou (2015) found that US market participants traded in the same direction because of fundamental economic information in various periods before the GFC, while, during the latter they just intentionally copy each other's actions. The relationship between herding and systemic risk has been connected also to the concept of portfolio diversification. In particular, Wagner (2010) argues that, nowadays, market participants tend to choose similar diversification strategies, worsening herding and not necessarily reducing systemic risk. Jorion (2007) examines the idea that financial institutions usually have very similar trading position before a period of turbulence, which could cause a value-at-risk herding behavior. However, his empirical results do not support this idea. On the contrary, he found high degree of diversification among the financial institutions in his sample.

Danielsson (2002) argues that a statistical risk model that works as advertised during crises should take into account herding, because, while in normal time market participants act individually, during crises, their actions become more similar. In particular, investors move from risky assets to safer ones. Adrian and Brunnermeier (2016) also connect the concept of herding with systemic risk. In particular, they coin the concept of an institution “systemic as a herd”. This concept stand in front of the “too-big-to-fail” one. The attention moves from the size of the institutions to their behavior. Institutions that behave in a similar way are expose to similar risks, this increases the probability of joint failure among herding institutions, threatening the financial stability of the system. Finally, herding can be related to systemic risk because financial institutions have the tendency to follow opportunistic decision, during distressed financial periods. This may lead to herding and create systemic risk (Boot, 2014).

The major findings of our study suggest that herding behavior is weak under normal conditions. However, during the EZC, we find significant herding coefficients in each Asia Pacific market, Latin and North American market, and European market except Greece, Ireland, Italy and Spain; while, during the China’s market crash, we find significant herding coefficients for all the market except Chile, China, Greece and Taiwan. These results suggest that herding behavior is linked to distressed periods not only related to the domestic market, but also to the foreign ones; and that different market turmoils may affect in different ways herding behavior. This evidence is straightened when we condition the analysis to UK economy conditions. In particular, we document important herding behavior evidences related to the UK economic conditions. We find herding behavior due to high UK un-healthy economic conditions, which becomes more pronounced isolating the high UK un-healthy economic conditions after the Brexit vote, entailing that the global equity market tensions due to Brexit strongly affect the herding behavior of investors.

We also find a strong relationship between herding and systemic risk. In particular, conditioning the herding analysis on different systemic risk levels, we find strong evidences of herding in case of high systemic risk level of the market. Moreover, the variance decomposition tests, based on an unrestricted Vector autoregressive (VAR) model – Appendix B.2, suggest that the variance of the systemic risk increases is affected by the return clustering. This effects is more pronounced for the Asia Pacific markets. The Granger causality tests indicate a two-way Granger causality in 112 cases, that cross-sectional absolute deviations (CSAD) Granger causes systemic risk increases in 52 cases, and, that systemic risk increases Granger cause CSAD in 44 cases. We find no Granger causality between these two variables in 56 cases. A two-way Granger causality is found for 26 countries during the GFC and for 13 counties, of which 8 European, during the EZC, entailing a stronger relationship between these two variables during the last two main crises. Finally, Johansen's vector error-correction model (VECM) suggests that a grater number of cases of interrelationship between CSAD and systemic risk increases, confirming the view of herding as an ex-ante aspect of systemic risk (Acharya and Yorulmazer, 2008).

The remainder of this Chapter is organized as follows. In Section 5.2 we outline the hypotheses, the tests and the data used in this study. The empirical results are presented in Section 5.3 while Section 5.4 concludes the analysis.

5.2 Methodology and data

For the empirical analysis we download the daily equity prices from all the constituent shares of the benchmark index of the countries included in our sample. In particular, our sample cover the Asia Pacific markets: Australia (S&P/ASX 200), China (SHASHR), Hong Kong (HSI), India (S&P BSE SENSEX), Indonesia (JCI), Japan (NIKKEI 225), Malaysia (FBMKLCI), Singapore (FSSTI), South Korea (KOSPI), Taiwan (TWSE), and Thailand (SET); the Latin American markets: Argentina (MERVAL), Brazil (IBOV), Chile (IPSA), and Mexico (S&P/BMV IPC); the North American markets: Canada (S&P/TSX), and the United States - USA (S&P 500); the European markets[1] divided into: Western European markets: Austria (ATX), Belgium (BEL 20), France (CAC 40), Germany (DAX), Ireland (ISEQ), Netherlands (AEX), Switzerland (SMI), and the United Kingdom - UK (FTSE 100);

Northern European markets: Denmark (OMXC 25), Finland (HEX), Norway (OSEBX), and Sweden (OMX); and, Southern European markets: Greece (ASE), Italy (FTSE MIB), Portugal (PSI 20), and Spain (IBEX 35). The data has been downloaded from Bloomberg for the period from the 1^{st} of January 2000 to the 31^{st} of January 2019. The share return at time t is calculated as $R_t = 100 \times (log(P_t) - log(P_{t-1}))$, where P_t denotes the constituent share price.

5.2.1 Detecting herding activity

Empirical investigations of herding behavior in financial markets classified two main types of measures that attempt to detect the presence of herding activity. The first type of measures focuses on cross-sectional data of equity returns (Christie and Huang, 1995; Chang, Cheng, and Khorana, 2000; Hwang and Salmon, 2004); while, the second type of measures is based on transaction data (Lakonishok, Shleifer, and Vishny, 1992; Wermers, 1999; Welch, 2000). Our study contributes to the empirical literature constructed on the first group of measures.

The two main measures built on cross-sectional dispersion of equity returns are the cross-sectional standard deviation (CSSD) and the CSAD developed by Christie and Huang (1995) and Chang, Cheng, and Khorana (2000), respectively. These measures are both based on the idea that herding behavior arises when investors follow the market consensus, neglecting their beliefs and information, entailing relatively low return dispersions. Christie and Huang (1995) were the first to highlight that this behavioural pattern is expected during distressed market periods. In particular, during these periods investors are incentivized to follow the market consensus to reduce or minimize their losses. This behavior contrasts the rational asset pricing models, which predict an increase in return dispersions during distressed market periods. The increase in return dispersions is justified by the different sensitivity of individual to market returns (Hwang and Salmon, 2004).

In order to conduct our empirical analysis we use the CSAD introduced by Chang, Cheng, and Khorana (2000) for two main reasons. First, the CSSD is considerably affected by the outliers in the data (Economou, Kostakis, and Philippas, 2011). Hence, Philippas, Economou, Babalos, and Kostakis (2013) argue that because the CSAD is less sensitive to returns outliers, it is the measure most commonly used in the empirical literature. Secondly, the model developed by Christie and Huang (1995) can exclusively analyze herding activity during tail market periods.[4]

The CSAD is defined as:

$$CSAD_t = \frac{\sum_{i=1}^{N} |R_{i,t} - R_{m,t}|}{N} \tag{5.1}$$

where $R_{i,t}$ is company i's return at time t and $R_{m,t}$ is the cross-sectional average return of the N companies considered in the universe we examine at time t. The average market portfolio return $R_{m,t}$ is constructed as the equally-weighted average of the N returns in the aggregate market portfolio at time t.[5]

In line with Chang, Cheng, and Khorana (2000), we use the following non-linear relationship between return dispersions and market returns to inspect the presence of herding activity:

$$CSAD_t = \alpha + \gamma_0 |R_{m,t}| + \gamma_1 R_{m,t}^2 + \varepsilon_t \tag{5.2}$$

The non-linear term ($R_{m,t}^2$) is introduced to capture herding. We employ Eq. (5.2) for each country to test for herding. In presence of herding we expect γ_1 to be negative and statistically significant.

As already mentioned, the previous literature reports that herding is more likely and pronounced during the periods of market distress. In order to examine whether or not

[4] Christie and Huang (1995) implemented the following regression in order to detect herding behavior: $CSSD_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + e_t$; where $CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(R_{i,t}-R_{m,t})^2}{N-1}}$, and D_t^L (D_t^U) is a dummy variable that takes the value 1 if the market return at time t lies in the extreme lower (upper) tail of the distribution, and 0 otherwise.

[5] In order to conduct a robustness test, we have alternatively used value-weighted average market portfolio returns. Results are both quantitative and qualitative similar and are available upon request.

herding is more pronounced during the EZC and the China's market crash, unlike Chiang and Zheng (2010) who use subperiods in Eq. (5.2), but similar to Tan, Chiang, Mason, and Nelling (2008), we augment Eq. (5.2) with a dummy variable D_1 that takes the value 1 during the market downturn period and 0 otherwise:

$$CSAD_t = \alpha + \gamma_0 |R_{m,t}| + \gamma_1 R_{m,t}^2 + D_1 \gamma_2 R_{m,t}^2 + \varepsilon_t \tag{5.3}$$

In Eq. (5.3) herding behavior is detected if γ_2 is negative and statistically significant.

According to Baur (2012), studies on financial crisis are to some degree dependent on the definition of crisis period. The prior literature offers three main methods to identify the crisis period. Forbes and Rigobon (2002) define the crisis period according to the major events characterizing the crisis; Boyer, Kumagai, and Yuan (2006) endogenously identify the crisis period from the data; while, Baur (2012) uses a mixture of the previous two methods. Our study relies on the former method. In particular, to define the crisis period, we consult the major characterizing events of the crisis. We define the EZC period from the 2^{nd} of May 2010, day of the first bailout package of the International Monetary Fund (IMF) for Greece, to the end of December 2012. The last quarter of 2012 has been characterized by the inception of the European Central Bank (ECB)'s Outright Monetary Transactions (OMT), which allowed free unlimited support for all the Eurozone countries; the establishment of the European Stability Mechanism (ESM); and, finally, the Greek government buy-back of €21 billion of their bonds.[6] Further, the China's market crash covers the period from the 12^{th} of June 2015, day in which the Shanghai index reached its peak to fell 30% in the subsequent three weeks, to the end of February 2016, month in which the Shanghai index gave the first signals of recovery.

When distress conditions impact many firms simultaneously, a negative stock price reaction to divestments is expected (Finlay, Marshall, and McColgan, 2018). On the 24^{th} of June

[6] Mobarek, Mollah, and Keasey (2014) define the same day for the beginning of the EZC; however, their sample period ends in February, while, our sample allows a more appropriate identification of this period.

2016, global equity markets lost more than 2 trillion dollars in value upon news of the Brexit vote results. This has been recognized as the largest single-day loss in absolute value ever experienced on global markets, which has driven the global economic policy uncertainty to record highs (Davis, 2016). Thus, herding behaviour may be prevalent in periods of market distress reflected by UK un-healthy economic conditions due to the Brexit vote. To capture the tensions due to Brexit, we use the Brexit barometer built by Bloomberg. This barometer is a custom index designed to show how the UK economy is responding to the Brexit process. It is powered by sub-indexes for employment, inflation, growth and uncertainty. The higher the value of the barometer, the healthier the economy, and vice versa. Similar to Chiang and Zheng (2010), we estimate the asymmetric behavior of return' dispersions as follows:

$$CSAD_t = \alpha + D^{Brexit}\gamma_0|R_{m,t}| + (1-D^{Brexit})\gamma_1|R_{m,t}| + D^{Brexit}\gamma_2 R^2_{m,t} + (1-D^{Brexit})\gamma_3 R^2_{m,t} + \varepsilon_t \tag{5.4}$$

where $R_{m,t}$ is the cross-sectional average of the N returns in the aggregate market portfolio at time t and D^{Brexit} is a dummy variable that takes the value 1 if the Brexit barometer on day t is worse than the previous 22-trading day (1-trading month) moving average and 0 otherwise. In order to test Eq. (5.4) during higher and lower UK un-healthy economic conditions strictly due to the Brexit vote, we consider two separate cases: i) we test Eq. (5.4) including all the observations from January 2000 to end-January 2019; and, ii) we test Eq. (5.4) including only the observations from June 2016 to end-January 2019. This allows us to isolate the UK un-healthy economic conditions that are strictly due to Brexit tensions. Herding effect is present if γ_2 (γ_3) is negative and statistically significant. If $\gamma_2 < \gamma_3$ and these values are significant, the herding effects are more pronounced during high UK un-healthy economic conditions.

All the hypotheses are tested using the classical OLS regression[7] and the quantile re-

[7]The West and Newey (1987) estimator has been used to obtain heteroskedasticity and autocorrelation consistent (HAC) co-variances for the OLS regression.

gression models.[8]

5.2.2 Measuring systemic risk

Systemic risk is configured as a broad concept, which does not have a unique definition. The definition of such risk varies according to its many dimensions[9] and different measures.[10] Acharya, Pedersen, Philippon, and Richardson (2017) define the systemic risk as a situation of market freezing, which could cause a significant reduction in financial intermediation activities, with potential adverse consequences for the real economy (Adrian and Brunnermeier, 2016).

In this study we use the well-know $\Delta CoVaR$ developed by Adrian and Brunnermeier (2016) as measure for systemic risk. The CoVaR is defined as the conditional-value at risk of the global financial system conditional on country i being in a particular state.[11] The main measure $\Delta CoVaR$ is estimated as the difference between the $CoVaR$ conditional on the distress of a country i and the $CoVaR$ conditional on the median state of the same.

We denote by $q\% - VaR_{q,i}$:

$$Pr(X_i \leq VaR_{q,i}) = q\% \tag{5.5}$$

where X_i is country i's *return loss* for which the $VaR_{q,i}$ is defined. $CoVaR_q^{Global|C(X_i)}$ is

[8]Unlike the classical linear regression methods, quantile regressions alleviate some of the statistical issues due to fat tails and outliers (Härdle and Song, 2010). Moreover, this model allows to consider a full range of conditional quantiles, which are usually associated with different states of the market. Because the previous literature found that herding is more pronounced during periods of market turbulence, we provide the results for all the hypotheses we test considering the 95^{th} and 99^{th} quantile, which are commonly associated with a distress state for the market (see, e.g, Adrian and Brunnermeier, 2016; Zhou and Anderson, 2013). For a detailed and complete description of the quantile regression method, readers can refer to Koenker and Bassett Jr (1978); Koenker (2005).

[9]According to Caruana (2010), systemic risk has two main dimensions: a cross-sectional dimension and a time dimension. The cross-sectional dimension relates to the structure of the financial system which paves the way to spreads difficulties from one or few subjects to the whole financial system. The time dimension relates to the progressive build-up of financial fragility and how aggregate risk evolves over time.

[10]For a detailed taxonomy of systemic risk measures, readers can refer to Bisias, Flood, Lo, and Valavanis (2012).

[11]Adrian and Brunnermeier (2016) defined the CoVaR as the conditional-value at risk of the whole financial sector conditional on institution i being in a particular state.

defined as the VaR of the global financial system conditional on some event $C(X_i)$ of country i. The event C is defined as an event equally likely across institutions. Usually C is country i's loss being at or above its $VaR_{q,i}$ level. $CoVaR_q^{Global|C(X_i)}$ is implicitly defined by the $q\%$-quantile of the conditional probability distribution:

$$Pr(X^{Global|C(X_i)} \leq CoVaR_q^{Global|C(X_i)}) = q\% \tag{5.6}$$

The $\Delta CoVaR$ of the global financial system conditional on country i being under distress is computed as follows:

$$\Delta CoVaR_q^{Global|i} = CoVaR_q^{Global|X_i=VaR_{q,i}} - CoVaR_q^{Global|X_i=VaR_{50^{th},i}} \tag{5.7}$$

The $\Delta CoVaR$ expressed in dollar terms is:

$$\Delta^{\$}CoVaR_q^{Global|i} = Size_i * \Delta CoVaR_q^{Global|i} \tag{5.8}$$

where $Size_i$ denotes the sum of the market value of equity of the constituents included in the benchmark index of country i.

We use quantile regression to estimate the $\Delta CoVaR$. In particular, following the approach of Adrian and Brunnermeier (2016), we estimate the following quantile regression:

$$X_{q,Global} = \alpha_q + \beta_q X_{q,i} \tag{5.9}$$

where $X_{q,Global}$ and $X_{q,i}$ denote the global financial system[12] and the country i return losses, respectively. Using the predicted value of $X_i = VaR_{q,i}$, we yields the $CoVaR_{q,i}$ measure as follow:

$$CoVaR_{q,i} = VaR_q^{Global|X_i=VaR_{q,i}} = \hat{\alpha}_q + \hat{\beta}_q VaR_{q,i} \tag{5.10}$$

[12] We use the MSCI World Index as benchmark for the global financial system. It is constituted by 1,649 constituents and covers approximately 85% of the free float-adjusted market capitalization across 23 developed markets. A detailed description of this index is available at: https://www.msci.com/world.

where $VaR_{q,i}$ is the $q\%$-quantile of country i losses.

Based on Eq. (5.7), the $\Delta CoVaR_{q,i}$ is estimated as:

$$\Delta CoVaR_{q,i} = CoVaR_{q,i} - CoVaR_q^{Global|X_i=VaR_{50^{th},i}} = \hat{\beta}_q(VaR_{q,i} - VaR_{50^{th},i}) \tag{5.11}$$

For each country included in our sample, we estimate the $\Delta CoVaR_{99^{th},i}$. Moreover, for each country, as per Adrian and Brunnermeier (2016), we obtain a panel of $\Delta^{\$}CoVaR_{99^{th},i}$, weighting the $\Delta CoVaR_{99^{th},i}$ at time t for the sum of the market capitalizations of the index constituents at time $t-1$.

As discussed in the introduction, a pivotal issue is to investigate whether or not herding behavior arises during high market systemic risk conditions. In order to test the herding activity conditional on different systemic risk condition, we augment Eq. (5.2) and estimate it as follow:[13]

$$CSAD_t = \alpha + \gamma_0|R_{m,t}| + \gamma_1 R_{m,t}^2 + D_1\gamma_2 R_{m,t}^2 + D_2\gamma_3 R_{m,t}^2 + \varepsilon_t \tag{5.12}$$

where, the dummy variable D_1 takes the value of 1 if the $\Delta^{\$}CoVaR_{99^{th},i}$ lies above the 3^{rd} quartile (75^{th} quantile) of the empirical distribution and 0 otherwise; and, the dummy variable D_2 takes the value of 1 if the $\Delta^{\$}CoVaR_{99^{th},i}$ lies below the 1^{st} quartile (25^{th} quantile) of the empirical distribution and 0 otherwise.

Estimating Eq. (5.12), γ_1, γ_2 and γ_3 reflect the herding activity in case of medium, high and low systemic risk, respectively. Herding effects are present if γ_i (i = 1, 2, 3) is negative and statistically significant, with $\gamma_i < \gamma_j$ (i = 1, 2, 3; j = 1, 2, 3; $i \neq j$) if these effects are more pronounced during the i systemic condition of the market.

In order to conduct a robustness test, we estimate Eq. (5.12) with the dummy vari-

[13] Galariotis, Krokida, and Spyrou (2016) use the same regression model to detect herding behavior during market conditions of high, medium and low market liquidity. The dummy variables D_1 and D_2 are conditioned to the Amihud illiquidity measure (Amihud, 2002) modified according to Karolyi, Lee, and Van Dijk (2012), in order to measure liquidity instead of illiquidity.

ables D_1 and D_2 constructed with: i) the marginal expected shortfall (MES) introduced by Acharya, Pedersen, Philippon, and Richardson (2017); and, ii) the long run MES (LRMES) of Brownlees and Engle (2016), which is the expected shortfall component of the SRISK. In particular, the dummy variable D_1 takes the value of 1 if the systemic risk measure (SRM) lies above the 3^{rd} quartile (75^{th} quantile) of the empirical distribution and 0 otherwise; and, the dummy variable D_2 takes the value of 1 if the SRM lies below the 1^{st} quartile (25^{th} quantile) of the empirical distribution and 0 otherwise.

The MES is defined as the the equal-weighted average return of any given country i for the 5% of the worst days for the global financial system returns:

$$MES_{5\%,i} = \frac{1}{\#days} \sum_{\text{t: system is in its 5\% tail}} R_{i,t} \tag{5.13}$$

The $LRMES_{i,t}$ is estimated as $1 - exp(log(1-d) * \beta)$, where d is the six-month crisis threshold for the global market index decline and its default value is 40%, and β is the firm's beta coefficient. For each country, we weight $MES_{5\%,i}$ and $LRMES_{i,t}$ at time t for the sum of the market capitalizations of the index constituents at time $t-1$.[14]

5.2.3 Granger causality

The short-term dynamics of cointegrated series is studied using the Granger causality test, which allows for specifying the direction of causality between systemic risk increases and the return clustering measure (CSAD) for each country in our sample. Granger causality allows to determine non-restrictions on lagged variables by assessing interdependence between the different time series in a given system. This ensures that information available on the past values of x_t does not have statistical impact on the present and/or future values of y_t.

The Null Hypothesis states that each variable "does not cause" the other. In particular,

[14] Results are both quantitative and qualitative similar and are available in Appendix B.1.

x_t does not Granger cause y_t if $P(y_t|y_{t-h}) = P(Y_T|x_{t-h}, y_{t-h})$. Where y_{t-h} (x_{t-h}) is the lagged value of y_t (x_t) – the lag length is chosen based on the Akaike information criterion (AIC).

It is important to recall that the Granger causality test is based on the notion of predictability, time-based succession and assumes the stationarity of the time series on the long term. Moreover, the Granger causality test does not imply that one variable is the effect of the other; more precisely, it indicates that one variable contains information about the other.

In order to obtain a more comprehensive analysis we present the results related to the full sample period and seven sub-periods, which span: i) the period prior to the GFC; ii) the GFC; iii) the period subsequent the GFC and prior to the EZC; iv) the EZC; v) the period subsequent the EZC and prior to the China's market crash; vi) China's market crash; and, finally, vii) the period after China's market crash, that concludes our sample period in January 2019.[15]

5.2.4 Johansen's vector error-correction model

Using Johansen's VECM, this study aims to examine the dynamic co-movement and the long-term relationship between systemic risk increases and the return clustering measure (CSAD). In a multivariate context, Engle and Granger (1987) two-step error-correction model may also be used. However, the VECM, which is a full information maximum likelihood estimation model, yields more efficient estimators of cointegrating vectors, allowing for testing for cointegration in a whole system of equations in one step and without requiring a specific variable to be normalized. This also remove the possibility to carrying over

[15] Our sub-periods are defined as follow: i) from the 1^{st} Jan. 2000 to the 8^{th} Aug. 2007; ii) from the 9^{th} Aug. 2007 to the 31^{st} March 2009; iii) from the 1^{st} April 2009 to the 1^{st} May 2010; iv) from the 2^{nd} May 2010 to the 31^{st} Dec. 2012; v) from the 1^{st} Jan. 2013 to the 11^{th} June 2015; vi) from the 12^{th} June 2015 to the 29^{th} Feb. 2016; vii) from the 1^{st} March 2016 to the 31^{th} Jan. 2019. We explain how we define a crisis period and how we defined the EZC and the China's market crash in Section 5.2.1. We use the same period identified by Galariotis, Rong, and Spyrou (2015) for the GFC. Major details for the usage of this period as proxy of the GFC can be found on the 79^{th} Annual Report of the Bank for International Settlements, (Bank for International Settlements, 2009).

errors from the first step into the second, as it would be in case of the model developed by Engle and Granger. Moreover, it has the advantage of not requiring a priori assumptions of endogenity or exogenity of the variables. The VECM is defined as follow:

$$\Delta y = \beta_0 + \sum_{i=1}^{n} \beta_i \Delta y_{t-i} + \sum_{i=0}^{n} \delta_i \Delta x_{t-i} + \phi z_{t-1} + \mu_t \tag{5.14}$$

Where z is the error correction term (ECT), which relates to the fact that the last period deviation from long-run equilibrium influences the short-run dynamics of the dependent variable. Thus ϕ is the speed of adjustment. A larger ϕ would suggest a faster convergence toward long-run equilibrium in cases of short-run deviations from this equilibrium.

5.3 Results

The first set of results, presented in Table 5.1, corresponds to the estimates from Eq. (5.2). The results are estimated for each market considering the full sample period (January 2000 to end-January 2019). As stated in Section 5.2.1, a negative and statistically significant coefficient γ_1 is consistent with the presence of herding. Figure 5.1 presents the geographical heat-map of our findings. It colours in red, orange and yellow countries where we find a statistically significant herding coefficient at 1% (***), 5% (**), and 10% (*) levels, respectively.

The OLS results indicate a positive and significant coefficient γ_0 for all the markets analyzed. This estimate confirms the standard asset pricing models, which imply that the CSAD increases with the magnitude of market returns. Likewise the squared market returns' coefficient (γ_1) is not significant for most of the markets analyzed. Indeed, apart from China, Indonesia and Taiwan for the Asia Pacific markets; Chile for the Latin American and Italy for the Southern European markets, we do not find evidence of herding based on the OLS estimates for all the remaining markets. The herding activity in the China's market is confirmed also by Chiang, Li, and Tan (2010). Moreover, the presence of herding in the

Table 5.1: Estimates of herding behavior in global stock markets.

Asia Pacific

		γ_0	γ_1	α	*Adj.* R^2
Australia	*OLS*	0.350***	0.021	1.202***	28.56%
	τ=95th	0.855***	-0.018	1.676***	25.20%
	τ=99th	0.953***	-0.079***	2.287***	26.37%
China	*OLS*	0.350***	-0.023***	1.111***	22.30%
	τ=95th	0.357***	-0.007	2.014***	19.46%
	τ=99th	0.528***	-0.028	2.509***	21.00%
Hong Kong	*OLS*	0.285***	0.005	0.990***	34.05%
	τ=95th	0.466***	0.004	1.613***	25.24%
	τ=99th	0.717***	-0.009	2.140***	29.48%
India	*OLS*	0.107	0.035	1.173***	23.87%
	τ=95th	0.218***	0.070***	1.838***	25.05%
	τ=99th	0.408***	0.057***	2.213***	37.78%
Indonesia	*OLS*	0.774***	-0.037***	1.430***	51.41%
	τ=95th	0.941***	-0.007	2.077***	42.71%
	τ=99th	1.152***	-0.036*	2.569***	49.09%
Japan	*OLS*	0.222***	0.002	1.073***	22.89%
	τ=95th	0.319	0.005	1.821***	15.98%
	τ=99th	0.451*	-0.015	2.480***	15.98%
Malaysia	*OLS*	0.486***	-0.008	0.699***	43.72%
	τ=95th	0.510***	0.012	1.241***	30.65%
	τ=99th	0.647***	-0.029	1.548***	38.27%
Singapore	*OLS*	0.309***	0.012*	0.878***	27.95%
	τ=95th	0.460***	0.028	1.532***	22.09%
	τ=99th	0.523	0.073	2.116***	23.64%
South Korea	*OLS*	0.228***	0.024***	1.655***	84.91%
	τ=95th	0.507***	0.019***	2.289***	40.71%
	τ=99th	0.777***	0.013***	2.724***	55.41%
Taiwan	*OLS*	0.234***	-0.050***	0.969***	3.97%
	τ=95th	0.626***	-0.089***	1.494***	13.97%
	τ=99th	0.542***	-0.058***	2.036***	10.71%
Thailand	*OLS*	0.584***	0.001	1.234***	58.84%
	τ=95th	0.779***	-0.007	1.759***	41.92%
	τ=99th	0.877***	-0.026***	2.190***	50.04%

Latin America

		γ_0	γ_1	α	*Adj.* R^2
Argentina	*OLS*	0.434***	0.006	1.137***	42.92%
	τ=95th	0.532***	0.033***	1.974***	30.34%
	τ=99th	0.806***	0.001	2.717***	35.75%
Brazil	*OLS*	0.188***	0.015***	1.297***	30.59%
	τ=95th	0.177**	0.053***	1.985***	22.87%
	τ=99th	0.323	0.026	2.453***	30.99%
Chile	*OLS*	0.373***	-0.010**	0.811***	33.60%
	τ=95th	0.469	0.025	1.254***	26.61%
	τ=99th	0.332	0.247	1.561***	36.28%
Mexico	*OLS*	0.369***	0.025***	0.934***	40.37%
	τ=95th	0.441	0.079	1.537***	31.35%
	τ=99th	0.867***	0.020	1.869***	36.94%

North America

		γ_0	γ_1	α	*Adj.* R^2
Canada	*OLS*	0.416***	0.028**	1.230***	35.17%
	τ=95th	0.587***	0.041	1.991***	24.73%
	τ=99th	0.633***	0.082	2.602***	30.81%
USA	*OLS*	0.294***	0.010*	0.957***	31.17%
	τ=95th	0.424***	-0.003	1.907***	21.07%
	τ=99th	0.396***	0.003	2.419***	26.84%

Western Europe

		γ_0	γ_1	α	*Adj.* R^2
Austria	*OLS*	0.312***	0.027***	0.883***	34.83%
	τ=95th	0.538***	0.052	1.471***	34.97%
	τ=99th	0.801***	0.020	2.057***	39.91%
Belgium	*OLS*	0.277***	0.041***	0.767***	37.57%
	τ=95th	0.490***	0.074**	1.399***	30.80%
	τ=99th	0.229	0.319***	2.177***	35.58%
France	*OLS*	0.266***	0.006	0.847***	27.10%
	τ=95th	0.532***	-0.011	1.572***	18.93%
	τ=99th	1.000***	-0.081***	2.207***	15.47%
Germany	*OLS*	0.248***	0.011**	0.855***	27.91%
	τ=95th	0.522***	-0.010**	1.538***	21.20%
	τ=99th	0.522***	-0.017**	2.312***	19.17%
Ireland	*OLS*	0.760***	0.047**	1.383***	52.94%
	τ=95th	1.221***	0.034***	2.433***	40.44%
	τ=99th	1.404***	0.016	3.376***	43.98%
Netherlands	*OLS*	0.256***	0.023**	0.918***	29.65%
	τ=95th	0.317*	0.055	1.758***	20.86%
	τ=99th	0.170	0.131***	2.595***	21.13%
Switzerland	*OLS*	0.293***	0.016*	0.676***	36.35%
	τ=95th	0.634***	-0.017*	1.266***	30.53%
	τ=99th	0.421***	0.134***	1.821***	33.95%
UK	*OLS*	0.232***	0.030***	0.963***	30.20%
	τ=95th	0.513**	0.017	1.610***	21.88%
	τ=99th	0.510***	0.043*	2.279***	24.97%

Northern Europe

		γ_0	γ_1	α	*Adj.* R^2
Denmark	*OLS*	0.187**	0.051**	1.001***	29.16%
	τ=95th	0.229***	0.131***	1.905***	23.03%
	τ=99th	0.365**	0.191***	2.541***	33.44%
Finland	*OLS*	0.560***	-0.020	1.257***	37.01%
	τ=95th	0.740***	-0.027	1.916***	26.76%
	τ=99th	0.520***	0.029	2.546***	25.58%
Norway	*OLS*	0.383***	0.017*	1.456***	37.73%
	τ=95th	0.485***	0.045*	2.268***	29.83%
	τ=99th	0.080	0.280***	3.087***	38.30%
Sweden	*OLS*	0.234***	0.006	0.892***	22.86%
	τ=95th	0.399***	-0.004	1.643***	16.65%
	τ=99th	0.602***	-0.034	2.145***	21.57%

Southern Europe

		γ_0	γ_1	α	*Adj.* R^2
Greece	*OLS*	0.296***	0.005	1.374***	36.12%
	τ=95th	0.494***	0.006***	2.083***	32.10%
	τ=99th	0.485***	0.015	2.670***	37.84%
Italy	*OLS*	0.303***	-0.016	0.866***	20.58%
	τ=95th	0.479***	-0.010***	1.449***	23.02%
	τ=99th	0.526***	-0.017***	1.973***	20.57%
Portugal	*OLS*	0.425***	-0.009*	0.828***	34.61%
	τ=95th	0.520***	0.026	1.484***	22.73%
	τ=99th	0.454***	0.050**	2.081***	28.78%
Spain	*OLS*	0.278***	0.004	0.799***	27.73%
	τ=95th	0.310***	0.027**	1.512***	19.17%
	τ=99th	0.437	0.052	1.963***	21.23%

Notes: The table reports the estimated coefficients of Eq. (5.2): $CSAD_t = \alpha + \gamma_0|R_{m,t}| + \gamma_1 R^2_{m,t} + \varepsilon_t$, where $CSAD_t$ is the cross-sectional absolute deviation and $R_{m,t}$ is the market return. A significant negative value of γ_1 suggests the presence of herding. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

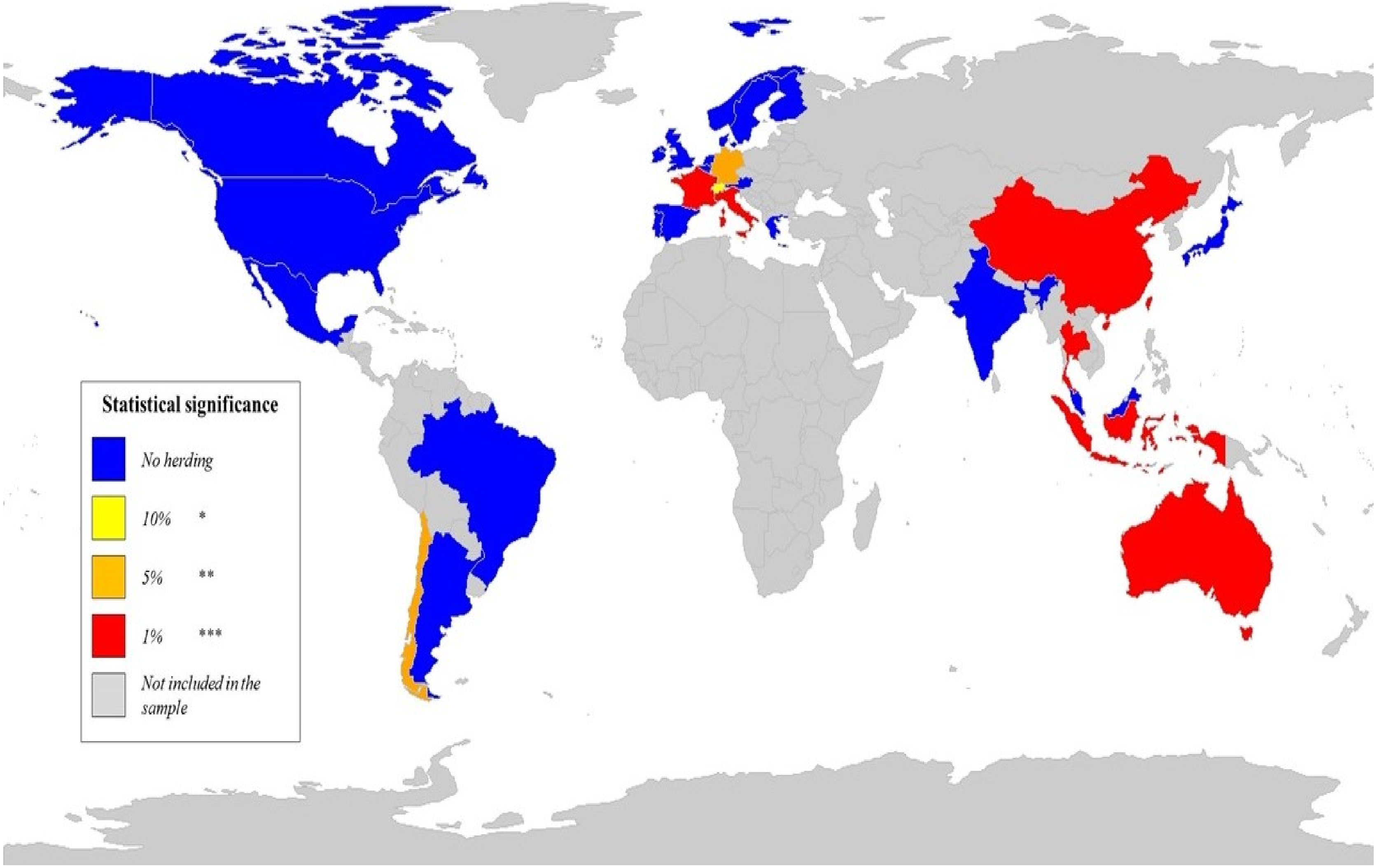


Figure 5.1: Herding behavior in global stock markets.

Notes: The Figure shows the estimated coefficients of Eq. (5.2): $CSAD_t = \alpha + \gamma_0 |R_{m,t}| + \gamma_1 R_{m,t}^2 + \varepsilon_t$. A significant negative value of γ_1 suggests the presence of herding; it is colored in: red, orange and yellow when significant at 1% (***), 5% (**), and 10% (*) levels, respectively. In countries colored in blue, no evidence of herding are found; while, countries in grey are not included in our analysis.

other mentioned Asia Pacific markets is in line with the finding of Chiang and Zheng (2010). The finding related to the Italy's market is supported by Economou, Kostakis, and Philippas (2011), who analyze a sample period from 1998 to 2008. However, Mobarek, Mollah, and Keasey (2014), analyzing a more recent period[16] compared to Economou, Kostakis, and Philippas (2011) but shorter compared to us, do not find any evidence of herding in Italy. Moreover, they find a veiled herding activity – i.e. γ_1 significant at 10% – in Finland that we do not find. In our case, the herding coefficient associated with Finland is negative, but not statistically significant. The absence of herding in all the Latin and Northern American, the remaining Asia Pacific and European markets is supported by the previous literature (see, among the others, Christie and Huang, 1995; Chang, Cheng, and Khorana, 2000; Chiang and Zheng, 2010 and Galariotis, Rong, and Spyrou, 2015).

Table 5.1 shows also the quantile estimates[17] with $\tau = 95^{th}$ and 99^{th}. We do not find any difference of sign, which remains positive, in the linear term; however, the significance and the sign of the non-linear term (γ_1) change across different quantiles. In particular, using quantile regressions, we find evidence of herding also for Australia and Thailand in the Asia Pacific markets; and for France, Germany and Switzerland in the Western European markets. The quantile regression estimates detect herding behavior, in the higher quantiles, in more Asia Pacific markets, namely Australia, Indonesia, Taiwan and Thailand,[18] entailing the presence of herding in case of distressed states for these markets. Moreover, herding is identified in advanced European markets, such as France and Germany. Voronkova (2004) found a strong linkage between emerging European stock markets, such as Hungary and Poland, and Western European markets, such as France and Germany. Moreover, Mobarek, Mollah, and Keasey (2014) found Germany to have the greatest influence on European markets such as

[16] Mobarek, Mollah, and Keasey (2014) consider a sample period from 2001 to 2012.

[17] For all the hypotheses tested in this study, we estimate the 10^{th}, 25^{th}, 50^{th}, 75^{th}, 95^{th} and 99^{th} quantiles. For reason of space and because herding is more pronounced during turbulent market periods, which are usually represented by high quantiles, we report only the estimates for the 95^{th} and 99^{th} quantiles. The estimates related to the other quantiles are available upon request.

[18] The quantile (with $\tau = 95^{th}$ and 99^{th}) herding estimate (γ_1) is found negative and not significant for China.

France, Greece, Italy, Norway and Sweden in term of herding spill over effects. This highlight that, this finding is of utmost importance for policymakers and supervisory authorities, because the presence of herding in advanced[19] European stock markets may imply contagion in emerging European markets, threatening the financial stability of Europe, and, at the same time, of the Eurozone.

5.3.1 Herding behavior during the Eurozone crisis and the China's market crash

As stated in Section 5.2.1, herding behavior is more pronounced in case of market turbulence. The prior literature offers a comprehensive analysis of herding behavior during the GFC (see, among others, Chiang and Zheng, 2010; Galariotis, Rong, and Spyrou, 2015; Mobarek, Mollah, and Keasey, 2014). This motivates us to analyze the presence of herding behavior during the last two main financial market drops, namely the EZC and the China's market crash of 2015-16.

Table 5.2 reports the estimates of Eq. (5.3) focusing on the dummy variable D_1 related to the EZC. Analyzing the OLS estimates of the Asia Pacific markets, we find that the herding coefficient (γ_2) is negative and significant for all the markets except Hong Kong, Indonesia and Japan. An interesting insight is that, for these three countries, the herding coefficient becomes negative and significant, analyzing the quantile regression estimates in the higher quantiles. In particular, comparing the OLS and the quantile estimates for each market, it is possible to observe that herding is also more pronounced in the higher quantiles for all the Asia Pacific markets, entailing a greater herding activity in these markets in case of distressed state of the market, during the EZC. The same result is found for all the Latin and Northern American markets. Figure 5.2 presents the geographical heat-map of our findings.

[19] According to the MSCI market classification, we classify: all the Western and Northern European and North American countries, Australia, Hong Kong, Italy, Japan, Portugal, Singapore and Spain as advanced market; Brazil, Chile, China, Greece, India, Indonesia, Malaysia, Mexico, South Korea, Taiwan and Thailand as emerging market; Argentina as frontier market.

Table 5.2: Estimates of herding behavior in global markets during the EZC.

Asia Pacific

		γ_0	γ_1	γ_2	$Adj.R^2$
Australia	*OLS*	0.397***	0.019	-0.108***	30.63%
	τ=95th	0.696***	0.016	-0.527***	28.43%
	τ=99th	0.808***	-0.050	-0.880***	30.73%
China	*OLS*	0.368***	-0.025***	-0.027***	22.84%
	τ=95th	0.311***	-0.003	-0.566***	22.59%
	τ=99th	0.474***	-0.023	-0.847***	24.16%
Hong Kong	*OLS*	0.295***	0.005	-0.021	34.35%
	τ=95th	0.432***	0.007	-0.409***	27.43%
	τ=99th	0.681***	-0.006	-0.821***	32.40%
India	*OLS*	0.115	0.034	-0.033*	23.97%
	τ=95th	0.167***	0.073***	-0.506***	28.27%
	τ=99th	0.290***	0.063***	-0.772***	40.17%
Indonesia	*OLS*	0.773***	-0.037***	0.001	51.40%
	τ=95th	0.886***	0.001	-0.484***	45.14%
	τ=99th	1.128***	-0.034*	-0.853***	52.15%
Japan	*OLS*	0.220***	0.003	-0.006	22.95%
	τ=95th	0.276***	0.015	-0.695***	20.87%
	τ=99th	0.412***	-0.010	-1.162***	21.91%
Malaysia	*OLS*	0.507***	-0.012	-0.114***	44.39%
	τ=95th	0.474***	0.029	-0.355***	33.07%
	τ=99th	0.561***	-0.013	-0.488***	40.40%
Singapore	*OLS*	0.338***	0.008	-0.090***	28.93%
	τ=95th	0.376***	0.045	-0.585***	26.01%
	τ=99th	0.450	0.086	-0.938***	28.06%
South Korea	*OLS*	0.236***	0.023***	-0.019*	84.95%
	τ=95th	0.460***	0.019***	-0.476***	42.91%
	τ=99th	0.697***	0.015***	-0.838***	57.20%
Taiwan	*OLS*	0.204***	-0.048***	0.059***	5.89%
	τ=95th	0.572***	-0.077***	-0.225***	15.12%
	τ=99th	0.531***	-0.057***	-0.522***	13.40%
Thailand	*OLS*	0.594***	0.002	-0.046***	59.37%
	τ=95th	0.721***	-0.001	-0.327***	43.44%
	τ=99th	0.831***	-0.020*	-0.508***	51.62%

Latin America

		γ_0	γ_1	γ_2	$Adj.R^2$
Argentina	*OLS*	0.438***	0.008	-0.031***	43.52%
	τ=95th	0.508***	0.035***	-0.369***	31.19%
	τ=99th	0.713	0.024	-0.702***	37.22%
Brazil	*OLS*	0.194***	0.016***	-0.034***	31.33%
	τ=95th	0.130	0.058***	-0.456***	25.11%
	τ=99th	0.295	0.029	-0.551***	32.87%
Chile	*OLS*	0.379***	-0.007*	-0.026***	34.10%
	τ=95th	0.488*	0.011	-0.132***	27.14%
	τ=99th	0.387	0.225	-0.166***	36.96%
Mexico	*OLS*	0.377***	0.029***	-0.069***	41.65%
	τ=95th	0.404	0.088	-0.275***	32.38%
	τ=99th	0.727***	0.046	-0.247	37.63%

North America

		γ_0	γ_1	γ_2	$Adj.R^2$
Canada	*OLS*	0.460***	0.025*	-0.117***	36.69%
	τ=95th	0.583***	0.038	-0.719***	28.99%
	τ=99th	0.836***	0.031	-1.086***	35.11%
USA	*OLS*	0.331***	0.010	-0.059***	33.82%
	τ=95th	0.331***	0.009	-1.019***	28.36%
	τ=99th	0.346***	0.009	-1.348***	33.44%

Western Europe

		γ_0	γ_1	γ_2	$Adj.R^2$
Austria	*OLS*	0.332***	0.027***	-0.032***	35.38%
	τ=95th	0.538***	0.050	-0.213***	35.27%
	τ=99th	0.782***	0.022	-0.328*	40.30%
Belgium	*OLS*	0.273***	0.051***	-0.039***	38.79%
	τ=95th	0.486***	0.070**	-0.190***	31.06%
	τ=99th	0.183	0.324***	-0.501***	36.57%
France	*OLS*	0.277***	0.009	-0.028***	28.07%
	τ=95th	0.461***	-0.003	-0.592***	21.85%
	τ=99th	0.842***	-0.067***	-1.122***	19.63%
Germany	*OLS*	0.272***	0.012**	-0.039***	29.30%
	τ=95th	0.452***	-0.004	-0.534***	23.66%
	τ=99th	0.441***	-0.007	-0.963***	22.88%
Ireland	*OLS*	0.753***	0.048**	0.013	52.94%
	τ=95th	1.216***	0.034***	0.100	40.48%
	τ=99th	1.404***	0.016	0.050	43.98%
Netherlands	*OLS*	0.279***	0.024**	-0.047***	30.96%
	τ=95th	0.360**	0.038	-0.669***	24.38%
	τ=99th	0.137	0.134***	-1.036***	25.43%
Switzerland	*OLS*	0.322***	0.015*	-0.051***	37.99%
	τ=95th	0.603***	-0.014	-0.454***	32.67%
	τ=99th	0.449***	0.129***	-0.691***	36.63%
UK	*OLS*	0.269***	0.029**	-0.063***	32.03%
	τ=95th	0.370***	0.050	-0.681***	26.32%
	τ=99th	0.384***	0.060***	-1.166***	30.37%

Northern Europe

		γ_0	γ_1	γ_2	$Adj.R^2$
Denmark	*OLS*	0.187**	0.051*	0.004	29.15%
	τ=95th	0.203***	0.133***	-0.306***	23.68%
	τ=99th	0.266*	0.202***	-0.614***	34.96%
Finland	*OLS*	0.529***	0.008	-0.062***	38.27%
	τ=95th	0.621***	0.017	-0.446***	29.40%
	τ=99th	0.466***	0.036	-0.742***	28.88%
Norway	*OLS*	0.398***	0.018*	-0.030***	38.29%
	τ=95th	0.467***	0.048*	-0.116	29.93%
	τ=99th	0.078	0.280***	-0.065	38.36%
Sweden	*OLS*	0.252***	0.008	-0.040***	24.62%
	τ=95th	0.348***	0.002	-0.590***	20.06%
	τ=99th	0.648***	-0.045	-0.779***	24.42%

Southern Europe

		γ_0	γ_1	γ_2	$Adj.R^2$
Greece	*OLS*	0.291***	0.001	0.027***	37.93%
	τ=95th	0.458***	0.008***	0.363***	33.50%
	τ=99th	0.492***	0.016	0.588***	39.12%
Italy	*OLS*	0.292***	-0.017	0.014	20.95%
	τ=95th	0.478***	-0.010***	0.114*	23.24%
	τ=99th	0.556***	-0.019***	0.732***	22.53%
Portugal	*OLS*	0.426***	-0.008	-0.011	34.65%
	τ=95th	0.523***	0.025	-0.020	22.74%
	τ=99th	0.419***	0.055**	-0.216***	29.32%
Spain	*OLS*	0.282***	0.005	-0.011	27.91%
	τ=95th	0.305***	0.029**	-0.070	19.26%
	τ=99th	0.448	0.049	-0.124	21.36%

Notes: The table reports the estimated coefficients of Eq. (5.3): $CSAD_t = \alpha + \gamma_0|R_{m,t}| + \gamma_1 R^2_{m,t} + D_1\gamma_2 R^2_{m,t} + \varepsilon_t$, where $CSAD_t$ is the cross-sectional absolute deviation, $R_{m,t}$ is the market return and D_1 is a dummy variable that equals 1 during the EZC and 0, otherwise. A significant negative value of γ_2 suggests the presence of herding during the EZC. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

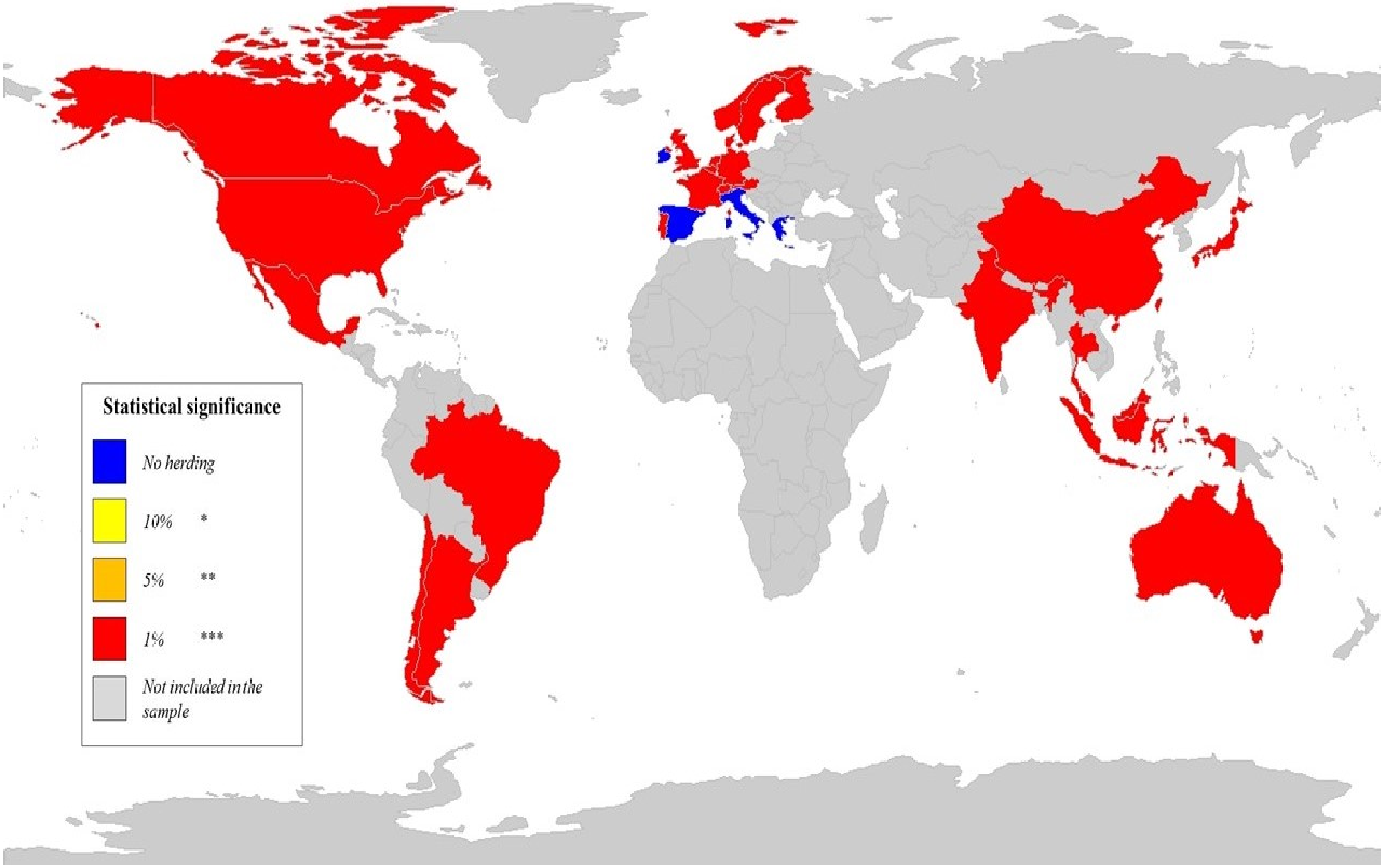


Figure 5.2: Herding behavior in global stock markets during the EZC.

Notes: The Figure shows the estimated coefficients of Eq.(5.3): $CSAD_t = \alpha + \gamma_0|R_{m,t}| + \gamma_1 R^2_{m,t} + D_1\gamma_2 R^2_{m,t} + \varepsilon_t$. D_1 is a dummy variable that equals 1 during the EZC and 0, otherwise. A significant negative value of γ_2 suggests the presence of herding; it is colored in: red, orange and yellow when significant at 1% (***), 5% (**), and 10% (*) levels, respectively. In countries colored in blue, no evidence of herding are found; while, countries in grey are not included in our analysis.

It colours in red, orange and yellow countries where we find a statistically significant herding coefficient, during the EZC, at 1% (***), 5% (**), and 10% (*) levels, respectively.

Analyzing the results related to the European countries, some very pivotal finding is pointed out. The OLS regression estimates show the presence of herding in all the advanced markets included in the Western European countries. Indeed, apart from Ireland, in all the other Western European markets the herding coefficient (γ_2) is negative and statistically significant. The same result is found for Finland, Norway and Sweden. Analyzing the quantile estimates, the result does not change. Moreover, the quantile regressions point out an other pivotal insight. Table 5.2 clearly shows the presence of herding behavior at the higher quantiles for all the European countries, except Italy, Ireland, Greece and Spain. This results enrich the findings of Mobarek, Mollah, and Keasey (2014), who find herding only in the Nordic markets, namely Norway, Denmark, and Sweden; and in Greece and Spain. However, compared to Mobarek, Mollah, and Keasey (2014), we use a sample that completely cover the EZC.[6]

Table 5.3 presents the estimates of Eq. (5.3) with the dummy variable D_1 related to the China's market crash. Surprisingly, we do not find evidences of herding in China. Liu, Uchida, and Yang (2012) argue that the intensive state ownership of Chinese companies mitigates financial constraints during times of financial crisis. However, excluding China and Taiwan, the herding coefficient (γ_2) is found negative and significant for all the Asia Pacific markets. The quantile estimates show, once again, that the herding is more pronounced for high quantiles. The Latin and Northern American markets present the same pattern of results. Only the herding coefficient of Chile is found negative but not significant during the China's market crash period. This event impacted the European markets as well. In particular, apart from Greece, herding is found in all the European countries, especially in the higher quantiles. These findings imply that herding behavior is linked to distressed periods not only related to the domestic market, but also to the foreign ones. Figure 5.3 presents the geographical heat-map of our findings. It colours in red, orange and yellow

Table 5.3: Estimates of herding behavior in global markets during the China's market crash.

Asia Pacific					
		γ_0	γ_1	γ_2	*Adj.R*^{2}
Australia	*OLS*	0.370***	0.019	-0.109***	29.38%
	τ=95th	0.836***	-0.013	-0.195***	25.78%
	τ=99th	0.953***	-0.079***	-0.205***	26.76%
China	*OLS*	0.370***	-0.033***	0.026***	25.05%
	τ=95th	0.367***	-0.021*	0.034***	20.70%
	τ=99th	0.352**	-0.019	0.104**	24.28%
Hong Kong	*OLS*	0.296***	0.004	-0.044***	34.68%
	τ=95th	0.469***	0.004	-0.077***	25.63%
	τ=99th	0.717***	-0.009	-0.124***	29.96%
India	*OLS*	0.109	0.035	-0.021*	23.94%
	τ=95th	0.223***	0.070***	-0.091***	25.26%
	τ=99th	0.408***	0.057***	-0.110***	38.00%
Indonesia	*OLS*	0.774***	-0.037***	-0.012	51.40%
	τ=95th	0.941***	-0.007	-0.118***	42.79%
	τ=99th	1.152***	-0.036*	-0.208***	49.17%
Japan	*OLS*	0.230***	0.002	-0.033***	23.79%
	τ=95th	0.280***	0.019	-0.058***	16.39%
	τ=99th	0.412	-0.008	-0.061***	16.31%
Malaysia	*OLS*	0.493***	-0.009	-0.072**	43.86%
	τ=95th	0.516***	0.021	-0.130***	30.74%
	τ=99th	0.647***	-0.029	-0.133***	38.43%
Singapore	*OLS*	0.317***	0.012*	-0.072***	28.30%
	τ=95th	0.422	0.047	-0.155**	22.47%
	τ=99th	0.398	0.152	-0.285	24.00%
South Korea	*OLS*	0.228***	0.024***	0.001	84.91%
	τ=95th	0.522***	0.018***	-0.086***	40.92%
	τ=99th	0.786***	0.013***	-0.172***	55.58%
Taiwan	*OLS*	0.236***	-0.052***	0.074***	5.17%
	τ=95th	0.649***	-0.095***	0.033***	14.53%
	τ=99th	0.718***	-0.125***	0.042***	12.79%
Thailand	*OLS*	0.589***	0.001	-0.065***	59.15%
	τ=95th	0.781***	-0.007	-0.087***	42.07%
	τ=99th	0.877***	-0.026***	-0.102***	50.14%

Latin America					
		γ_0	γ_1	γ_2	*Adj.R*^{2}
Argentina	*OLS*	0.441***	0.006	-0.027***	43.12%
	τ=95th	0.544***	0.032***	-0.071***	30.65%
	τ=99th	0.805***	0.001	-0.099***	35.86%
Brazil	*OLS*	0.185***	0.016***	0.014*	30.63%
	τ=95th	0.186**	0.051***	-0.033***	22.89%
	τ=99th	0.345	0.021	-0.059***	31.21%
Chile	*OLS*	0.373***	-0.010**	-0.009	33.59%
	τ=95th	0.478	0.022	-0.077	26.65%
	τ=99th	0.370	0.233	-0.045	36.33%
Mexico	*OLS*	0.377***	0.023**	-0.118***	40.65%
	τ=95th	0.449	0.076	-0.249***	31.73%
	τ=99th	0.822***	0.056	-0.436***	37.32%

North America					
		γ_0	γ_1	γ_2	*Adj.R*^{2}
Canada	*OLS*	0.430***	0.028**	-0.047**	35.38%
	τ=95th	0.621***	0.035	-0.152***	25.15%
	τ=99th	0.633***	0.082	-0.246***	31.36%
USA	*OLS*	0.309***	0.008	-0.093***	31.84%
	τ=95th	0.435***	-0.004	-0.144***	21.52%
	τ=99th	0.396***	0.003	-0.171***	27.20%

Western Europe					
		γ_0	γ_1	γ_2	*Adj.R*^{2}
Austria	*OLS*	0.328***	0.025***	-0.064***	35.24%
	τ=95th	0.552***	0.051	-0.147***	35.42%
	τ=99th	0.807***	0.020	-0.203***	40.29%
Belgium	*OLS*	0.297***	0.040***	-0.088***	38.48%
	τ=95th	0.492***	0.074**	-0.166***	31.13%
	τ=99th	0.282	0.311***	-0.280***	36.16%
France	*OLS*	0.285***	0.005	-0.069***	28.30%
	τ=95th	0.516***	-0.004	-0.105***	19.53%
	τ=99th	1.000***	-0.081***	-0.147***	16.03%
Germany	*OLS*	0.268***	0.010*	-0.070***	29.19%
	τ=95th	0.535***	-0.011**	-0.101***	21.73%
	τ=99th	0.527***	-0.018**	-0.134***	19.73%
Ireland	*OLS*	0.760***	0.047**	0.001	52.93%
	τ=95th	1.237***	0.033***	-0.006	40.45%
	τ=99th	1.441***	0.013	-0.125***	44.08%
Netherlands	*OLS*	0.274***	0.022**	-0.064***	30.49%
	τ=95th	0.328*	0.057	-0.126***	21.39%
	τ=99th	0.206	0.127***	-0.208***	21.85%
Switzerland	*OLS*	0.321***	0.013	-0.114***	38.07%
	τ=95th	0.644***	-0.018**	-0.162***	31.15%
	τ=99th	0.421***	0.134***	-0.283***	34.69%
UK	*OLS*	0.249***	0.029***	-0.075***	30.98%
	τ=95th	0.499***	0.033	-0.149***	22.36%
	τ=99th	0.510***	0.043**	-0.196***	25.47%

Northern Europe					
		γ_0	γ_1	γ_2	*Adj.R*^{2}
Denmark	*OLS*	0.205**	0.051*	-0.090***	30.26%
	τ=95th	0.239***	0.130***	-0.176***	23.68%
	τ=99th	0.365**	0.191***	-0.282***	34.09%
Finland	*OLS*	0.565***	-0.017	-0.084***	37.59%
	τ=95th	0.656***	0.023	-0.153***	27.16%
	τ=99th	0.520***	0.029	-0.157***	25.91%
Norway	*OLS*	0.386***	0.018*	-0.041***	38.03%
	τ=95th	0.476***	0.049*	-0.100***	30.12%
	τ=99th	0.080	0.280***	-0.285***	38.78%
Sweden	*OLS*	0.248***	0.005	-0.048***	23.49%
	τ=95th	0.399***	-0.004	-0.086***	17.02%
	τ=99th	0.758***	-0.060	-0.078	21.82%

Southern Europe					
		γ_0	γ_1	γ_2	*Adj.R*^{2}
Greece	*OLS*	0.352***	-0.009	0.037***	39.16%
	τ=95th	0.458***	0.001	0.091	33.42%
	τ=99th	0.421**	0.024	0.233**	40.03%
Italy	*OLS*	0.309***	-0.016	-0.020	20.83%
	τ=95th	0.494***	-0.011***	-0.034***	23.30%
	τ=99th	0.522**	-0.012	-0.057**	20.91%
Portugal	*OLS*	0.429***	-0.008	-0.023***	34.79%
	τ=95th	0.519***	0.037	-0.082**	23.12%
	τ=99th	0.455***	0.050**	-0.107***	28.90%
Spain	*OLS*	0.288***	0.003	-0.041***	28.21%
	τ=95th	0.326***	0.025*	-0.089***	19.51%
	τ=99th	0.437	0.052	-0.159***	21.83%

Notes: The table reports the estimated coefficients of Eq. (5.3): $CSAD_t = \alpha + \gamma_0|R_{m,t}| + \gamma_1 R^2_{m,t} + D_1\gamma_2 R^2_{m,t} + \varepsilon_t$, where $CSAD_t$ is the cross-sectional absolute deviation, $R_{m,t}$ is the market return and D_1 is a dummy variable that equals 1 during China's market crash and 0, otherwise. A significant negative value of γ_2 suggests the presence of herding during the China's market crash. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

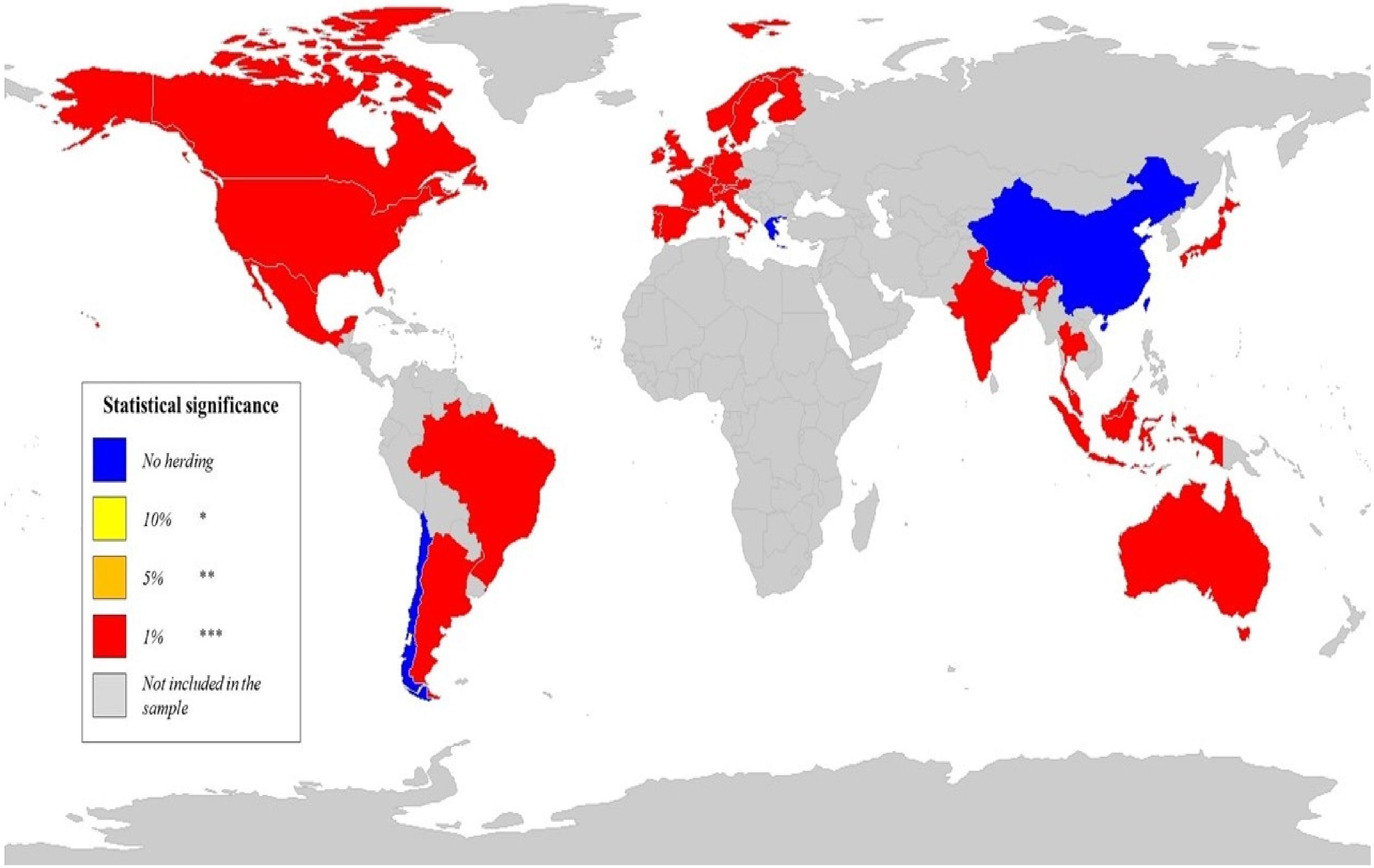


Figure 5.3: Herding behavior in global stock markets during the China's market crash.

Notes: The Figure shows the estimated coefficients of Eq.(5.3): $CSAD_t = \alpha + \gamma_0|R_{m,t}| + \gamma_1 R_{m,t}^2 + D_1\gamma_2 R_{m,t}^2 + \varepsilon_t$. D_1 is a dummy variable that equals 1 during China's market crash and 0, otherwise. A significant negative value of γ_2 suggests the presence of herding; it is colored in: red, orange and yellow when significant at 1% (***), 5% (**), and 10% (*) levels, respectively. In countries colored in blue, no evidence of herding are found; while, countries in grey are not included in our analysis.

countries where we find a statistically significant herding coefficient, during the the China's market crash, at 1% (***), 5% (**), and 10% (*) levels, respectively.

5.3.2 Herding behavior under asymmetric Brexit conditions

Table 5.4 describes the estimates of Eq. (5.4) with the dummy variable D^{Brexit} related to high and low UK un-healthy economic conditions. Both OLS and quantile estimates point out herding effects due to high (γ_2) and low (γ_3) UK un-healthy economic conditions for all the markets considered, excluding only Brazil. While for Australia, India, Indonesia, Taiwan and Thailand in Asia Pacific; Argentina, Mexico and USA (95^{th}) in America; and, Belgium, Germany (95^{th}), Finland and Portugal in Europe, the herding effect is stronger during low UK un-healthy economic conditions, entailing herding maybe not strictly due to the UK economic conditions; in all the other countries analysed, herding results more pronounced in case of high UK un-healthy economic conditions. Overall, this entails that the UK economic conditions affect herding behavior not only in the domestic economy (UK) but also in foreign markets.

Table 5.5 represents the analysis of herding behavior in case of asymmetry conditions of the market related to high and low UK un-healthy economic conditions after the Brexit vote. As described in Section 5.2.1, to isolate the effects of the tensions strictly due to the Brexit, we employ Eq. (5.4) including only the observations from June 2016 to end-January 2019. The results indicate that herding due to high UK un-healthy economic conditions after the Brexit vote is more pronounced in Western and Southern European equity markets. In particular, excluding Austria, Netherlands and Switzerland, all the countries included in the Western and Southern Europe are founded to herd in case of high UK un-healthy economic conditions after the Brexit vote; moreover, the herding coefficient (γ_2) results lower compared to its value reported in Table 5.4. This may suggest that herding in Western and Southern European countries has been affected by the tension due to Brexit. Figure 5.4 presents the geographical heat-map of our findings. It colours in red, orange and yellow countries where we find a statistically significant herding coefficient, related to high UK un-healthy economic conditions after the Brexit vote, at 1% (***), 5% (**), and 10% (*) levels, respectively.

The results discussed in this Section imply that even if no spill-over effects are detected from the UK to the US (Galariotis, Rong, and Spyrou, 2015), the state of the UK economy affects herding behavior in the US and most of the other global equity markets considered. Moreover, when we condition the analysis to the UK economic conditions after the Brexit vote, the results suggest a stronger herding effects for Western and Southern European equity markets.

5.3.3 Herding behavior under asymmetric systemic risk conditions

As explained in Section 5.1, herding behavior may undermine the financial stability of a country, posing unhedgeable systemic risk to market participants and financial institutions (Economou, Kostakis, and Philippas, 2011). Thus, it is of fundamental importance the analysis of herding behavior during periods of high systemic risk for the market. Table 5.6 presents the estimates from Eq. (5.12), which is conditioned on different systemic risk circumstances of the market. In particular, Eq. (5.12) allows to analyze herding in case of medium (γ_1), high (γ_2) and low (γ_3) systemic risk of the market. Figure 5.5 presents the geographical heat-map of our findings. It colours in red, orange and yellow countries where we find a statistically significant herding coefficient, related to a high systemic risk level of the market, at 1% (***), 5% (**), and 10% (*) levels, respectively.

Overall, the OLS and quantile regressions indicate positive estimates when systemic risk is medium (γ_1) or low (γ_3). This finding is consistent with the leak of herding behavior. On the other hand, the estimates conditioned on high systemic risk level of the market (γ_2) point out the presence of herding behavior and an increasing tendency of investors to herd in extreme tail events, i.e. in the higher quantiles. It seems that high systemic risk is strongly related to herding behavior.

Table 5.4: Estimates of herding behavior in global markets due to UK un-healthy economic conditions.

Asia Pacific				
		γ_2	γ_3	$Adj.R^2$
Australia	*OLS*	-0.003	0.025	24.90%
	τ=95th	-0.031***	0.010	19.87%
	τ=99th	-0.025***	-0.075***	18.78%
China	*OLS*	-0.009***	-0.009***	24.77%
	τ=95th	0.001	-0.005	24.14%
	τ=99th	-0.013**	-0.010*	24.65%
Hong Kong	*OLS*	-0.008***	0.003	28.68%
	τ=95th	-0.013***	0.020	19.25%
	τ=99th	-0.015*	0.020	20.30%
India	*OLS*	-0.004	-0.004	20.22%
	τ=95th	0.001	-0.015***	25.54%
	τ=99th	-0.002	-0.020***	30.92%
Indonesia	*OLS*	-0.027***	-0.025***	49.36%
	τ=95th	-0.017***	-0.025***	35.94%
	τ=99th	-0.022***	-0.025***	38.33%
Japan	*OLS*	-0.005***	-0.003	21.21%
	τ=95th	-0.004	0.006	12.49%
	τ=99th	-0.008***	0.001	11.72%
Malaysia	*OLS*	-0.049***	-0.025	36.06%
	τ=95th	-0.027***	0.044	21.52%
	τ=99th	-0.028***	0.024	24.16%
Singapore	*OLS*	-0.011***	-0.004	22.33%
	τ=95th	-0.016	0.036	16.49%
	τ=99th	-0.027***	0.050	15.97%
South Korea	*OLS*	-0.013***	-0.002***	32.08%
	τ=95th	-0.013***	-0.003***	31.60%
	τ=99th	-0.019***	-0.003***	34.06%
Taiwan	*OLS*	-0.022***	-0.036***	12.69%
	τ=95th	-0.033	-0.023	26.58%
	τ=99th	-0.029***	-0.045***	23.68%
Thailand	*OLS*	-0.021***	-0.046***	52.40%
	τ=95th	-0.020***	-0.052***	36.43%
	τ=99th	-0.021***	-0.047***	39.40%

Latin America				
		γ_2	γ_3	$Adj.R^2$
Argentina	*OLS*	-0.008***	-0.017***	36.70%
	τ=95th	-0.003	-0.018*	22.64%
	τ=99th	-0.004	-0.024***	22.77%
Brazil	*OLS*	-0.002	0.012***	25.60%
	τ=95th	0.003	0.022**	17.63%
	τ=99th	-0.003	0.022***	23.29%
Chile	*OLS*	-0.027***	-0.016***	26.34%
	τ=95th	-0.024***	0.065	20.70%
	τ=99th	-0.028***	0.114	27.24%
Mexico	*OLS*	-0.017***	-0.019**	33.72%
	τ=95th	-0.020	-0.009	23.47%
	τ=99th	-0.025***	-0.030*	25.42%

North America				
		γ_2	γ_3	$Adj.R^2$
Canada	*OLS*	-0.013***	0.010	30.02%
	τ=95th	-0.023***	-0.005	18.78%
	τ=99th	-0.039***	0.063	22.32%
USA	*OLS*	-0.009***	0.001	26.26%
	τ=95th	-0.012***	-0.015***	14.59%
	τ=99th	-0.010***	0.013	17.35%

Western Europe				
		γ_2	γ_3	$Adj.R^2$
Austria	*OLS*	-0.012***	-0.010	30.13%
	τ=95th	-0.011**	-0.024***	26.07%
	τ=99th	0.016	-0.023	27.24%
Belgium	*OLS*	-0.013***	-0.012**	29.59%
	τ=95th	-0.024***	-0.016	22.24%
	τ=99th	-0.003	-0.025***	22.20%
France	*OLS*	-0.009***	0.000	25.69%
	τ=95th	-0.018***	-0.012	14.32%
	τ=99th	-0.024***	-0.028***	10.20%
Germany	*OLS*	-0.007**	0.008	23.69%
	τ=95th	-0.015***	-0.022**	15.60%
	τ=99th	-0.015***	-0.015*	12.56%
Ireland	*OLS*	-0.029***	-0.019***	42.15%
	τ=95th	-0.023***	-0.015***	29.29%
	τ=99th	-0.023***	-0.009***	27.71%
Netherlands	*OLS*	-0.007*	-0.001	25.03%
	τ=95th	0.009	0.005	15.08%
	τ=99th	0.038**	0.154	14.50%
Switzerland	*OLS*	-0.009**	0.003	27.80%
	τ=95th	-0.023***	0.006	21.78%
	τ=99th	-0.021***	0.111	22.89%
UK	*OLS*	-0.004	0.015*	26.23%
	τ=95th	-0.023***	0.005	16.84%
	τ=99th	-0.015	-0.014	16.60%

Northern Europe				
		γ_2	γ_3	$Adj.R^2$
Denmark	*OLS*	-0.004	0.002	21.32%
	τ=95th	-0.001	0.022**	15.13%
	τ=99th	-0.009**	0.004	18.49%
Finland	*OLS*	-0.029***	-0.033***	34.17%
	τ=95th	-0.039***	-0.044***	21.10%
	τ=99th	-0.020	0.017	18.24%
Norway	*OLS*	-0.007***	0.016	32.45%
	τ=95th	-0.006	0.030***	23.64%
	τ=99th	0.009	0.084	29.25%
Sweden	*OLS*	-0.008***	0.002	19.63%
	τ=95th	-0.014***	0.003	12.33%
	τ=99th	-0.025***	0.062	15.32%

Southern Europe				
		γ_2	γ_3	$Adj.R^2$
Greece	*OLS*	-0.008***	-0.008**	32.38%
	τ=95th	-0.001	-0.007***	25.24%
	τ=99th	0.023***	-0.005***	28.41%
Italy	*OLS*	-0.013***	-0.013***	27.97%
	τ=95th	-0.010***	-0.010	17.90%
	τ=99th	-0.014***	-0.011	15.17%
Portugal	*OLS*	-0.028***	-0.033***	29.61%
	τ=95th	-0.018	-0.004	16.10%
	τ=99th	-0.002	0.047	18.53%
Spain	*OLS*	-0.013***	-0.005	24.45%
	τ=95th	-0.011***	0.054	15.20%
	τ=99th	-0.014***	0.031	17.68%

Notes: The table reports the estimated coefficients of Eq. (5.4): $CSAD_t = \alpha + D^{Brexit}\gamma_0|R_{m,t}| + (1 - D^{Brexit})\gamma_1|R_{m,t}| + D^{Brexit}\gamma_2 R^2_{m,t} + (1 - D^{Brexit})\gamma_3 R^2_{m,t} + \varepsilon_t$, where $CSAD_t$ is the cross-sectional absolute deviation, $R_{m,t}$ is the market return and D_{Brexit} is a dummy variable that takes the value 1 for UK un-healthy economic conditions and the value 0 otherwise. A significant negative value of γ_2 suggests the presence of herding. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 5.5: Estimates of herding behavior in global markets due to UK un-healthy economic conditions after the Brexit vote.

Asia Pacific

		γ_2	γ_3	$Adj.R^2$
Australia	*OLS*	0.072***	-0.058***	17.66%
	τ=95th	0.035	0.026	10.30%
	τ=99th	0.26	-0.009	14.01%
China	*OLS*	-0.006**	0.023**	43.04%
	τ=95th	-0.015***	0.04	40.62%
	τ=99th	-0.005	-0.104**	31.86%
Hong Kong	*OLS*	0.025*	0.023**	15.66%
	τ=95th	0.017	0.018	11.75%
	τ=99th	-0.059***	-0.008	12.32%
India	*OLS*	0.043***	0.063***	26.14%
	τ=95th	0.036***	0.199	22.09%
	τ=99th	0.046***	0.597	31.87%
Indonesia	*OLS*	-0.008	-0.022	40.42%
	τ=95th	0.068**	0.24	30.04%
	τ=99th	0.008	-0.015	43.84%
Japan	*OLS*	0.002	-0.01	19.23%
	τ=95th	0.057***	-0.024***	18.71%
	τ=99th	-0.017	-0.067***	26.41%
Malaysia	*OLS*	-0.07**	-0.028	35.62%
	τ=95th	0.018	0.185	21.36%
	τ=99th	0.048	0.247	16.10%
Singapore	*OLS*	0.052	0.01	15.08%
	τ=95th	0.034	-0.063	12.09%
	τ=99th	0.193**	-0.088***	16.58%
South Korea	*OLS*	0.007	0.004	38.39%
	τ=95th	0.104***	-0.012	34.51%
	τ=99th	0.085***	-0.064***	50.38%
Taiwan	*OLS*	-0.013***	-0.024***	39.74%
	τ=95th	-0.016***	-0.029***	32.01%
	τ=99th	-0.034***	-0.018***	36.71%
Thailand	*OLS*	-0.022***	-0.03	47.86%
	τ=95th	-0.035***	0.012	33.24%
	τ=99th	0.307*	0.033	48.98%

Latin America

		γ_2	γ_3	$Adj.R^2$
Argentina	*OLS*	-0.001	-0.003	28.05%
	τ=95th	-0.009***	-0.016***	23.21%
	τ=99th	-0.014***	-0.001	25.46%
Brazil	*OLS*	0.008*	0.02	25.91%
	τ=95th	0.025	0.052**	20.46%
	τ=99th	0.107	-0.006	35.70%
Chile	*OLS*	-0.012***	-0.026***	25.50%
	τ=95th	-0.015***	-0.043***	25.40%
	τ=99th	-0.013**	-0.062**	23.40%
Mexico	*OLS*	0.003	-0.009	16.81%
	τ=95th	0.034	-0.025	14.54%
	τ=99th	-0.031***	-0.029	16.77%

North America

		γ_2	γ_3	$Adj.R^2$
Canada	*OLS*	-0.013	-0.036	33.55%
	τ=95th	-0.093***	-0.074	20.66%
	τ=99th	-0.082***	0.609	8.91%
USA	*OLS*	-0.002	-0.027	21.10%
	τ=95th	0.002	-0.039	12.33%
	τ=99th	-0.011	-0.015	11.49%

Western Europe

		γ_2	γ_3	$Adj.R^2$
Austria	*OLS*	0.017	-0.011	22.67%
	τ=95th	0.123***	0.127	21.81%
	τ=99th	0.098***	-0.095	38.99%
Belgium	*OLS*	-0.009	0.057	17.38%
	τ=95th	-0.020	0.078	13.27%
	τ=99th	-0.060***	0.142	21.23%
France	*OLS*	-0.002	0.031	21.22%
	τ=95th	-0.012***	-0.016	20.52%
	τ=99th	-0.095***	-0.029***	24.41%
Germany	*OLS*	-0.006	0.010	15.49%
	τ=95th	-0.014*	0.037	12.21%
	τ=99th	-0.058***	-0.014	20.57%
Ireland	*OLS*	-0.041***	-0.010	53.25%
	τ=95th	-0.035***	0.003	39.02%
	τ=99th	-0.047***	-0.014	41.55%
Netherlands	*OLS*	0.013	-0.008	24.74%
	τ=95th	0.038**	0.182	16.51%
	τ=99th	0.063***	0.567**	30.54%
Switzerland	*OLS*	0.027**	-0.040	13.46%
	τ=95th	0.015	0.043	11.23%
	τ=99th	0.015	-0.069	21.53%
UK	*OLS*	0.017*	-0.017	28.73%
	τ=95th	-0.007	-0.024	23.01%
	τ=99th	-0.057***	-0.050**	37.43%

Northern Europe

		γ_2	γ_3	$Adj.R^2$
Denmark	*OLS*	-0.021**	0.002	11.81%
	τ=95th	-0.054***	0.060	9.54%
	τ=99th	-0.091***	-0.074	10.28%
Finland	*OLS*	-0.013	-0.025	32.90%
	τ=95th	0.078	-0.022	23.01%
	τ=99th	0.145*	-0.090**	33.30%
Norway	*OLS*	0.013	0.007	26.71%
	τ=95th	0.009	-0.038**	18.05%
	τ=99th	0.001	-0.018	32.20%
Sweden	*OLS*	-0.003	0.025	9.31%
	τ=95th	-0.036***	-0.113***	7.65%
	τ=99th	-0.038***	-0.092*	21.47%

Southern Europe

		γ_2	γ_3	$Adj.R^2$
Greece	*OLS*	-0.009*	0.010	47.57%
	τ=95th	0.017**	0.092	36.82%
	τ=99th	0.023***	0.369	50.97%
Italy	*OLS*	-0.009***	-0.004	24.95%
	τ=95th	-0.007***	0.005	20.13%
	τ=99th	0.015	0.082	26.82%
Portugal	*OLS*	-0.011	0.002	22.51%
	τ=95th	-0.018**	-0.006	13.83%
	τ=99th	0.079	0.138	14.73%
Spain	*OLS*	-0.009***	-0.004	21.62%
	τ=95th	-0.021***	-0.018**	18.15%
	τ=99th	-0.071***	-0.001	28.67%

Notes: The table reports the estimated coefficients of Eq. (5.4): $CSAD_t = \alpha + D^{Brexit}\gamma_0|R_{m,t}| + (1 - D^{Brexit})\gamma_1|R_{m,t}| + D^{Brexit}\gamma_2 R^2_{m,t} + (1 - D^{Brexit})\gamma_3 R^2_{m,t} + \varepsilon_t$, where $CSAD_t$ is the cross-sectional absolute deviation, $R_{m,t}$ is the market return and D_{Brexit} is a dummy variable that takes the value 1 for UK un-healthy economic conditions and the value 0 otherwise. The sub-sample analysed spans the period from the 1^{st} June 2016 to end-January 2019. A significant negative value of γ_2 suggests the presence of herding. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

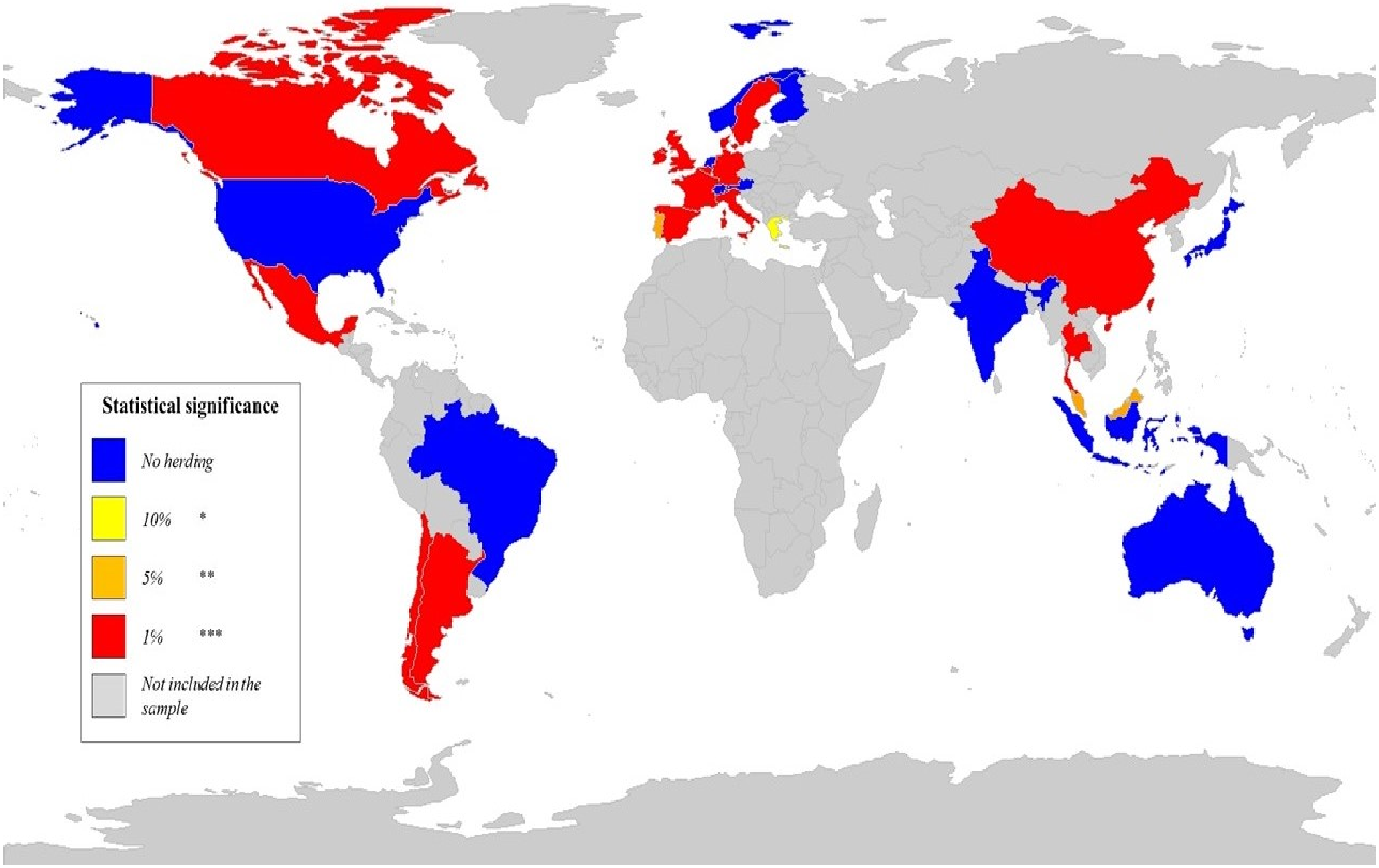


Figure 5.4: Herding behavior in global stock markets due to UK un-healthy economic conditions after the Brexit vote.

Notes: The Figure shows the estimated coefficients of Eq.(5.4): $CSAD_t = \alpha + D^{Brexit}\gamma_0|R_{m,t}| + (1 - D^{Brexit})\gamma_1|R_{m,t}| + D^{Brexit}\gamma_2 R^2_{m,t} + (1 - D^{Brexit})\gamma_3 R^2_{m,t} + \varepsilon_t$. The sub-sample analysed spans the period from the 1^{st} June 2016 to end-January 2019. A significant negative value of γ_2 suggests the presence of herding; it is colored in: red, orange and yellow when significant at 1% (***), 5% (**), and 10% (*) levels, respectively. In countries colored in blue, no evidence of herding are found; while, countries in grey are not included in our analysis.

More specifically, the OLS estimates show that for all the Asia Pacific markets, apart from Indonesia and Taiwan, which has been found to herd in high and low, and low systemic risk conditions, respectively; herding behavior is present in the case of high systemic risk. Analyzing the quantile estimates, herding during high systemic risk conditions becomes aggravated in the higher quantiles. In the Latin American markets, the OLS estimates show a veiled presence (significant at 10%) of herding conditioned on medium systemic risk level of the market for Argentina. The coefficient γ_2 is found negative and significant only for Mexico. The quantile regression analysis replicates the same result for the last, adding evidences of herding in case of high systemic risk for Argentina and Brazil, in the higher quantiles. The North American markets are found to herd in case of high systemic risk circumstances in both OLS and quantile regressions. The quantile regressions point out the presence of herding also in case of low systemic risk in Canada. However, the herding coefficient (γ_2) related to high systemic risk conditions is greater, in absolute value, then γ_3 – coefficient related to low systemic risk conditions. Once again, also for the American markets, the results show a strong relationship between herding behavior and systemic risk.

For the European markets, we find evidences of herding conditioned on high systemic risk of the market for all the countries analyzed except Ireland. Portugal, in the OLS estimates, and Sweden, in the quantile estimates ($\tau = 99^{th}$), are found to herd also in case of medium systemic risk circumstances. The same result is found for Germany at the 99^{th} quantile. Moreover, Germany is found to herd in all the three market conditions at the 95^{th} quantile. However, Portugal is found to herd in case of high systemic risk (γ_2) more than medium systemic risk conditions (γ_1). Moreover, analyzing the quantile estimates, we find evidences of herding only in case of γ_2. In Sweden, the herding coefficient γ_1 changes the sign, to negative from positive, only in the highest quantile, while the OLS analysis and the quantiles below the 99^{th} show evidence of herding only in case of high systemic risk. In all the cases we find herding in Germany, the estimates related to high systemic risk is, in absolute value, greater than the coefficients related to medium or low systemic risk conditions, entailing

Table 5.6: Estimates of herding behavior in global markets due to systemic risk ($\Delta CoVaR$).

Asia Pacific					
		γ_1	γ_2	γ_3	$Adj.R^2$
Australia	*OLS*	0.012	-0.165***	-0.031	32.53%
	$\tau=95^{th}$	-0.014	-0.206***	-0.097**	27.03%
	$\tau=99^{th}$	-0.092***	-0.194***	-0.081***	27.14%
China	*OLS*	-0.015***	0.014***	-0.001	31.99%
	$\tau=95^{th}$	-0.007	0.030***	0.011	21.53%
	$\tau=99^{th}$	-0.003	0.091**	0.021	24.20%
Hong Kong	*OLS*	0.004	-0.057***	0.007	38.05%
	$\tau=95^{th}$	0.013	-0.068***	0.052**	29.47%
	$\tau=99^{th}$	0.037*	-0.098***	0.004	33.00%
India	*OLS*	0.013	-0.039***	0.046***	49.78%
	$\tau=95^{th}$	0.029	-0.063**	0.035	28.60%
	$\tau=99^{th}$	0.002	-0.069***	0.048***	41.06%
Indonesia	*OLS*	-0.002	-0.120***	-0.029***	64.04%
	$\tau=95^{th}$	0.010	-0.165***	-0.002	45.00%
	$\tau=99^{th}$	0.011	-0.188***	0.046	51.65%
Japan	*OLS*	0.003	-0.033***	0.016**	28.99%
	$\tau=95^{th}$	0.021	-0.046	0.042	20.52%
	$\tau=99^{th}$	0.001	-0.048***	0.086**	24.94%
Malaysia	*OLS*	-0.013*	-0.156***	0.009	43.87%
	$\tau=95^{th}$	0.027	-0.155	0.002	30.08%
	$\tau=99^{th}$	0.010	-0.149**	-0.036	37.56%
Singapore	*OLS*	0.011*	-0.155***	0.034***	32.11%
	$\tau=95^{th}$	0.057	-0.172***	0.083	23.70%
	$\tau=99^{th}$	0.129	-0.286***	0.315***	26.67%
South Korea	*OLS*	-0.004	-0.058***	0.015	39.67%
	$\tau=95^{th}$	0.007	-0.087***	0.027	30.24%
	$\tau=99^{th}$	0.004	-0.099*	0.031	38.66%
Taiwan	*OLS*	0.014	0.020	-0.090***	20.40%
	$\tau=95^{th}$	-0.039	-0.050**	-0.060**	17.54%
	$\tau=99^{th}$	-0.066***	-0.036**	-0.042*	13.33%
Thailand	*OLS*	-0.008	-0.038***	0.029***	62.90%
	$\tau=95^{th}$	-0.013	-0.052***	0.064	43.04%
	$\tau=99^{th}$	-0.017	-0.061***	0.160	53.41%

Latin America					
		γ_1	γ_2	γ_3	$Adj.R^2$
Argentina	*OLS*	-0.018*	-0.008	0.040***	46.85%
	$\tau=95^{th}$	-0.007	-0.020***	0.083***	32.76%
	$\tau=99^{th}$	0.032	-0.061	0.189	37.08%
Brazil	*OLS*	0.016***	-0.010	0.004	32.81%
	$\tau=95^{th}$	0.055**	-0.037***	-0.012	25.61%
	$\tau=99^{th}$	0.044	-0.040	0.110***	33.61%
Chile	*OLS*	0.002	-0.008	0.090***	35.83%
	$\tau=95^{th}$	0.029	-0.043	0.208	28.65%
	$\tau=99^{th}$	-0.016	0.186	0.317***	39.28%
Mexico	*OLS*	0.032***	-0.054***	0.054***	40.92%
	$\tau=95^{th}$	0.100**	-0.115***	0.112***	32.23%
	$\tau=99^{th}$	0.102**	-0.163***	0.267	39.71%

North America					
		γ_1	γ_2	γ_3	$Adj.R^2$
Canada	*OLS*	0.029*	-0.049*	0.084*	42.21%
	$\tau=95^{th}$	0.028	-0.164***	-0.057**	32.03%
	$\tau=99^{th}$	-0.029	-0.277***	-0.229***	38.07%
USA	*OLS*	0.001	-0.103***	0.011	41.45%
	$\tau=95^{th}$	-0.015	-0.138***	0.020*	31.98%
	$\tau=99^{th}$	-0.013	-0.077***	0.034	33.56%

Western Europe					
		γ_1	γ_2	γ_3	$Adj.R^2$
Austria	*OLS*	0.018***	-0.109***	-0.052*	45.64%
	$\tau=95^{th}$	0.045***	-0.194***	-0.056	37.88%
	$\tau=99^{th}$	0.008	-0.249***	-0.149***	42.41%
Belgium	*OLS*	0.038***	-0.087***	0.013	42.18%
	$\tau=95^{th}$	0.076*	-0.158***	0.051	33.58%
	$\tau=99^{th}$	0.292***	-0.330***	-0.138***	39.96%
France	*OLS*	0.010**	-0.034*	0.037***	34.35%
	$\tau=95^{th}$	-0.002	-0.006	0.074***	23.71%
	$\tau=99^{th}$	-0.006	-0.006	0.047***	19.32%
Germany	*OLS*	0.010*	-0.066***	0.011**	34.55%
	$\tau=95^{th}$	-0.016***	-0.104***	-0.024***	26.19%
	$\tau=99^{th}$	-0.026**	-0.045***	-0.012	23.72%
Ireland	*OLS*	0.004	0.023	0.040**	54.07%
	$\tau=95^{th}$	-0.011	0.036	0.053	40.99%
	$\tau=99^{th}$	0.043	0.044	0.315	45.33%
Netherlands	*OLS*	0.009	-0.045***	0.043***	38.39%
	$\tau=95^{th}$	0.033*	-0.039***	0.098***	27.42%
	$\tau=99^{th}$	0.026	-0.028***	0.124***	28.72%
Switzerland	*OLS*	0.012	-0.034**	0.024**	41.76%
	$\tau=95^{th}$	0.011	-0.042	0.080***	33.32%
	$\tau=99^{th}$	0.045	-0.082	0.075	36.61%
UK	*OLS*	0.027***	-0.121***	0.025**	37.91%
	$\tau=95^{th}$	0.083***	-0.238***	-0.046**	28.41%
	$\tau=99^{th}$	0.033**	-0.198***	-0.112***	29.29%

Northern Europe					
		γ_1	γ_2	γ_3	$Adj.R^2$
Denmark	*OLS*	0.041**	-0.088***	0.057***	35.95%
	$\tau=95^{th}$	0.100***	-0.147***	0.110**	26.19%
	$\tau=99^{th}$	0.247***	-0.279***	0.083	38.28%
Finland	*OLS*	-0.056***	-0.044**	0.099***	42.47%
	$\tau=95^{th}$	-0.009	-0.036*	0.236	30.61%
	$\tau=99^{th}$	-0.066	-0.008	0.249	29.30%
Norway	*OLS*	0.014	-0.057***	0.019**	39.69%
	$\tau=95^{th}$	0.045	-0.115***	0.030	31.48%
	$\tau=99^{th}$	0.280***	-0.279**	0.096	40.16%
Sweden	*OLS*	0.002	-0.036***	0.013*	27.63%
	$\tau=95^{th}$	0.017	-0.041**	0.072	20.77%
	$\tau=99^{th}$	-0.048**	-0.017**	0.230***	23.78%

Southern Europe					
		γ_1	γ_2	γ_3	$Adj.R^2$
Greece	*OLS*	0.014**	-0.014**	-0.011	42.39%
	$\tau=95^{th}$	0.032**	-0.043***	-0.008	34.95%
	$\tau=99^{th}$	0.067*	-0.080***	-0.050***	40.31%
Italy	*OLS*	0.017**	-0.018**	0.019***	33.48%
	$\tau=95^{th}$	0.051	-0.047	0.002	24.65%
	$\tau=99^{th}$	0.069	-0.062	0.109**	21.98%
Portugal	*OLS*	-0.009***	-0.036***	-0.010	33.70%
	$\tau=95^{th}$	-0.009	-0.051***	0.045	21.55%
	$\tau=99^{th}$	-0.027	-0.051***	0.138***	24.80%
Spain	*OLS*	0.010*	-0.013	0.030***	31.63%
	$\tau=95^{th}$	0.030**	-0.032***	0.049	22.74%
	$\tau=99^{th}$	0.052	-0.071	-0.016	29.77%

Notes: The table reports the estimated coefficients of Eq. (5.12): $CSAD_t = \alpha + \gamma_0|R_{m,t}| + \gamma_1 R^2_{m,t} + D_1\gamma_2 R^2_{m,t} + D_2\gamma_3 R^2_{m,t} + \varepsilon_t$, where $CSAD_t$ is the cross-sectional absolute deviation and $R_{m,t}$ is the market return. Dummy variable D_1 equals 1 if the $\Delta CoVaR_{99^{th},i}$ lies in the upper 25% of the distribution and 0, otherwise; dummy variable D_2 equals 1 if the $\Delta CoVaR_{99^{th},i}$ lies in the lower 25% of the distribution and 0, otherwise. A significant negative value of γ_1, γ_2, γ_3 suggest the presence of herding in case of medium, high and low systemic risk, respectively. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

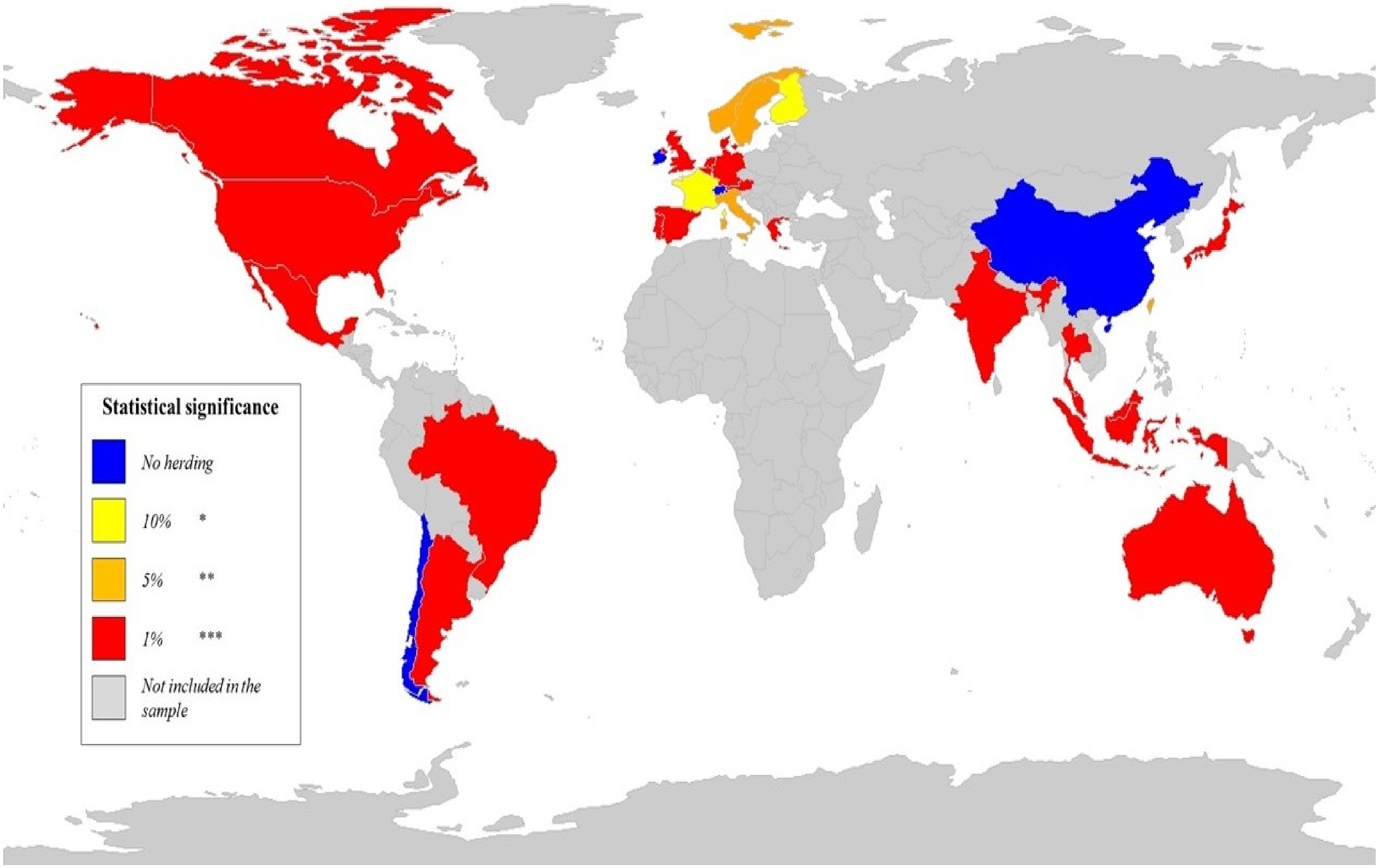


Figure 5.5: Herding behavior in global stock markets due to systemic risk ($\Delta CoVaR$).

Notes: The Figure shows the estimated coefficients of Eq.(5.12): $CSAD_t = \alpha + \gamma_0|R_{m,t}| + \gamma_1 R^2_{m,t} + D_1\gamma_2 R^2_{m,t} + D_2\gamma_3 R^2_{m,t} + \varepsilon_t$. Dummy variable D_1 equals 1 if the $\Delta CoVaR_{99^{th},i}$ lies in the upper 25% of the distribution and 0, otherwise; dummy variable D_2 equals 1 if the $\Delta CoVaR_{99^{th},i}$ lies in the lower 25% of the distribution and 0, otherwise. A significant negative value of γ_2 suggests the presence of herding in case of high systemic risk. Countries colored in: red, orange and yellow are found herd at 1% (***), 5% (**), and 10% (*) significance levels, respectively. In countries colored in blue, no evidence of herding are found; while, countries in grey are not included in our analysis.

a greater herding effect due to distressed market conditions that depend on systemic risk. UK is found to herd in case of high and low systemic risk conditions at the 99^{th} quantile. However, once again, the herding coefficient γ_2 is greater than γ_3, implicating that tail events due to high systemic risk cause greater herding than tail events not attributable to systemic risk.

It is the first time, to the best of our knowledge, that this finding is reported. This analysis may be of fundamental importance for regulators and supervisory authorities in order to implement the regulation and the supervision of stock markets in case of a systemic event.

5.3.4 Granger causality tests

Table 5.7 reports the values of the Granger causality test between the systemic risk increases and the return clustering measure for each country[3] (the lag length is chosen based on the Akaike information criterion). In order to have a more complete and detailed analysis, we consider the full sample periods and the seven sub-periods described in Section 5.2.3. The Null Hypothesis states that each variable "does not cause" the other. Recall that the Granger causality test does not imply that one variable is the effect of the other; more precisely, it indicates that one variable contains information about the other.

Analyzing the results, the first pivotal result is that the Granger causality between systemic risk increases (return clustering) and return clustering (systemic risk increases) is country and period dependent. Overall, the results related to the full sample period highlight that, for most of the markets analyzed there is a two-way Granger causality effect between the two variables analyzed. For Austria, Malaysia and Sweden, we find that the systemic risk increases Granger cause the CSAD, the opposite result is found for Denmark, Ireland and Greece, while, it seems not to exist any Granger causality in Brazil between these two variables.

The results related to the sub-periods point out that there is a two-way Granger causality

Table 5.7: Granger causality test between CSAD and $\Delta CoVaR_{99^{th},i}$.

	Asia Pacific								
	Australia	China	Honk Kong	India	Indonesia	Japan	Malaysia	Singapore	South Korea
Full sample period									
CSAD does not cause S. Risk	2.3087***	31.9568***	1.9052**	1.6726*	6.1841***	3.8351***	2.3472	10.3757***	2.4772**
S. Risk does not cause CSAD	1.5826*	2.9837***	3.2518***	2.3319***	3.0306***	3.9020***	5.6085***	2.7489***	3.0433***
Pre-Global financial crisis period									
CSAD does not cause S. Risk	3.3645***	5.5013***	0.0961	0.8768	4.6016***	3.8691***	0.8526	7.8046***	1.8617*
S. Risk does not cause CSAD	1.5729	3.4731***	1.5285*	1.3987	2.3371***	1.7311**	4.3981***	1.4170	1.5298
Global financial crisis period									
CSAD does not cause S. Risk	2.9892***	19.6961***	2.0661**	1.0090	3.0970***	2.2813**	1.2032	4.6363***	3.6964*
S. Risk does not cause CSAD	1.9881*	1.9225*	2.9250***	0.5221	5.2409***	2.5921***	3.4775***	3.2817***	3.3319***
Pre-Eurozone crisis period									
CSAD does not cause S. Risk	2.6134	35.6768***	16.1259***	5.3085**	5.7823**	5.7072**	6.5870**	5.1258***	1.2236
S. Risk does not cause CSAD	2.3233***	3.2162**	1.1813	5.8084***	0.8967	2.9013**	1.3297	2.1046*	0.6359
Eurozone crisis period									
CSAD does not cause S. Risk	1.6783	32.0427***	1.6710	0.5685	5.8326***	5.0750***	0.6002	0.0988	1.3150
S. Risk does not cause CSAD	5.3902***	0.7167	2.6794***	1.0048	2.9551***	4.0447***	1.0645	1.3649	0.3684
Pre-China's stock market crash									
CSAD does not cause S. Risk	3.2091**	17.1467***	11.9138***	1.6627	5.1048***	9.5362***	0.7121	0.0920	0.9439
S. Risk does not cause CSAD	0.6015	4.3296***	1.3839	2.7392***	4.9015***	3.0998**	1.9221*	2.2146**	0.8211
China's stock market crash									
CSAD does not cause S. Risk	0.0000	15.5551***	2.1267	1.5304	3.9695**	0.1659	2.0657	0.2114	5.9746***
S. Risk does not cause CSAD	1.7476	0.8694	2.1124	1.7378	1.6719*	0.8968	2.5104	5.2331***	0.8437
Post crises period									
CSAD does not cause S. Risk	2.1771*	20.1918***	3.9368***	0.1970	0.3210	5.8071**	0.3717	2.3742*	5.6970***
S. Risk does not cause CSAD	1.7746*	0.6358	1.7416	3.2847**	1.2249	1.7619	1.7743	1.6805	2.2176**

			Latin America				North America	
	Taiwan	Thailand	Argentina	Brazil	Chile	Mexico	Canada	USA
Full sample period								
CSAD does not cause S. Risk	7.5180***	8.8940***	2.7704*	1.1429	2.2190***	3.9020***	3.5884***	3.4919***
S. Risk does not cause CSAD	4.9587***	2.8108***	2.4148***	1.3080	4.9634***	4.5064***	2.0821***	7.5002***
Pre-Global financial crisis period								
CSAD does not cause S. Risk	2.4208	5.5335***	3.5374**	0.0033	0.1259	2.1337**	1.6320*	5.2352***
S. Risk does not cause CSAD	2.6834***	2.1193**	3.9051***	1.0215	4.4041***	2.6392***	3.3285***	7.0758***
Global financial crisis period								
CSAD does not cause S. Risk	0.5618	6.7434***	1.2642	1.7728	1.5189	5.4094***	3.3065***	2.1029***
S. Risk does not cause CSAD	0.7863	2.5635***	0.5750	3.6175***	2.2894***	6.5885***	2.7338**	4.1595***
Pre-Eurozone crisis period								
CSAD does not cause S. Risk	17.7207***	1.9395	0.6274	3.5051*	11.2210***	4.9673**	0.7679	1.8341
S. Risk does not cause CSAD	1.8086**	1.8438	1.9812**	0.5788	2.6390*	0.3179	1.2112	1.0973
Eurozone crisis period								
CSAD does not cause S. Risk	6.8956***	8.5705***	0.0931	2.3518*	1.8101*	0.9409	1.9475*	1.3237
S. Risk does not cause CSAD	1.2852	1.0625	1.2943	4.1040***	5.1019***	0.9947	2.5438***	2.1368*
Pre-China's stock market crash								
CSAD does not cause S. Risk	18.0657***	30.0412***	0.0979	0.7849	1.8587	1.4155	5.4710***	1.6660
S. Risk does not cause CSAD	1.9713**	2.6486**	2.6638**	2.4239**	2.8594***	2.4716***	1.7296**	2.2265**
China's stock market crash								
CSAD does not cause S. Risk	7.3775***	14.6075***	5.4388**	1.1951	0.6865	0.4710	0.0076	3.2826**
S. Risk does not cause CSAD	3.0989**	0.3380	1.4122	0.5934	0.6879	0.5017	2.5262**	0.6572
Post crises period								
CSAD does not cause S. Risk	5.9524**	4.4734***	4.6622***	3.3922***	1.7435**	3.2444**	0.3214	6.8351***
S. Risk does not cause CSAD	0.9335	9.2679***	0.3518	3.7429**	0.4778	1.8348	1.3263	1.6187*

Notes: The Table reports the F-Statistics from the Granger causality test between the CSAD and the systemic risk increases ($S.Risk$) measured with the $\Delta CoVaR_{99^{th},i}$. The null hypothesis is each variable "does not Granger Cause" the other. The lag length is chosen based on the Akaike information criterion. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 5.7: Granger causality test between CSAD and $\Delta CoVaR_{99^{th},i}$. (*Continued*)

	Western Europe							
	Austria	Belgium	France	Germany	Ireland	Netherlands	Switzerland	UK
Full sample period								
CSAD does not cause S. Risk	1.1868	7.8663***	3.4981***	2.8897***	2.5745**	2.5459***	3.2978**	6.1572***
S. Risk does not cause CSAD	2.3332***	5.4199***	3.7142***	3.8218***	1.1923	1.9198***	1.4667*	4.1493***
Pre-Global financial crisis period								
CSAD does not cause S. Risk	2.7906*	4.0684***	3.7015***	2.0064**	1.0945	2.0567**	3.4034*	2.5766***
S. Risk does not cause CSAD	1.1495	5.2335***	2.3225***	2.1516***	1.1366	1.1315	0.7557	2.4097***
Global financial crisis period								
CSAD does not cause S. Risk	1.1539	7.2599***	3.4348***	2.1465**	2.7337***	2.9889**	3.8464***	2.5103**
S. Risk does not cause CSAD	4.2686***	8.2497***	2.7664***	2.1630**	2.4614**	3.0100***	2.0557**	2.8343***
Pre-Eurozone crisis period								
CSAD does not cause S. Risk	1.4964	0.0107	0.4764	2.9660*	7.5655***	2.1347	0.5639	4.0407***
S. Risk does not cause CSAD	2.0276**	3.2413**	1.4088	1.6015	1.6414	1.3788	1.3444	3.4212***
Eurozone crisis period								
CSAD does not cause S. Risk	6.6785***	2.9568**	2.3590*	0.1923	2.6716***	1.7164	1.2275	0.2270
S. Risk does not cause CSAD	2.4270***	1.8914*	2.1959**	2.5212**	1.5243	3.4012***	0.9586	1.7488
Pre-China's stock market crash								
CSAD does not cause S. Risk	0.0031	2.0227**	3.8037*	0.3464	0.1031	0.0010	4.0826***	0.3363
S. Risk does not cause CSAD	0.3484	2.5681**	1.8529**	0.8841	2.7092***	1.9907**	1.5131	1.8572**
China's stock market crash								
CSAD does not cause S. Risk	1.2544	0.0208	0.1281	0.0855	2.4664	0.0969	10.6911***	4.1791***
S. Risk does not cause CSAD	1.9227	3.7739**	1.5145	2.0337**	0.0059	2.1990	0.6195	2.5638***
Post crises period								
CSAD does not cause S. Risk	1.3847	3.8583***	2.3695**	4.2424***	3.2727***	2.5614***	3.5734***	12.0705***
S. Risk does not cause CSAD	2.2086	0.0968	1.1231	1.1284	0.4325	1.2639	4.1648***	2.2715*

	Northern Europe				Southern Europe			
	Denmark	Finland	Norway	Sweden	Greece	Italy	Portugal	Spain
Full sample period								
CSAD does not cause S. Risk	4.0539***	2.8360***	2.9796***	1.1807	2.7679***	3.7498***	2.7391***	2.2142**
S. Risk does not cause CSAD	1.3408	2.7487***	3.8123***	3.4241***	1.0765	5.1603***	2.9102***	5.5829***
Pre-Global financial crisis period								
CSAD does not cause S. Risk	2.4721**	2.3628*	1.3168	0.1513	2.2124***	0.0854	1.2165	6.4171***
S. Risk does not cause CSAD	0.9509	1.8810**	2.0010**	3.6728***	1.5833	2.7301***	1.8333**	3.2273***
Global financial crisis period								
CSAD does not cause S. Risk	5.2889**	2.3664*	3.1873***	2.5602*	2.8928***	2.7531**	6.8454***	2.3076*
S. Risk does not cause CSAD	2.7837**	1.9381**	3.7590***	1.8470**	3.4345***	3.8508***	2.2496**	1.9345*
Pre-Eurozone crisis period								
CSAD does not cause S. Risk	8.8411***	3.8003**	0.5858	6.6668**	1.5811	3.2888***	0.0336	0.4169
S. Risk does not cause CSAD	1.3736	0.6817	1.1376	0.6515	1.6911	1.3017	0.0901	2.2679*
Eurozone crisis period								
CSAD does not cause S. Risk	4.6645***	1.9579**	1.9697*	0.3432	2.3062*	3.2195***	2.4669*	2.8402**
S. Risk does not cause CSAD	0.9515	7.4952***	3.3132***	1.4826	2.4873***	2.7176***	1.6694	2.1008*
Pre-China's stock market crash								
CSAD does not cause S. Risk	0.6838	3.6840*	0.0858	0.3436	2.6196***	1.9781	1.3750	0.9130
S. Risk does not cause CSAD	1.0205	2.9165**	0.9878	0.2911	1.6889*	3.1585***	0.4675	2.4643***
China's stock market crash								
CSAD does not cause S. Risk	0.1151	0.0000	0.9152	1.3121	12.1509***	3.9902***	1.0177	0.0220
S. Risk does not cause CSAD	1.6141	4.3566***	1.8731	1.6551	1.2121	2.4815**	2.1501	0.8737
Post crises period								
CSAD does not cause S. Risk	11.7890***	1.9448	2.5692	1.6368	9.6338***	7.8401***	3.7144***	5.4265***
S. Risk does not cause CSAD	2.5597*	0.1547	2.6785***	0.7086	2.2392**	1.9977**	2.9630***	1.5894*

Notes: The Table reports the F-Statistics from the Granger causality test between the CSAD and the systemic risk increases ($S.Risk$) measured with the $\Delta CoVaR_{99^{th},i}$. The null hypothesis is each variable "does not Granger Cause" the other. The lag length is chosen based on the Akaike information criterion. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

effect during the GFC in all the European markets except Austria; all the North American markets, and Mexico; and, all the Asia Pacific markets except India, Malaysia and Taiwan. During the EZC, we do not find the same pattern of results. In particular, a two-way Granger causality is found mainly for the European markets, 3 out of 8 in the Western Europe, 2 out of 4 in Northern Europe, and 3 out of 4 in Southern Europe. The same result is found for India and Japan in the Asia Pacific markets, Brazil and Chile in the Latin American markets, and, Canada in the North American markets. Overall, we find (out of 264 total cases analyzed) a two-way Granger causality in 112 cases, that CSAD Granger causes systemic risk increases in 52 cases, and, that systemic risk increases Granger cause CSAD in 44 cases. We find no Granger causality between these two variables in 56 cases. We observe a two-way Granger causality for 26 countries during the GFC and for 13 counties, of which 8 European, during the EZC. This finding point out a stronger relationship between these two variables during crisis periods.

5.3.5 Interrelationship between herding behavior and systemic risk

In estimating the VECM, we first check for stationarity and unit root through the augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests on the variables in levels and first differences. To ascertain the integrated relationship between systemic risk and herding behavior, we build appropriate models for k = 7 – 13. The model with k = 10 had the lowest AIC for all the markets except Chile (8), Finland (9), Honk Kong (9), Indonesia (9) and Japan (8). In such a situation, we decide to show the results for the model with k = 10 for all the markets considered in this study.[20]

Tables 5.8 to 5.10 reports the parameters of our VECM for the Asia Pacific, Latin and Northern American, and European markets, respectively. Both variables used in our VECM

[20]Results with k = 8 for Chile and Japan, and k = 9 for Finland, Hong Kong and Indonesia, are both quantitative and qualitative similar and are available upon request.

Table 5.8: Asia Pacific markets: Vector Error Correction Model.

	Asia Pacific											
	Australia		China		Honk Kong		India		Indonesia		Japan	
	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$
ECT	0.0001**	0.0024***	-0.011***	0.0067***	0.0017*	0.0015***	0.0008	0.0019***	0.0004	0.0047***	-0.0010	0.0034***
β_0	0.0001	0.0025	0.0042	-0.002***	0.0000	0.0002	0.0001	0.0006**	0.0000	-0.001**	0.0000	9.8619
β_{t-1}	-0.678***	0.0279	-0.587***	-0.047***	-0.706***	0.0000	-0.687***	-0.003**	-0.634***	-0.004*	-0.577***	0.0000
δ_{t-1}	0.0683*	0.3444***	-1.338***	-0.157***	0.6260	-0.0040	0.0170	0.2901***	0.1872	0.0600	-0.904**	0.1510***
β_{t-2}	-0.508***	-0.0130	-0.449***	-0.028***	-0.547***	0.0000	-0.515***	0.0000	-0.517***	0.0034	-0.390***	0.0000
δ_{t-2}	0.0682*	0.3121***	-1.220***	-0.168***	0.6471	-0.0340	-0.3240	0.2637***	0.0320	0.0539	-1.066**	0.1093**
β_{t-3}	-0.433***	0.0434	-0.346***	-0.020***	-0.433***	0.0000	-0.436***	-0.0020	-0.420***	-0.005*	-0.306***	0.0000
δ_{t-3}	0.0719**	0.1351***	-1.132***	-0.148***	0.3040	0.0057	-0.3620	0.2337***	-0.0250	0.0341	-1.001**	0.1042**
β_{t-4}	-0.345***	0.0562*	-0.290***	-0.015***	-0.373***	0.0002	-0.366***	-0.0010	-0.328***	-0.0020	-0.232***	0.0027
δ_{t-4}	0.0667**	0.1243***	-0.862***	-0.125***	0.4260	0.0295	-0.3490	0.2138***	-0.0490	0.0234	-0.921**	0.0706
β_{t-5}	-0.265***	0.1177***	-0.222***	-0.012***	-0.307***	-0.0010	-0.302***	0.0000	-0.262***	5.3559	-0.181***	-0.0020
δ_{t-5}	0.0585**	0.0807*	-0.625***	-0.089**	0.2976	0.0204	-0.3050	0.2007***	0.0087	0.0139	-0.819**	0.0611
β_{t-6}	-0.207***	0.0956***	-0.235***	-0.010**	-0.250***	-0.0020	-0.231***	2.8288	-0.225***	0.0012	-0.144***	0.0011
δ_{t-6}	0.0453*	0.0792**	-0.440**	-0.090**	0.0646	0.0382	-0.4200	0.1725***	-0.0960	9.8690	-0.950***	-0.067*
β_{t-7}	-0.202***	0.0628**	-0.194***	-0.014***	-0.196***	-0.0010	-0.201***	0.0000	-0.174***	0.0026	-0.088***	0.0000
δ_{t-7}	0.0433**	0.1881***	-0.350**	-0.061*	-0.3770	0.0484	-0.3710	0.1683***	-0.1310	0.0110	-0.769***	-0.0160
β_{t-8}	-0.155***	0.0624**	-0.145***	-0.011***	-0.148***	-0.0010	-0.183***	0.0000	-0.122***	0.0025	-0.039**	-0.0010
δ_{t-8}	0.0348**	-0.069**	-0.330**	-0.0380	-0.5230	0.0333	-0.1560	0.0420	-0.0130	0.0159	-0.505**	-0.0380
β_{t-9}	-0.130***	0.0105	-0.090***	-0.0040	-0.094***	0.0000	-0.114***	-0.0010	-0.077***	0.0077***	-0.063***	0.0026
δ_{t-9}	0.0239*	0.0264	-0.1730	-0.0300	-0.590**	0.0069	-0.3730	0.0265	-0.1050	0.0045	-0.419**	-0.0080
β_{t-10}	-0.050***	0.0147	-0.0140	-0.006**	-0.067***	0.0000	-0.051***	-0.0010	-0.036**	0.0134***	-0.037**	-0.0020
δ_{t-10}	0.0161*	0.0729***	-0.0630	-0.0250	-0.394**	0.0161	-0.0690	0.0206	0.0291	0.0034	-0.359***	0.0007

	Malaysia		Singapore		South Korea		Taiwan		Thailand	
	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$
ECT	-0.0020	0.0155***	0.0007	0.0052***	-0.001**	0.0033***	0.0000	-0.005***	0.0005	0.0038***
β_0	-0.0010	0.0043**	0.0000	0.0007*	0.0000	0.0000	0.0002	0.0030**	0.0000	-0.000**
β_{t-1}	-0.653***	-0.0070	-0.695***	0.0008	-0.627***	-0.011***	-0.677***	0.0043	-0.598***	-0.015***
$\delta t-1$	-0.1430	0.0053	0.2191	0.0487	-0.436**	0.0395	0.1309	0.0178	-0.0030	-0.0600
β_{t-2}	-0.524***	-0.016**	-0.572***	-0.005***	-0.430***	-0.0050	-0.586***	0.0029	-0.414***	-0.012***
δ_{t-2}	-0.1390	0.0022	0.1271	0.0977*	-0.447**	0.0400	0.2086	0.0281	-0.1100	-0.0630
β_{t-3}	-0.458***	-0.0110	-0.474***	-0.004**	-0.366***	-0.0010	-0.435***	0.0043	-0.349***	-0.006***
δ_{t-3}	-0.1250	0.0052	0.1717	0.0972**	-0.347*	0.0505	0.3352**	0.0289	-0.0560	-0.144***
β_{t-4}	-0.380***	-0.0100	-0.383***	-0.006***	-0.308***	-0.0020	-0.373***	0.0103	-0.257***	-0.0020
δ_{t-4}	-0.0950	0.0022	0.0957	0.0573	-0.1280	0.0199	0.2053	0.0186	-0.2500	-0.144***
β_{t-5}	-0.320***	-0.0040	-0.312***	-0.004*	-0.250***	-0.0050	-0.293***	0.0102	-0.221***	0.0012
δ_{t-5}	-0.0800	0.0030	0.3956	0.0379	-0.1350	-0.0150	0.1173	0.0300	-0.2880	-0.098**
β_{t-6}	-0.277***	-0.0110	-0.273***	-0.0010	-0.220***	-0.0020	-0.246***	0.0062	-0.204***	0.0000
δ_{t-6}	-0.0520	-0.0080	0.4070	0.0362	-0.1300	0.0054	0.1086	0.0174	-0.4440	-0.118***
β_{t-7}	-0.201***	0.0043	-0.225***	-0.004*	-0.190***	0.0002	-0.208***	0.0096	-0.155***	0.0019
δ_{t-7}	0.0194	-0.0010	0.2700	0.0545*	-0.1300	0.0167	0.1217	0.0046	-0.1600	-0.131***
β_{t-8}	-0.184***	-0.015*	-0.177***	-0.0030	-0.156***	0.0019	-0.129***	0.0136**	-0.126***	0.0004
δ_{t-8}	0.0024	0.0029	0.6029**	0.0434	-0.0540	-0.0030	0.2664***	0.0090	-0.400*	-0.058**
β_{t-9}	-0.123***	-0.017**	-0.116***	-0.004**	-0.107***	0.0002	-0.113***	0.0048	-0.116***	0.0000
δ_{t-9}	-0.0190	0.0023	0.5624***	-0.0010	-0.158*	0.0151	0.0275	0.0122	-0.1810	-0.041*
β_{t-10}	-0.072***	-0.0100	-0.063***	-0.003**	-0.029*	-0.0010	-0.0150	0.0039	-0.074***	0.0000
δ_{t-10}	-0.0360	0.0019	0.3178**	-0.0070	-0.0740	0.0114	0.0179	0.0104	-0.0700	-0.036**

Notes: The Table reports the estimates of the VECM – Eq. (5.14). The *S.Risk* variable refers to $\Delta CoVaR_{99^{th},i}$. β_{t-i} and δ_{t-i} refer to $\Delta CSAD$ and $\Delta(\Delta CoVaR_{99^{th},i})$, respectively. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 5.9: Latin and Northern American markets: Vector Error Correction Model.

	Latin America								North America			
	Argentina		Brazil		Chile		Mexico		Canada		USA	
	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$
ECT	0.0002	0.0005***	0.0000	0.0012***	0.0004	0.0021***	0.0028	0.0026***	0.0013**	0.0010***	0.0008***	0.0003***
β_0	0.0002	0.0012***	-5.9330	0.0001	1.4323	0.0007***	0.0001	0.0005***	0.0000	0.0002	0.0007	0.0005***
β_{t-1}	-0.712***	0.0027**	-0.701***	0.0006	-0.712***	0.0000	-0.700***	-0.003***	-0.713***	-0.005***	-0.558***	-0.003***
δ_{t-1}	0.3614	0.0732	-0.1420	-0.0180	0.1789	0.0599	0.1419	0.2007***	1.1938*	0.0081	2.7514***	0.2489***
β_{t-2}	-0.578***	0.0037**	-0.553***	0.0018	-0.553***	0.0011	-0.572***	-0.001**	-0.568***	-0.003**	-0.411***	-0.003***
δ_{t-2}	0.3107	0.0622	-0.3590	-0.0240	-0.3020	0.0637	-0.2870	0.1590***	0.4644	-0.0690	1.7278**	0.1675***
β_{t-3}	-0.470***	0.0022	-0.470***	0.0004	-0.461***	-0.0010	-0.471***	-0.0010	-0.457***	-0.0020	-0.338***	-0.005***
δ_{t-3}	0.3275	0.0571	-0.4440	-0.0410	-0.2140	0.0405	-0.6740	0.1545***	0.1784	0.0515	1.3413*	0.1750***
β_{t-4}	-0.389***	0.0021	-0.391***	0.0000	-0.373***	-0.0020	-0.411***	0.0000	-0.379***	-0.0010	-0.280***	-0.002**
δ_{t-4}	0.0093	0.0726*	-0.5700	-0.0620	-0.2030	0.0069	-1.0080	0.1039**	0.1004	0.1157**	0.8679	0.1716***
β_{t-5}	-0.328***	0.0016	-0.322***	0.0030	-0.299***	-0.003**	-0.343***	0.0006	-0.263***	-0.0020	-0.176***	-0.0020
δ_{t-5}	-0.1780	0.0745**	-0.5420	-0.0370	-0.2120	-0.0640	-1.553**	0.1138***	0.0782	0.0956**	0.5726	0.1275***
β_{t-6}	-0.306***	0.0036*	-0.255***	0.0020	-0.246***	-0.0010	-0.276***	0.0001	-0.226***	0.0000	-0.153***	-0.002*
δ_{t-6}	-0.3200	0.0460	-0.4740	-0.0380	-0.3950	-0.080**	-1.0340	0.1147***	0.1335	0.0387	0.4361	0.1396***
β_{t-7}	-0.248***	0.0042**	-0.225***	0.0030	-0.211***	-0.0010	-0.199***	6.0923	-0.202***	-0.0020	-0.163***	-0.003**
δ_{t-7}	-0.5340	0.0354	-0.663**	-0.056*	-0.3580	-0.084***	-1.214**	0.0972***	0.3652	-0.0420	0.3507	0.0832**
β_{t-8}	-0.194***	0.0018	-0.170***	0.0006	-0.141***	3.9220	-0.149***	0.0008	-0.149***	0.0000	-0.163***	-0.0020
δ_{t-8}	-0.480*	0.0297	-0.3250	-0.063**	0.0011	-0.0290	-1.080**	0.0569**	0.2975	-0.074**	0.4091	0.0911***
β_{t-9}	-0.119***	0.0016	-0.102***	0.0011	-0.115***	-0.0010	-0.128***	0.0000	-0.112***	-0.0010	-0.121***	-0.0010
δ_{t-9}	-0.2970	0.0164	-0.2810	-0.077***	-0.1660	-0.039*	-0.795*	0.0096	0.0121	-0.081***	0.0835	0.0631***
β_{t-10}	-0.060***	0.0013	-0.060***	0.0010	-0.049***	0.0000	-0.048***	0.0000	-0.068***	0.0001	-0.0210	0.0000
δ_{t-10}	-0.1770	0.0216	-0.0610	-0.036**	-0.2290	-0.043***	-0.1970	0.0025	-0.1040	-0.061***	0.3247	0.0541***

Notes: The Table reports the estimates of the VECM – Eq. (5.14). The $S.Risk$ variable refers to $\Delta CoVaR_{99^{th},i}$. β_{t-i} and δ_{t-i} refer to $\Delta CSAD$ and $\Delta(\Delta CoVaR_{99^{th},i})$, respectively. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 5.10: European markets: Vector Error Correction Model.

	Western Europe															
	Austria		Belgium		France		Germany		Ireland		Netherlands		Switzerland		United Kingdom	
	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$
ECT	-1.9400	-0.002***	0.0033***	0.0011***	0.0006***	0.0002***	0.0005	0.0005***	-0.0020	0.0036***	0.0000	-0.000***	0.0010	0.0014***	0.0017**	0.0011***
β_0	0.0002	0.0011***	0.0017	0.0006**	0.0003	0.0004*	0.0000	0.0002	0.0017	-0.001***	0.0000	0.0002	0.0003	0.0004	1.2321	0.0002
β_{t-1}	-0.799***	-1.4980	-0.770***	-0.002***	-0.709***	2.9199	-0.725***	0.0000	-0.778***	-0.003***	-0.755***	0.0000	-0.750***	-0.001*	-0.689***	-0.005***
δ_{t-1}	-0.0010	0.1428***	2.7767***	0.1236**	2.4749***	0.2016***	0.2872	0.0625	-0.8910	0.1898***	0.5986	0.0096	0.5367	0.0154	0.9579	0.0187
β_{t-2}	-0.673***	-0.0020	-0.628***	-0.003***	-0.564***	0.0000	-0.596***	-0.002**	-0.632***	-0.003***	-0.611***	-0.002*	-0.617***	-0.002*	-0.564***	-0.005***
δ_{t-2}	-0.2030	0.1168**	1.9057**	0.0866*	1.7982**	0.1380***	-0.2230	0.0107	-0.7140	0.1553***	0.1539	-0.0270	0.3917	-0.0190	0.2046	-0.0110
β_{t-3}	-0.544***	-7.3550	-0.519***	-0.004***	-0.486***	0.0000	-0.491***	-0.002*	-0.529***	-0.002*	-0.513***	-0.0010	-0.513***	-0.0020	-0.479***	-0.005***
δ_{t-3}	-0.1620	0.1084**	0.7969	0.0458	1.4442**	0.1053**	-0.4500	0.0034	-0.6450	0.0894*	-0.0280	-0.0300	-0.1490	0.0220	-0.3850	-0.0530
β_{t-4}	-0.470***	0.0008	-0.431***	-0.003***	-0.363***	0.0016	-0.380***	-0.0010	-0.428***	-0.0010	-0.428***	0.0000	-0.402***	-0.0020	-0.369***	-0.003**
δ_{t-4}	0.0045	0.0480	0.6135	0.0207	1.1888*	0.1329***	-0.4400	0.0280	-0.7040	0.0806*	-0.1690	0.0059	-0.4390	0.0305	-0.7710	-0.0020
β_{t-5}	-0.392***	0.0014	-0.365***	-0.002*	-0.250***	0.0016	-0.279***	0.0000	-0.355***	0.0005	-0.346***	0.0009	-0.330***	0.0000	-0.247***	-0.002*
δ_{t-5}	0.0569	0.0643*	0.4772	0.0002	0.9912*	0.1021***	-0.6050	0.0000	-0.1160	0.0378	-0.4490	0.0104	-0.2800	0.0187	-0.986*	0.0152
β_{t-6}	-0.314***	-0.0010	-0.262***	0.0003	-0.210***	0.0010	-0.215***	0.0003	-0.277***	0.0000	-0.245***	0.0010	-0.265***	0.0009	-0.206***	-0.003**
δ_{t-6}	-0.0560	0.0728**	0.0621	0.0050	0.6464	0.0691**	-0.6360	0.0000	-0.3230	-0.0460	-0.3200	-0.0190	-0.3380	0.0014	-0.912*	0.0080
β_{t-7}	-0.240***	5.8047	-0.213***	-4.9960	-0.201***	0.0000	-0.160***	-0.0010	-0.229***	-0.0010	-0.234***	0.0017	-0.210***	0.0000	-0.186***	-0.003**
δ_{t-7}	0.3619	0.0720**	-0.3880	0.0000	0.4362	0.0674**	-0.3590	-0.0050	-0.4220	0.0223	-0.2890	-0.0230	-0.0340	0.0063	-0.783*	0.0183
β_{t-8}	-0.196***	0.0009	-0.173***	0.0007	-0.189***	-0.0010	-0.129***	-0.0010	-0.167***	-0.0010	-0.192***	0.0011	-0.174***	0.0015	-0.183***	-0.002*
δ_{t-8}	0.2395	0.0218	-0.3870	0.0168	0.1997	0.0785***	-0.5120	0.0081	-0.4230	0.0125	-0.1540	-0.0200	-0.1720	0.0201	-0.5630	0.0183
β_{t-9}	-0.142***	0.0000	-0.148***	0.0000	-0.132***	-0.002*	-0.095***	0.0000	-0.125***	-0.0010	-0.145***	0.0001	-0.121***	0.0012	-0.117***	-0.0010
δ_{t-9}	-0.1600	-0.0070	-0.4460	-0.0330	-0.0390	0.0392**	-0.3260	-0.0150	-0.4230	0.0003	-0.0910	-0.0170	-0.1680	0.0138	-0.504*	0.0017
β_{t-10}	-0.097***	0.0000	-0.085***	0.0000	-0.048***	0.0000	-0.0220	0.0000	-0.059***	0.0000	-0.072***	0.0007	-0.053***	0.0008	-0.038**	-4.4590
δ_{t-10}	-0.1240	0.0041	-0.2100	-0.037**	0.0292	0.0121	-0.0380	-0.046***	-0.3220	0.0009	0.0386	-0.026*	0.0208	0.0000	-0.2500	-0.0020

	Northern Europe								Southern Europe							
	Danmark		Finland		Norway		Sweden		Greece		Italy		Portugal		Spain	
	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$	$\Delta CSAD$	$\Delta S.Risk$
ECT	0.0008*	0.0005***	-8.012***	-3.711***	0.0011	0.0017***	0.0004*	0.0002***	-0.000**	-0.000***	-0.002***	-0.001***	0.0011**	0.0007***	-1.236***	-3.411***
β_0	0.0004	0.0005**	-5.0300	0.0001	7.1163	-4.3220	0.0001	0.0002	4.0261	0.0004	0.0002	0.0002	-3.1380	0.0002	0.0007	0.0003
β_{t-1}	-0.755***	-0.001**	-0.687***	0.0014	-0.758***	-0.008***	-0.699***	-5.7160	-0.704***	-0.004**	-0.775***	-0.002***	-0.697***	-0.002**	-0.737***	-0.0010
δ_{t-1}	1.6896*	0.1373***	1.7346***	0.0512	0.5657	0.2277***	1.1898	0.1185**	0.6852	-0.0050	1.6043*	0.1415***	1.8779**	0.2156***	3.3131***	0.1589***
β_{t-2}	-0.610***	-0.002***	-0.530***	-0.0020	-0.633***	-0.006***	-0.546***	0.0000	-0.581***	-0.005**	-0.637***	-0.0010	-0.567***	-0.0010	-0.587***	-0.0010
δ_{t-2}	1.4366	0.1390***	1.4000***	0.0317	-0.0700	0.0955	0.2595	0.0827*	0.4785	-0.0390	0.7494	0.1298***	1.0442	0.2208***	1.9534**	0.1065**
β_{t-3}	-0.544***	-0.0010	-0.427***	-0.0010	-0.516***	-0.008***	-0.448***	-9.4530	-0.475***	-0.0020	-0.483***	0.0000	-0.484***	0.0000	-0.492***	-0.0010
δ_{t-3}	1.1440	0.0785*	1.1105**	-0.0110	-0.2520	0.0377	0.2867	0.0268	0.4039	-0.0400	0.2070	0.0975**	0.8209	0.1854***	1.1616	0.0621
β_{t-4}	-0.456***	0.0000	-0.326***	0.0000	-0.444***	-0.006***	-0.354***	0.0006	-0.387***	0.0000	-0.394***	-0.0010	-0.389***	0.0002	-0.407***	0.0000
δ_{t-4}	0.2810	0.1220***	1.1123**	0.0090	-0.5400	0.0172	0.4328	0.0418	0.1689	-0.0560	-0.5820	0.0989**	-0.2210	0.1883***	0.5666	0.0672
β_{t-5}	-0.377***	0.0000	-0.246***	0.0007	-0.383***	-0.004**	-0.268***	0.0009	-0.299***	0.0032	-0.317***	-0.0010	-0.340***	0.0006	-0.307***	-0.0010
δ_{t-5}	0.4207	0.0878**	0.7094*	-0.0150	-0.6240	-0.0230	0.6136	0.0036	0.1929	-0.0450	-0.9110	0.0350	-0.3440	0.1570***	0.7260	0.0261
β_{t-6}	-0.292***	0.0001	-0.205***	0.0014	-0.295***	-0.005**	-0.207***	0.0000	-0.276***	0.0037	-0.279***	-0.0010	-0.275***	0.0001	-0.239***	0.0000
δ_{t-6}	0.3770	0.0320	0.6114	-0.0500	-0.792*	-0.0700	0.3381	-0.0230	0.0178	-0.0520	-1.159*	0.0548	-0.4860	0.1297***	0.5685	0.0168
β_{t-7}	-0.236***	0.0004	-0.185***	2.5837	-0.222***	-0.005**	-0.174***	0.0000	-0.223***	0.0019	-0.231***	-0.002**	-0.213***	0.0007	-0.203***	0.0000
δ_{t-7}	0.0394	0.0182	0.3625	-0.0260	-1.011**	-0.0520	0.0695	0.0142	-0.0820	-0.0390	-1.173**	0.0691**	-0.1860	0.1367***	0.1568	0.0233
β_{t-8}	-0.171***	0.0006	-0.134***	0.0005	-0.155***	-0.0010	-0.126***	0.0000	-0.155***	0.0020	-0.171***	-0.002**	-0.166***	0.0006	-0.168***	0.0000
δ_{t-8}	-0.1290	0.0226	-0.0500	-0.0040	-0.786**	-0.0210	-0.0510	0.0079	-0.2560	-0.0290	-1.527***	0.0845***	-0.3650	0.1294***	0.0544	0.0349
β_{t-9}	-0.099***	0.0001	-0.079***	0.0000	-0.119***	-0.0020	-0.103***	0.0000	-0.111***	0.0000	-0.119***	-0.002***	-0.117***	0.0003	-0.105***	8.2091
δ_{t-9}	0.0538	0.0037	-0.0870	0.0015	-0.511**	-0.0260	0.0658	0.0000	-0.2290	-0.0180	-1.085***	0.0327	-0.4840	0.0997***	-0.0850	0.0118
β_{t-10}	-0.045***	-9.4480	-0.069***	0.0014	-0.066***	-0.003**	-0.061***	0.0000	-0.072***	0.0000	-0.042***	-0.002***	-0.049***	0.0022***	-0.044***	0.0005
δ_{t-10}	-0.1020	-0.0020	0.0069	-0.0190	-0.1650	-0.0050	-0.2670	-0.0220	-0.1080	-0.0010	-0.645**	0.0000	-0.0870	0.0946***	0.4052	-0.0200

Notes: The Table reports the estimates of the VECM – Eq. (5.14). The $S.Risk$ variable refers to $\Delta CoVaR_{99^{th},i}$. β_{t-i} and δ_{t-i} refer to $\Delta CSAD$ and $\Delta(\Delta CoVaR_{99^{th},i})$, respectively. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

model – $\Delta^{\$}CoVaR_{99^{th},i}$ and CSAD, only assume positive values. Thus, a negative and statistically significant coefficient β_{t-i} (δ_{t-i}) would imply an increase (decrease) in systemic risk – $\Delta S.Risk$ (for the return clustering measure – $\Delta CSAD$, leading to herding).[21] For the Asia Pacific markets, we find a negative and significant β_{t-i} (δ_{t-i}) in China, India, Indonesia, Malaysia, Singapore, South Korea and Thailand (China, Japan and South Korea); in Latin and Northern America markets in Canada, Chile, Mexico and USA (Argentina, Brazil and Mexico); while, in European markets in Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Switzerland, United Kingdom, (Italy, Norway and United Kingdom). These results point out a greater number of cases of interrelationship between CSAD and systemic risk increases, confirming the view of herding as an ex-ante aspect of systemic risk (Acharya and Yorulmazer, 2008).

5.4 Conclusions

This Chapter investigates investors' herding behavior for 33 countries classified into three groups: Asia Pacific markets (Australia, China, Hong Kong, India, Indonesia, Japan, Malaysia, Singapore, South Korea, Taiwan, and Thailand); Latin American markets (Argentina, Brazil, Chile, and Mexico); North American markets (Canada, and the United States); and, European markets,[1] which are divided into: Western European markets (Austria, Belgium, France, Germany, Ireland, Netherlands, Switzerland, and the United Kingdom); Northern European markets (Denmark, Finland, Norway, and Sweden); and Southern European markets (Greece, Italy, Portugal, and Spain). By applying daily data, the analysis is undertaken during the period from January 2000 to end-January 2019. We use the return clustering measure (CSAD) introduced by Chang, Cheng, and Khorana (2000) and, in addition to the common practice of OLS regression, as per Zhou and Anderson (2013)

[21] In particular, when $\Delta CSAD = CSAD_t - CSAD_{t-i} < 0$, meaning that $CSAD_t < CSAD_{t-i}$, a negative and statistically significant coefficient β_{t-i} would lead to a systemic risk increase; while, when $\Delta S.Risk = S.Risk_t - S.Risk_{t-i} > 0$, meaning that $S.Risk_t > S.Risk_{t-i}$, a negative and statistically significant coefficient δ_{t-i} would lead to herding by decreasing the $\Delta CSAD$.

and Chiang, Li, and Tan (2010), we use quantile regression (Koenker and Bassett Jr, 1978) in order to have a more complete and detailed analysis, alleviating some statistical issues related to the OLS.[8]

The comparative country-wise analysis, based on the OLS, suggests that apart from China, Indonesia and Taiwan for the Asia Pacific markets, Chile for the Latin American and Italy for the Southern European markets, herding is not significant for all the remaining markets. However, the quantile regression analysis detects herding, in the higher quantiles, also for Australia and Thailand in the Asia Pacific markets, and for France, Germany and Switzerland in the Western European markets. Conditioning the analysis to the EZC, we observe significant evidences that support herding in each Asia Pacific, American (Latin and North), and European market except Greece, Ireland, Italy and Spain. When we condition on the China's market crash, we find significant herding coefficients for all the markets except Chile, China, Greece and Taiwan. These findings imply that herding behavior is linked to distressed periods not only related to the domestic market, but also to the foreign ones, and, that different market drops may affect in different ways herding behavior. These evidences is straightened by conditioning the analysis to UK economy conditions. Moreover, herding behavior seems to be amplified after the Brexit vote for most of the European countries.

This study pioneers research by conditioning the investigation of herding behavior on different systemic risk levels of the market. The $\Delta CoVaR$ developed by Adrian and Brunnermeier (2016) is used as measure for systemic risk. Our findings are inconsistent with the presence of herding behavior in case of medium or low systemic risk, while the estimates conditioned on high systemic risk level of the market point out the presence of herding behavior and an increasing tendency of investors to herd in extreme tail events in each market except Chile, China and Ireland. This finding shows a strong linkage between systemic risk and herding behavior. The variance decomposition tests, based on an unrestricted VAR model, indicate that, overall, the variance of the return clustering is not affected by the systemic risk increases, while the variance of the systemic risk increases appears affected by the return clustering. This effect is more pronounced for the Asia Pacific markets, which include most of the emerging markets considered in our sample. Granger causality tests point out: a two-way Granger causality in 112 cases; that CSAD Granger causes systemic risk increases in 52 cases; and, that systemic risk increases Granger cause CSAD in 44 cases. We find no Granger causality between these two variables in 56 cases. In particular, the evidence reveals a two-way Granger causality for 26 countries during the GFC and for 13 counties, of which 8 European, during the EZC, strengthening the hypothesis that the relationship between these two variables becomes stronger during crisis periods. Finally, using VECM, we find multiple statistically significant cases of interrelationship between CSAD and systemic risk increases. This evidence confirms the intuition of Acharya and Yorulmazer (2008) that herding may be an ex-ante aspect of systemic risk.

CHAPTER 6

Herding behaviour of corporates in the U.S. and the Eurozone through different market conditions

"Policymakers need to design appropriate policies to deal with the negative effects of herd behavior on asset prices in financial markets not only during periods of market stress but also during normal market conditions."

Demirer, Kutan, and Chen (2010)

6.1 Introduction

The Global Financial Crisis (GFC) and the Eurozone Crisis (EZC) emphasized that stock market prices may deviate from their fundamentals due to waves of irrational market sentiment. This may lead to herding, which could undermine financial stability and could pose unhedgeable systemic risk to market participants and financial institutions. Herding is commonly described as a behavioral tendency for investors to suppress their own beliefs and mimic collective actions in the market, leading to a convergence or a correlated patterns of actions (see Nofsinger and Sias, 1999; Welch, 2000; Hwang and Salmon, 2004).

In this Chapter we test for herding towards the market consensus for the US and the Eurozone equity markets and financial industries. We find little evidence of herding based on the standard OLS technique but, applying the more insightful quantile regression methods, we detect that herding is more likely to be present in the high quantiles. Herding appears more pronounced when we condition on the financial crises periods and our results support the herding presence in case of asymmetric conditions of volatility, credit deterioration, funding illiquidity and economic policy uncertainty. In addition, we investigate the presence of herding for corporates due to fundamental or non-fundamental information. We extend this analysis to the last two main global financial crises, highlighting new evidence of "spurious" and "intentional" herding activity, suggesting that different crises may affect herding behavior in different ways.

Policymakers and supervisory authorities are interested in identifying correlated patterns of trades that may aggravate returns' volatility, eroding the financial stability (Demirer, Kutan, and Chen, 2010). Previous literature identifies several reasons why investors would herd. Avery and Zemsky (1998) point out that in turbulent states of the economy, market participants herd because they think that other investors may have more accurate information. Likewise Devenow and Welch (1996) advocate that investors may have an intrinsic preference for conformity with the market consensus. Money managers may imitate collective actions because of the incentives provided by the compensation scheme and terms of employment, as discussed in Bikhchandani and Sharma (2000). Another possible cause was suggested by Bernile and Jarrell (2009) and Carow, Heron, Lie, and Neal (2009) who argue that, particularly after the arrival of public information, there are systematic patterns in institutional activities that may destabilize market prices, causing herding by private investors.

Hott (2009) developed a model for herding formation that shows how a price bubble is generated by herding behavior without assuming any speculative motivations. Herding may trigger important informational inefficiencies in the market, contributing to, on average, to 4% of the asset's expected value Cipriani and Guarino (2014). In corporate bond markets institutional investors' herding is higher than the reported level observed in equities, and impact of herding is highly asymmetric (Cai, Han, Li, and Li, 2019). However, Bernile, Sulaeman, and Wang (2015) find that the anticipated trades by institutional investors ahead of other firms is more likely to reflect their superior ability to process publicly available information, rather than their access to private information.

A large body of research covered herding effects in several stock markets. Christie and Huang (1995) examined twelve US industries, while Chang, Cheng, and Khorana (2000) analyzed the investment behavior of market participants within five markets, namely US, Hong Kong, Japan, South Korea, and Taiwan. There is a comprehensive analysis of herding that focuses on the Chinese stock markets (see, among others, Demirer and Kutan, 2006; Tan, Chiang, Mason, and Nelling, 2008; Chiang, Li, and Tan, 2010). Guney, Kallinterakis, and Komba (2017) investigate herding in eight African markets. Gleason, Mathur, and Peterson (2004) use intra-day data to examine herding on nine S&P500 sectors of Exchange Traded Funds during periods of market's extreme movements. Recent studies of herding behavior provide evidence of cross-country herding effects. In particular, Chiang and Zheng (2010), first, examine herding within eighteen countries, which are then grouped into advanced markets (seven), Latin American markets (four) and Asian markets (seven), and then, focus on the presence of cross-country herding effects from the US market to the others. Economou, Kostakis, and Philippas (2011) provide evidence of cross-country herding for four South European markets, while Mobarek, Mollah, and Keasey (2014) enlarged the sample under analysis to eleven developed European markets. The US REIT market is examined by Philippas, Economou, Babalos, and Kostakis (2013), who find that the herding is more prevalent during days of extreme negative returns. This finding is confirmed by Zhou and Anderson (2013), over a larger sample period (1980 – 2010) and using quantile regression in order to study herding in high quantiles (ie, turbulent states of the market). During earlier financial crises, Galariotis, Rong, and Spyrou (2015) report evidence[1] of herding for

[1] A more recent analysis of "spurious" and "intentional" herding of the US financial industries is done by Humayun Kabir (2018). Compared to Humayun Kabir (2018), we do not consider any difference between

US investors when fundamental macroeconomic announcements are released and spillover herding effects from the US to the UK markets. Moreover, they examine the presence of "spurious" and "intentional" herding in these two markets. In a follow up study, Galariotis, Krokida, and Spyrou (2016) provide new evidence on the relation between herding behavior and equity market's liquidity for the G5 markets, namely US, France, Germany, UK and Japan. Overall, emerging markets are found to herd more likely than developed markets.

In our analysis we focus on corporates' herding during the GFC and EZC for the US and Eurozone equity markets and zooming within the financial industries as well. Moreover, in our analysis of the US equity market, we consider all the companies included in the S&P500, hence capturing approximately 80% coverage of available US market capitalization. As a robustness check we consider also the short-selling bans imposed in the United States during the GFC and in the Eurozone during both crises. This robustness analysis[2] is fundamental because, as argued by Diamond and Verrecchia (1987), the short-selling bans moderate the trading activity of informed traders, preventing bad news from being rapidly impounded into stock prices, in the belief that such bad news are "unwarranted", in the sense that it represents a negative bubble or herding behavior rather than fundamental information. To the best of our knowledge, this type of analysis has been never reported in the earlier herding literature.

The main reason behind our motivation to study the presence of herding in the Eurozone at aggregate level, rather than considering "stand-alone countries", is that, as empirically demonstrated by Kim, Moshirian, and Wu (2005), the macroeconomic convergence associated with the introduction of the European Monetary Union increased the regional and global stock market integration of the Eurozone. Moreover, Schmitz and Von Hagen (2011) show that upon the introduction of a common currency the elasticity with respect to per-capita incomes of net capital flows within the Eurozone has increased for its members. There is

commercial and investment banks, but, according to the GICS[3] framework, we consider more financial industries. In particular, we present the results for the diversified financials and the real estate industries that, to the best of our knowledge, have been never reported in the earlier literature.

[2] A more detailed description of the robustness test is described in Appendix C.1.

therefore increasing financial integration in the Eurozone. Herding threatens the financial stability of the Eurozone, and therefore all the Eurozone markets would experience extreme tail conditions that would call upon the European Central Bank (ECB) intervention.

Our study enriches the existing literature by examining the existence of herding effects in the US and Eurozone equity markets and it contributes to provide new evidence on herding in the financial sector and its industries,[3] namely banks, diversified financials, insurance and real estate, for the period from January 2005 to December 2017, and in particular during the GFC and the EZC. It extends the investigation on herding under market asymmetry conditions, providing evidence of herding in case of higher/lower volatility, credit deterioration, funding illiquidity, and economic policy uncertainty. Moreover, it provides new insights about spillover herding effects from the financial sector and its industries to the domestic equity market, and it continues the analysis of the presence of "spurious" and "intentional" herding in the US and Eurozone markets and financial industries during the entire sample period and the last two main crises.

The remainder of this Chapter is organized as follows. Section 6.2 describes the framework of our study and presents the testing methodologies. Section 6.3 summarizes the characteristics of the data used in this study. In Section 6.4 we discuss the empirical results. Finally, Section 6.5 provides concluding remarks.

[3]Considering the Global Industry Classification Standard (GICS) framework, the financial sector is composed by the banking, insurance and diversified financial industries. We include also the real estate industry because, before the 31^{st} of August 2016, the GICS considered this industry as part of the financial sector. However, because of the increase in size and importance of the real estate industry, the GICS moved this industry from the financial sector to an independent real estate sector. For a detailed description of the GICS methodology, readers can refer to: "Global Industry Classification Standard (GICS) Methodology", Standard & Poor's, 2009; or, https://www.msci.com/gics.

6.2 Methodology

6.2.1 Detecting herding behavior

In the literature, there are two main types of measures of herding behavior at this moment in time: the first class is based on cross-sectional data on stock returns (Christie and Huang, 1995; Chang, Cheng, and Khorana, 2000; Hwang and Salmon, 2004) and, the second class is spanned by measures constructed on transaction data (Lakonishok, Shleifer, and Vishny, 1992; Wermers, 1999; Welch, 2000).

Our study continues and enriches the line of research that focuses on the cross-sectional dispersion of stock returns in extreme market conditions. The main studies of Christie and Huang (1995) and Chang, Cheng, and Khorana (2000) introduced as a measure to detect herding effects the cross-sectional standard deviation (CSSD) and the cross-sectional absolute deviation (CSAD), respectively. These herding measures rely on the fact that investors tend to ignore their prior heterogeneous beliefs and information in order to follow the market consensus.

Christie and Huang (1995) were the first to point out that herding behavior is more likely to appear in periods of market turbulence. They argue that when individual returns cluster around the market consensus, return dispersions should be relatively low. By contrast, rational asset pricing models predict an increase of return dispersions in periods of market turbulence because individual returns differ in their sensitivity to the market returns (Hwang and Salmon, 2004). However, one criticism of the model developed by Christie and Huang (1995) is that it can only be used to analyse herding effects during period of market distress[4] and it does not allow to model herding during tranquil periods of the market (Hwang and Salmon, 2004). Therefore, we employ the more robust CSAD herding measure introduced

[4] Christie and Huang (1995) developed the following regression to test for herding: $CSSD_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + e_t$; where $CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(R_{i,t}-R_{m,t})^2}{N-1}}$, and D_t^L (D_t^U) is a dummy variable that takes the value 1 if the market return at time t lies in the extreme lower (upper) tail of the distribution, and 0 otherwise.

by Chang, Cheng, and Khorana (2000) as:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N} |R_{i,t} - R_{m,t}| \tag{6.1}$$

where $R_{i,t}$ is the company i return at time t, $R_{m,t}$ is the cross-sectional average return of the N companies considered in the universe at time t. The testing is organised looking at the non-linear relationship between return dispersions and the market return as follows:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + e_t \tag{6.2}$$

where $R_{m,t}$ is the cross-sectional average of the N returns in the aggregate market portfolio at time t. The non-linear term ($R_{m,t}^2$) is introduced to capture the herding effect.[5] We employ the regression model (6.2) for each market (and financial industry) to test whether or not there is herding behavior within the US and Eurozone markets (and their financial industries) for the entire sample period analyzed. Hence, in presence of herding one would expect γ_2 to be negative and statistically significant.

Chiang and Zheng (2010) study the herding effects in advanced and emerging markets during the Asian, Mexican, Argentinian and Global Financial crises. They find that herding behavior is more apparent in US and Latin American markets; while, it is less obvious in the other markets. We examine whether or not the herding effects are more pronounced during the last two main financial crises, namely the GFC and the EZC. To this end, we augment the Eq. (6.2) with a dummy variable D^{Crisis} that takes the value 1 during the crisis period and 0 otherwise:

$$CSAD_t = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2 (1 - D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R_{m,t}^2 + \gamma_4 (1 - D^{Crisis}) R_{m,t}^2 + e_t \tag{6.3}$$

In Eq. (6.3), herding behavior is detected if γ_3 is negative and significant.

[5]The West and Newey (1987) estimator has been used to obtain heteroskedasticity and autocorrelation consistent (HAC) co-variances for all the OLS regressions.

In order to determine the crisis period, we follow (Forbes and Rigobon, 2002) and consider that the GFC covers the period from the 9^{th} August of 2007, when BNP Paribas froze three funds because of subprime mortgage sector problems, to the 31^{th} of March 2009, the day marking the first signs of stabilization.[6] Furthermore, the EZC covers the period from the 2^{nd} of May 2010, which is considered the beginning of the crisis because of the first bailout package of the International Monetary Fund (IMF) for Greece, to the 31^{th} of December 2012, month in which the Greek government bought-back €21 billion of their bonds.[7] Moreover, this event precedes the ECB announcement of free unlimited support for all the Eurozone countries through the Outright Monetary Transactions and the establishment of the European Stability Mechanism, which took place in September.

Other studies (see, among others, Chiang and Zheng, 2010; Zhou and Anderson, 2013; Mobarek, Mollah, and Keasey, 2014) examine and document herd behavior around market asymmetries, such as negative and positive market returns and also high or low trading volume or return volatility.

When distress conditions impact many firms simultaneously, a negative stock price reaction to divestments is expected (Finlay, Marshall, and McColgan, 2018). Thus, herding behaviour could be prevalent in periods of market distress reflected by high values of volatility, credit deterioration, funding illiquidity and economic policy uncertainty. Thus, we employ four sub-cases to capture asymmetric market conditions of higher and lower: (i) market volatility; (ii) credit deterioration; (iii) funding illiquidity; and (iv) economic policy uncertainty, respectively. Similar to Chiang and Zheng (2010), the asymmetric behavior of returns' dispersion is estimated as follows:

$$CSAD_t = \alpha + \gamma_1 D^{High}|R_{m,t}| + \gamma_2(1-D^{High})|R_{m,t}| + \gamma_3 D^{High} R^2_{m,t} + \gamma_4(1-D^{High})R^2_{m,t} + e_t \quad (6.4)$$

[6] Major explanations for the usage of this period as proxy of the GFC can be found on the 79^{th} Annual Report of the Bank for International Settlements, (Bank for International Settlements, 2009).

[7] We identify the beginning of the EZC as in Mobarek, Mollah, and Keasey (2014); however, their sample period ends in February. Our sample period permits a more appropriate identification of the EZC.

where $R_{m,t}$ is the cross-sectional average of the N returns in the aggregate market portfolio at time t and D^{High} is a dummy variable that, according to the market asymmetry analyzed, takes the value 1 if the variable used to measure the market asymmetry on day t is greater than the previous 22-trading day (1-trading month) moving average and 0 otherwise.[8] One would expect that the cross-sectional dispersion of stock returns would be reduced during days with high volatility, credit deterioration, funding illiquidity and economic policy uncertainty. More formally, herding effects is present if γ_3 (γ_4) is negative and statistically significant. If $\gamma_3 < \gamma_4$ and these values are significant, the herding effects are more pronounced during the market distressed periods.

The GFC, and then the EZC, emphasized the importance of the financial sector and the industries within it. Bekaert, Ehrmann, Fratzscher, and Mehl (2014) analyze the contagion of the GFC from US, due to global and domestic factors, to 415 country-industry equity portfolios. While, they find small effects of contagion from the U.S. and the global financial sector, their main findings indicate that there has been a substantial domestic contagion phenomenon. Baur (2012) shows that the GFC led to an increased co-movement of returns and thus contagion between financial sector and the domestic market while Brunnermeier (2009) argues that through the "fire sales" an initial negative shocks is amplified and spreads across the system. Others, like Allen and Gale (2000), suggest that financial crises or shocks initially affect only few financial institutions, and then spread, by contagion, to the rest of the financial sector, infecting other sectors and the whole domestic market later on. Furthermore, it is often advocated that, in periods of financial distress, herd behavior may pose a threat to the financial stability because initial negative shocks in the financial sector, or into one of its industries, may be amplified via pro-cyclical market mechanism affecting other sectors and ultimately the whole domestic market. For this reason, we are motivated to analyse

[8] In order to test Eq. (6.4) during higher and lower economic policy uncertainty periods, we use the US EPU index with daily frequency for the U.S., and the European EPU index with monthly frequency for the Eurozone. It means that the empirical analysis related to the Eurozone has been conducted aggregating data by month and considering the dummy variable D^{High} with the value of 1 if the European EPU index at month t is greater than the previous month $t-1$ and 0 otherwise.

the existence of spillover of herding effects, from the financial sector, and its industries to the domestic market. This analysis is of pivotal relevance for policymakers and supervisory authorities, because the presence of spillover herding effects from the financial sector and its industries to the domestic market may lead to a systemic crisis.

The following models underpin our analysis for the US and Eurozone, respectively:

$$CSAD_{US,m,t} = \alpha + \gamma_1 |R_{US,m,t}| + \gamma_2 R^2_{US,m,t} + \delta_1 CSAD_{US,j,t} + \delta_2 R^2_{US,j,t} + e_t \tag{6.5}$$

$$CSAD_{EZ,m,t} = \alpha + \gamma_1 |R_{EZ,m,t}| + \gamma_2 R^2_{EZ,m,t} + \delta_1 CSAD_{EZ,j,t} + \delta_2 R^2_{EZ,j,t} + e_t \tag{6.6}$$

where $CSAD_{US,m,t}$ ($CSAD_{EZ,m,t}$) is the CSAD referring to the N stock in the aggregate market portfolio at time t, $R_{US,m,t}$ ($R_{EZ,m,t}$) is the cross-sectional average of the corresponding N returns at time t,[9] $CSAD_{US,j,t}$ ($CSAD_{EZ,j,t}$) is the CSAD referring to the n stock in the financial sector portfolio, or financial industry portfolio, at time t and $R^2_{US,j,t}$ ($R^2_{EZ,j,t}$) is the squared cross-sectional average of the corresponding n returns at time t. In the U.S., the presence of herding effects between the market "m" and the financial sector, or one of its industry, "j", is highlighted by δ_2 negative and statistically significant in model (6.5) (Eq. (6.6) for the Eurozone).

Considering the study of Bikhchandani and Sharma (2000), arguing that investors herding may be either "spurious", in the sense of deviations due to changes in fundamental information (fundamental driven) or "intentional", in the sense of deviations due to other reasons (non-fundamental driven), Galariotis, Rong, and Spyrou (2015) investigate the fundamental and non-fundamental driven herding behavior. In order to explore this issue, the CSAD measure is decomposed into deviations due to fundamental information and deviations due to non-fundamental information. The intuition behind this decomposition of the CSAD is

[9] The aggregate market portfolio has been computed excluding all the companies included within the financial sector, or financial industry, in order to avoid spurious correlation between the variables involved in models (6.5) and (6.6). Keeping these companies within the aggregate market portfolio means that herding affecting the financial sector, or the financial industry, would mechanically impact the equity market even in absence of spillover effects between the two variables.

that the return factors such as the one in Fama and French (1995, 1996) and Carhart (1997) capture adequately important fundamental information that may affect investor decisions on a market level. Thus, the CSAD due to non-fundamental information is estimated as the residuals of the following regression model:

$$CSAD_t = \alpha + \beta_1(R_{m,t} - Rf_t) + \beta_2 HML_t + \beta_3 SMB_t + \beta_4 MOM_t + \varepsilon_t \tag{6.7}$$

where $(R_{m,t} - Rf_t)$ is the market risk premium, HML_t is the High Minus Low return factor, SMB_t is the Small Minus Big return factor, and MOM_t is the Momentum factor, at time t. The residuals of model (6.7) represent the measure of clustering due to investors responding to non-fundamental information:

$$CSAD_{NONFUND,t} = \varepsilon_t \tag{6.8}$$

It follows that the difference between the total $CSAD_t$ and the $CSAD_{NONFUND,t}$ represents the measure of clustering due to investors responding to fundamental information:

$$CSAD_{FUND,t} = CSAD_t - CSAD_{NONFUND,t} \tag{6.9}$$

Once $CSAD_{NONFUND,t}$ and $CSAD_{FUND,t}$ are estimated, "spurious" and "intentional" herding can be separated by estimating the two regressions:

$$CSAD_{NONFUND,t} = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + e_t \tag{6.10}$$

$$CSAD_{FUND,t} = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + e_t \tag{6.11}$$

In Eq. (6.10) and (6.11), herding effects driven by, respectively, non-fundamental and fundamental information are associated with a negative and statistically significant γ_2.

Moreover, we investigate the herding effects due to non-fundamental and fundamental information during the GFC and the EZC. We estimate the coefficients of the following two regressions, similar to Eq. (6.3):

$$CSAD_{NONFUND,t} = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1 - D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R^2_{m,t} + \gamma_4(1 - D^{Crisis}) R^2_{m,t} + e_t \quad (6.12)$$

$$CSAD_{FUND,t} = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1 - D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R^2_{m,t} + \gamma_4(1 - D^{Crisis}) R^2_{m,t} + e_t \quad (6.13)$$

D^{Crisis} is a dummy variable that takes the value 1 during the crisis and 0 otherwise. In the presence of herding effects driven by non-fundamental and fundamental information, during the crisis period, γ_3 is negative and statistically significant in Eq. (6.12) and (6.13), respectively.

6.2.2 Quantile regression analysis

Herding behavior has been already studied through quantile regressions by Zhou and Anderson (2013) and Chiang, Li, and Tan (2010). However, the findings are limited to the US REIT (Zhou and Anderson, 2013) and China's markets (Chiang, Li, and Tan, 2010). We offer new insights of herding behavior for the US and Eurozone markets, financial sectors and industries, which are based on quantile regressions. In particular, in order to have a comprehensive analysis of the herding effects, we use this method for testing all the employed models in this study described in Section 6.2.1.

In this Section, we offer a brief and intuitive description of the quantile regression method.[10] Koenker and Bassett Jr (1978) and Koenker (2005) argue that Classical linear regression methods can only provide inference on the conditional mean functions. In this

[10] For a detailed description of the quantile regression method, readers can refer to Koenker and Bassett Jr (1978) and Koenker (2005).

case, information about the tails of the distribution is lost. To address this issue, Koenker and Bassett Jr (1978) developed quantile regression in order to estimate models for the conditional median function, and the full range of all the other conditional quantile functions.

In financial markets, extreme outliers can significantly affect the tail values of a distribution, and in turn, this could affect and distort the estimated herding coefficients. Unlike the classical linear regression methods, it is well known that quantile regression alleviate some of the statistical issues due to outliers, especially for fat-tailed distributions[11] (Härdle and Song, 2010). Therefore, we use quantile regressions[12] to test whether the herding effects is sensitive to different quantiles of returns' dispersion.

In the simplest terms, quantile regression allows the estimation of a collection of conditional quantiles equations, which can be generically written as:

$$y_i = \alpha_\tau + \beta_\tau x_i' + \varepsilon_{\tau,i} \tag{6.14}$$

where y_i is the dependent variable, x_i' is a vector of predictors, α_τ is the constant, β_τ is the vector of the estimated coefficients and ε_τ is the error term. The subscript $\tau \in(0,1)$ represents the quantile. We write the τ^{th} conditional quantile function as $Q_\tau(y|x) = \beta_\tau x'$.

The estimator $\hat{\beta}_\tau$ is computed by minimizing a weighted sum of the absolute errors, where the weights are dependent on the quantile values:

$$\hat{\beta}_\tau = arg\ min\left(\sum_{i=y_i>x_i'\beta_\tau} \tau \Big| y_i - x_i\beta_\tau \Big| \quad + \sum_{i=y_i<x_i'\beta_\tau} (1-\tau) \Big| y_i - x_i\beta_\tau \Big| \right) \tag{6.15}$$

As previously explained, the quantile regression focuses on estimating the interrelationship between the dependent variables and its predictors at the median level ($\tau = 0.5 = 50^{th}$) and at any other specific quantile.[13]

[11] For symmetric conditional distributions the quantile curve coincides with the mean regression, ie the quantile estimate with $\tau = 0.5$ (median) coincides with the nonparametric mean regression estimate.

[12] For a detailed description of the quantile regression method, readers can refer to Koenker (2005).

[13] In our study, we consider the estimates at the 10^{th}, 25^{th}, 50^{th}, 75^{th}, 95^{th} and 99^{th} quantiles. In the existing literature, low quantiles (e.g. up to the 50^{th}) are considered as tranquil periods for the market;

6.3 Data

For the empirical analysis we collect daily equity prices from all the constituent stocks of S&P500 and S&P Europe 350, for the US and Eurozone equity markets, respectively. The S&P500 index includes 500 leading companies and captures approximately 80% coverage of available market capitalization; while, the S&P Europe 350 index is designed to be reflective of the Eurozone market, accounting for around 70% of the region's market capitalization.

In order to examine the herding behavior related to the US (Eurozone) financial industries, namely banks, diversified financials, insurance and real estate, we collect data on daily equity prices from all the constituent stocks of S&P 500 Banks Industry Group GICS Level 2 (S&P Europe 350 Banks Industry Group GICS Level 2), S&P 500 Diversified Financials Industry Group GICS Level 2 (S&P Europe 350 Diversified Financials Industry Group GICS Level 2), S&P 500 Insurance Industry Group GICS Level 2 (S&P Europe 350 Insurance Industry Group GICS Level 2) and S&P 500 Real Estate Industry Group GICS Level 2 (S&P Europe 350 Real Estate Industry Group GICS Level 2). We are strongly motivated to consider the GICS framework[3] because it has become widely recognized by market participants worldwide and enables meaningful comparisons of sectors and industries across countries, regions, and globally. Moreover, MSCI and Standard & Poor's review the entire framework annually to ensure an accurate representation of the marketplace.

The sample covers the period from January 2005 to December 2017. Note that we restrict the sample to the active stocks. We calculate daily returns as $R_{i,t} = ln(P_{i,t}/P_{i,t-1}) \times 100$. Following the existing literature, we construct the average market portfolio return $R_{m,t}$ as the equally-weighted of the N returns in the aggregate market portfolio at time t.[14] The calculation of $R_{m,t}$ is required to estimate the CSAD as in Eq. (6.1) The sample consists of

while, high quantiles (e.g. above the 75^{th}) represent a distress state for the market (see, e.g., Adrian and Brunnermeier, 2016)

[14]For robustness purposes, we have alternatively used a value-weighted market portfolio returns to test all the employed models in this study. Results are both quantitative and qualitative similar and are available upon request.

3271 daily return observations for the US market, and 3327 observations for the Eurozone. The equity prices are obtained from Bloomberg.

The economic and financial variables we consider in order to detect the herding behavior in case of market asymmetries, for the US (Eurozone) market, are the VIX (VSTOXX) index, the CDX (iTraxx) index, and the US (EU) TED spread. They are all taken at daily frequency from Bloomberg. We also consider the indicators of economic policy uncertainty (EPU index) for the U.S. and Europe[15] developed by Baker, Bloom, and Davis (2016). The daily returns of the SMB, HML and MOM factors have been downloaded from Kenneth French's online data library.[16]

Table 6.1 reports the summary statistics of the US (Panel A) and Eurozone (Panel B) equity markets and the corresponding financial sector and industries. The statistics show that the means and standard deviations of CSAD and R_m are similar across the US and Eurozone markets, sectors and industries. However, the t-tests point out a significant difference in means only for the CSAD, excluding the equity markets. The US equity market, financial sector and industries reach maximum and minimum values, for CSAD and R_m, respectively, consistently higher and lower than the Eurozone. This gives the impression that herding effects given asymmetric market conditions might have place in the US markets.

6.4 Empirical evidence

This Section presents the main results concerning the hypotheses discussed in Section 6.2.1.

[15] This EPU indexes for the U.S. and Europe are available, with daily and monthly frequency, respectively, at: http://www.policyuncertainty.com/.

[16] This data library is available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 6.1: Descriptive statistics of CSAD and R_m for the US and Eurozone equity markets, financial sectors and industries.

Panel A: US equity market

	All US Equities		All Financial Industries		Banks		Diversified Financials		Insurance		Real Estate	
	CSAD	R_m	CSAD	R_m	CSAD	R_m	CSAD	R_m	CSAD	R_m	CSAD	R_m
Mean	1.0764	0.0344	1.0031	0.0213	0.8206	-0.0002	0.9873	0.0300	0.8369	0.0198	0.8477	0.0267
Median	0.9387	0.0819	0.7760	0.0850	0.5458	0.0246	0.7907	0.0840	0.6050	0.0740	0.6756	0.0777
Maximum	5.3164	10.6113	8.3621	16.2744	11.4353	19.8522	8.3038	14.6941	11.9944	14.5828	7.9450	20.7379
Minimum	0.3723	-10.9360	0.2800	-17.9567	0.1324	-22.8871	0.2321	-16.4871	0.1095	-14.6277	0.2112	-20.6799
Std. deviation	0.5175	1.3229	0.7780	1.8666	0.9111	2.4463	0.7058	1.8844	0.8812	1.7686	0.6412	2.0250
N	3271		3271		3271		3271		3271		3271	

Panel B: Eurozone equity market

	All Eurozone Equities		All Financial Industries		Banks		Diversified Financials		Insurance		Real Estate	
	CSAD	R_m	CSAD	R_m	CSAD	R_m	CSAD	R_m	CSAD	R_m	CSAD	R_m
Mean	1.0778	0.0227	1.0695	0.0005	1.1369	-0.0191	0.9304	0.0249	0.8715	0.0123	0.7861	0.0018
Median	0.9533	0.0749	0.8984	0.0376	0.9435	0.0158	0.7936	0.0894	0.6856	0.0649	0.6193	0.0389
Maximum	4.6379	8.5677	7.5325	12.6799	14.2199	15.4843	5.7161	14.9928	8.2454	13.3316	7.1109	9.8592
Minimum	0.4032	-8.0514	0.3644	-12.3752	0.2332	-15.8685	0.2067	-12.0040	0.1911	-13.9029	0.0000	-11.2021
Std. deviation	0.4551	1.2131	0.6358	1.6453	0.7608	1.9354	0.5343	1.5462	0.6732	1.6769	0.6232	1.5455
N	3327		3327		3327		3327		3327		3327	

	All Market Equities	All Financial Equities	Banks	Diversified Financials	Insurance	Real Estate
H_0: CSAD	0.368	3.914***	15.499***	-3.458***	1.968**	-3.809***
H_0: R_m	-0.400	-0.391	-0.189	-0.126	-0.130	-0.555

Notes: The table provides the descriptive statistics of daily cross-sectional absolute deviations (CSAD) and daily market returns (R_m) for the US and Eurozone equity markets (All US – Eurozone Equities), the corresponding financial sector (All Financial Industries) and industries (Banks, Diversified Financials, Insurance, and Real Estate), for the period from January 2005 to December 2017. The last two rows report the t-statistic of the t-tests, which investigate the equality (H_0: US = Eurozone) of the mean of the CSAD and R_m between the US and the Eurozone. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

6.4.1 Estimates of herding behavior

We investigate the existence of herding effects in the US and Eurozone equity markets and financial industries, based on model (6.2). Table 6.2 presents the estimated results, using daily data for the period from January 2005 to December 2017, for the U.S. and the Eurozone, respectively. As stated earlier, a significant negative value on the coefficient of $R_{m,t}^2$ (γ_2) is consistent with herding. The OLS results indicate a positive and significant coefficients on the linear term $|R_{m,t}|$ for all the cases analyzed in both equity markets. This result confirms that the CSAD increases with the magnitude of market returns, a feature in line with standard asset pricing models. We find a positive and significant coefficient for the squared market returns ($R_{m,t}^2$) as well. Thus, our analysis based on the OLS estimates does *not* find any evidence of herding in the US and Eurozone equity markets and financial industries. For the U.S., these results are consistent with the finding in the previous literature (Christie and Huang, 1995; Chang, Cheng, and Khorana, 2000; Gleason, Mathur, and Peterson, 2004), which also do not support the evidence of herding in the US equity markets. In the previous literature, evidence regarding the presence of herding behavior in the Eurozone appears mixed. Some evidence of herding has mainly found for the PIGS country, especially for Portugal, Italy and Greece (Economou, Kostakis, and Philippas, 2011).

Analyzing the quantile regression estimates, we do not find evidence for differences in the linear term. However, there is evidence indicating that the significance and the sign of the non-linear term (γ_2) changes across different quantiles. In the U.S., apart the insurance industry, this coefficient achieves negative and significant value for high quantiles, for all the cases analyzed. More specifically, γ_2 comes out positive and significant until the 75^{th} quantile, then switches the sign from positive to negative at some extreme quantiles. In the Eurozone, we find the same result for the equity market and the insurance industry. There is no evidence of herding effects in the other Eurozone financial industries; even for the high quantiles. Figure 6.1 displays a more detailed insight of the quantile-varying feature of γ_2.

Table 6.2: Estimates of herding behavior for the US and Eurozone equity markets and financial industries, during the period from January 2005 to December 2017.

	Panel A: United States				Panel B: Eurozone			
	γ_1	γ_2	α	Adj. R^2	γ_1	γ_2	α	Adj. R^2
All Market Equities								
OLS	0.261***	1.568***	0.008***	46.98%	0.209***	2.765***	0.009***	41.52%
Quantile Regression								
τ=10th	0.106***	1.936***	0.006***	12.57%	0.079***	3.088***	0.007***	13.42%
τ=25th	0.112***	2.639***	0.007***	14.96%	0.092***	3.677***	0.007***	16.00%
τ=50th	0.139***	3.729***	0.008***	20.40%	0.127***	4.212***	0.008***	19.97%
τ=75th	0.214***	4.382***	0.009***	27.15%	0.211***	3.894***	0.009***	25.22%
τ=95th	0.646***	-1.964**	0.012***	39.38%	0.581***	-1.229	0.012***	30.29%
τ=99th	0.517***	-1.621*	0.021***	36.07%	0.685***	-4.308**	0.020***	31.02%
Banks								
OLS	0.278***	0.466*	0.004***	53.64%	0.220***	1.774*	0.008***	44.74%
Quantile Regression								
τ=10th	0.077*	0.913	0.002***	14.31%	0.138***	1.011***	0.004***	15.54%
τ=25th	0.114***	0.947***	0.003***	19.36%	0.164***	1.315***	0.005***	18.34%
τ=50th	0.178***	0.993***	0.004***	26.04%	0.189***	1.797**	0.007***	21.93%
τ=75th	0.301***	0.775***	0.005***	32.86%	0.182***	3.155***	0.010***	26.23%
τ=95th	0.632***	0.039	0.009***	46.46%	0.328***	4.088***	0.015***	32.82%
τ=99th	1.091***	-2.887***	0.016***	47.56%	0.465***	2.602***	0.025***	33.15%
Diversified Financials								
OLS	0.281***	0.576	0.006***	47.93%	0.198***	1.111***	0.007***	32.53%
Quantile Regression								
τ=10th	0.132***	0.585***	0.004***	13.08%	0.067***	1.634***	0.004***	9.03%
τ=25th	0.128***	1.716***	0.005***	16.37%	0.100***	1.390***	0.005***	10.54%
τ=50th	0.180***	1.768***	0.006***	21.94%	0.141***	1.817***	0.006***	13.56%
τ=75th	0.283***	1.186***	0.008***	29.52%	0.225***	1.343***	0.008***	17.93%
τ=95th	0.540***	-0.293	0.012***	37.38%	0.466***	0.080	0.012***	26.10%
τ=99th	0.991***	-3.839***	0.020***	38.54%	0.318	3.649	0.022***	25.54%
Insurance								
OLS	0.306***	2.001***	0.005***	60.21%	0.223***	1.969***	0.006***	46.32%
Quantile Regression								
τ=10th	0.047	3.045*	0.003***	13.96%	0.073***	2.023***	0.004***	13.52%
τ=25th	0.087***	3.349***	0.004***	19.63%	0.073***	3.113***	0.004***	16.95%
τ=50th	0.143***	3.325***	0.005***	26.69%	0.121***	3.116***	0.005***	21.77%
τ=75th	0.267***	3.502***	0.006***	35.47%	0.215***	2.599**	0.007***	27.15%
τ=95th	0.809***	-0.483	0.008***	51.48%	0.725***	-1.440**	0.010***	37.49%
τ=99th	1.175***	-3.346	0.016***	52.39%	0.992***	-3.847***	0.019***	36.35%
Real Estate								
OLS	0.274***	0.251	0.005***	58.90%	0.131***	2.708***	0.006***	25.92%
Quantile Regression								
τ=10th	0.105***	0.701***	0.004***	15.47%	0.023	2.298*	0.003***	5.46%
τ=25th	0.128***	1.050*	0.004***	19.49%	0.046***	2.698***	0.004***	8.25%
τ=50th	0.174***	1.169	0.005***	26.10%	0.069***	3.466***	0.005***	10.78%
τ=75th	0.206***	1.683*	0.007***	35.22%	0.141***	3.637***	0.007***	14.96%
τ=95th	0.482***	-0.144	0.009***	49.70%	0.457***	1.714	0.012***	21.57%
τ=99th	0.967***	-3.128***	0.013***	48.45%	0.603	0.996	0.022***	21.07%

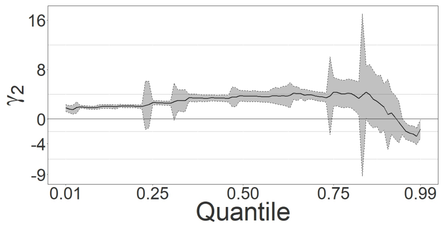
Notes: The table reports the estimated coefficients for the benchmark model (6.2): $CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation and $R_{m,t}$ is the market return. West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

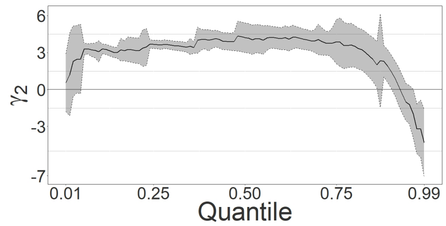
Figure 6.1: Quantile regression estimates of herding behavior for the US and Eurozone equity markets and financial industries, during the period from January 2005 to December 2017.

(a) Panel A: United States

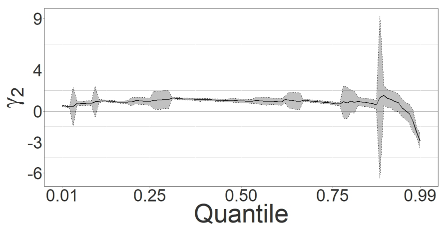
(b) Panel B: Eurozone

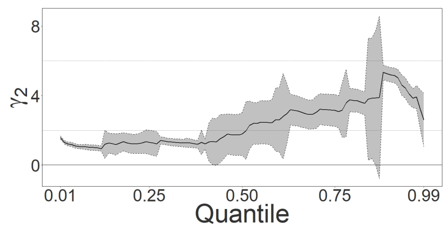
All Market Equities



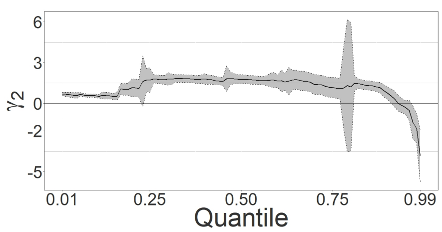


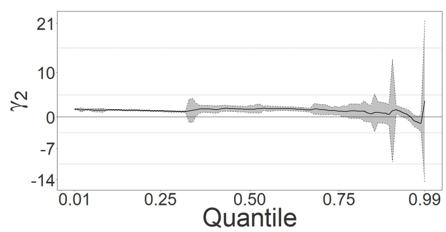
Banks



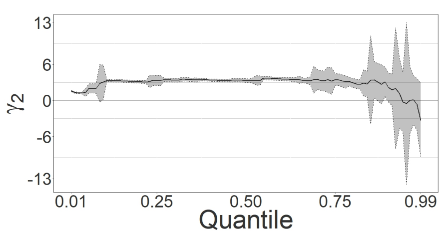


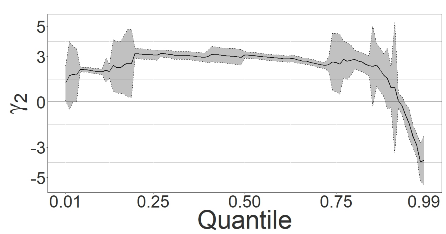
Diversified Financials



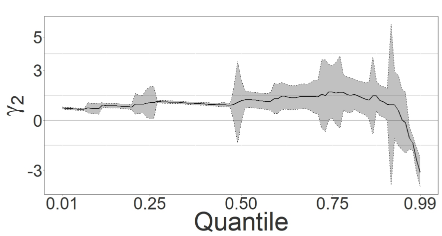


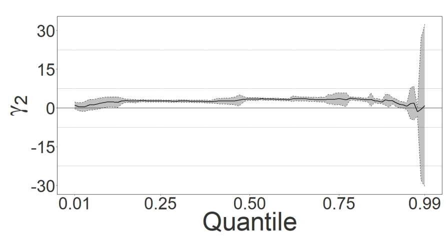
Insurance





Real Estate





Notes: The graphs show the quantile herding coefficient (γ_2) for the US (a) and Eurozone (b) equity markets and financial industries. The herding coefficient (γ_2) has been estimated from Eq. (6.2): $CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation and $R_{m,t}$ is the market return. The solid line represents the point estimates of γ_2, and the dashed lines bound the 95% confidence intervals.

Combining the information on quantile estimates from Table 6.2 with that in Figure 6.1 (Panel A), we deduce that for the US equity market and its financial industries, the returns' dispersion increases in the lower range of quantiles, but decreases in the upper quantile range. These results entail that herding effects are more pronounced when the market is experiencing a stressful condition, and it can be interpreted as the investors change their previous beliefs and become more likely to herd during these periods. Moreover, analyzing the estimates of γ_2 from Figure 6.1 (Panel A), we can see that herding becomes more pronounced when the market becomes more turbulent; as described by the increasing quantile. The results related to the US pointed out the presence of herding effects in the equity market and the financial industries, except for the insurance. In the Eurozone, the same conclusion is valid only for the equity market and the insurance industry. Figure 6.1 (Panel B) clearly shows a positive return dispersion for banks, diversified financials and real estate for the entire range of quantiles. The results analyzed in this Section illustrate the advantages of the quantile regression, which can offer a more detailed analysis in order to detect herding effects.

6.4.2 Herding behavior during crises

The results in Section 6.4.1 show that herding behavior is more pronounced during turbulent periods for the market. This motivates us to inspect whether the reduction in the returns' dispersion was more pronounced during the last two main financial crises. We use model (6.3) in order to test how the GFC, first, and then the EZC affect herding.

Table 6.3 reports the estimated coefficients, with the D^{Crisis} dummy variable related to the GFC period, for the U.S. and the Eurozone, respectively. The OLS estimates for the herding coefficient γ_3 are significant and negative for both the U.S. and the Eurozone equity markets and diversified financials. In the U.S. the same result is found also for the real estate industry. These evidences support the hypothesis that herding was more pronounced during the GFC. Moreover, the quantile regression estimates demonstrate that the returns' dispersion strongly decreased during this period and herding increased when the market

Table 6.3: Estimates of herding behavior for the US and Eurozone equity markets and financial industries, during the GFC.

	Panel A: United States						Panel B: Eurozone					
	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2
All Market Equities												
OLS	0.528***	0.019	-1.842***	3.430***	0.009***	62.85%	0.529***	-0.007	-2.270**	5.947***	0.009***	57.65%
Quantile Regression												
τ=10th	0.283***	0.081***	0.256	1.678***	0.006***	18.54%	0.259***	0.070***	1.006***	2.379**	0.007***	18.03%
τ=25th	0.390***	0.076***	-0.509**	1.817***	0.007***	23.26%	0.336***	0.064***	0.500	3.099***	0.008***	22.51%
τ=50th	0.502***	0.063***	-1.519***	2.764***	0.008***	31.27%	0.494***	0.053***	-1.568***	4.243***	0.009***	29.83%
τ=75th	0.687***	0.038	-3.429***	3.947**	0.010***	42.05%	0.748***	0.023	-5.150***	6.492***	0.010***	38.92%
τ=95th	0.942***	-0.229	-5.730***	12.889*	0.014***	55.23%	1.229***	-0.118	-10.883***	11.481***	0.013***	50.48%
τ=99th	0.814***	-1.161**	-5.229**	48.094*	0.022***	52.07%	1.691**	-0.291	-16.271**	14.930	0.017***	51.39%
Banks												
OLS	0.413***	0.024	-0.439	1.961***	0.005***	61.79%	0.382***	0.139***	0.528	1.697***	0.008***	49.44%
Quantile Regression												
τ=10th	0.203***	0.040***	-0.049	1.274***	0.003***	18.09%	0.194***	0.108***	0.598***	1.222***	0.005***	16.59%
τ=25th	0.270***	0.052***	-0.131	1.478***	0.003***	24.72%	0.271***	0.127***	0.366	1.699***	0.006***	19.86%
τ=50th	0.397***	0.085***	-0.545**	1.217***	0.004***	33.52%	0.344***	0.180***	0.419	1.308***	0.007***	23.67%
τ=75th	0.566***	0.098*	-0.900***	1.267	0.006***	42.29%	0.508***	0.164***	-0.352	2.343***	0.009***	29.46%
τ=95th	0.947***	-0.023	-2.162***	4.218**	0.011***	57.36%	0.892***	-0.027	-0.609	5.673	0.016***	42.33%
τ=99th	1.613**	-0.491	-5.235*	13.071	0.019***	61.04%	1.440**	-0.585	-4.351	19.712	0.026***	47.75%
Diversified Financials												
OLS	0.474***	0.031	-1.169***	2.440**	0.008***	59.56%	0.360***	0.000	-0.721*	3.974***	0.008***	40.96%
Quantile Regression												
τ=10th	0.300***	0.074***	-0.570***	0.914***	0.004***	19.47%	0.176***	0.026	0.339	2.301***	0.004***	11.25%
τ=25th	0.376***	0.085***	-0.944***	1.191**	0.005***	23.86%	0.252***	0.030	-0.423	2.294***	0.005***	13.97%
τ=50th	0.462***	0.046***	-1.516***	2.773***	0.007***	30.52%	0.340***	0.008	-0.547	3.950***	0.007***	18.79%
τ=75th	0.597***	0.058**	-1.664***	3.255***	0.008***	38.41%	0.472***	0.035	-1.252***	3.585***	0.009***	25.31%
τ=95th	1.158***	-0.111	-5.077***	8.165*	0.013***	51.84%	0.822***	-0.115	-3.793***	11.780	0.013***	36.05%
τ=99th	1.349***	-0.496	-6.340***	19.642	0.019***	56.64%	0.640***	-1.030***	-3.043***	42.265***	0.024***	36.24%
Insurance												
OLS	0.525***	0.081**	-0.046	2.066**	0.006***	67.89%	0.451***	0.026	-0.337	3.428***	0.006***	56.46%
Quantile Regression												
τ=10th	0.172***	0.053***	2.305***	1.588***	0.003***	18.42%	0.182***	0.054***	1.201***	1.878***	0.004***	16.93%
τ=25th	0.242***	0.061***	1.887***	1.872***	0.004***	24.17%	0.205***	0.046**	1.868***	2.637***	0.005***	20.32%
τ=50th	0.427***	0.092***	0.794**	2.163***	0.005***	32.39%	0.341***	0.051***	0.760**	3.313***	0.006***	26.72%
τ=75th	0.648***	0.095***	-0.338	2.834**	0.006***	43.52%	0.661***	0.091***	-2.048**	3.061***	0.007***	35.17%
τ=95th	1.357***	0.131**	-4.790***	3.068**	0.010***	61.18%	1.282***	0.007	-5.524***	5.434	0.011***	53.84%
τ=99th	2.510***	-0.392	-13.061***	21.010	0.018***	65.84%	2.067	-0.387	-11.466	21.104	0.017	54.30%
Real Estate												
OLS	0.372***	0.041*	-0.545***	1.549***	0.006***	67.63%	0.412***	-0.095***	-1.429	4.988***	0.007***	38.10%
Quantile Regression												
τ=10th	0.212***	0.049***	0.116***	1.218***	0.004***	21.59%	0.186*	0.050*	-0.402	0.159	0.003***	8.32%
τ=25th	0.260***	0.069***	-0.132**	0.927***	0.005***	26.32%	0.277***	0.006	-1.020	2.430**	0.004***	12.05%
τ=50th	0.321***	0.077***	-0.101	0.979	0.006***	33.6%	0.388***	-0.048***	-1.481*	4.554***	0.006***	17.33%
τ=75th	0.452***	0.054	-0.919***	2.110*	0.007***	43.73%	0.667***	-0.016	-3.871***	4.136***	0.007***	25.00%
τ=95th	0.848***	-0.078	-2.490***	5.875	0.011***	59.72%	1.078***	-0.431***	-6.525***	17.920***	0.014***	37.91%
τ=99th	1.251	-0.209	-4.551	7.675	0.016***	62.33%	1.279***	-1.050	-9.171***	35.464	0.024***	40.59%

Notes: The table reports the estimated coefficients for the augmented model (6.3): $CSAD_t = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1-D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis}R^2_{m,t} + \gamma_4(1-D^{Crisis})R^2_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation, $R_{m,t}$ is the market return and D^{Crisis} is a dummy variable that takes the value 1 during the period of the GFC and the value 0 otherwise. West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

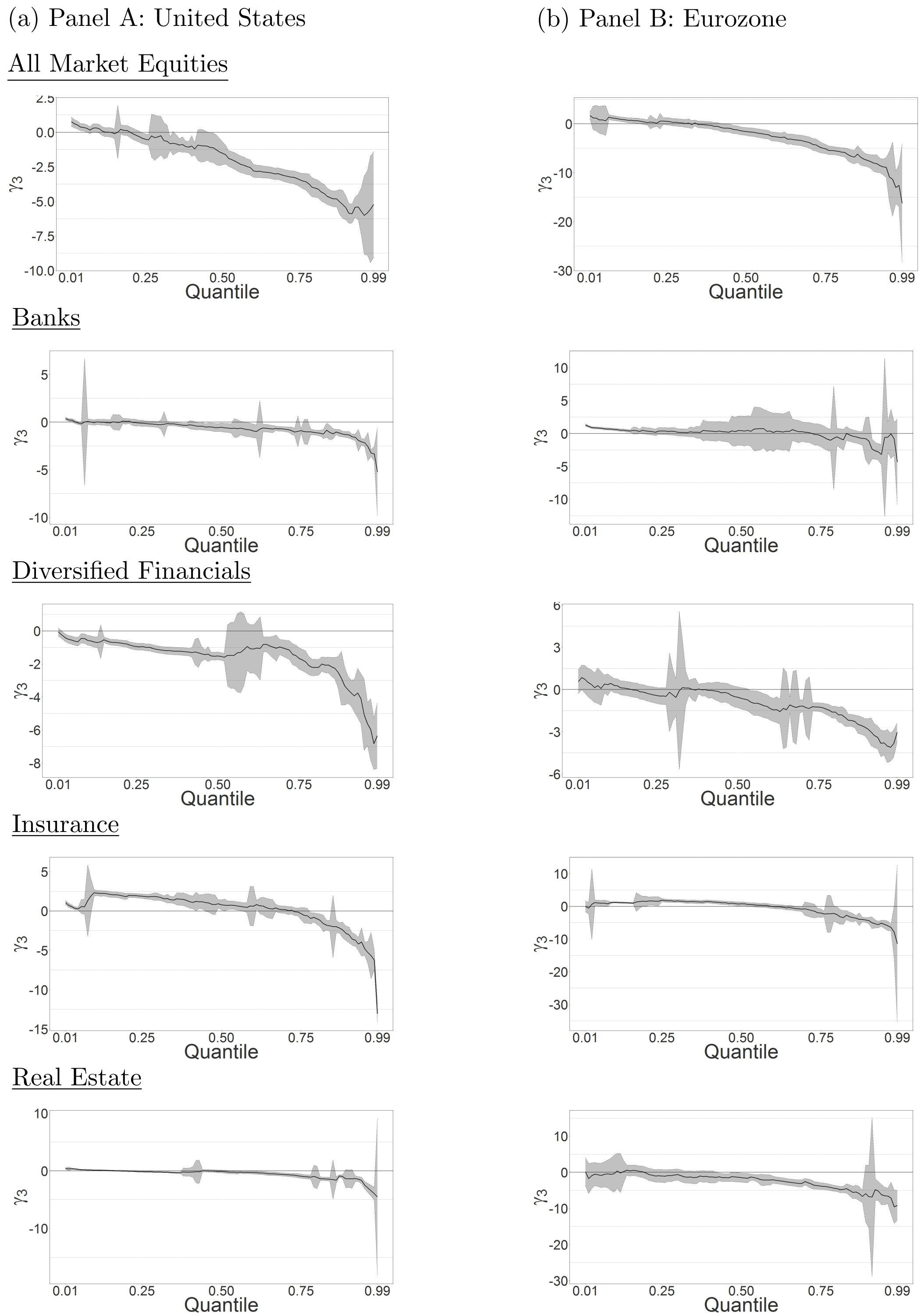
became more turbulent, across all the financial industries.[17]

Figure 6.2, which plots the herding coefficient (γ_3) for the entire range of quantiles during the GFC, shows the presence of herding behavior during this period and strengthen the hypothesis that herding is more pronounced for the high ranges of quantiles. In most of the cases analysed, γ_3 is negative and significant starting from the median, providing evidence of herding also during tranquil states of the market; and, it decreases in the upper tail of the quantiles, confirming that herding is more pronounced during turbulent states of the market. The results for the US market in Table 6.3 and Figure 6.2 (Panel A) imply that, during the GFC, investors tended to herd also for quantiles lower than the 75^{th}. Based on the combined results for the Eurozone in Table 6.3 and Figure 6.2 (Panel B), we conclude that herding behavior is present and more pronounced mainly for high quantiles, indicating that investors changed their beliefs for extremely turbulent conditions of the market.

Table 6.4 presents the herding estimates for the US and Eurozone equity markets and financial industries, during the EZC. Contrary to the GFC, the results do not detect the presence of herding behavior for both equity markets. The OLS and quantile estimates indicate a positive value of the non-linear term (γ_3). Analysing the financial industries, we find that the herding coefficient is negative and significant for the middle range of quantiles for banks in both U.S. and Eurozone. Evidence of herding are found also for the insurance industry in the U.S. through the OLS estimate and until the 95^{th} quantile; while, in the Eurozone, the real estate industry points out the presence of herding during this period in the lower quantiles, with also the OLS regression detecting it. Figure 6.3 plots the herding coefficient (γ_3) estimated during the EZC, for the entire range of quantiles. The γ_3 estimate, rather than becoming negative and significant only when the market is in extremely stressed conditions, as mainly evidenced during the GFC, is found negative for almost all the quantiles for banks and not necessary in the high quantiles for the other financial industries. This entails that during the EZC, herding was pronounced also during tranquil market states.

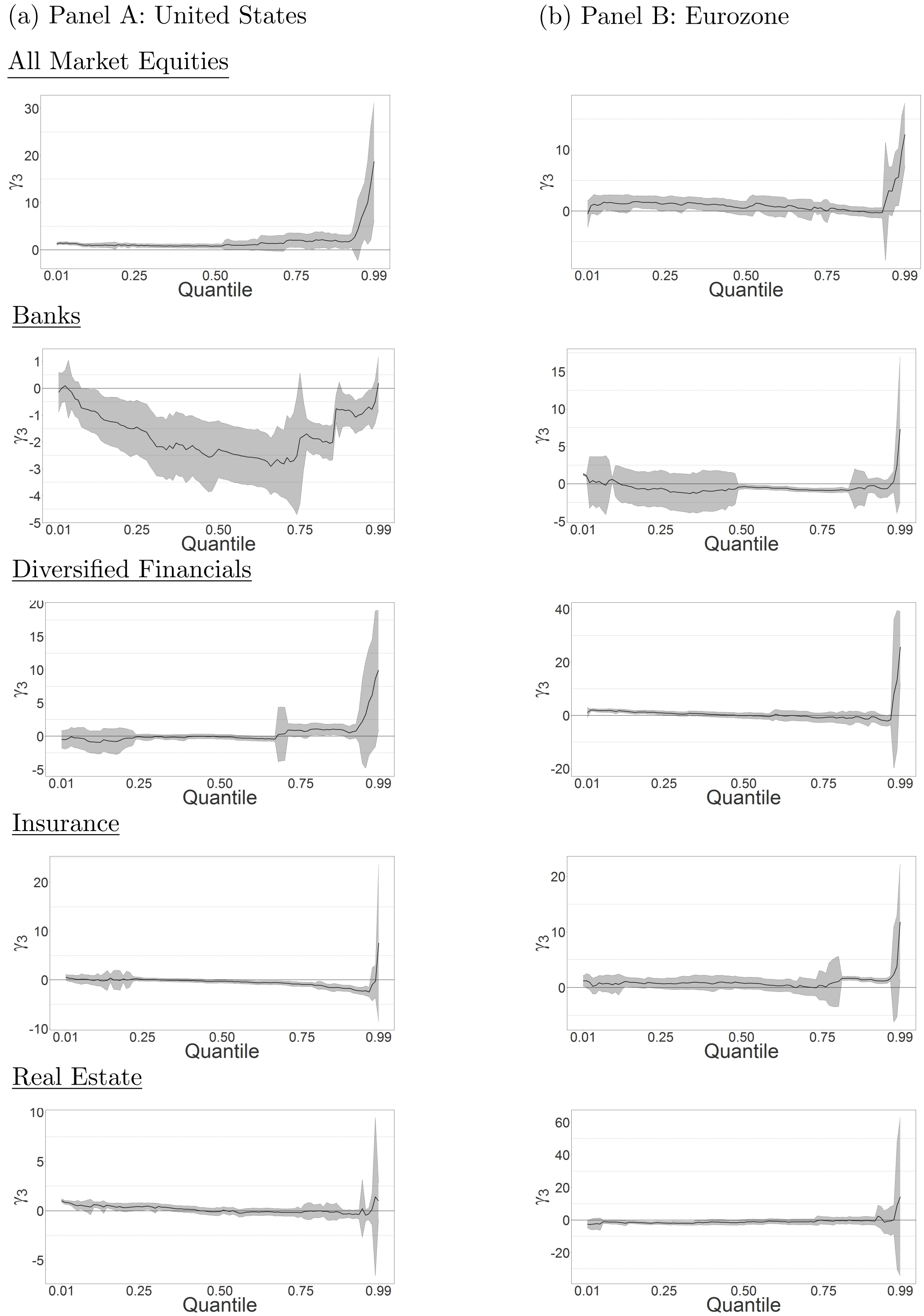
[17] In the Eurozone, the herding coefficient for banks decreases in the upper quantiles. However, the estimates are not statistically significant.

Figure 6.2: Quantile regression estimates of herding behavior for the US and Eurozone equity markets and financial industries, during the GFC.



Notes: The graphs show the quantile herding coefficient (γ_3) for the U.S. (a) and Eurozone (b) equity markets and financial industries during the GFC. The herding coefficient (γ_3) has been estimated from Eq. (6.3): $CSAD_t = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1 - D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R^2_{m,t} + \gamma_4(1 - D^{Crisis}) R^2_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation, $R_{m,t}$ is the market return and D^{Crisis} is a dummy variable that takes the value 1 during the GFC period and 0 otherwise. The solid line represents the point estimates of γ_3, and the dashed lines bound the 95% confidence intervals.

Figure 6.3: Quantile regression estimates of herding behavior for the US and Eurozone equity markets and financial industries, during the EZC.



Notes: The graphs show the quantile herding coefficient (γ_3) for the U.S. (a) and Eurozone (b) equity markets and financial industries during the EZC. The herding coefficient (γ_3) has been estimated from Eq. (6.3): $CSAD_t = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1 - D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R^2_{m,t} + \gamma_4(1 - D^{Crisis})R^2_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation, $R_{m,t}$ is the market return and D^{Crisis} is a dummy variable that takes the value 1 during the EZC period and 0 otherwise. The solid line represents the point estimates of γ_3, and the dashed lines bound the 95% confidence intervals.

Table 6.4: Estimates of herding behavior for the US and Eurozone equity markets and financial industries, during the EZC.

	Panel A: United States						Panel B: Eurozone					
	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2
All Market Equities												
OLS	0.138***	0.332***	0.969***	0.925*	0.008***	50.76%	0.195***	0.241***	0.895	2.619***	0.009***	42.66%
Quantile Regression												
τ=10th	0.134***	0.123***	0.945***	1.878***	0.006***	13.00%	0.147***	0.065***	1.251	3.426***	0.007***	14.01%
τ=25th	0.127***	0.136***	0.992***	3.267***	0.007***	16.22%	0.159***	0.093***	1.173*	3.713***	0.007***	16.42%
τ=50th	0.130***	0.184***	0.783***	3.263***	0.008***	22.43%	0.196***	0.121***	0.481	4.766***	0.008***	20.52%
τ=75th	0.106***	0.307***	2.011**	2.803*	0.009***	30.13%	0.249***	0.257***	-0.011	3.935***	0.009***	26.08%
τ=95th	-0.040	0.739***	6.653*	-3.646***	0.012***	44.16%	0.169**	0.735***	3.219	-3.470***	0.012***	33.92%
τ=99th	-0.657***	0.527***	18.721**	-1.736*	0.021***	40.97%	-0.326***	0.895***	12.468***	-7.223***	0.019***	35.98%
Banks												
OLS	0.260***	0.317***	-1.234	0.257	0.004***	54.92%	0.297***	0.213***	-0.380*	2.074**	0.008***	45.53%
Quantile Regression												
τ=10th	0.178***	0.059***	-0.796*	1.092***	0.002***	15.90%	0.192***	0.100***	0.581***	1.643***	0.005***	16.51%
τ=25th	0.212***	0.082***	-1.442**	1.395***	0.003***	20.71%	0.280***	0.130***	-0.600	1.681***	0.006***	19.83%
τ=50th	0.283***	0.168***	-2.266***	1.199***	0.004***	27.13%	0.311***	0.127**	-0.406**	3.383*	0.007***	23.46%
τ=75th	0.306***	0.337***	-1.862	0.620***	0.005***	33.92%	0.356***	0.124*	-0.862***	4.525**	0.009***	27.52%
τ=95th	0.275***	0.668***	-0.819**	-0.228	0.009***	48.51%	0.344***	0.389***	-0.632	3.658***	0.015***	34.34%
τ=99th	0.090	1.133***	0.185	-3.100***	0.017***	51.29%	-0.225	0.664***	7.276	1.180	0.025***	37.83%
Diversified Financials												
OLS	0.176***	0.339***	-0.123	0.171	0.006***	50.71%	0.174***	0.220***	0.241	0.931**	0.007***	33.05%
Quantile Regression												
τ=10th	0.184***	0.141***	-0.868	0.603***	0.004***	13.32%	0.080***	0.062***	1.450***	1.686***	0.004***	9.06%
τ=25th	0.162***	0.157***	-0.094	1.735***	0.005***	17.49%	0.115***	0.104***	0.895*	1.363***	0.005***	10.56%
τ=50th	0.159***	0.214***	-0.098	1.566***	0.006***	23.45%	0.173***	0.149***	-0.118	1.784***	0.006***	13.72%
τ=75th	0.151***	0.343***	0.897	0.655***	0.008***	31.60%	0.238***	0.256***	-0.849	1.334	0.008***	18.38%
τ=95th	0.034	0.645***	3.262	-1.035*	0.012***	40.74%	0.328***	0.564***	-2.146*	-0.937	0.012***	27.45%
τ=99th	-0.348*	1.089***	9.949*	-4.521***	0.020***	44.07%	-0.630**	0.518	25.668***	-0.013	0.022***	29.34%
Insurance												
OLS	0.258***	0.384***	-1.070**	1.421**	0.004***	62.64%	0.167***	0.275***	1.096	1.611***	0.006***	47.98%
Quantile Regression												
τ=10th	0.133***	0.049***	-0.088	3.411***	0.003***	15.78%	0.121***	0.070***	0.471	2.175***	0.004***	13.78%
τ=25th	0.176***	0.098***	0.101	3.417***	0.004***	20.98%	0.135***	0.084***	0.702	3.123***	0.004***	17.59%
τ=50th	0.205***	0.164***	-0.272	3.643***	0.005***	27.73%	0.173***	0.136***	0.816	3.012***	0.005***	22.31%
τ=75th	0.252***	0.370***	-0.927***	2.516***	0.006***	37.29%	0.226***	0.248***	0.336	2.701***	0.007***	27.83%
τ=95th	0.341***	0.917***	-2.252***	-1.259	0.008***	54.14%	0.217***	0.883***	1.247***	-2.586***	0.010***	41.91%
τ=99th	-0.172	1.273***	7.537	-4.541***	0.017***	56.27%	-0.326	1.192***	11.793*	-5.216***	0.017***	42.03%
Real Estate												
OLS	0.167***	0.309***	-0.346	0.023	0.005***	61.17%	0.131***	0.171***	-0.988*	2.400***	0.006***	27.62%
Quantile Regression												
τ=10th	0.108***	0.113***	0.374	0.852***	0.004***	15.89%	0.098***	0.008	-1.300*	3.006***	0.003***	6.76%
τ=25th	0.107***	0.142***	0.419*	1.046***	0.004***	20.52%	0.148***	0.058***	-1.865***	2.710***	0.003***	9.09%
τ=50th	0.148***	0.208***	-0.081	0.945***	0.005***	27.55%	0.145***	0.094***	-1.452	3.306***	0.005***	11.59%
τ=75th	0.154***	0.281***	-0.178	0.944	0.006***	37.16%	0.141***	0.182***	-0.233	3.450***	0.007***	15.84%
τ=95th	0.146***	0.578***	-0.459	-1.162***	0.009***	52.29%	0.181	0.626***	-0.816	-1.065	0.011***	23.53%
τ=99th	0.028	1.054***	0.994	-3.555***	0.014***	51.89%	-0.335	0.770	14.242	-2.943	0.022***	24.51%

Notes: The table reports the estimated coefficients for the augmented model (6.3): $CSAD_t = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1-D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R^2_{m,t} + \gamma_4(1-D^{Crisis})R^2_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation, $R_{m,t}$ is the market return and D^{Crisis} is a dummy variable that takes the value 1 during the period of the EZC and the value 0 otherwise. West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

These results provide new insights for the US and Eurozone equity markets and financial industries. They suggest that during crises the mutual imitation leading to a convergence of actions may start even without extremely stressed conditions for the equity markets or financial industries.

6.4.3 Herding behavior under asymmetric market conditions

We focus on four sub-cases to investigate the herding effects in case of asymmetric market conditions captured by model (6.4). Tables 6.5–6.8 report the results related to any significant herding effects during asymmetric market conditions. To this end, we investigate whether there is herding during periods of higher and lower volatility (Table 6.5), higher and lower credit deterioration (Table 6.6), higher and lower funding illiquidity (Table 6.7) and higher and lower economic policy uncertainty (Tables 6.8), for the US and Eurozone markets and financial industries, respectively.

We present the first set of our results in Table 6.5 for the U.S. and the Eurozone, comparatively. The implied market volatility has been employed as a measure of investors' sentiment (see, for instance, Baker and Wurgler, 2006). This motivates us to study the herding behavior related to asymmetric market conditions of higher and lower volatility. The OLS estimates for the US and Eurozone equity markets and financial industries show that there is no evidence of herding effects during higher and lower volatility conditions of the market. However, the quantile regression analysis detects evidence of herding effects in higher volatility conditions for the equity market and all the financial industries, except the insurance, in the U.S.. The herding effects is encountered for high quantiles, indicating a more likely herding behavior during extreme stressed market in case of higher volatility.

Overall, for the US market, we find evidence that herding is likely to occur more in higher (γ_3) than lower (γ_4) conditions of market volatility, which is indicative of the asymmetry of herding behavior. Analyzing the quantile regression coefficients, we observe that γ_3 is negative and significant over a wider distribution range of quantiles compared to γ_4. It implies

Table 6.5: Estimates of herding behavior for the US and Eurozone equity markets and financial industries, during days of high and low volatility.

	Panel A: United States							Panel B: Eurozone						
	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2	$\gamma_3=\gamma_4$	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2	$\gamma_3=\gamma_4$
All Market Equities														
OLS	0.236***	0.248***	1.532***	3.018***	0.008***	47.77%	-1.486	0.183***	0.244***	3.038***	2.731**	0.009***	41.88%	0.307
Quantile Regression														
τ=10th	0.075***	0.089***	2.168***	3.358**	0.006***	13.46%	-1.190	0.062***	0.097***	3.418***	3.730***	0.007***	14.11%	-0.312
τ=25th	0.102***	0.119***	2.139***	3.523***	0.007***	15.73%	-1.385***	0.086***	0.118***	3.346***	4.032***	0.007***	16.52%	-0.686
τ=50th	0.125***	0.140***	3.393***	4.544***	0.008***	20.81%	-1.151**	0.114***	0.136***	3.996***	5.012***	0.008***	20.15%	-1.016
τ=75th	0.192***	0.202***	3.519***	6.476***	0.009***	27.83%	-2.957*	0.201***	0.263***	3.827***	3.481***	0.009***	25.46%	0.346
τ=95th	0.543**	0.674***	-0.653	-2.300***	0.012***	39.51%	1.647	0.517***	0.724***	-0.312	-5.321***	0.012***	30.50%	5.009***
τ=99th	0.533***	0.442***	-2.430***	-0.767	0.021***	36.26%	-1.663*	0.704***	0.558***	-4.660***	-4.459***	0.020***	31.43%	-0.201
Banks														
OLS	0.259***	0.305***	0.635**	0.204	0.004***	53.73%	0.431	0.193***	0.259***	1.996**	1.384*	0.008***	44.91%	0.612
Quantile Regression														
τ=10th	0.075***	0.093***	0.735***	0.923***	0.002***	14.79%	-0.188	0.120***	0.152***	1.078***	1.187***	0.005***	16.17%	-0.108
τ=25th	0.086***	0.137***	1.293**	0.691***	0.003***	19.81%	0.602	0.143***	0.188***	1.491***	1.518***	0.005***	18.77%	-0.027
τ=50th	0.146***	0.202***	1.156***	0.713***	0.004***	26.32%	0.443**	0.166***	0.191***	1.991**	2.285***	0.007***	22.04%	-0.294
τ=75th	0.265***	0.351***	1.055	0.087	0.005***	33.07%	0.968	0.127***	0.228***	4.162***	2.440***	0.010***	26.51%	1.721**
τ=95th	0.610***	0.617***	0.183	0.444	0.009***	46.45%	-0.261	0.237***	0.536***	4.758***	0.237	0.015***	33.46%	4.521
τ=99th	1.287***	0.877***	-3.751***	-2.059	0.016***	48.32%	-1.692	0.478***	0.799***	2.531**	-3.852***	0.025***	33.34%	6.382***
Diversified Financials														
OLS	0.277***	0.295***	0.692	0.255	0.006***	47.98%	0.438	0.176***	0.204***	1.063***	1.915***	0.007***	33.30%	-0.852
Quantile Regression														
τ=10th	0.131***	0.157***	0.597***	0.281**	0.004***	13.26%	0.316**	0.058***	0.064***	1.608***	2.485***	0.004***	9.58%	-0.877***
τ=25th	0.121***	0.139***	1.787**	1.732***	0.005***	16.52%	0.055	0.088***	0.116***	1.401***	2.114***	0.005***	11.22%	-0.713*
τ=50th	0.160***	0.211***	1.930***	1.159***	0.006***	22.19%	0.770***	0.123	0.131***	1.505	2.848**	0.007***	13.80%	-1.343
τ=75th	0.266***	0.296***	1.338***	0.988	0.008***	29.62%	0.350	0.201***	0.216***	1.422***	3.125***	0.008***	18.30%	-1.704***
τ=95th	0.598***	0.568***	-0.693	-1.351	0.012***	37.52%	0.658	0.456***	0.542***	-0.953*	-0.478	0.012***	26.44%	-0.475
τ=99th	1.193***	0.571***	-5.282***	-2.063**	0.020***	40.28%	-3.220*	0.245	0.617	3.405	-0.030	0.021***	26.45%	3.435
Insurance														
OLS	0.312***	0.291***	1.843**	2.383***	0.005***	60.25%	-0.539	0.200***	0.265***	2.217***	1.475**	0.006***	46.50%	0.742
Quantile Regression														
τ=10th	0.072***	0.058***	1.965***	3.354***	0.003***	14.82%	-1.389***	0.059***	0.088***	2.127***	2.091***	0.004***	13.96%	0.036
τ=25th	0.081***	0.110***	3.238***	3.280***	0.004***	19.88%	-0.043	0.063***	0.096***	3.192***	2.995***	0.004***	17.27%	0.197
τ=50th	0.135***	0.142***	3.301***	3.784***	0.005***	26.94%	-0.483***	0.097***	0.153***	3.290***	2.588***	0.005***	22.05%	0.702**
τ=75th	0.241***	0.288***	3.758***	3.035***	0.006***	35.53%	0.723	0.193***	0.237***	2.890**	2.628	0.007***	27.23%	0.262
τ=95th	0.847***	0.773***	0.025	-0.713	0.008***	51.70%	0.737	0.618***	0.918***	1.043	-4.554***	0.009***	38.05%	5.597
τ=99th	1.266**	1.054	-4.434	0.434	0.017***	52.47%	-4.868	1.007***	1.125***	-3.932***	-7.061***	0.018***	36.62%	3.129*
Real Estate														
OLS	0.263***	0.288***	0.205	0.274	0.005***	59.16%	-0.069	0.089***	0.197***	3.409***	1.621**	0.006***	26.64%	1.788*
Quantile Regression														
τ=10th	0.100***	0.123***	0.665***	0.810***	0.004***	16.51%	-0.146	0.027	0.050	2.159	2.051*	0.003***	5.93%	0.108
τ=25th	0.116***	0.144***	0.830***	1.055***	0.004***	20.17%	-0.225	0.034**	0.058***	2.892***	2.700***	0.004***	8.53%	0.192
τ=50th	0.170***	0.188***	0.848***	1.152***	0.005***	26.47%	-0.304	0.048***	0.098***	3.755***	3.135***	0.005***	11.04%	0.620
τ=75th	0.207***	0.250***	1.304**	1.248	0.006***	35.50%	0.055	0.104***	0.223***	4.216***	2.482**	0.007***	15.44%	1.734
τ=95th	0.523***	0.506***	-0.509	-0.805***	0.009***	49.82%	0.296	0.362***	0.537***	2.109	0.237	0.012***	21.87%	1.872
τ=99th	0.984***	1.076***	-3.839***	-3.654***	0.013***	48.62%	-0.185	0.280	0.696*	10.62	-1.097	0.022***	21.63%	11.717

Notes: The table reports the estimated coefficients for the augmented model (6.4): $CSAD_t = \alpha + \gamma_1 D^{High}|R_{m,t}| + \gamma_2(1-D^{High})|R_{m,t}| + \gamma_3 D^{High} R^2_{m,t} + \gamma_4(1-D^{High})R^2_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation, $R_{m,t}$ is the market return and D^{High} is a dummy variable that takes the value 1 for high volatility market conditions and the value 0 otherwise. The last column of Panel A and B reports the result for the hypothesis test $\gamma_3 = \gamma_4$. West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

that herding is more pronounced during distressed market period due to high conditions of market volatility. In cases where we find herding effects for both conditions of the market, we conduct an equality test for the two herding coefficients ($\gamma_3 = \gamma_4$), confirming the evidence that herding asymmetry is more apparent for higher volatility conditions.

In the Eurozone, we find the same pattern for the equity market. However, we find evidence of herding effects only for the higher quantiles of the diversified financials and insurance industries, in case of high volatility. No evidence of herding was found for the real estate industry; while, for the banking and insurance industries, herding is more likely in the case of lower volatility conditions. In particular, for the insurance industry, we find that the difference between the two herding coefficients ($\gamma_3 = \gamma_4$) at the 99^{th} quantile is statistically significant. Thus, for the banks and insurance of the Eurozone, herding is more likely under distressed market state not due to high volatility conditions of the market.

Norden and Weber (2009) report that positive stock returns are associated with negative CDS spread changes. Furthermore, Friewald, Wagner, and Zechner (2014) advocate that firms' CDS forward curves are strongly related to equity excess returns and Zhang, Zhou, and Zhu (2009) argue that the equity volatility alone predicts 48% of the variation in CDS spread levels. Given this background, we investigate next the herding during higher and lower credit deterioration conditions of the market.

Table 6.6 presents the analysis of herding behavior in case of asymmetry conditions of the market related to deterioration in the credit condition for the U.S. and the Eurozone, respectively. The OLS regression coefficients do not portray any herding effects, neither in the lower nor in the higher credit deterioration conditions, for both equity markets and the respective financial industries. Analyzing the quantile estimates, the US equity market and all its financial industries tend to herd more in the case of higher credit deterioration conditions (γ_3) more than lower (γ_4), in the high quantiles. The herding coefficient related to high credit deterioration conditions (γ_3) is negative and statistically significant over a wider range of quantiles compared to γ_4. In the case where both estimates are negative

Table 6.6: Estimates of herding behavior for the US and Eurozone equity markets and financial industries, during days of high and low credit deterioration.

	Panel A: United States							Panel B: Eurozone						
	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2	$\gamma_3 = \gamma_4$	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2	$\gamma_3 = \gamma_4$
All Market Equities														
OLS	0.262***	0.263***	1.307**	2.047**	0.008***	47.16%	-0.740	0.19***	0.179***	2.825***	5.361***	0.009***	41.98%	-2.536*
Quantile Regression														
τ=10th	0.104***	0.135***	1.902***	1.913***	0.006***	13.04%	-0.011	0.063***	0.060	3.378***	5.146**	0.007***	13.76%	-1.768
τ=25th	0.114***	0.120***	1.978***	3.512***	0.007***	15.35%	-1.534**	0.073***	0.062***	3.867***	6.673***	0.008***	16.50%	-2.806**
τ=50th	0.146***	0.130***	3.135***	4.658***	0.008***	20.59%	-1.523**	0.121***	0.113***	3.875***	6.073***	0.008***	20.37%	-2.198**
τ=75th	0.245***	0.192***	2.773***	5.316***	0.009***	27.46%	-2.543	0.201***	0.149*	3.677***	10.049*	0.010***	25.61%	-6.372
τ=95th	0.734***	0.575***	-3.557***	-1.093	0.012***	39.62%	-2.464***	0.547***	0.557***	-0.744	-0.049	0.012***	30.22%	-0.695
τ=99th	0.559***	0.342***	-2.773***	0.390	0.021***	36.52%	-3.163***	0.678***	0.461	-4.411**	-1.771	0.021***	31.63%	-2.640
Banks														
OLS	0.256***	0.298***	0.714***	0.285	0.004***	53.72%	0.429	0.222***	0.158***	1.082***	4.027***	0.008***	47.31%	-2.945***
Quantile Regression														
τ=10th	0.060***	0.092***	1.203***	0.705***	0.002***	14.70%	0.498*	0.128***	0.117***	1.030***	2.218***	0.005***	16.33%	-1.188***
τ=25th	0.089***	0.125***	1.375***	0.744***	0.003***	19.72%	0.631***	0.156***	0.160***	1.148***	2.375***	0.005***	18.98%	-1.227*
τ=50th	0.159***	0.192***	1.036***	1.059***	0.004***	26.26%	-0.023	0.195***	0.153***	1.252***	3.636***	0.007***	22.42%	-2.384***
τ=75th	0.258***	0.324***	1.256	0.674***	0.005***	32.94%	0.582	0.161***	0.129***	3.084***	5.710***	0.010***	26.66%	-2.626***
τ=95th	0.633***	0.630***	0.031	-0.098	0.009***	46.42%	0.129	0.254*	0.386***	5.269**	3.680***	0.015***	32.91%	1.589
τ=99th	1.338***	0.874***	-4.702***	-1.941***	0.016***	49.19%	-2.761***	0.755***	0.447	-2.723	2.732	0.025***	33.46%	-5.455
Diversified Financials														
OLS	0.272***	0.288***	0.772	0.384	0.006***	47.98%	0.388	0.18***	0.166***	1.063***	2.989***	0.007***	33.31%	-1.926**
Quantile Regression														
τ=10th	0.112*	0.147***	1.075	0.496***	0.004***	13.34%	0.579	0.061***	0.080***	1.582***	1.776***	0.004***	9.25%	-0.194
τ=25th	0.119***	0.151	1.939***	1.084	0.005***	16.50%	0.855	0.085***	0.085**	1.482***	3.410*	0.005***	10.89%	-1.928
τ=50th	0.180***	0.193***	1.613***	1.710***	0.006***	22.03%	-0.097	0.116***	0.118***	1.951***	3.484***	0.007***	14.07%	-1.533**
τ=75th	0.296***	0.255***	1.065**	1.436	0.008***	29.67%	-0.371	0.2***	0.179***	1.427***	3.504***	0.008***	18.40%	-2.077***
τ=95th	0.637***	0.494***	-0.972	-0.172	0.012***	37.61%	-0.800	0.523***	0.373***	-1.524***	6.054	0.012***	26.35%	-7.578
τ=99th	1.165***	0.656***	-5.056***	-1.997**	0.020***	39.63%	-3.059**	0.272	0.002	2.095	15.007	0.023***	26.39%	-12.912
Insurance														
OLS	0.277***	0.367***	2.303***	1.359	0.004***	60.43%	0.944	0.216***	0.233***	2.021***	1.967*	0.006***	46.30%	0.054
Quantile Regression														
τ=10th	0.040***	0.092***	3.390***	1.168***	0.003***	14.29%	2.222***	0.07***	0.071***	2.045***	2.162***	0.004***	13.62%	-0.117
τ=25th	0.075***	0.117***	3.590***	2.814***	0.004***	19.95%	0.776***	0.072***	0.080***	3.119***	2.993***	0.004***	17.01%	0.126
τ=50th	0.130***	0.147***	3.415***	3.939***	0.005***	26.94%	-0.524	0.104***	0.128***	3.096***	3.479***	0.005***	22.03%	-0.383
τ=75th	0.275***	0.296***	2.822***	3.751***	0.006***	35.79%	-0.929	0.204***	0.201***	2.450***	3.844***	0.007***	27.42%	-1.394*
τ=95th	0.805***	0.712***	-0.943*	3.268*	0.008***	51.87%	-4.211**	0.755***	0.794***	-1.650**	-3.336**	0.009***	37.54%	1.686
τ=99th	1.194***	0.811	-4.023***	7.414	0.017***	52.70%	-11.437	1.234***	1.077***	-5.484***	-7.471***	0.017***	36.55%	1.987
Real Estate														
OLS	0.259***	0.290***	0.428	0.114	0.005***	59.01%	0.314	0.107***	0.179***	3.305***	1.652**	0.006***	26.36%	1.653*
Quantile Regression														
τ=10th	0.084***	0.123***	1.084***	0.555***	0.004***	15.76%	0.529***	0.024	0.031*	2.256*	2.744***	0.003***	5.93%	-0.488
τ=25th	0.119***	0.140***	1.023***	1.074***	0.004***	19.73%	-0.051	0.035	0.062***	2.880***	2.493***	0.004***	8.53%	0.387
τ=50th	0.161***	0.198***	1.369***	0.773***	0.005***	26.34%	0.596**	0.066***	0.104***	3.507***	2.729**	0.005***	10.98%	0.778
τ=75th	0.200***	0.243***	1.749**	1.121	0.006***	35.37%	0.628	0.128***	0.171***	3.828***	2.766*	0.007***	15.06%	1.062
τ=95th	0.593***	0.426***	-1.335**	0.561	0.009***	50.03%	-1.896	0.426**	0.476***	2.682	1.327	0.012***	21.57%	1.355
τ=99th	1.028***	0.870***	-4.615***	-2.663**	0.014***	48.95%	-1.952*	0.026	0.648***	14.748**	-5.332***	0.023***	21.97%	20.080***

Notes: The table reports the estimated coefficients for the augmented model (6.4): $CSAD_t = \alpha + \gamma_1 D^{High}|R_{m,t}| + \gamma_2(1 - D^{High})|R_{m,t}| + \gamma_3 D^{High} R^2_{m,t} + \gamma_4(1 - D^{High}) R^2_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation, $R_{m,t}$ is the market return and D^{High} is a dummy variable that takes the value 1 for high credit instability conditions and the value 0 otherwise. The last column of Panel A and B reports the result for the hypothesis test $\gamma_3 = \gamma_4$. West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 6.7: Estimates of herding behavior for the US and Eurozone equity markets and financial industries, during days of high and low funding illiquidity.

	Panel A: United States							Panel B: Eurozone						
	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2	$\gamma_3=\gamma_4$	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2	$\gamma_3=\gamma_4$
All Market Equities														
OLS	0.215***	0.302***	1.649***	1.698*	0.008***	48.24%	-0.049	0.172***	0.242***	3.062***	2.548***	0.009***	41.97%	0.515
Quantile Regression														
τ=10th	0.092***	0.114	2.005***	2.443	0.006***	12.96%	-0.438	0.075***	0.083***	3.214***	3.020***	0.007***	13.45%	0.194
τ=25th	0.101***	0.117***	2.149***	3.546***	0.007***	15.85%	-1.398***	0.102***	0.093***	3.087***	3.880***	0.007***	16.04%	-0.793
τ=50th	0.119***	0.159***	3.365***	4.205***	0.008***	21.13%	-0.840	0.126***	0.137***	3.817***	4.757***	0.008***	20.11%	-0.940
τ=75th	0.161***	0.299***	3.503**	3.135*	0.009***	28.22%	0.368	0.197***	0.276***	3.411***	3.363***	0.009***	25.59%	0.048
τ=95th	0.407**	0.729***	2.487	-2.939***	0.012***	40.04%	5.426	0.373***	0.768***	1.765	-4.538***	0.012***	31.53%	6.304***
τ=99th	0.542***	0.517***	-2.584***	-1.621*	0.021***	36.10%	-0.963	0.496***	0.737***	-1.609	-5.480***	0.020***	31.39%	3.870*
Banks														
OLS	0.222***	0.331***	0.793**	0.157	0.004***	54.35%	0.637	0.202***	0.186***	1.196***	3.169**	0.008***	46.70%	-1.973
Quantile Regression														
τ=10th	0.073***	0.098***	0.746***	0.896***	0.002***	15.14%	-0.150	0.128***	0.132***	1.025***	1.366***	0.005***	15.76%	-0.341
τ=25th	0.086***	0.140***	1.136***	0.761***	0.003***	20.05%	0.374	0.151***	0.162***	1.265***	1.976**	0.005***	18.66%	-0.711
τ=50th	0.132***	0.206***	1.539***	0.819***	0.004***	26.54%	0.720***	0.195***	0.178***	1.211***	2.896**	0.007***	22.26%	-1.685
τ=75th	0.235***	0.393***	1.082***	-0.076	0.005***	33.73%	1.157***	0.168***	0.232***	2.996***	3.454***	0.009***	26.80%	-0.458
τ=95th	0.471***	0.690***	1.118**	-0.142	0.009***	47.02%	1.260	0.034	0.396***	7.958***	3.581***	0.015***	34.04%	4.377**
τ=99th	0.875***	1.186***	-1.942***	-3.579	0.016***	48.08%	1.637	0.089	0.607***	9.865	1.562	0.026***	33.93%	8.303
Diversified Financials														
OLS	0.261***	0.298***	0.584	0.625	0.006***	48.19%	-0.041	0.170***	0.216***	1.185***	1.163**	0.007***	32.88%	0.022
Quantile Regression														
τ=10th	0.123***	0.131***	0.638***	1.277***	0.004***	13.53%	-0.638**	0.058***	0.086***	1.713***	1.341***	0.004***	9.20%	0.372*
τ=25th	0.136***	0.153***	1.060***	1.633***	0.005***	16.96%	-0.572*	0.082***	0.107***	1.504***	1.851***	0.005***	10.73%	-0.346
τ=50th	0.152***	0.191***	1.740***	1.949***	0.006***	22.29%	-0.209	0.112***	0.153***	2.001***	1.760***	0.007***	13.72%	0.241
τ=75th	0.244***	0.302	1.441	1.401	0.008***	29.78%	0.039	0.194***	0.241***	1.487***	1.760	0.008***	18.21%	-0.273
τ=95th	0.489***	0.545***	-0.153	-0.340	0.012***	37.40%	0.187	0.393***	0.546***	-0.358	-0.746	0.012***	26.51%	0.388
τ=99th	1.228***	1.003***	-5.823**	-3.907***	0.019***	38.71%	-1.916	-0.036	0.335	16.410	3.337	0.022***	26.16%	13.073
Insurance														
OLS	0.251***	0.363***	2.369***	1.584***	0.005***	60.69%	0.785	0.186***	0.259***	2.137***	1.814***	0.006***	46.79%	0.322
Quantile Regression														
τ=10th	0.084***	0.074***	1.261***	3.390***	0.003***	16.13%	-2.130***	0.061***	0.085***	2.114***	2.004***	0.004***	13.81%	0.110
τ=25th	0.074***	0.128***	3.111***	3.182***	0.004***	20.63%	-0.071	0.069**	0.078***	3.012***	3.170***	0.004***	17.05%	-0.158
τ=50th	0.100***	0.184***	3.535***	3.030***	0.005***	27.27%	0.505**	0.110***	0.143***	2.767***	3.026***	0.005***	22.09%	-0.260
τ=75th	0.185***	0.374***	4.309***	2.033**	0.006***	36.13%	2.276**	0.173***	0.274***	3.135**	2.111	0.007***	27.60%	1.024
τ=95th	0.643***	0.915***	2.697	-2.446***	0.008***	51.95%	5.143	0.447*	0.860***	1.447	-2.431***	0.010***	38.59%	3.877
τ=99th	1.069***	0.784	-2.276	7.739	0.018***	52.76%	-10.015	1.127***	1.215***	-6.401***	-5.357***	0.017***	36.45%	-1.044
Real Estate														
OLS	0.238***	0.310***	0.319	0.103	0.005***	59.72%	0.216	0.071***	0.198***	3.620***	1.653**	0.006***	26.88%	1.967**
Quantile Regression														
τ=10th	0.101***	0.117***	0.658***	1.095***	0.004***	16.52%	-0.436*	0.031	0.026*	1.511	2.965***	0.003***	6.14%	-1.454
τ=25th	0.122***	0.141***	0.542***	1.065***	0.004***	20.32%	-0.523***	0.042**	0.062***	2.507***	2.659***	0.004***	8.58%	-0.151
τ=50th	0.142***	0.206***	1.502	0.978***	0.005***	26.71%	0.524	0.043***	0.113***	3.797***	2.769***	0.005***	11.17%	1.028
τ=75th	0.173***	0.302***	1.652***	0.729	0.006***	36.35%	0.924	0.098***	0.220***	4.252***	2.052***	0.007***	15.39%	2.199***
τ=95th	0.206***	0.565***	3.433***	-1.100***	0.010***	50.64%	4.533***	0.295*	0.710***	5.175	-4.189*	0.012***	22.35%	9.364*
τ=99th	0.856***	1.132***	-3.215***	-3.921***	0.013***	49.42%	0.706	-0.304	0.689*	20.989***	-3.467	0.024***	23.17%	24.455**

Notes: The table reports the estimated coefficients for the augmented model (6.4): $CSAD_t = \alpha + \gamma_1 D^{High}|R_{m,t}| + \gamma_2(1-D^{High})|R_{m,t}| + \gamma_3 D^{High} R^2_{m,t} + \gamma_4(1-D^{High})R^2_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation, $R_{m,t}$ is the market return and D^{High} is a dummy variable that takes the value 1 for high funding illiquidity conditions and the value 0 otherwise. The last column of Panel A and B reports the result for the hypothesis test $\gamma_3 = \gamma_4$. West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

and significant, the difference between the two herding coefficients ($\gamma_3 = \gamma_4$) is statistically significant, entailing that herding is more likely during distressed market states due to high credit deterioration conditions. In the Eurozone, the equity market, the diversified financials and the insurance are found to herd in larger size (in the sense of absolute value) in the case of higher credit deterioration. There is no evidence of herding for the banks, while, the real estate tend to herd in case of lower credit deterioration, in the extreme quantiles.

Previous literature indicates that high values of the TED spread lead to tighter funding liquidity. By construction, a widening of this spread would suggest a destabilizing spiral between the liquidity of the equity market and the margin loan market (Brunnermeier and Pedersen, 2008) and therefore, the TED spread provides a useful basis for gauging the severity of a liquidity crisis and it can be used as a proxy for funding liquidity. Moreover, Oh (2018) argues that firms facing a severe liquidity constrain may be forced to sell a large part of their assets to avoid bankruptcy, causing a fire sale effect that could impact the entire industry, entailing correlated patterns of actions. Analysing the GFC, Cornett, McNutt, Strahan, and Tehranian (2011) found that time variation in the TED tracked the severity of the GFC very closely. Thus, it is relevant to analyze herding effects during periods of higher and lower funding illiquidity, which is measured by the TED spread.

The results in Table 6.7 indicate that, in both the U.S. and the Eurozone, there is no evidence of herding through the OLS regression analysis. On the other hand, the quantile regression estimates offer a richer introspective and the evidence points to a change across the two markets. In the U.S., except for the insurance industry, which has been found to herd in the lower funding illiquidity conditions, we find evidence of herding effects in case of higher funding illiquidity for the equity market and the other financial industries, in the upper quantiles. This points out that in the U.S. herding is more likely during period of strict funding liquidity. The results related to the Eurozone are different, we could not find any evidence of herding for the banks and the diversified financials. The Eurozone equity market and the real estate industry tend to herd during lower conditions of funding

Table 6.8: Estimates of herding behavior for the US and Eurozone equity markets and financial industries, during days of high and low economic policy uncertainty.

	Panel A: United States							Panel B: Eurozone						
	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2	$\gamma_3=\gamma_4$	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2	$\gamma_3=\gamma_4$
All Market Equities														
OLS	0.219***	0.277***	2.785***	1.032	0.008***	47.35%	1.753*	-0.144	0.525	295.732***	141.891	0.009***	39.94%	153.840
Quantile Regression														
τ=10th	0.060	0.117***	3.689*	1.759***	0.006***	12.96%	1.930	-0.506	-0.469	241.969***	263.042***	0.008***	12.87%	-21.073
τ=25th	0.070***	0.131***	4.132***	1.874***	0.007***	15.59%	2.258***	-0.938***	-0.614***	412.230***	268.875***	0.009***	15.48%	143.355***
τ=50th	0.110***	0.151***	4.451***	3.524***	0.008***	20.58%	0.928	-0.628**	-0.149	372.704***	208.573***	0.009***	20.89%	164.130**
τ=75th	0.210***	0.250***	4.480***	3.051	0.009***	27.22%	1.428	-0.347	-0.031	322.590***	192.417***	0.011***	26.35%	130.173
τ=95th	0.648***	0.675***	-1.987**	-3.090***	0.012***	39.47%	1.103	3.333***	7.924***	-88.036	-765.310***	0.011***	37.12%	677.274***
τ=99th	0.498***	0.459***	-1.113	-1.826***	0.021***	36.35%	0.712	4.059***	8.451***	-192.436	-853.523***	0.012***	54.65%	661.087***
Banks														
OLS	0.253***	0.295***	0.935***	0.125	0.004***	54.24%	0.810**	-0.034	0.964	168.478***	43.904	0.009***	52.41%	124.574**
Quantile Regression														
τ=10th	0.075***	0.075***	0.812***	1.012***	0.002***	14.48%	-0.200*	-0.042	0.190*	110.604***	71.943***	0.006***	20.15%	38.662***
τ=25th	0.092***	0.117***	1.412***	0.909***	0.003***	19.58%	0.503	-0.221	0.307	131.659***	61.025**	0.007***	21.27%	70.634*
τ=50th	0.155***	0.183***	1.436***	0.923***	0.004***	26.38%	0.513***	-0.665*	0.045	220.582***	136.443***	0.009***	23.10%	84.139*
τ=75th	0.265***	0.338***	1.541***	0.182**	0.005***	33.35%	1.359***	0.081	0.783**	157.782***	67.374**	0.010***	31.58%	90.408**
τ=95th	0.608***	0.596***	0.502	0.229	0.009***	46.47%	0.273	0.006	3.801***	310.837**	-121.043	0.013***	52.71%	431.881***
τ=99th	1.055**	1.172***	-2.132	-3.914***	0.015***	47.77%	1.782	1.754**	2.423***	93.445	-14.547	0.017***	62.91%	107.992
Diversified Financials														
OLS	0.259***	0.296***	0.907*	0.352	0.006***	48.02%	0.555	-0.648**	0.265	275.358***	123.095*	0.008***	33.72%	152.264*
Quantile Regression														
τ=10th	0.121***	0.145***	0.538***	0.505***	0.004***	13.30%	0.033	-0.373	-0.032	132.906***	66.991**	0.006***	8.73%	65.916
τ=25th	0.125***	0.148	1.830***	1.168	0.005***	16.51%	0.662	-0.716**	-0.677**	177.097***	193.616***	0.008***	6.92%	-16.519
τ=50th	0.175***	0.201***	1.831***	1.387***	0.006***	22.02%	0.444*	-1.229***	-0.579***	370.579***	174.965***	0.008***	13.81%	195.614***
τ=75th	0.273***	0.291***	1.150***	1.112**	0.008***	29.60%	0.037	-0.789*	-0.553	315.137***	269.621***	0.009***	20.98%	45.515
τ=95th	0.459***	0.545***	1.130	-0.341	0.012***	37.39%	1.472	-0.311	4.662***	391.515**	-239.725	0.012***	40.95%	631.240***
τ=99th	1.044***	0.761***	-4.598***	-2.219*	0.020***	39.06%	-2.379*	0.944**	6.670***	141.004**	-584.031***	0.013***	51.64%	725.035***
Insurance														
OLS	0.294***	0.319***	2.290***	1.708**	0.005***	60.27%	0.581	0.363	0.359	105.748***	126.095***	0.007***	45.91%	-20.347
Quantile Regression														
τ=10th	0.028*	0.083***	3.584***	1.846***	0.003***	14.50%	1.738***	-0.254**	-0.433***	145.243***	181.699***	0.005***	17.95%	-36.456*
τ=25th	0.080***	0.098***	3.419***	3.058***	0.004***	19.73%	0.361	-0.260	-0.424**	143.530***	176.221***	0.006***	20.57%	-32.691
τ=50th	0.139***	0.127***	3.271***	3.885***	0.005***	26.83%	-0.614***	-0.067	-0.348**	129.919***	200.610***	0.007***	25.32%	-70.691***
τ=75th	0.264***	0.285***	3.537***	3.072***	0.006***	35.52%	0.465	0.717***	0.525**	82.625***	126.336***	0.007***	31.39%	-43.711
τ=95th	0.763***	0.773***	1.514	-0.716	0.008***	51.68%	2.230	4.004***	7.386***	-114.554	-446.877**	0.008***	39.71%	332.323
τ=99th	0.910	1.176*	10.229	-3.593	0.017	52.46%	13.821	-9.258***	-0.040	1426.186***	-9.886	0.034***	28.26%	1436.072***
Real Estate														
OLS	0.258***	0.288***	0.433**	0.099	0.005***	59.02%	0.334	0.047	-0.296	137.499***	189.716***	0.007***	33.99%	-52.217
Quantile Regression														
τ=10th	0.082***	0.109***	1.051***	0.621***	0.004***	15.72%	0.430***	-0.477***	-0.583***	187.079***	192.655***	0.005***	15.33%	-5.576
τ=25th	0.112***	0.137***	1.209***	0.918**	0.004***	19.65%	0.292	-0.358**	-0.371**	174.612***	170.393***	0.005***	17.91%	4.218
τ=50th	0.171***	0.184***	0.903***	1.046	0.005***	26.29%	-0.143	-0.080	-0.169	145.732***	150.116***	0.006***	20.89%	-4.384
τ=75th	0.220**	0.222***	1.295	1.526*	0.006***	35.35%	-0.231	-0.163	-1.048	137.492	357.26***	0.008***	22.89%	-219.767*
τ=95th	0.530***	0.494***	-0.628	-0.448	0.009***	49.76%	-0.180	-0.247	1.320	392.088	28.558	0.012***	27.89%	363.530
τ=99th	0.951***	1.021***	-3.049***	-4.016***	0.013***	48.74%	0.967	-10.220***	-5.471***	1326.608***	473.041**	0.037***	10.52%	853.567***

Notes: The table reports the estimated coefficients for the augmented model (6.4): $CSAD_t = \alpha + \gamma_1 D^{High}|R_{m,t}| + \gamma_2(1-D^{High})|R_{m,t}| + \gamma_3 D^{High} R^2_{m,t} + \gamma_4(1-D^{High})R^2_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation, $R_{m,t}$ is the market return and D^{High} is a dummy variable that takes the value 1 for high economic policy uncertainty conditions and the value 0 otherwise. The last column of Panel A and B reports the result for the hypothesis test $\gamma_3 = \gamma_4$. West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

illiquidity. Finally, there is evidence that the insurance industry in Europe herds during low and high funding illiquidity conditions, with the herding estimate during strict funding liquidity conditions (γ_3) greater in absolute value than its relative γ_4, in the highest quantile (99^{th}).

We use the EPU indexes developed by Baker, Bloom, and Davis (2016) to test whether herding is more pronounced during periods of higher economic policy uncertainty. Table 6.8 presents the results in the case of asymmetric conditions of the market related to economic policy uncertain for the U.S. and the Eurozone,[8] respectively. Again, the OLS analysis does not show any evidence of herding effects during periods of economic policy uncertainty in both markets. However, analyzing the outcomes of the quantile regression, we find that the herding effects during higher economic policy uncertainty conditions (γ_3) are smaller than during lower conditions (γ_4) for the US equity market and the related banking and real estate industries. The difference between γ_3 and γ_4 is significant in the US equity market for the 95^{th} quantile and in the real estate industry for the 99^{th} quantile. The diversified financials is the only industry characterized by a coefficient γ_3 greater (in absolute value) than γ_4 at the 99^{th} quantile, indicating a more pronounced herding behavior in case of higher economic policy uncertainty. In the Eurozone, there was no evidence of herding effects related to γ_3. We only find that the herding coefficient γ_4 is negative and significant for the equity market and the related diversified financials and insurance industries, in the upper extreme quantiles.

Overall, these results suggest to reject the hypothesis that herding behavior is more likely during higher economic policy uncertainty conditions for the market. The quantile regression analysis reveals, once again, that herding effects are most associated with extreme turbulent conditions of the market that, however, may not be necessary due to high level of economic policy uncertainty.

Table 6.9: Estimates of herding behavior between the US and Eurozone equity markets and the related financial sectors and industries.

	Panel A: United States						Panel B: Eurozone					
	γ_1	γ_2	δ_1	δ_2	α	Adj. R^2	γ_1	γ_2	δ_1	δ_2	α	Adj. R^2
j = Financial Sector												
OLS	0.062***	-0.083	0.560***	0.113	0.005***	88.78%	0.089***	0.794	0.602***	-0.530*	0.004***	85.83%
τ=10th	0.056***	0.414	0.471***	-0.023	0.004***	45.19%	0.074***	1.473**	0.498***	-0.931***	0.003***	44.78%
τ=25th	0.051***	0.103	0.500***	0.272***	0.004***	50.11%	0.050***	1.640***	0.523***	-0.482	0.004***	49.47%
τ=50th	0.049***	0.171	0.578***	0.070	0.004***	56.82%	0.061***	1.254*	0.581***	-0.411	0.004***	56.02%
τ=75th	0.058***	-0.029	0.622***	0.071	0.005***	65.69%	0.074***	1.168***	0.671***	-0.488***	0.004***	64.11%
τ=95th	0.061**	-0.406	0.785***	-0.043	0.005***	78.14%	0.154***	-1.515*	0.807***	-0.070	0.004***	74.96%
τ=99th	0.028	0.432	0.894***	-0.431	0.006***	81.08%	0.223***	-3.771***	0.918***	0.261	0.004***	77.21%
j = Banks												
OLS	0.137***	0.999***	0.338***	-0.026	0.007***	71.98%	0.112***	1.936**	0.410***	-0.398	0.005***	73.75%
Quantile Regression												
τ=10th	0.094***	1.240***	0.238***	-0.082**	0.005***	27.34%	0.080***	1.466*	0.272***	-0.010	0.005***	29.03%
τ=25th	0.091***	1.041***	0.255***	0.191	0.006***	30.87%	0.071***	1.547***	0.297***	0.097	0.005***	34.55%
τ=50th	0.097***	1.473***	0.334***	0.123***	0.007***	38.23%	0.071***	2.120***	0.387***	-0.064	0.005***	42.27%
τ=75th	0.124***	0.916**	0.426***	0.048	0.007***	48.95%	0.089***	2.446**	0.505***	-0.330*	0.005***	51.86%
τ=95th	0.083	2.047**	0.761***	-0.107	0.008***	64.46%	0.170***	0.823*	0.674***	-0.578***	0.006***	66.06%
τ=99th	0.032	1.285	0.986***	0.717	0.010***	67.31%	0.331***	-2.146**	0.746***	-0.474	0.006***	67.75%
j = Diversified Financials												
OLS	0.078***	0.530	0.549***	0.014	0.005***	81.05%	0.127***	1.227	0.536***	-0.084	0.005***	71.45%
Quantile Regression												
τ=10th	0.052***	1.009*	0.371***	0.067	0.004***	34.01%	0.085***	2.163**	0.282***	-0.197	0.005***	25.25%
τ=25th	0.061***	0.001	0.442***	0.521***	0.004***	39.76%	0.078***	2.475***	0.353***	-0.237**	0.005***	30.44%
τ=50th	0.058***	-0.418	0.534***	0.666**	0.005***	47.92%	0.092***	1.451	0.492***	0.310	0.005***	38.96%
τ=75th	0.066***	-0.200	0.617***	0.589***	0.005***	57.78%	0.116***	-0.022	0.625***	1.217**	0.005***	50.24%
τ=95th	0.058	0.723	0.825***	-0.044	0.006***	73.00%	0.136***	-2.296*	0.825***	2.352**	0.006***	65.39%
τ=99th	-0.020	1.820***	1.003***	-0.428***	0.007***	75.94%	0.173***	-2.256**	1.068***	1.230*	0.006***	69.06%
j = Insurance												
OLS	0.107***	1.744***	0.450***	-0.956***	0.006***	75.81%	0.136***	-0.186	0.498***	-0.114	0.005***	77.29%
Quantile Regression												
τ=10th	0.055***	2.095***	0.315***	-0.687***	0.005***	30.22%	0.083***	1.360***	0.339***	-0.262**	0.005***	30.79%
τ=25th	0.070***	1.976***	0.395***	-0.902**	0.005***	34.94%	0.088***	0.681***	0.410***	0.012	0.005***	36.26%
τ=50th	0.073***	1.738***	0.492***	-0.903***	0.006***	42.64%	0.108***	-0.121	0.485***	0.094	0.005***	44.08%
τ=75th	0.108***	1.166	0.578***	-0.831	0.006***	52.65%	0.109***	-0.366	0.589***	0.495	0.006***	53.98%
τ=95th	0.147***	0.881	0.838***	-1.121***	0.007***	68.09%	0.185***	-1.527	0.746***	0.166	0.006***	67.74%
τ=99th	0.128	0.794	1.155***	-1.045	0.007***	70.04%	0.237***	-2.110	0.854***	-0.482	0.007***	68.94%
j = Real Estate												
OLS	0.114***	0.010	0.623***	-0.096	0.005***	81.69%	0.147***	1.473***	0.366***	0.342	0.006***	63.84%
Quantile Regression												
τ=10th	0.092***	-0.193	0.462***	0.137*	0.004***	35.50%	0.075***	2.564***	0.170***	0.169	0.006***	21.10%
τ=25th	0.080***	0.543	0.530***	-0.093	0.004***	40.45%	0.080***	2.286***	0.213***	0.713***	0.006***	25.24%
τ=50th	0.091***	0.381	0.620***	-0.047	0.004***	48.03%	0.109***	1.913***	0.309***	0.773*	0.007***	32.58%
τ=75th	0.118***	-0.331	0.703***	0.126	0.005***	57.81%	0.153***	1.146***	0.446***	0.918***	0.007***	42.59%
τ=95th	0.114***	-0.378	0.917***	0.078	0.006***	72.10%	0.191***	1.441**	0.741***	0.725	0.008***	57.87%
τ=99th	0.105	1.246	1.241***	-0.537	0.006***	72.60%	0.274***	-0.192	0.997***	1.916	0.008***	62.34%

Notes: The table reports the estimated coefficients for the augmented models (6.5) and (6.6). West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

6.4.4 The role of the financial sector and industries

In addition to an investigation on herding behavior under asymmetric market conditions, we are also interested in examining how the financial sector and industries affect herding, given their role in the equity market[9]. As discussed in Section 6.2.1, initial negative shocks may be exacerbated and amplified via pro-cyclical market mechanisms in other sectors, and this in turn may lead to a crisis in the whole domestic market. Therefore, it is worth testing whether herding forces get synchronized across the domestic equity market and the financial sector and industries.

The results in Table 6.9 describe the estimates of models (6.5) and (6.6). One would expect that the domestic equity market is potentially subject to spillover herding effects from the financial sector and industries due to bilateral trade and payoffs. For both equity markets, the cross-sectional dispersion in the domestic equity market is strongly affected by the measure of dispersion and the returns of the financial sector and industries. This is demonstrated by the adjusted-R^2 reported in Table 6.9 that, in all the cases, takes a value that is almost double that of the respective estimated from model (6.2) (without the CSAD and the return of the financial sector or industry) in Table 6.2. The positive and highly significant CSAD coefficient δ_1 across all the cases suggests a dominant influence of the financial sector and industries in the domestic equity market.

For the US equity market, we do not find evidence of herding around the financial sector δ_2. The results change when we consider individual financial industries. First, there is no evidence of spillovers from the real estate industry. However, we find that the US equity market herds around the banks for the lowest quantiles (we report $\tau = 10^{th}$) and the diversified financials during distressed states for the market ($\tau = 99^{th}$). The results referring to the insurance industry are very interesting. We find evidence of herding emerging from both the OLS and the quantile analyses. The OLS regression has a negative and significant δ_2. Considering the quantile regression estimates of δ_2, we can see that this value decreases when the quantiles increase, suggesting that the herding of the US equity market around the insurance industry intensifies when the market becomes more turbulent. This result underlines the relevance of the insurance industry in the U.S. economy.

The OLS regression implies that the Eurozone equity market herd around the financial sector. Analyzing the different quantile estimations, we can see that the spillover herding effect decreases when the quantile increases, implying that the herding behavior around the financial sector is more intense when the market is in a tranquil period. Almost the same result appears for the diversified financials and the insurance industries. No spillover herding is detected from the real estate industry. Contrary to what we found for the other financial industries, Table 6.9 reveals that the Eurozone equity market herds around the banks when the market becomes more stressed, that is in high quantiles. These results mark the importance of the banking industry as major systemic risk source in the Eurozone, in line with Bernal, Gnabo, and Guilmin (2014), and Black, Correa, Huang, and Zhou (2016), who argue that the systemic contribution of this industry significantly increased during the EZC.

Our results highlight the fact that any shockwave in the financial sector or industries (real estate excluded) tends to impact the domestic equity market depending on the state of the economy. This could help policymakers and supervisory authorities to observe efficiently these industries, namely the insurance industry in the U.S. and the banks in the Eurozone, more affected by herding behavior of the equity market during distressed states of the economy.

6.4.5 Herding on fundamental information

The results in Table 6.10 describe the estimates, for the U.S. and the Eurozone, of models (6.10) and (6.11) for the non-fundamental driven CSAD ($CSAD_{NONFUND,t}$) and the fundamental driven CSAD ($CSAD_{FUND,t}$), respectively. From the OLS regressions, for the US and the Eurozone markets and financial industries, we have no evidence of herding be-

Table 6.10: Estimates of herding behavior due to non-fundamentals and fundamentals for the US and Eurozone equity markets and financial industries.

	Panel A: United States				Panel B: Eurozone			
	$CSAD_{NONFUND,t}$		$CSAD_{FUND,t}$		$CSAD_{NONFUND,t}$		$CSAD_{FUND,t}$	
	γ_1	γ_2	γ_1	γ_2	γ_1	γ_2	γ_1	γ_2
All Market Equities								
OLS	0.253***	1.693***	0.008**	-0.133	0.184***	2.751***	0.019***	0.071
Quantile Regression								
τ=10th	0.108***	1.737***	-0.014***	-0.204***	0.056**	2.840***	-0.009	0.024
τ=25th	0.120***	2.472	-0.013*	-0.007	0.084***	2.908***	-0.001	-0.024
τ=50th	0.147***	3.261***	0.001	0.014	0.120***	3.821***	0.017***	0.039
τ=75th	0.211***	4.011*	0.017***	0.018	0.229***	3.032***	0.028***	0.374***
τ=95th	0.608***	-1.797***	0.028*	0.082	0.546***	-1.115	0.070***	0.101
τ=99th	0.473***	-1.380**	0.027	0.330	0.661***	-4.362***	0.099***	-0.127
Banks								
OLS	0.274***	0.451*	0.005**	0.006	0.204***	1.767*	0.010***	0.034
Quantile Regression								
τ=10th	0.077***	0.814	-0.027***	0.107***	0.107***	1.259***	-0.003	-0.043
τ=25th	0.110***	0.998***	-0.011***	0.066***	0.148***	1.372***	-0.006*	0.139***
τ=50th	0.176***	0.996***	0.003	0.029	0.174***	1.981**	0.006	0.082
τ=75th	0.297***	0.763***	0.024***	-0.074***	0.165***	3.226***	0.020***	0.003
τ=95th	0.640***	-0.229	0.047***	-0.120**	0.324***	4.039***	0.033	0.210
τ=99th	1.156***	-3.210***	0.055***	-0.167	0.466***	2.447***	0.064***	-0.120
Diversified Financials								
OLS	0.272***	0.634	0.005**	-0.040	0.176***	1.154***	0.016***	-0.001
Quantile Regression								
τ=10th	0.124***	0.631***	-0.011***	-0.062***	0.038***	1.801***	-0.008	0.050
τ=25th	0.124***	1.726***	-0.007***	-0.013	0.079***	1.480***	-0.003	0.073***
τ=50th	0.175***	1.715***	0.003*	-0.021	0.138***	1.257***	0.012**	0.005
τ=75th	0.259***	1.598**	0.013***	0.010	0.192***	1.541***	0.021***	0.205**
τ=95th	0.501***	0.036	0.027***	-0.063	0.429***	0.569	0.057***	-0.146**
τ=99th	0.902***	-3.165***	0.036***	-0.100	0.331	2.925	0.072	0.154
Insurance								
OLS	0.301***	2.034***	0.005**	-0.037	0.204***	1.995***	0.014***	0.010
Quantile Regression								
τ=10th	0.051	2.832**	-0.026***	0.106***	0.050***	1.987***	-0.008*	0.044
τ=25th	0.082***	3.452***	-0.014***	0.062	0.053***	3.024***	0.000	0.035
τ=50th	0.139***	3.324***	0.002	0.016	0.098***	3.070***	0.010**	0.079
τ=75th	0.270***	3.203***	0.019***	-0.075**	0.201***	2.922**	0.023***	0.027
τ=95th	0.790***	-0.373	0.033***	-0.070***	0.730***	-1.440***	0.050***	0.033
τ=99th	1.201***	-3.791***	0.037***	-0.070	0.971***	-3.639***	0.100***	-0.514***
Real Estate								
OLS	0.274***	0.240	0.002	-0.004	0.113***	2.783***	0.011***	-0.003
Quantile Regression								
τ=10th	0.116***	0.594***	-0.012***	-0.031	0.028	1.839	-0.004	-0.072
τ=25th	0.125***	1.112***	-0.010***	0.061***	0.029*	2.711***	-0.001	0.032
τ=50th	0.172***	1.213**	0.001	0.005	0.058***	3.479***	0.003	0.075
τ=75th	0.204***	1.899***	0.010***	-0.026***	0.123**	3.609*	0.016*	0.065
τ=95th	0.466***	0.020	0.018***	0.050	0.428***	1.187	0.045***	-0.042
τ=99th	0.989***	-3.249***	0.025*	0.002	0.359	4.824	0.059	0.203

Notes: The table reports the estimated coefficients for the augmented models (6.10) and (6.11): $CSAD_{NONFUND,t} = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + e_t$, and $CSAD_{FUND,t} = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + e_t$; $CSAD_{NONFUND,t} = \varepsilon_t$, form regression (6.7): $CSAD_t = \alpha + \beta_1(R_{m,t} - R_f) + \beta_2 HML_t + \beta_3 SMB_t + \beta_4 MOM_t + \varepsilon_t$; $CSAD_{FUND,t} = CSAD_t$ - $CSAD_{NONFUND,t}$. West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

havior due to either non-fundamental or fundamental information. The quantile regressions show a more interesting pattern of the herding coefficients.

A more refined analysis based on the quantile estimates indicate that, in the U.S., herding due to fundamental information is detected in the lower range of quantiles (with $\tau = 10^{th}$, the γ_2 estimates are also statistically significant) for the equity market and the diversified financials. The real estate industry is characterized by a negative and significant γ_2 due to fundamental information at the median level ($\tau = 50^{th}$), while the banks and the insurance industries are in the upper range of quantiles. Hence, herding due to fundamental information appears in tranquil periods for the US equity market, the diversified financials and real estate industries. However, banks and insurance tend to herd on fundamental information when the market becomes more turbulent, stating from the 75^{th} quantile. On the other hand, we find that the non-fundamental information driven herding behavior is detected for the US equity market and the related financial industries only for the extreme upper quantiles, indicating that herding effects due to non-fundamental information are more likely during tail events of the market.

In the Eurozone, we find evidence that the fundamental driven herding is present for the diversified financials and the insurance industries, while the non-fundamental driven herding is detected for the equity market and the insurance industry. In both cases, we find that the herding coefficients are negative and significant only for the extreme upper distribution of the quantiles, implicating that "intentional" and "spurious" herding are present only during extreme turbulent periods of the related market.

Table 6.11 illustrates the results of testing based on models (6.12) and (6.13) during the GFC, for the U.S. and the Eurozone, respectively. We find that the US investors herd due to fundamental information during the GFC. The OLS analysis shows a negative and significant herding coefficient γ_3 for the equity market, diversified financials and real estate. The results related to the US market become more interesting analyzing the estimates of the quantile regression. There is evidence that the US equity market and all the financial industries herd starting from intermediate turbulent conditions of the market ($\tau = 50^{th}$). Overall, our results indicate that the herding behavior detected during the GFC in the U.S.

was “spurious” more than “intentional”. The above analysis shows that there is herding effect during the GFC for the US equity market and financial industries.

Our results are in line with Galariotis, Rong, and Spyrou (2015) for the US equity market and with Humayun Kabir (2018) the US financial industries during the GFC. Our analysis is more comprehensive, including the estimates for all the US financial industries and, moreover, considering the quantile regression methodology that provides a better understanding of herding across different states of the economy.

The GFC impacts the herding effects due to non-fundamental and fundamental information in the Eurozone as well. For the fundamental driven herding, the OLS analysis does not show any evidence of herding behavior, apart for the equity market, which coefficient γ_3 is found negative and significant. The quantile regression analysis shows herding evidence for all the financial industries, except for banks, which are found to herd due to non-fundamental information. Similar to what we find in the U.S., the herding effects due to fundamental information is more pronounced in the left-half of the quantiles and the estimates again suggest that herding was “spurious” more than “intentional” during this period.

Finally, Table 6.12 reports the estimates of models (6.12) and (6.13) used to test herding behavior due to non-fundamental and fundamental information during the EZC, for the U.S. and the Eurozone, respectively. During the EZC, the OLS analysis reveal the presence of herding due to non-fundamental information for the US and the Eurozone equity markets and financial industries.

In the U.S., the quantile regression analysis in Table 6.12 shows evidence of “intentional” herding in the equity markets and all the financial sectors especially in the lower quantiles, implying that investors were herding due to non-fundamental information during the EZC. There are no evidence of “spurious” herding. The findings related to the Eurozone are very close to the US case, the results suggesting that the equity market and the financial industries tended to herd due to non-fundamental information, during the EZC.

Overall, our results indicate that different crises may affect in different ways herding

Table 6.11: Estimates of herding behavior due to non-fundamentals and fundamentals for the US and Eurozone equity markets and financial industries, during the GFC.

	Panel A: United States				Panel B: Eurozone			
	$CSAD_{NONFUND,t}$		$CSAD_{FUND,t}$		$CSAD_{NONFUND,t}$		$CSAD_{FUND,t}$	
	γ_3	γ_4	γ_3	γ_4	γ_3	γ_4	γ_3	γ_4
All Market Equities								
OLS	0.112	-0.279	-1.920***	3.948***	0.214	-0.106	-2.195**	6.258***
Quantile Regression								
τ=10th	-0.025	0.915***	-0.355	1.804***	0.213**	0.812***	1.072**	2.261**
τ=25th	0.873**	-4.349**	-0.875***	1.638***	2.297***	-0.580	-0.474	3.141***
τ=50th	0.054	-0.214**	-2.907***	2.669***	0.256	0.152	-2.415***	4.627***
τ=75th	-0.679***	0.359	-3.077***	6.059***	-1.080***	0.115	-3.873***	7.437***
τ=95th	-0.309***	0.723**	-4.108***	14.283	-0.486***	0.671	-8.018***	12.167***
τ=99th	-0.125***	1.498***	-3.547**	35.024	-0.256***	0.908***	-13.163	21.573
Banks								
OLS	0.019	-1.540***	-0.411	3.543***	0.136	-0.641***	0.628	2.475***
Quantile Regression								
τ=10th	-0.116**	-0.901**	-0.390	1.308***	-0.172***	-0.377	0.501***	1.384***
τ=25th	0.099	-8.574***	-0.545**	1.716***	0.405**	-4.870***	-0.030	2.146***
τ=50th	0.160*	-0.529***	-1.004***	2.702***	0.717**	-0.246***	-0.042	3.678***
τ=75th	-0.393***	-0.362***	-0.357**	7.808***	-0.734***	-0.099	1.056	4.632***
τ=95th	-0.141***	0.938*	-1.699***	5.524***	-0.320***	0.388	0.403	6.916**
τ=99th	-0.081***	1.347***	-3.892	7.208	-0.146***	0.486***	-2.912	20.662
Diversified Financials								
OLS	0.011	-0.245	-1.122**	2.896**	-0.012	-0.152	-0.565	4.211***
Quantile Regression								
τ=10th	-0.119*	0.583***	-0.650***	0.996***	0.062***	-0.249	0.213	2.238***
τ=25th	0.366***	-2.799**	-1.052***	1.449**	0.483***	-2.196***	-0.366	2.577***
τ=50th	-0.031	-0.143*	-1.600***	3.316***	0.000	0.138	-0.690	3.871***
τ=75th	-0.437***	-0.073	-0.901	5.762***	-0.528***	0.157	-1.051***	3.907***
τ=95th	-0.181***	1.058**	-3.720***	6.406	-0.219***	0.770	-3.255***	13.634
τ=99th	-0.090***	1.200***	-6.098***	15.312	-0.090*	0.951**	-2.655***	44.341***
Insurance								
OLS	0.109	-1.810***	-0.144	4.011***	0.177	-0.351	-0.402	3.845***
Quantile Regression								
τ=10th	0.153**	1.130***	0.188	1.885***	0.006	0.615***	1.246***	1.662***
τ=25th	0.525***	-12.33***	0.180	2.039***	0.676***	-4.572***	0.249	2.225***
τ=50th	-0.202	-0.730***	-0.665	3.311***	0.012	-0.204	-0.371	3.338***
τ=75th	-0.706***	-0.347**	0.887**	10.704***	-0.880***	-0.296**	-0.116	4.247***
τ=95th	-0.306***	1.501*	-3.810***	5.921***	-0.229***	0.616	-5.071***	3.778***
τ=99th	-0.122***	1.367***	-11.699***	13.412	-0.097***	1.144**	-7.570	30.943
Real Estate								
OLS	0.122	0.032	-0.676***	1.549**	0.334	-0.115	-1.522	5.404***
Quantile Regression								
τ=10th	0.047	0.577	-0.122	0.966***	-0.400	-0.072	-0.773	0.832
τ=25th	1.057***	-0.554	-0.513***	0.941***	1.560***	-0.678***	-0.936	2.241
τ=50th	-0.069	0.207	-0.830***	0.758***	0.695***	-0.012	-2.518***	4.702***
τ=75th	-0.287***	0.067	-0.841***	1.320	-0.689***	0.042	-3.903***	5.085***
τ=95th	-0.118***	1.186*	-1.754*	5.387	-0.192***	0.656	-4.854***	19.322***
τ=99th	-0.075***	1.370***	-3.687***	6.958	-0.061*	0.720**	-9.476***	30.770

Notes: The table reports the estimated coefficients for the augmented models (6.12) and (6.13): $CSAD_{NONFUND,t} = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1-D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis}R^2_{m,t} + \gamma_4(1-D^{Crisis})R^2_{m,t} + e_t$, and $CSAD_{FUND,t} = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1-D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis}R^2_{m,t} + \gamma_4(1-D^{Crisis})R^2_{m,t} + e_t$; $CSAD_{NONFUND,t} = \varepsilon_t$, form regression (6.7): $CSAD_t = \alpha + \beta_1(R_{m,t} - R_f) + \beta_2 HML_t + \beta_3 SMB_t + \beta_4 MOM_t + \varepsilon_t$; $CSAD_{FUND,t} = CSAD_t$ - $CSAD_{NONFUND,t}$. D^{Crisis} is a dummy variable that takes the value 1 during the period of the global financial crisis and the value 0 otherwise. West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

behavior. During the GFC, investors tended to herd due to "spurious" herding. This result changes during the EZC, because investors are found to show "intentional" more than "spurious" herding.

6.5 Conclusions

Herding arises when investors exhibit collective actions in the market. It has important implications for policymakers, supervisory authorities and academia. This study provides a comprehensive analysis, testing for the existence of herding effects in the US and Eurozone equity markets, financial sector and its industries, namely banks, diversified financials, insurance and real estate. Our study follows the approach based on the CSAD proposed by Chang, Cheng, and Khorana (2000) and, in addition to the common practice of OLS regression, we employed quantile regression analysis in order to have a more complete analysis of herding behavior, and alleviate some statistical issues related to OLS. The main findings are summarized in Table 6.13.

The analysis based on the entire sample period documents a weak presence of herding behavior. In particular, only the quantile regression estimates show the presence of herding in the high quantiles for the US equity market, banks, diversified financials and real estate industries, while for the Eurozone, for the equity market and the insurance industry. These findings indicate the presence of herding only for distressed market states.

We find evidence of herding during the GFC, with both OLS and quantile regressions, for the US and Eurozone equity markets and financial industries, except banks in the Eurozone. On the other hand, we do not find significant herding effects during the EZC for both equity markets. In the U.S., banks and insurance industries, and in the Eurozone, banks, diversified financials and real estate industries, are found to herd during the EZC. The results suggest that during the GFC, investors tended to herd also when the market was moderately turbulent; while, during the EZC this behavior was bordered to specific industries only.

Table 6.12: Estimates of herding behavior due to non-fundamentals and fundamentals for the US and Eurozone equity markets and financial industries, during the EZC.

	Panel A: United States				Panel B: Eurozone			
	$CSAD_{NONFUND,t}$		$CSAD_{FUND,t}$		$CSAD_{NONFUND,t}$		$CSAD_{FUND,t}$	
	γ_3	γ_4	γ_3	γ_4	γ_3	γ_4	γ_3	γ_4
All Market Equities								
OLS	-2.582***	0.294	3.614***	0.481	-2.642***	0.467*	4.171***	2.128***
Quantile Regression								
τ=10th	-11.692***	0.317***	1.633***	1.856***	-10.794***	0.405***	3.324***	3.521***
τ=25th	-7.162***	0.744***	1.395***	2.608***	-3.84***	2.088***	3.219***	3.473***
τ=50th	-1.689***	0.225***	2.391**	1.088*	-1.691***	0.266***	3.133***	3.399***
τ=75th	-1.235***	0.448	7.868***	-0.078	-1.197***	0.653**	6.027***	1.615***
τ=95th	0.516*	-0.262***	15.636***	-2.797***	0.522	-0.401***	10.012***	-3.043***
τ=99th	1.133***	-0.097**	23.071***	-2.149**	1.092***	-0.158	14.016***	-5.206***
Banks								
OLS	-2.836***	-0.003	1.825***	0.241	-1.582***	-0.027	1.555**	2.205**
Quantile Regression								
τ=10th	-11.878***	0.102	0.828***	0.841***	-7.895***	0.198**	1.311***	1.371***
τ=25th	-10.947***	-0.023	0.703*	1.085***	-7.662***	0.035	0.887***	1.598***
τ=50th	-2.198***	0.152***	0.514	0.548***	-1.312***	0.107	3.553***	3.898***
τ=75th	-1.905***	0.048	6.657***	0.834***	-0.886***	0.231*	3.198***	4.082***
τ=95th	0.507	-0.157***	6.341*	-0.563	0.294	-0.221***	1.382**	4.140***
τ=99th	1.477***	-0.052***	4.719**	-2.823***	0.878***	-0.026	8.730	0.655
Diversified Financials								
OLS	-1.866***	0.134	1.915***	0.008	-1.791***	0.098	2.675***	0.836***
Quantile Regression								
τ=10th	-9.349***	0.188***	0.763***	0.576***	-5.951***	0.082***	2.938***	1.502***
τ=25th	-5.251***	0.373***	0.376	1.374***	-4.165***	0.391***	2.508***	1.228***
τ=50th	-1.559***	0.178***	0.940	0.781**	-1.548***	0.078	2.641**	1.475**
τ=75th	-1.122***	0.215	4.877***	0.418	-1.046***	0.239**	2.881**	0.997***
τ=95th	0.574	-0.167***	10.485**	-1.005*	0.450	-0.207***	3.957	-0.318
τ=99th	1.172***	-0.068***	13.766***	-4.084***	1.378***	-0.046	28.149***	0.095
Insurance								
OLS	-4.289***	0.145	3.198***	1.181**	-2.305***	0.335	3.697***	1.246**
Quantile Regression								
τ=10th	-16.957***	0.208**	2.188***	3.096***	-11.19***	0.301***	2.213***	1.880***
τ=25th	-16.93***	0.490***	1.911***	2.903***	-9.338***	0.645***	3.111***	2.436***
τ=50th	-3.241***	0.234	2.049**	1.427***	-2.046***	0.250***	3.674***	1.591***
τ=75th	-2.786***	-0.012	10.351***	2.158***	-1.597***	0.141	5.172**	1.642***
τ=95th	0.680*	-0.290***	8.616	-1.217	0.407	-0.170***	7.343	-2.184***
τ=99th	1.783***	-0.080**	19.801*	-5.169***	1.103***	-0.086***	14.364**	-4.878***
Real Estate								
OLS	-2.373***	0.202	1.957***	-0.251	-2.684***	0.460***	2.424*	1.922***
Quantile Regression								
τ=10th	-13.934***	0.145***	1.189***	0.568***	-9.116***	0.277***	-0.079	2.818***
τ=25th	-7.637**	0.731***	0.940***	0.084	-2.513***	1.609***	-0.006	1.975***
τ=50th	-1.879***	0.235***	0.915***	-0.118	-2.060***	0.373***	1.831*	1.976
τ=75th	-1.695***	-0.083	6.218***	-0.122	-1.331***	0.617***	4.178***	1.732***
τ=95th	0.328	-0.140***	12.182*	-0.866	0.743**	-0.148**	9.149	-0.810
τ=99th	1.242***	-0.056***	7.584	-3.103***	1.432***	-0.053	30.259	1.169

Notes: The table reports the estimated coefficients for the augmented models (6.12) and (6.13): $CSAD_{NONFUND,t} = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1-D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R^2_{m,t} + \gamma_4(1-D^{Crisis})R^2_{m,t} + e_t$, and $CSAD_{FUND,t} = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1-D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R^2_{m,t} + \gamma_4(1-D^{Crisis})R^2_{m,t} + e_t$; $CSAD_{NONFUND,t} = \varepsilon_t$, form regression (6.7): $CSAD_t = \alpha + \beta_1(R_{m,t} - R_f) + \beta_2 HML_t + \beta_3 SMB_t + \beta_4 MOM_t + \varepsilon_t$; $CSAD_{FUND,t} = CSAD_t$ - $CSAD_{NONFUND,t}$. D^{Crisis} is a dummy variable that takes the value 1 during the period of the Eurozone crisis and the value 0 otherwise. West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 6.13: Summary of the results.

	Panel A: United States					Panel B: Eurozone				
	All Market Equities	Banks	Diversified Financials	Insurance	Real Estate	All Market Equities	Banks	Diversified Financials	Insurance	Real Estate
Herding behavior during the full sample (Jan. 2005 - Dec. 2017)	Yes - $\tau = 95^{th}$ and 99^{th}	Yes - $\tau = 99^{th}$	Yes - $\tau = 99^{th}$	No	Yes - $\tau = 99^{th}$	Yes - $\tau = 99^{th}$	No	No	Yes - $\tau = 95^{th}$ and 99^{th}	No
Herding behavior during crises										
Global financial crisis	Yes - OLS and $\tau = 25^{th}$ to 99^{th}	Yes - $\tau = 50^{th}$ to 99^{th}	Yes - OLS and $\tau = 10^{th}$ to 99^{th}	Yes - $\tau = 95^{th}$ and 99^{th}	Yes - OLS and $\tau = 25^{th}$ to 99^{th}	Yes - OLS and $\tau = 50^{th}$ to 99^{th}	No	Yes - OLS and $\tau = 75^{th}$ to 99^{th}	Yes - $\tau = 75^{th}$ and 95^{th}	Yes - $\tau = 50^{th}$ to 99^{th}
Eurozone Crisis	No	Yes - $\tau = 10^{th}$ to 95^{th}	No	Yes - OLS and $\tau = 75^{th}$ and 95^{th}	No	No	Yes - OLS and $\tau = 50^{th}$ and 75^{th}	$\tau = 95^{th}$	No	Yes - OLS and $\tau = 10^{th}$ and 25^{th}
Herding behavior under asymmetric market conditions										
(i) High volatility	Yes - $\tau = 99^{th}$	Yes - $\tau = 99^{th}$	Yes - $\tau = 99^{th}$	No	Yes - $\tau = 99^{th}$	Yes - $\tau = 99^{th}$	No	Yes - $\tau = 95^{th}$	Yes - $\tau = 99^{th}$	No
(i) Low volatility	Yes - $\tau = 95^{th}$	No	Yes - $\tau = 99^{th}$	No	Yes - $\tau = 95^{th}$ and 99^{th}	Yes - $\tau = 95^{th}$ and 99^{th}	Yes - $\tau = 99^{th}$	No	Yes - $\tau = 95^{th}$ and 99^{th}	No
(ii) High credit deterioration	Yes - $\tau = 95^{th}$ and 99^{th}	Yes - $\tau = 99^{th}$	Yes - $\tau = 99^{th}$	Yes - $\tau = 99^{th}$	Yes - $\tau = 95^{th}$ and 99^{th}	Yes - $\tau = 99^{th}$	No	Yes - $\tau = 95^{th}$	Yes - $\tau = 95^{th}$ and 99^{th}	No
(ii) Low credit deterioration	No	Yes - $\tau = 99^{th}$	Yes - $\tau = 99^{th}$	No	Yes - $\tau = 99^{th}$	No	No	No	Yes - $\tau = 95^{th}$ and 99^{th}	Yes - $\tau = 99^{th}$
(iii) High funding illiquidity	Yes - $\tau = 99^{th}$	Yes - $\tau = 99^{th}$	Yes - $\tau = 99^{th}$	No	Yes - $\tau = 99^{th}$	No	No	No	Yes - $\tau = 99^{th}$	No
(iii) Low funding illiquidity	Yes - $\tau = 95^{th}$ and 99^{th}	No	Yes - $\tau = 99^{th}$	Yes - $\tau = 95^{th}$	Yes - $\tau = 95^{th}$ and 99^{th}	Yes - $\tau = 95^{th}$ and 99^{th}	No	No	Yes - $\tau = 95^{th}$ and 99^{th}	Yes - $\tau = 95^{th}$ and 99^{th}
(iv) High economic policy uncertainty	Yes - $\tau = 95^{th}$	No	Yes - $\tau = 99^{th}$	No	Yes - $\tau = 99^{th}$	No	No	No	No	No
(iv) Low economic policy uncertainty	Yes - $\tau = 95^{th}$ and 99^{th}	Yes - $\tau = 99^{th}$	Yes - $\tau = 99^{th}$	No	Yes - $\tau = 99^{th}$	Yes - $\tau = 95^{th}$ and 99^{th}	No	Yes - $\tau = 99^{th}$	Yes - $\tau = 95^{th}$	No
Herding spillovers										
Financial sector	No					Yes - OLS and $\tau = 10^{th}$ and 75^{th}				
Banks	Yes - $\tau = 10^{th}$					Yes - $\tau = 95^{th}$				
Diversified Financials	Yes - $\tau = 99^{th}$					Yes - $\tau = 25^{th}$				
Insurance	Yes - OLS and $\tau = 10^{th}$ to 50^{th} and 95^{th}					Yes - $\tau = 10^{th}$				
Real Estate	No					No				
Non-fundamental and fundamental herding										
Full sample (Jan. 2005 - Dec. 2017)										
Non-fundamental herding	Yes - $\tau = 95^{th}$ and 99^{th}	Yes - $\tau = 99^{th}$	Yes - $\tau = 99^{th}$	Yes - $\tau = 99^{th}$	Yes - $\tau = 99^{th}$	Yes - $\tau = 99^{th}$	No	No	Yes - $\tau = 95^{th}$ and 99^{th}	No
Fundamental herding	Yes - $\tau = 10^{th}$	Yes - $\tau = 75^{th}$ and 95^{th}	Yes - $\tau = 10^{th}$	Yes - $\tau = 95^{th}$	Yes - $\tau = 75^{th}$	No	Yes - $\tau = 25^{th}$	No	Yes - $\tau = 10^{th}$	No
Global financial crisis										
Non-fundamental herding	Yes - $\tau = 75^{th}$ to 99^{th}	Yes - $\tau = 10^{th}$ and 75^{th} to 99^{th}	Yes - $\tau = 10^{th}$ and 75^{th} to 99^{th}	Yes - $\tau = 75^{th}$ to 99^{th}	Yes - $\tau = 75^{th}$ to 99^{th}	Yes - $\tau = 75^{th}$ to 99^{th}	Yes - $\tau = 10^{th}$ and 75^{th} to 99^{th}	Yes - $\tau = 75^{th}$ to 99^{th}	Yes - $\tau = 75^{th}$ to 99^{th}	Yes - $\tau = 75^{th}$ to 99^{th}
Fundamental herding	Yes - OLS and $\tau = 25^{th}$ to 99^{th}	Yes - $\tau = 25^{th}$ to 95^{th}	Yes - OLS and $\tau = 10^{th}$ to 99^{th}	Yes - $\tau = 75^{th}$ and 99^{th}	Yes - OLS and $\tau = 25^{th}$ to 99^{th}	Yes - OLS and $\tau = 50^{th}$ to 99^{th}	No	Yes - $\tau = 75^{th}$ to 99^{th}	Yes - $\tau = 95^{th}$	Yes - $\tau = 50^{th}$ to 99^{th}
Eurozone Crisis										
Non-fundamental herding	Yes - OLS and $\tau = 10^{th}$ to 75^{th}	Yes - OLS and $\tau = 10^{th}$ to 75^{th}	Yes - OLS and $\tau = 10^{th}$ to 75^{th}	Yes - OLS and $\tau = 10^{th}$ to 75^{th}	Yes - OLS and $\tau = 10^{th}$ to 75^{th}	Yes - OLS and $\tau = 10^{th}$ to 75^{th}	Yes - OLS and $\tau = 10^{th}$ to 75^{th}	Yes - OLS and $\tau = 10^{th}$ to 75^{th}	Yes - OLS and $\tau = 10^{th}$ to 75^{th}	Yes - OLS and $\tau = 10^{th}$ to 75^{th}
Fundamental herding	No	No	No	No	No	No	No	No	No	No

Notes: The table presents the main results concerning our analyses. In case herding is detected, we report "Yes", and "No" otherwise. OLS ($\tau = n^{th}$) indicates the presence of herding detected with OLS (quantile) regression (at the n^{th} quantile).

We showed that herding in the US is more likely during extreme distressed market states in case of higher volatility, while, in the Eurozone, this trend is documented only for the diversified financials industry. Eurozone's banks and insurance industries tend to herd more in case of lower volatility. We find that credit deterioration impacts herding in the US and Eurozone equity markets and financial industries, except of the banks industry in the Eurozone. Similar results are found in the case of funding illiquidity market asymmetry conditions.

Furthermore, we inspect the presence of spillover herding effects from the financial sector and industries to the domestic equity market. Our results indicate, mainly, the presence of spillover herding effects from the insurance industry to the domestic market in the U.S. and from the banks to the domestic market in the Eurozone. In line with prior studies on systemic risk, our results confirm the systemic importance of the insurance and banks industries in the U.S. and the Eurozone, respectively.

We find evidence of "intentional" herding in the US equity market and all the financial industries. On the other hand, in the Eurozone, there is herding detected for the corporates in the equity market and the insurance industry, while we find presence of "spurious" herding for the diversified financials corporates and, again, for companies in the insurance industries. Analyzing the GFC, our results indicate that the herding behavior detected during this period was "spurious" more than "intentional". During the EZC, the companies in the US and the Eurozone equity markets and financial industries tended to herd due to non-fundamental information – "intentional" herding, highlighting that the two recent financial crises affect in different ways the companies herding behavior.

CHAPTER 7

Conclusion

> *"In many spheres of human endeavor, from science to business to education to economic policy, good decisions depend on good measurement."*
>
> Bernanke (2012)

We have attempted to address two fields within finance that are currently attracting many supervisory authorities, central bankers, regulators and academics. This thesis has shown that important information can still be extracted from: i) the three leading market-based measures of systemic risk – namely, the delta conditional value at risk ($\Delta CoVaR$) developed by Adrian and Brunnermeier (2016), the marginal expected shortfall (MES) of Acharya, Pedersen, Philippon, and Richardson (2017) and the $SRISK$ proposed by Brownlees and Engle (2016) and discussed in more detail in Engle (2018); and, ii) the analysis of herding behavior based on the cross-sectional absolute deviations (CSAD) introduced by Chang, Cheng, and Khorana (2000).

More specifically, we have shown how the signal information content and the effect of estimation uncertainty of the three main market-based systemic risk measures (SRM) can be used on selecting and assigning capital surcharges to global systemically important banks (G-SIB). Furthermore, by focusing on China's financial system, we have assessed the level of systemic risk of China's financial sectors over the period from January 2010 to December

2016. In addition, we have shown that there is a solid relationship between the measures of systemic risk shortfall[1] and herding behavior, used in this thesis. Finally, we have presented a comprehensive analysis of herding behavior based on equities and financial industries, in case of the last crises, periods of financial instability and asymmetric market conditions. We have also revealed new evidence of “spurious” and “intentional” herding.

First, we have shown that estimating the SRMs by conditioning the analysis on the global index allows a more meaningful comparison with Basel Committee for Banking Supervision’s (BCBS) assessment methodology for G-SIBs. We used the bootstrap Kolmogorov-Smirnov (KS) test to demonstrate that the three SRMs collectively produce a relatively similar classification of banks into systemic and non-systemic as the Financial Stability Board’s (FSB) G-SIBs list. However, this is not necessary reflected into the systemic risk buckets as defined by the FSB. In particular, we found that they are generally different from those constructed in a full pairwise comparison approach based on the market-based SRMs. We have shown that the systemic risk assessments based on different SRMs may lead to different conclusions. This implies that categorizing a financial firm as systemically risky may be SRM dependent. However, since the FSB classification of G-SIBs has been proven controversial (Benoit, Hurlin, and Pérignon, 2019), we have demonstrated that market-based SRMs may provide an useful and transparent tool to test whether G-SIBs assigned by the FSB do contribute more than the other banks to the overall systemic risk. In particular, we proposed an alternative approach to designate G-SIBs. It is based on confidence intervals and cluster analyses and is able to classify as systemically important Nordea Bank in 2015, 2016 and 2017, and Royal Bank of Scotland Group in 2017. These banks have been designated as G-SIBs thorough supervisory judgment – i.e., with a G-SIB score lower than $130bps$.

This research has contributed to the debate on systemic risk and financial stability by assessing the systemic risk of G-SIBs; comparing the classification of G-SIBs based on market-based SRMs with the one provided by the financial authority; and, developing a

[1] $\Delta CoVaR$, MES and $LRMES$.

new designation tool for G-SIBs based on market-based SRMs. Since our analysis is based on higher-frequency market data, which are public, the proposed methodology could be useful to live-monitor whether G-SIBs assigned by the FSB do contribute more than the other banks to the overall systemic risk. In addition, compared to the methodology used by the financial authority, the SRMs we use can be replicated, allowing a more transparent computation. This may also contribute to a more efficient regulation. To the best of our knowledge, the analysis presented in Chapter 3 represents the first academic attempt to analyze and compare the regulatory approach with a market based one for the designation and regulation of G-SIBs.

Second, we contributed also to the empirical literature on systemic risk by assessing the level of systemic risk of China's financial system and sectors – namely, banks, insurance and brokerage industries, and real estate; during China's property bubble of 2010, the banking liquidity crisis of 2013, and the stock market crash of 2015. In particular, by using the $\Delta CoVaR$ as measure for systemic risk, we have monitored the systemic risk in China during these events. We have shown that the systemic risk level of China's financial system decreased following the deflation of the property bubble in 2012, increased during the banking liquidity crisis in 2013, and reached a major peak during the market crash in 2015. We have further shown, through the Wilcoxon signed rank test, that the systemic risk level of the financial system and sectors significantly increased after the main systemic events. In order to provide a formal systemic risk ranking of the financial sectors, through the bootstrap KS test, We have found that each of the financial sectors considered, over all the sub-periods, is systemically relevant (at 1% significance level), significantly contributing to the systemic risk in China's financial system. The banking sector has been found to contribute the most over all the sub-periods; while, the real estate took over the insurance and brokerage industries after the deflating of the property bubble.

The results discussed in Chapter 4 may be useful to supervisory authorities and regulators. In particular, since different financial sectors are found to contribute differently to systemic risk, the Chinese supervisory authorities and regulators could potentially develop different courses of action depending upon the characteristics of the financial sectors.

In addition, we aimed to pioneer a new strand of literature that investigates the relationship between the market systemic risk and herding behavior. The analysis presented in Chapter 5 could provide new insightful evidence on this relationship to central bankers, supervisory authorities and regulators, which may plan market interventions in preventing both herding behavior and the spread of systemic risk across the financial system. The latter has been demonstrated to be affected by herding in the antecedent periods of the main market downturns. Moreover, we also contribute to the empirical literature on herding behavior in equity markets. Using OLS and quantile regressions and applying daily data for 33 countries, we have shown that herding is more likely in Asia Pacific, Latin American and European markets. During the Eurozone crisis and the China's market crash of 2015-16, we found significant evidence of herding for most of the countries analysed. In addition, important herding behavior evidences related to Brexit and the UK's economy are also exhibited.

To the best of our knowledge, by including 33 local equity markets, this research represents the largest data-set analysis of herding behavior. Second, we have empirically shown that different investing behavior may be related to different sub-periods. Moreover, we filled the gap in the literature related to the analysis of herding during the last main market turbulences. Furthermore, analysing the existing relationship between the return clustering of the market – i.e., the measure used to detect herding; and the systemic risk increases, we presented evidence of a strong relationship between herding and systemic risk.

This research has also contributed to and continued the empirical literature on herding behavior and spillover in financial sector, industries and equity market. We tested for herding towards the market consensus for the US and the Eurozone equity markets and financial industries. We are the first to study herding in the Euro area by considering the Eurozone at aggregate level, rather than considering "stand-alone" countries. We motivated this study considering that the macroeconomic convergence associated with the introduction of the European Monetary Union increased the regional and global stock market integration of the Eurozone; and, that herding may threat the financial stability of the Eurozone through the increasing financial integration. This would call upon the European Central Bank (ECB) intervention, instead of the respective national authorities. We have shown that herding appears more pronounced when we condition on the financial crises periods and our results supported the herding presence in the case of asymmetric conditions of volatility, credit deterioration, funding illiquidity and economic policy uncertainty. We continued the literature on the presence of herding due to fundamental or non-fundamental information. Conditioning the analysis to the global financial crisis (GFC) and the Eurozone crisis (EZC), as a robustness check we considered the short-selling bans imposed in the United States during the GFC and in the Eurozone during both crises. This analysis strongly reinforced our results on herding. To the best of our knowledge, the analysis presented in Chapter 6 has never been reported in the earlier herding literature.

Moreover, in Chapter 5 and Chapter 6, we have presented the analysis of herding behavior based on quantile regressions, which have been applied only by Chiang, Li, and Tan (2010) and Zhou and Anderson (2013), in the existing literature. The research points out that herding is more likely to be present in the high quantiles, which are commonly associated with stressed states of the market.

We strongly believe that many areas of finance may benefit from the tools and results presented in this thesis. Moreover, there are several areas in which this research could be developed and extended further. First of all, future research should point to a better understanding of the contagion in financial markets due to systemic risk. In particular, by using the market-based SRMs of capital shortfall,[1] it would be of interest to evaluate contagion in financial markets as co-exceedances. Bae, Karolyi, and Stulz (2003) introduced this concept and a model to study it. Adapting this model to SRMs would allow to build a network based on systemic risk and understand the main drivers of the financial contagion due to systemic risk. This analysis could have advantages for financial stability purposes as well as precautionary policy makers' decisions.

Another channel in which this research could be directed encompasses the use of market-based SRMs as risk measures in risk-budgeting (parity) portfolios (Roncalli, 2013). In particular, a diversification problem in terms of systemic risk could be formulated. The latter may lead to an optimal strategic asset allocation based on systemic risk. This would be considered the first attempt to build a systemic risk budgeting portfolio. A risk budgeting approach could be useful to define the optimal systemic contribution of financial firms to the overall systemic risk of the market. From a macroprudential side, such an exercise may help supervisory authorities to limit (budget) the market-based systemic risk of financial institutions. Moreover, the portfolio construction based on systemic risk budgeting may be of interests also to academics as well as practitioners.

An interesting future research path may also be strictly related to the BCBS' assessment methodology for G-SIBs. In particular, while the BCBS defines the methodology for the designation of the G-SIBs, which decision is implemented by the FSB; the European Banking Authority holds the guidelines for the identification and the designation of the other systemically important institutions (O-SII) (European Banking Authority, 2013); whose implementation is entrusted to the EU National Central Banks. The two methodologies differs only i) in the number of systemic categories (and indicators) included in the final score used to designate the systemically important institutions and ii) in the designation threshold considered. As highlighted by Engle, Jondeau, and Rockinger (2015), the main driver of financial firm's systemic risk is represented by the domestic market. Since the data of the G-SIBs are publicly disclosed, it would be interesting to investigate whether or not the inclusion of an indicator that captures the domestic systemic importance of the banks – such as the total assets of the banking sector over the GDP, would change the ranking defined through the BCBS' assessment methodology. In addition, closely related to the former idea, it would be interesting to investigate whether or not, after the introduction of an increasing number of supervisory capital requirements (CET1, AT1, T2, CCB, CCyB, G-SIB, O-SII and SRB), which have the scope to improve the resiliency of the banking sector, the systemic risk of individual banks and the whole banking sector have significantly decreased.

In addition, related to systemic risk, even more novel would be to investigate the relationship between this kind of risk and climate-change risks. As argued by Dietz, Bowen, Dixon, and Gradwell (2016), investors and financial regulators are increasingly aware of climate-change risks and the impact of climate change itself on asset values. Climate change means we may face more frequent or severe weather events like flooding, droughts and storms (Batten, Sowerbutts, and Tanaka, 2016). These events represents a "physical risk" that affects our society as well as the financial sector. In particular, if these events happen more frequently, people will become more reliant on insurance to cover their asset values – such as houses and cars. As weather-related insurance claims rise, insurance companies have more to pay out. This affects their liabilities and threats the financial stability. The systemic importance of the insurance sector has been already highlighted during the GFC with the government bailout, worth about USD 150 billion, of the American International Group Inc. (better known as AIG). For this reason, considering the insurance sector and its participants, it would be extremely interesting to study the interrelationship between market-based systemic risk and climate-change liability risk. This research would contribute to the financial literature both under a macroprudential perspective and also under a international portfolios selection perspective. The results may help regulators and supervisory authority to assess this new type of risk and may also feed into supervisors' decisions about individual insurance firms.

Finally, the herding investigation may be extended to the option market. In particular, rather than relying on backward looking information, information extracted from the options market would allow the expansion into a new avenue of research by considering forward looking information on herding. This could provide a new ex-ante tool helpful in preventing herding behavior in equity markets, financial sector and industries. Using a metaphor, including forward looking information on herding may help supervisory authorities to close the Pandora's box before markets' prices distortion causes a systemic crisis.

Overall, the five continuation stands of this thesis may have potential implications on the financial literature related to financial contagion and regulation, systemic risk, macroprudential policy, climate-change risks, international portfolios selection strategies and herding behavior. We strongly believe that this thesis has been only the first step towards a fast growing financial area looking at improved measures of systemic risk and herding behavior. To recall the discussion in the introduction of this thesis, it is of fundamental importance to better understand systemic risk and herding behavior because they may affect the main rationale for financial and banking regulation, prudential supervision and crisis management. Having more reliable – i.e., less uncertainty; timely and directional risk monitoring tools and measures may be pivotal for the beginning of new literature's avenues in areas such as risk management, financial regulation and stability, predictability and international finance.

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Appendices

APPENDIX A

Additional material for Chapter 3

A.1 Measuring systemic risk

We measure the systemic risk of the banks included in the G-SIBs assessment sample (Table 3.2) according to three main SRMs. All the estimates consider only positive value of systemic risk because negative capital shortfalls indicate a capital surplus (Brownlees and Engle, 2016).

A.1.1 Definition of ΔCoVaR

If X^i is institution i's return loss, $CoVaR_q^{j|C(X^i)}$ is defined (Adrian and Brunnermeier, 2016) as institution j's (or the *financial system*) VaR conditional on some event $C(X^i)$ of institution i. The event C is defined as an event equally likely across institutions. $CoVaR_q^{j|C(X^i)}$ is implicitly defined by the q%-quantile of the conditional probability distribution:

$$Pr(X^{j|C(Xi)} \leq CoVaR_q^{j|C(Xi)}) = q\% \tag{A.1}$$

The $\Delta CoVaR$ of j conditional on institution i being under distress is defined as:

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i=VaR_q^i} - CoVaR_q^{j|X^i=VaR_{50^{th}}^i} \tag{A.2}$$

while its $\Delta CoVaR$ weighted for the size of the institution considered is defined as follows:

$$\Delta^{\$} CoVaR^{j|i}_{q,t} = Size^{i}_{t} \times \Delta CoVaR^{j|i}_{q,t} \tag{A.3}$$

where the $Size$ of the institution is defined as the market value of equity.

While Adrian and Brunnermeier (2016) estimate $\Delta CoVaR$ by applying the quantile regression (Koenker and Bassett Jr, 1978) with a set of lagged state variables M_{t-1}, we estimate the $\Delta CoVaR$ employing the following quantile regression:

$$X_{q,j} = \alpha_q + \beta_q X_{q,i} \tag{A.4}$$

where $X_{q,j}$ and $X_{q,i}$ denote the respective domestic index for Panel A (the global index for Panel B) and the bank i return losses, respectively. Using the predicted value of $X_i = VaR_{q,i}$, we yields the $CoVaR_{q,i}$ measure as follow:

$$CoVaR_{q,i} = VaR^{j|X_i = VaR_{q,i}}_{q} = \hat{\alpha}_q + \hat{\beta}_q VaR_{q,i} \tag{A.5}$$

where $VaR_{q,i}$ is the q%-quantile of bank i losses.

Based on Eq. (A.2), the $\Delta CoVaR_{q,i}$ is estimated as:

$$\Delta CoVaR_{q,i} = CoVaR_{q,i} - CoVaR^{j|X_i = VaR_{50^{th},i}}_{q} = \hat{\beta}_q (VaR_{q,i} - VaR_{50^{th},i}) \tag{A.6}$$

Adrian and Brunnermeier (2016) report that both methods lead to similar results in practice, and, like Danielsson, James, Valenzuela, and Zer (2016), we chose daily stock return measure so as to avoid very difficult errors in variable problem.

A.1.2 Definition of Marginal Expected Shortfall

Acharya, Pedersen, Philippon, and Richardson (2017) introduced[1] the marginal expected shortfall (MES) to measure the contribution to systemic risk of each institution. The MES indicates the losses of the institution in the tail of the aggregate sector's loss distribution. In order to define this measure, they consider as a measure of firm-level risk the expected shortfall (ES) defined as $ES_q = E[R|R \leq VaR_q]$.

The focus on the ES is motivated by the fact that asymmetric yet very risky bets may not produce a large VaR. By decomposing the bank's return R into:

$$R = \sum_i y_i r_i \tag{A.7}$$

where r_i is the return of each group i and y_i its weight, from (A.7) the ES can be written as:

$$ES_q = \sum_i y_i E[r_i|R \leq VaR_q] \tag{A.8}$$

The MES_a^i is then obtained as:

$$\frac{\partial ES_q}{\partial y_i} = E[r_i|R \leq VaR_q] \equiv MES_q^i \tag{A.9}$$

For a financial system, the MES can be interpreted as each bank's losses when the system is in a tail event. The MES is estimated at $q\%$=5%, as in Acharya, Pedersen, Philippon, and Richardson (2017), and using the daily equity returns. This measure estimates the equal-weighted average return of any given firm (R^i) for the $q\%$ worst days of the market returns

[1] Acharya, Pedersen, Philippon, and Richardson (2017) also introduced the Systemic Expected Shortfall (SES). This measure represents the contribution of each institution to the overall systemic risk as the propensity of the same to be undercapitalized when the entire financial system is undercapitalized. However, Brownlees and Engle (2016) argue that: *"it is unclear how SES can be estimated in real time, as it requires observing a systemic crisis to infer the level of systemic risk of an institution "*. Hence, we confine our study to the other measure introduced by Acharya, Pedersen, Philippon, and Richardson (2017), the MES, which is defined as the average return during the 5% worst days for the market.

(R^m):

$$MES^i_{q\%} = \frac{1}{\#days} \sum R^i_t \tag{A.10}$$

In order to compare different sized institutions using the MES, we weight this risk measure by their $Size$, obtaining a size-weighted measure $MES^{\$}_{i,t} = Size_{i,t} \times MES_{i,t}$.

A.1.3 Definition of SRISK

Brownlees and Engle (2016) developed the SRISK to measure the systemic risk contribution of an institution to a system made up of N financial institutions. For each institution i at time t the *Capital Shortfall* is formally defined as:

$$CS_{i,t} = kA_{i,t} - W_{i,t} \tag{A.11}$$

with $A_{i,t} = D_{i,t} + W_{i,t}$. It is possible to rewrite (A.11) as:

$$CS_{i,t} = k(D_{i,t} + W_{i,t}) - W_{i,t} \tag{A.12}$$

where $W_{i,t}$ is the market value of equity, $D_{i,t}$ is the book value of debt, $A_{i,t}$ is the value of quasi assets and k is the prudential capital fraction.[2] If the Capital Shortfall is negative, the institution experiences a surplus; instead, if it is positive, the institution experiences a distress. Brownlees and Engle (2016) define the SRISK as the expected capital shortfall conditional on a systemic event, which is defined as the market return between period $t+1$ and $t+h$ (h is 22 here) below a threshold C, equal to 10%.

$$SRISK_{i,t} = E_t(CS_{i,t+h} | R_{m,t+1:t+h} < C) \tag{A.13}$$

[2] As explained in Engle, Jondeau, and Rockinger (2015), to take into account the differences in accounting standards between European and other banks, we adopt for European banks a capital ratio of $k = 5.5\%$, which approximately corresponds to a capital ratio of 8% in the other banking systems considered.

Combining (A.12) and (A.13) gives:

$$SRISK_{i,t} = E_t(D_{i,t+h}|R_{m,t+1:t+h} < C) - (1-k)E_t(W_{i,t+h}|R_{m,t+1:t+h} < C) \tag{A.14}$$

The authors assume that in case of a systemic event debt cannot be renegotiated. This implies that $E_t(D_{i,t+h}|R_{m,t+1:t+h} < C) = D_{i,t}$ and consequently:

$$SRISK_{i,t} = kD_{i,t} - (1-k)W_{i,t}(1 - LRMES_{i,t}) \tag{A.15}$$

Introducing the quasi leverage ratio:

$$LVG^c_{i,t} = \frac{D_{i,t} + W_{i,t}}{W_{i,t}} \tag{A.16}$$

equation (A.15) becomes:

$$SRISK_{i,t} = W_{i,t}[kLVG_{i,t} + (1-k)LRMES_{i,t} - 1] \tag{A.17}$$

The term $LRMES_{i,t}$ is defined as the Long Run Marginal Expected Shortfall, i.e. the expectation of the firm equity multi-period arithmetic return conditional on the systemic event:

$$LRMES_{i,t} = -E_t(R_{i,t+1:t+h}|R_{m,t+1:t+h} < C) \tag{A.18}$$

Acharya, Engle, and Richardson (2012) used the following approximation of this term:

$$LRMES_{i,t} = 1 - exp(-18 \times MES_{i,t}) \tag{A.19}$$

where the MES is the one day loss expected if market returns are less than 2%. A system-wide measure of financial distress that measures the total amount of systemic risk in the financial system is:

$$SRISK_t = \sum_{i=1}^{N} max(SRISK_{i,t}, 0) \tag{A.20}$$

The percentage version of SRISK, which indicate the systemic risk share, is denoted by $SRISK\%_{i,t} = \frac{SRISK_{i,t}}{SRISK_t}$.

A.2 The magnitude of systemic risk

Figure A.1 displays the magnitude of the systemic risk at aggregate level for the banks included in the BCBS' assessment sample of G-SIBs – ie, the global banking sector, during the period from January 2008 to December 2018. The systemic risk has been estimated conditioning the measures to the domestic index (Panel A) and to the global index (Panel B). Following the previous studies by Adrian and Brunnermeier (2016), Black, Correa, Huang, and Zhou (2016) and Brownlees and Engle (2016), we look closely at some of the major dates in order to measure the magnitude of this risk and the response of the SRMs to the two main crises and the events related to them. The dates considered are: (1) the Lehman Brothers bankruptcy on September 15^{th}, 2008; (2) the agreement between the Greek government and the IMF for the First bailout package of €110 billion on May 2^{nd}, 2010; (3) the peak of 44.21% reached by the Greek 10-year bond yields on March 9^{th}, 2012; (4) the Chinese market crash on August 24^{th}, 2015; (5) the Brexit referendum result on June 24^{th}, 2016; (6) the US presidential election on November 8^{th}, 2016; and, (7) the tech crash on September 21^{st}, 2018.

As shown in Figure A.1 different SRMs produce different systemic risk estimates. From a policy supervision point of view, this may suggest that systemic risk assessments based on a single measure may lead to contradictory assessments. However, the time-series patterns of the SRMs are very similar, although these three SRMs seem to provide inconsistent estimates with each other, similar to the conclusions in Zhang, Vallascas, Keasey, and Caif (2015). In the majority of the cases, the SRMs estimated conditioning the analysis to the domestic indexes of each bank included in the sample is below the global systemic risk (Panel B). This underlines the global systemic importance of these banks. The time-series patterns clearly highlight the subprime mortgage crisis, that reached its peak with the bankruptcy of Lehman Brothers (1). It seems that the $\Delta^{\$}CoVaR_{95^{th}}$ and the $MES^{\$}$ react immediately,[3] with two peaks, to the first main event of the subprime crisis; while, the $SRISK$ increases its value more smoothly but to higher values.

The three SRMs react differently to market downturns. The graphs in Figure A.1 illustrate the dramatic increase of the three measures after the bankruptcy of Lehman Brothers; however, after the peak is reached, $\Delta^{\$}CoVaR_{95^{th}}$ and the $MES^{\$}$ sharply reduce their value, while the $SRISK$ continues to stay at values higher than the pre-crisis period. The sovereign-debt crisis also hits the systemic risk of these banks, which reach new peaks of the measures during the period form 2010 to 2013. All SRMs react to the Greece agreement of the First bailout package – marked by (2), decreasing their levels. A decreasing trend is observed after this event. However, the systemic risk level increases again when the Greek 10-year bond yields reach the peak of 44.21% as indicated by the event marked by (3). At the beginning of 2013, there is a stable, decreasing in case of the $SRISK$, trend for all SRMs. Another interesting feature is that the systemic risk level after the subprime crisis is still high and has not reverted back so far to the level experienced before the subprime crisis. The China's market crash (4) and the Brexit referendum results (5) also affect the systemic risk level of the global banking sector; while, the US presidential election (6) and the tech crash (7) seem to have less impact on the stability of the global banking sector.[4]

Table A.1 presents the descriptive statistics for the systemic risk estimates of the global

[3] Zhang, Vallascas, Keasey, and Caif (2015) inspect whether market-based SRMs offer early warning signals on the systemic importance of large financial institutions. In particular, considering as market-based SRMs the $\Delta CoVaR$ as developed by Adrian and Brunnermeier (2016), its modified version of López-Espinosa, Moreno, Rubia, and Valderrama (2012), the SRISK (Brownlees and Engle, 2016), and the Expected Shortfall as implemented by Lehar (2005), they test whether the SRMs provide additional information that are not already provided by conventional risk proxies or simpler firm characteristics liked to systemic risk (e.g. the size of the company). They found that only the $\Delta CoVaR$ as developed by Adrian and Brunnermeier (2016), in the case of the subprime crisis, slightly increased the predictive power of conventional early warning models.

[4] The Wilcoxon signed rank sum test in Section 3.4.1 points out the same results.

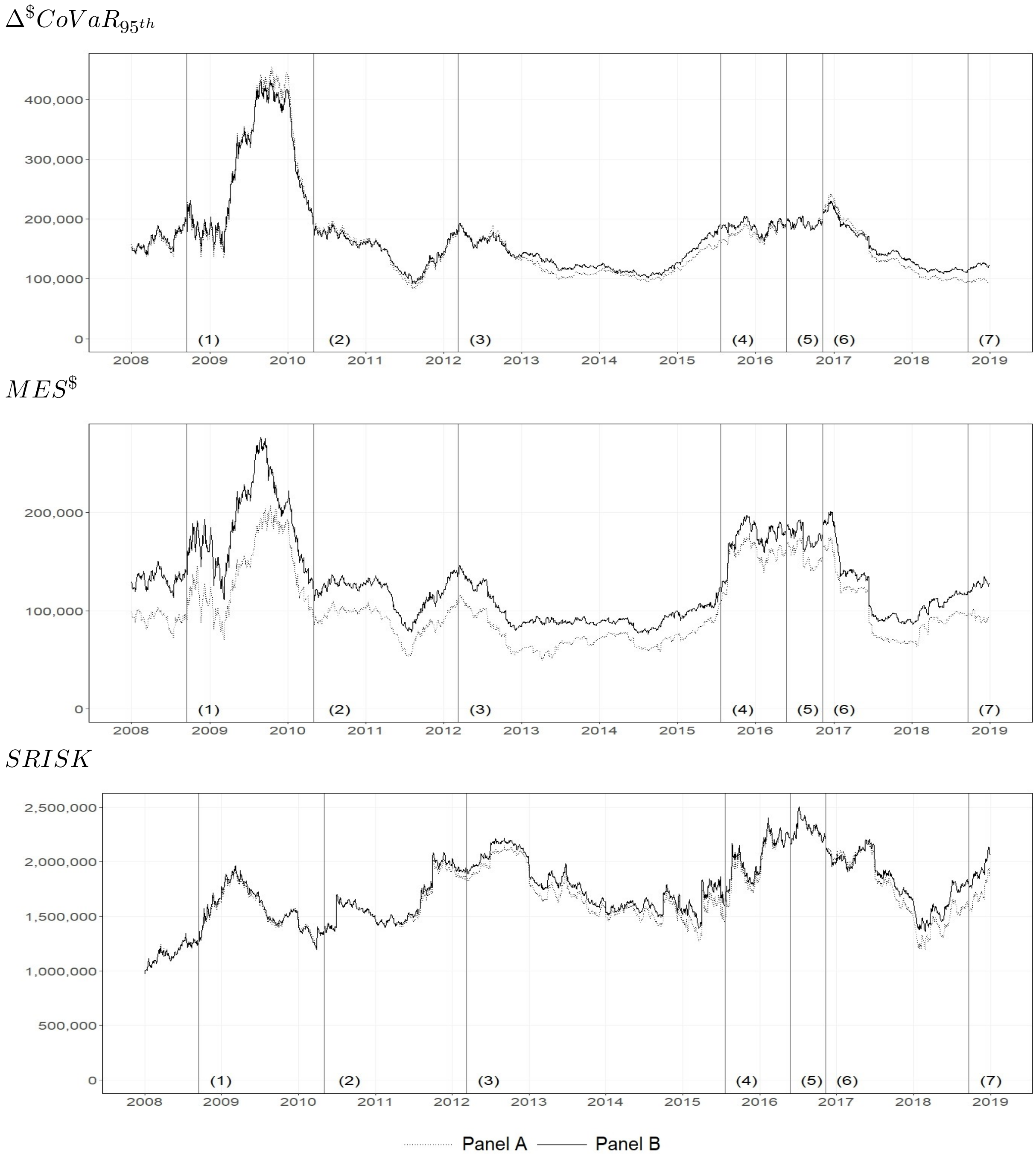


Figure A.1: Evolution of systemic risk measures for the banks in the BCBS' assessment sample of G-SIBs.

Notes: The Figures show the time series (daily-frequency) of the systemic risk measures (SRM) – $\Delta^{\$}CoVaR_{95^{th}}$, $MES^{\$}$ and $SRISK$, for the banks included in the G-SIBs assessment sample. The systemic risk is measured conditioned to the respective domestic index (Panel A) and the global index (Panel B). The vertical axis reports the value of the SRMs in EUR. The horizontal axis reports the years. The solid vertical lines mark: (1) the Lehman Brothers bankruptcy, (2) the first bailout package for Greece, (3) the Greek 10-year bond yields peak, (4) the Chinese market crash, (5) the Brexit referendum result, (6) the US presidential election, and (7) the tech crash.

Table A.1: Descriptive statistics of the banking sector systemic risk.

Panel A: Domestic Index

	Mean	Median	Std. dev.	Min	Max	N. obs.
$\Delta^{\$}CoVaR_{95^{th}}$	170,066.68	158,101.76	66,660.62	91,877.85	431,909.18	2870
$MES^{\$}$	129,988.57	123,747.48	41,341.23	76,063.77	276,825.08	2870
$SRISK$	1,733,859.55	1,721,536.53	296,938.61	967,405.16	2,501,174.96	2870

Panel B: Global Index

	Mean	Median	Std. dev.	Min	Max	N. obs.
$\Delta^{\$}CoVaR_{95^{th}}$	165,125.31	156,035.34	73,406.38	82,588.04	454,101.25	2870
$MES^{\$}$	101,760.66	93,238.09	35,895.50	49,637.06	207,373.85	2870
$SRISK$	1,679,028.11	1,627,953.93	295,619.09	979,433.28	2,504,142.52	2870

Notes: The descriptive statistics of the banking sector systemic risk expressed in EUR. The systemic risk is measured with $\Delta^{\$}CoVaR_{95^{th}}$ (equity-weighted average), $MES^{\$}$ (equity-weighted average) and $SRISK$ (sum), for the banks included in the G-SIBs assessment sample. The columns (2-7) describe average, median, standard deviation, minimum value, maximum value, and number of observation.

banking sector. Within each panel, the $SRISK$ has higher values than the other two risk measures; however, the $SRISK$ conditioned to the domestic indexes (Panel A) has summery statistics close to measure estimated for the global analysis (Panel B). Overall, the summary statistic of estimates of the $\Delta^{\$}CoVaR_{95^{th}}$ and the $MES^{\$}$ reach higher values in Panel A. The difference in the estimates of the three SRMs may be explained considering that $\Delta^{\$}CoVaR_{95^{th}}$ and the $MES^{\$}$ are a function of: (i) the sensitivity of the financial institution to market decline and (ii) the size of the firm; while, the $SRISK$ considers also the leverage of the financial institution and it requires a more severe decline condition[5] than the other two systemic measures. This may also explain the comparative trends since, after a peak, the $\Delta^{\$}CoVaR_{95^{th}}$ and the $MES^{\$}$ reduce their values in a shorter period compared to the $SRISK$, which does not react immediately[6] to a change in market conditions because it takes into consideration balance-sheet variables, which do not have daily frequency. Overall, the information on systemic risk provided by the three measures is quite heterogeneous, confirming the criticism detailed in Danielsson, James, Valenzuela, and Zer (2016) that it would be difficult for the regulator to select a single SRM for a targeted macro-prudential approach.

A.3 Non-overlapping block bootstrap for the SRMs – Results

Figures A.2 to A.4 (A.5 to A.7) depict the bootstrapped distribution of the three SRMs – the $\Delta CoVaR_{95^{th}}$, the MES and the $SRISK\%$, respectively; for Panel A (Panel B) at end-2017.[7] In particular, as explained in Section 3.2.1, we build confidence intervals based on the mean applying the non-overlapping block bootstrap as described in Carlstein et al. (1986) with a re-sampling of (n=) 1000 and considering a block with a length of 1-year. The bootstrapping methodology allows to incorporate the uncertainty in the estimation of the SRMs and also to define: i) the designation of the G-SIBs through the market-based systemic threshold "η" estimated with the cluster analyses; ii) the allocation of the G-SIBs in five populated buckets; and, iii) the additional capital surcharges associated with each bucket.

[5] The $SRISK$ computation includes the long-run marginal expected shortfall (LRMES), which measures the expected capital shortfall of a financial institution in case of a financial crisis. To be specific, a financial crisis is defined as a fall of the broad index by 40% over the next six months (Acharya, Engle, and Richardson, 2012).

[6] Homar, Kick, and Salleo (2017) accounting for size reveals that the stress impact on bank capital implied by $SRISK$ is only marginally correlated with the stress impact as modelled for the ECB/EBA stress test, and key components thereof such as credit losses and trading losses.

[7] These bootstrapped estimates have been used for the designation of the G-SIBs in 2018 (Section 3.4.2). The same exercise has been repeated for the estimates at end-2014, end-2015 and end-2016, for the designation of the G-SIBs in 2015, 2016 and 2017, respectively.

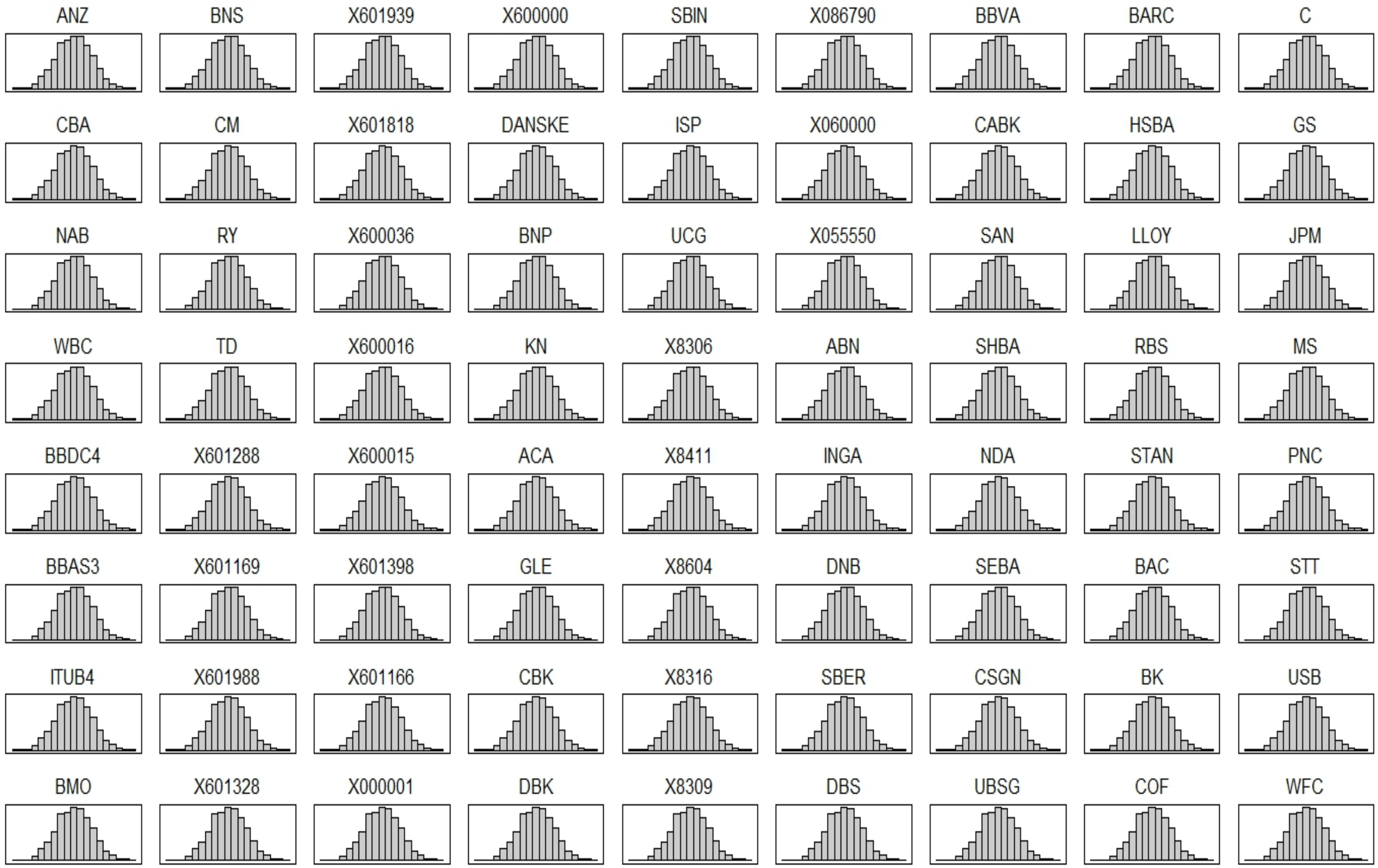


Figure A.2: Bootstrap distribution of the $\Delta CoVaR_{95^{th}}$ (Panel A).

Notes: The Figure shows the distribution of the bootstrapped (n=1000) $\Delta CoVaR_{95^{th}}$ in 2017. The systemic risk is measured conditioned to the respective domestic index (Panel A). The title of each sub-chart indicates the Bloomberg ticker of the specific bank included in the BCBS' assessment sample of G-SIBs.

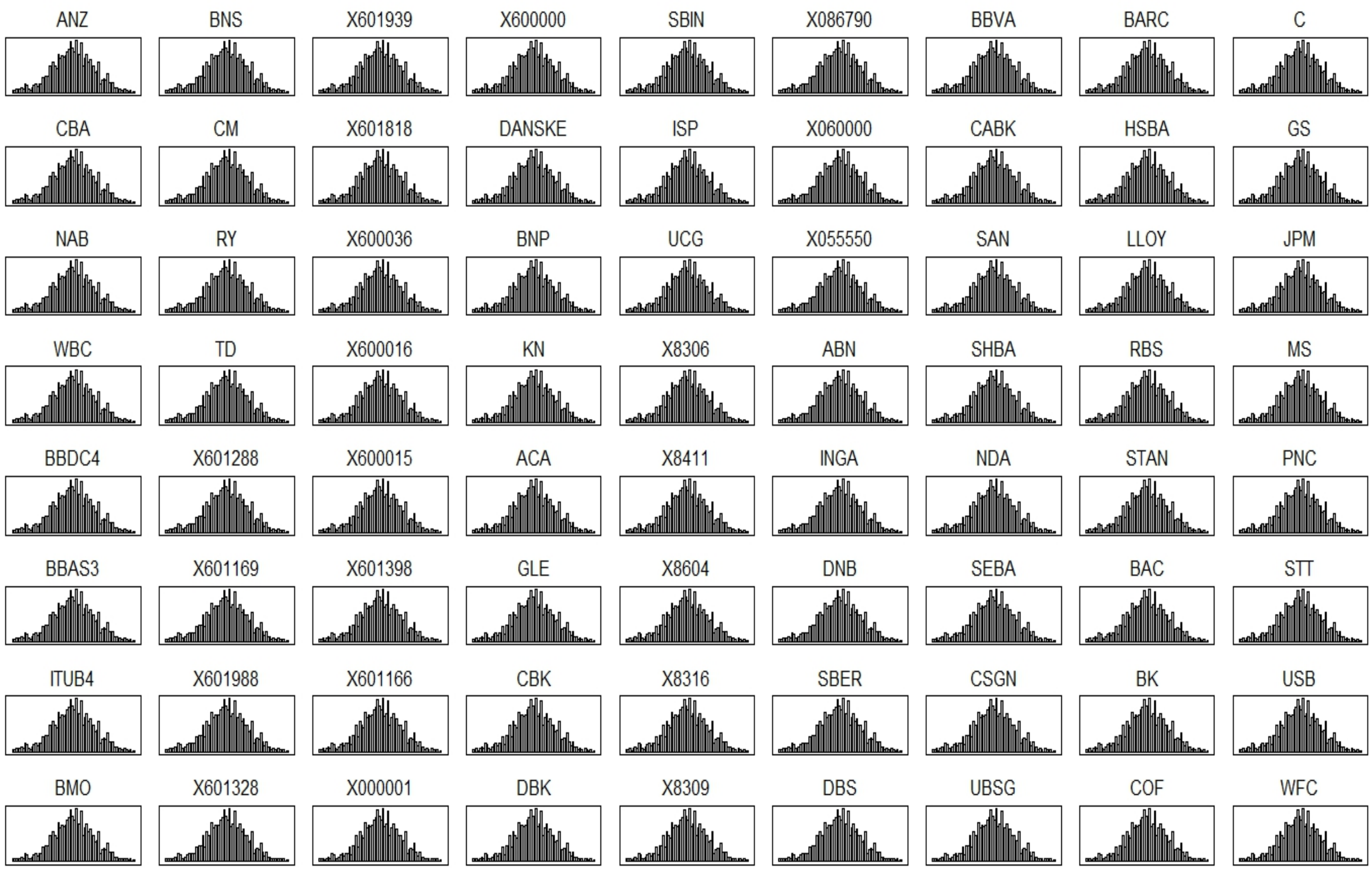


Figure A.3: Bootstrap distribution of the MES (Panel A).

Notes: The Figure shows the distribution of the bootstrapped (n=1000) MES in 2017. The systemic risk is measured conditioned to the respective domestic index (Panel A). The title of each sub-chart indicates the Bloomberg ticker of the specific bank included in the BCBS' assessment sample of G-SIBs.

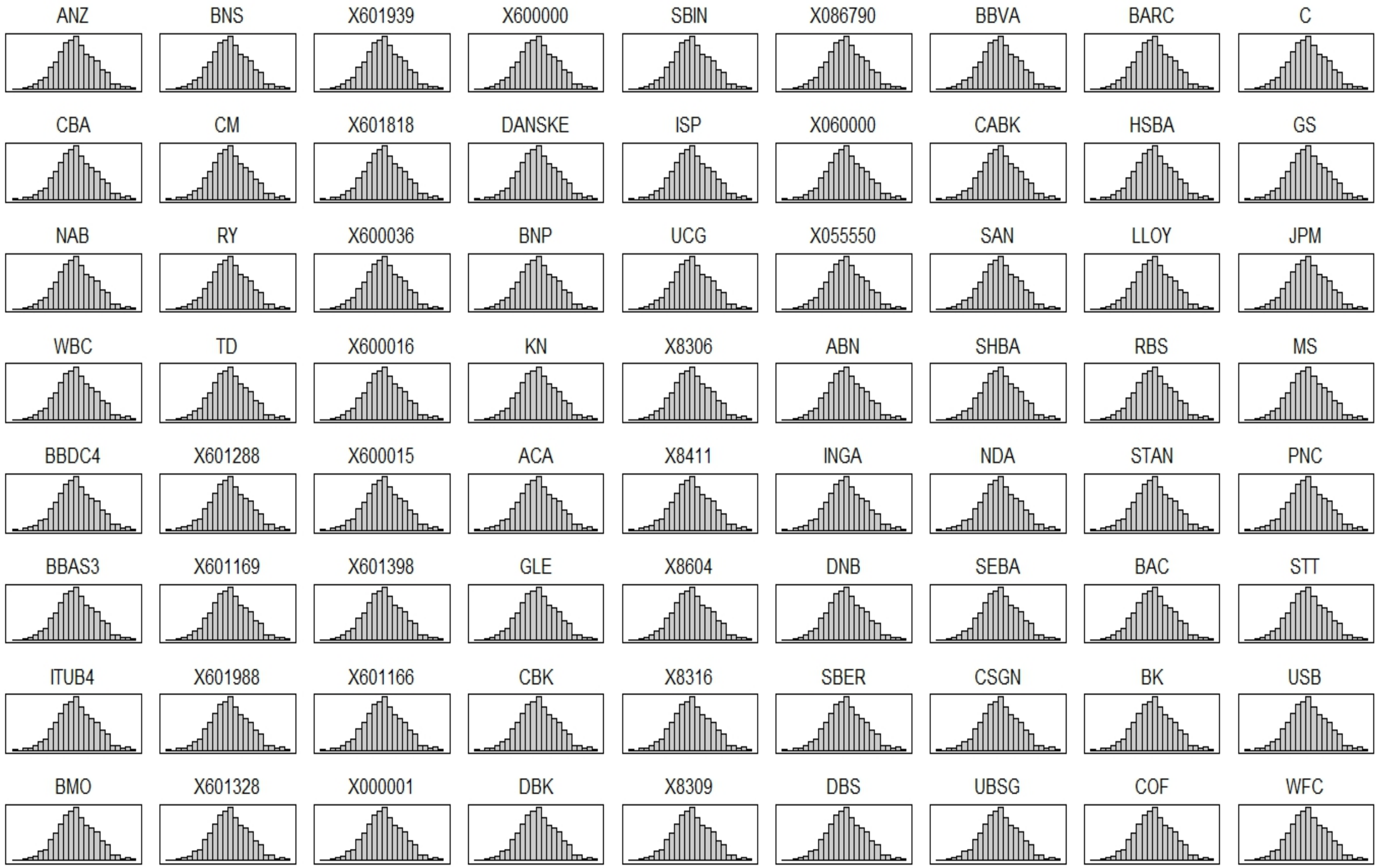


Figure A.4: Bootstrap distribution of the $SRISK\%$ (Panel A).

Notes: The Figure shows the distribution of the bootstrapped (n=1000) $SRISK\%$ in 2017. The systemic risk is measured conditioned to the respective domestic index (Panel A). The title of each sub-chart indicates the Bloomberg ticker of the specific bank included in the BCBS' assessment sample of G-SIBs.

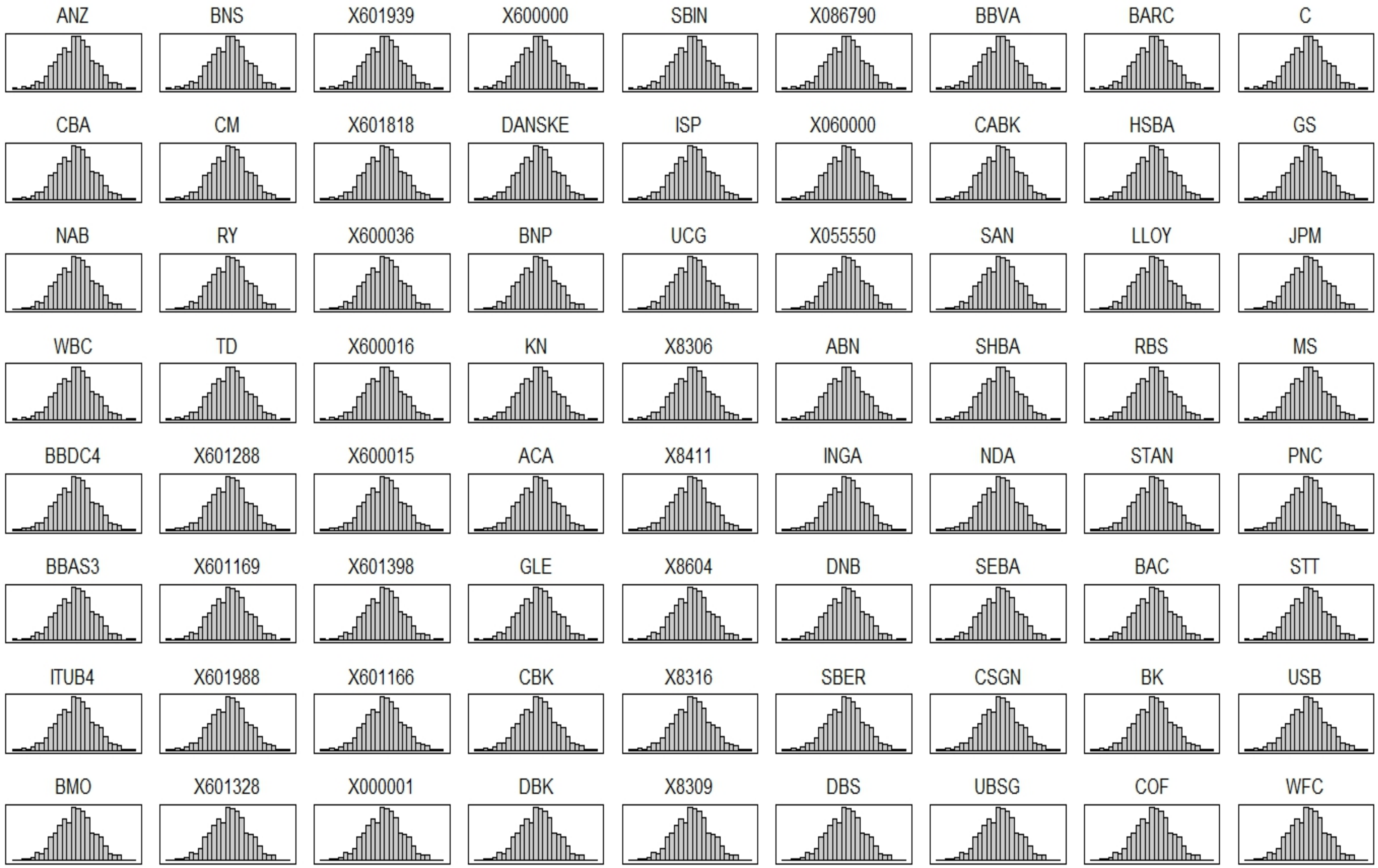


Figure A.5: Bootstrap distribution of the $\Delta CoVaR_{95^{th}}$ (Panel B).

Notes: The Figure shows the distribution of the bootstrapped (n=1000) $\Delta CoVaR_{95^{th}}$ in 2017. The systemic risk is measured conditioned to the global index (Panel B). The title of each sub-chart indicates the Bloomberg ticker of the specific bank included in the BCBS' assessment sample of G-SIBs.

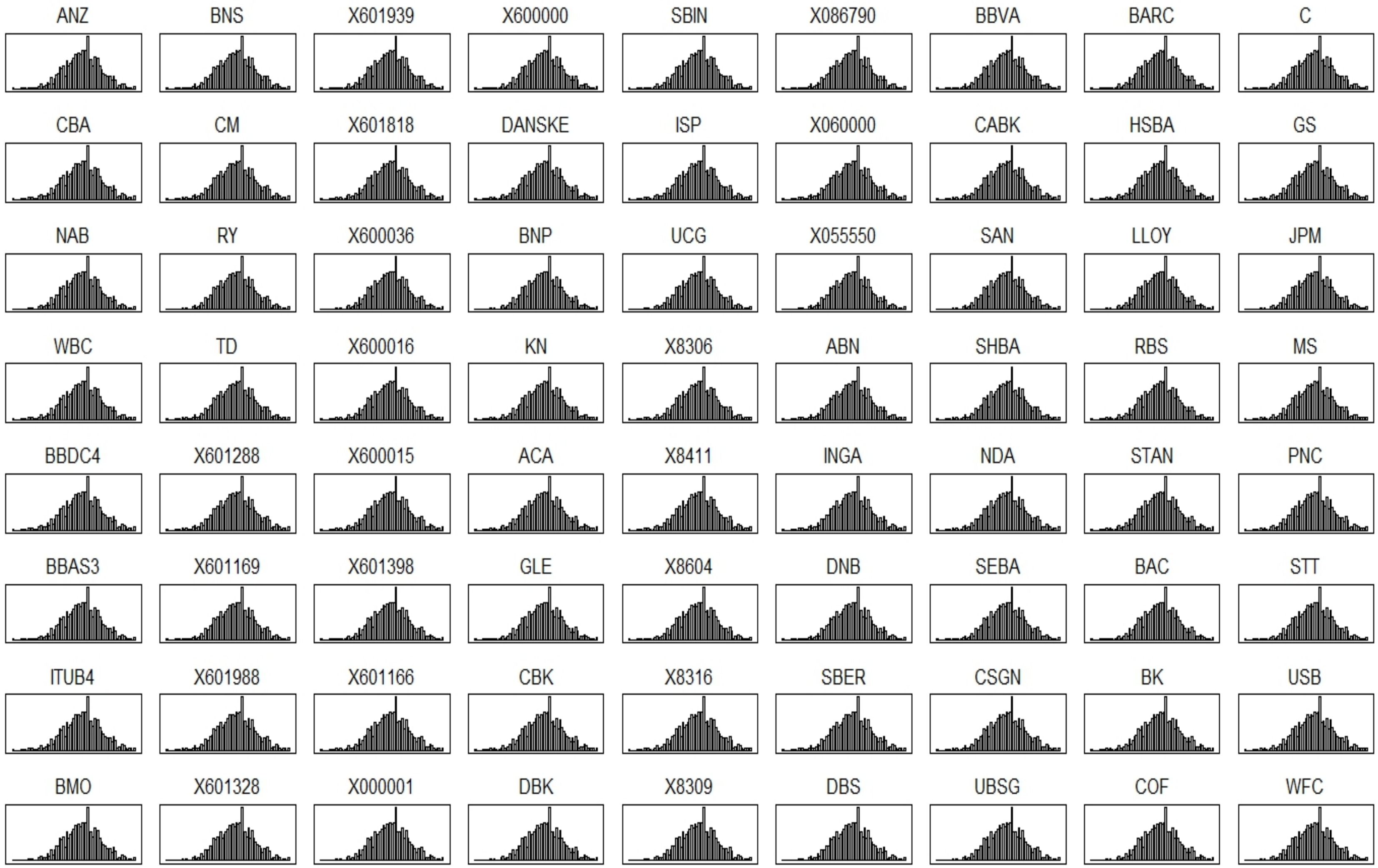


Figure A.6: Bootstrap distribution of the MES (Panel B).

Notes: The Figure shows the distribution of the bootstrapped (n=1000) MES in 2017. The systemic risk is measured conditioned to the global index (Panel B). The title of each sub-chart indicates the Bloomberg ticker of the specific bank included in the BCBS' assessment sample of G-SIBs.

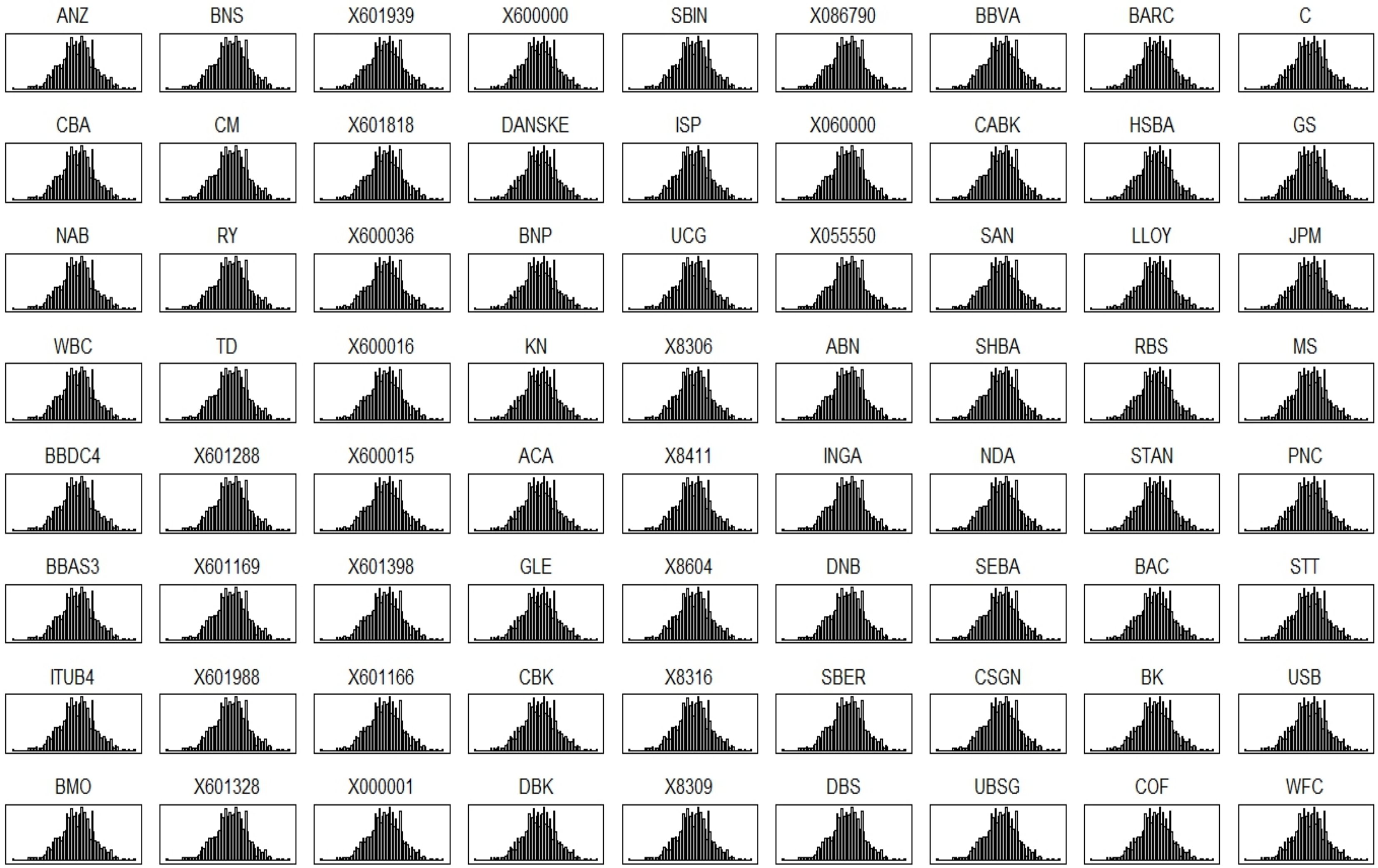


Figure A.7: Bootstrap distribution of the $SRISK\%$ (Panel B).

Notes: The Figure shows the distribution of the bootstrapped (n=1000) $SRISK\%$ in 2017. The systemic risk is measured conditioned to the global index (Panel B). The title of each sub-chart indicates the Bloomberg ticker of the specific bank included in the BCBS' assessment sample of G-SIBs.

A.4 Concordance analysis

Here we study the concordance between the rankings obtained under each SRM vis-a-vis with the benchmark scoring obtained under BCBS' assessment methodology for G-SIBs.

A.4.1 Kendall τ distance

The Kendall tau rank distance is a metric that counts the number of pairwise disagreements between two ranking lists. The larger the distance, the more dissimilar the two lists are.

A concordant pair is a pair of observations, each on two variables, (X_1, Y_1) and (X_2, Y_2), having the property that $\operatorname{sgn}(X_2 - X_1) = \operatorname{sgn}(Y_2 - Y_1)$ where sgn is the sign function. A discordant pair is a pair of two-variable observations such that $\operatorname{sgn}(X_2 - X_1) = -\operatorname{sgn}(Y_2 - Y_1)$. The Kendall tau distance between two series is the total number of discordant pairs.

A.4.2 Kendall τ coefficient

Let $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$ be a set of observations of the joint random variables X and Y respectively, such that all the values of x_i and y_i are unique. Any pair of observations (x_i, y_i) (x_j, y_j), where $i \neq j$, are said to be concordant if the ranks for both elements (more precisely, the sort order by x and by y) agree: that is, if both $x_i > x_j$ and $y_i > y_j$; or if both $x_i < x_j$ and $y_i < y_j$. They are said to be discordant, if $x_i > x_j$ and $y_i < y_j$; or if $x_i < x_j$ and $y_i > y_j$. If $x_i = x_j$ or $y_i = y_j$, the pair is neither concordant nor discordant. The Kendall τ coefficient is defined as:

$$\tau = \frac{(\text{number of concordant pairs}) - (\text{number of discordant pairs})}{n(n-1)/2}$$

Computationally this coefficient can be calculated using the formula

$$\tau = \frac{1}{n(n-1)} \sum_{i \neq j} \operatorname{sgn}(x_i - x_j)\operatorname{sgn}(y_i - y_j)$$

The denominator is the total number of pair combinations, so the coefficient must be in the range $-1 \leq \tau \leq 1$. If the agreement between the two rankings is perfect the coefficient has value 1, if the disagreement between the two rankings is perfect the coefficient has value -1 while if X and Y are independent, then we would expect the coefficient to be roughly zero.

The Kendall rank coefficient can be applied as a test statistic to establish whether two variables may be regarded as statistically dependent. This test is non-parametric, as it does not rely on any assumptions on the distributions of X or Y or the distribution of (X,Y). Under the null hypothesis of independence of X and Y, the sampling distribution of τ has an expected value of zero.

When there are ties the Kendall τ_b coefficient is used. This is calculated as follows

$$\tau_b = \frac{n_c - n_d}{\sqrt{(n_0 - n_1)(n_0 - n_2)}}$$

where $n_0 = n(n-1)/2$, $n_1 = \sum_i t_i(t_i - 1)/2$, and $n_2 = \sum_j u_j(u_j - 1)/2$ where n_c is the number of concordant pairs, n_d is the number of discordant pairs, t_i is the number of tied values in the i-th group for the first variable and u_j is the number of tied values in the j-th group of ties for the second variable.

Another way to look at τ_b is by considering for a given ranking X of n entities the $n \times n$ score matrix $\{x_{ij}\}$ defined as follows

$$x_{ij} = \begin{cases} 1, & \text{entity } i \text{ is ranked ahead of entity } j; \\ -1, & \text{entity } i \text{ is ranked behind entity } j; \\ 0, & \text{if the entities are tied, or if } i = j \ . \end{cases}$$

Then, for two different ranking systems X and Y we can calculate τ_b as

$$\tau_b(X,Y) = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij}y_{ij}}{\sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij}^2 \sum_{i=1}^{n}\sum_{j=1}^{n} y_{ij}^2}} \tag{A.21}$$

Emond and Mason (2002) pointed out that Kendall's τ_b is not a proper metric and, moreover, it has problems resulting from the way in which it handles ties. This problem led Kemeny and Snell (1962) to derive axiomatically another measure that is a metric for comparing ranking systems, given by

$$d(X,Y) = \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} |x_{ij} - y_{ij}| \tag{A.22}$$

Emond and Mason (2002) proposed an adjustment to Kendall's measure by redefining the scoring matrix. Thus, under their methodology

$$x_{ij} = \begin{cases} 1, & \text{entity } i \text{ is ranked ahead of or tied to, entity } j; \\ -1, & \text{entity } i \text{ is ranked behind entity } j; \\ 0, & \text{ if } i = j\ . \end{cases}$$

Their new measure is called τ_x and it is defined as

$$\tau_x(X,Y) = \frac{1}{n(n-1)}\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij}y_{ij} \tag{A.23}$$

Emond and Mason (2002) proved that the Kemeny-Snell metric is equivalent to τ_x.

A.5 Measuring and testing rankings similarity

Finally, we are trying to answer whether rankings under different SRMs are very similar to the ranking under BCBS' assessment methodology for G-SIBs (FSB ranking), and also what is the similarity between the results under different SRMs. In order to verify these similarities, we employ the Kendall's τ_b ranking correlation coefficient measure and an improved theoretical variant of this coefficient – τ_x introduced by Emond and Mason (2002). The methodologies of these two rank correlation coefficient are described in Appendix A.4. The τ_b and τ_x coefficients are measures of concordance for ranking lists. These measures take values between -1 and +1, with +1 when the lists are identical and -1 when the lists are in reverse order, respectively. The value 0 indicates the absence of any association.

Figure A.8 presents the daily estimates of τ_b and τ_x for each pair of SRMs for Panel A and Panel B, respectively. The estimates of τ_b and τ_x are almost equivalent within the same panel and similar between the analysis conditioned to the respective domestic index (Panel A) and to the global index (Panel B). Moreover, their values are always positive, suggesting a positive association between the various systemic risk methods. The daily-association between $\Delta^{\$}CoVaR_{95^{th}}$ and $MES^{\$}$ is the highest among all compared pairs, in both panels, the τ_b and τ_x between these two SRMs rarely go below the value of 0.75. This association decreases in the cases of $\Delta^{\$}CoVaR_{95^{th}}$ and $MES^{\$}$ versus the $SRISK$.[8] However, in both cases, τ_b and τ_x estimates drastically increase in the aftermath of the last two financial crises, suggesting that rankings between these two combinations of SRMs are in accordance during turbulent periods for the market.

Figure A.9 presents the daily estimates of τ_b and τ_x between the FSB ranking and each SRM. The estimates of τ_b and τ_x take only positive values, and they are almost equivalent within the same panel. The concordance tests with the FSB ranking as a benchmark are, again, similar between the analysis conditioned to the respective domestic index (Panel A) and to the global index (Panel B).[9] The association (τ_b and τ_x) between the FSB Ranking vs. $\Delta^{\$}CoVaR_{95^{th}}$ and vs. $MES^{\$}$ is very close to 0.50 for the entire period of investigation.

[8]We conduct also the Kendall τ_b test for each of the cases analyzed. We find that the τ_b estimates, in percentage of total observation, in Panel A (Panel B) are significant at 1%, 5% and 10%: 100% (100%) in the case of $\Delta^{\$}CoVaR_{95^{th}}$ vs. $MES^{\$}$; 53.89%, 68.62% and 75.68% (60.25%, 73.66% and 80.92%) in the case of $MES^{\$}$ vs. $SRISK$; and 67.62%, 82.97% and 90.10% (78.26%, 87.78% and 89.09%) in case of $SRISK$ vs. $\Delta^{\$}CoVaR_{95^{th}}$.

[9]Also in this case, we conduct the Kendall τ_b test for each of the cases analyzed. We find that the τ_b estimates in Panel A (Panel B), in percentage of total observation, are significant at 1%: 100% (100%) in the case of FSB Ranking vs. $\Delta^{\$}CoVaR_{95^{th}}$; 100% (100%) in the case of FSB Ranking vs. $MES^{\$}$; and 100% (100%) in case of FSB Ranking vs. $SRISK$.

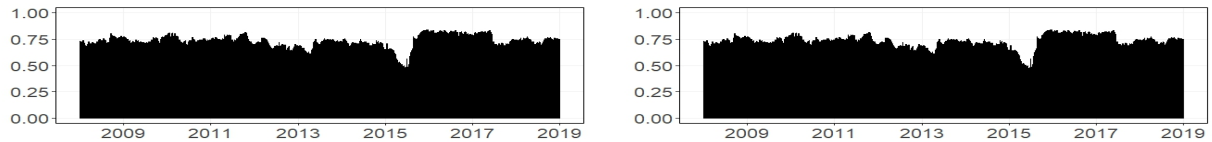
The estimates related to the cases of FSB Ranking vs. $SRISK$ show a slightly increase after 2015 to values above 0.5.

Table A.2 contains the result of the t-test that aims to determine whether the mean (μ), according both τ_b and τ_x, of the difference between the rankings conditioned to the global index (Panel B) and to the respective domestic index (Panel A) is significantly equal, lower or greater than 0. The results in Table A.2 point out that the concordances estimated under a global framework (Panel B) are significantly greater than the ones under a domestic framework (Panel A). This, together with the evidence discussed in Section 3.4.1, entails a higher comparability between the SRMs estimated under Panel B and the BCBS' assessment methodology for G-SIBs.

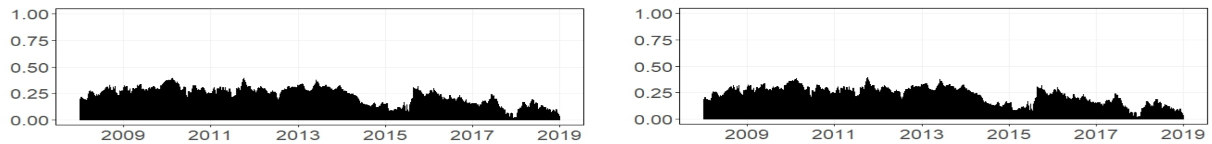
Panel A: Domestic Index

(a) τ_b (b) τ_x

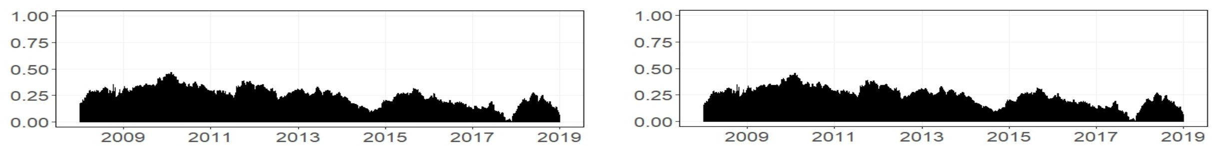
$\Delta^{\$}CoVaR_{95^{th}}$ vs. $MES^{\$}$



$MES^{\$}$ vs. $SRISK$



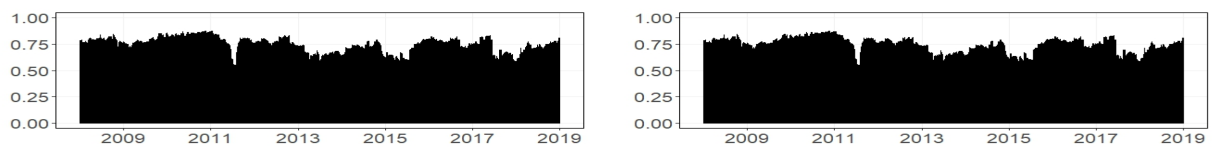
$SRISK$ vs. $\Delta^{\$}CoVaR_{95^{th}}$



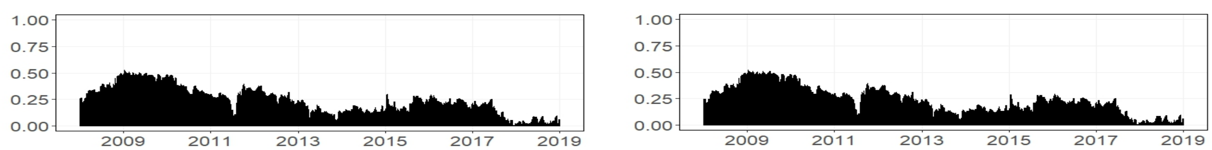
Panel B: Global Index

(c) τ_b (d) τ_x

$\Delta^{\$}CoVaR_{95^{th}}$ vs. $MES^{\$}$



$MES^{\$}$ vs. $SRISK$



$SRISK$ vs. $\Delta^{\$}CoVaR_{95^{th}}$

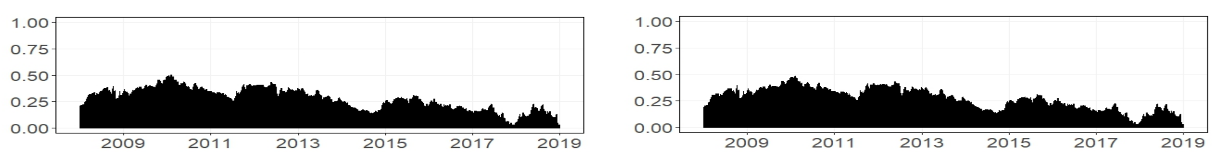


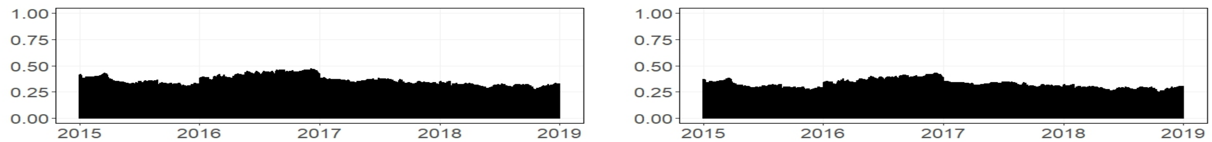
Figure A.8: Market-based systemic risk measures: τ_b and τ_x.

Notes: The Figure shows the daily τ_b (a) and τ_x (b) of each pair of market-based systemic risk measures. The τ_b and τ_x coefficients are computed using the ranking of all the banks included in the G-SIBs assessment sample. The systemic risk is measured with $\Delta^{\$}CoVaR_{95^{th}}$, $MES^{\$}$ and $SRISK$, conditioned to the respective domestic index (Panel A) and to the global index (Panel B).

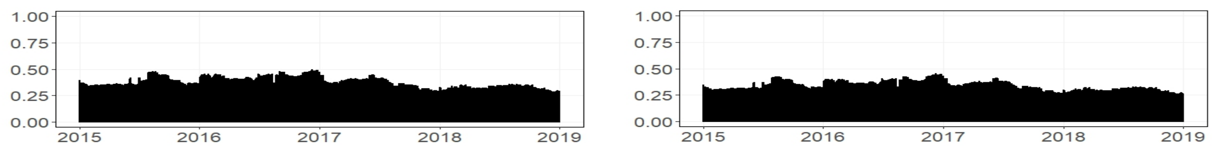
Panel A: Domestic Index

(a) $\underline{\tau_b}$ (b) $\underline{\tau_x}$

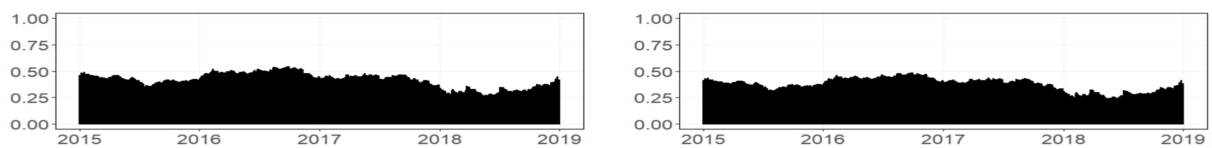
FSB Ranking vs. $\Delta^{\$}CoVaR_{95^{th}}$



FSB Ranking vs. $MES^{\$}$

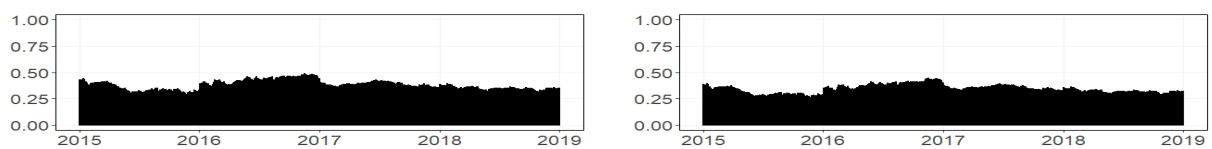


FSB Ranking vs. $SRISK$

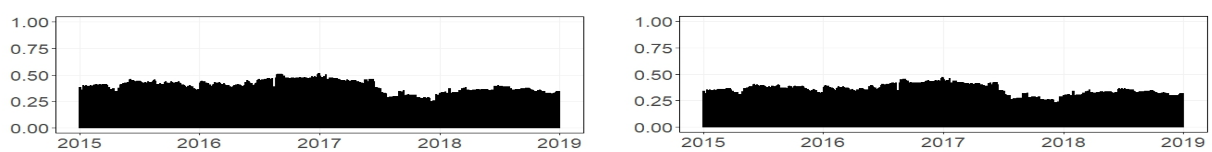


Panel B: Global Index

FSB Ranking vs. $\Delta^{\$}CoVaR_{95^{th}}$



FSB Ranking vs. $MES^{\$}$



FSB Ranking vs. $SRISK$

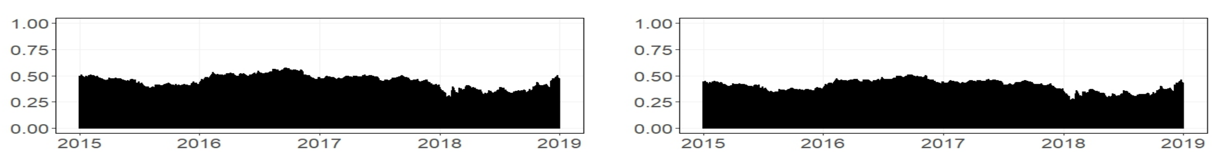


Figure A.9: FSB Ranking vs. market-based systemic risk measures: τ_b and τ_x.

Notes: The Figure shows the daily τ_b (a) and τ_x (b) that associate the ranking of the G-SIBs and each market-based systemic risk measures. The τ_b and τ_x coefficients are computed using the ranking of all the banks included in the G-SIBs assessment sample. The systemic risk is measured with $\Delta^{\$}CoVaR_{95^{th}}$, $MES^{\$}$ and $SRISK$, conditioned to the respective domestic index (Panel A) and to the global index (Panel B).

Table A.2: T-test for global vs. domestic τ_b (and τ_x) for the FSB Ranking vs. each SRMs.

	H_0: $\mu = 0$	H_0: $\mu > 0$	H_0: $\mu < 0$
	(1)	(2)	(3)
i) tau_b			
FSB Ranking vs. $\Delta^{\$}CoVaR_{95^{th}}$	0.00	1.00	0.00
FSB Ranking vs. $MES^{\$}$	0.00	1.00	0.00
FSB Ranking vs. $SRISK$	0.00	1.00	0.00
$\Delta^{\$}CoVaR_{95^{th}}$ vs. $MES^{\$}$	0.00	1.00	0.00
$MES^{\$}$ vs. $SRISK$	0.00	1.00	0.00
$SRISK$ vs. $\Delta^{\$}CoVaR_{95^{th}}$	0.00	1.00	0.00
ii) tau_x			
FSB Ranking vs. $\Delta^{\$}CoVaR_{95^{th}}$	0.00	1.00	0.00
FSB Ranking vs. $MES^{\$}$	0.00	1.00	0.00
FSB Ranking vs. $SRISK$	0.00	1.00	0.00
$\Delta^{\$}CoVaR_{95^{th}}$ vs. $MES^{\$}$	0.00	1.00	0.00
$MES^{\$}$ vs. $SRISK$	0.00	1.00	0.00
$SRISK$ vs. $\Delta^{\$}CoVaR_{95^{th}}$	0.00	1.00	0.00

Notes: The results of the t-test, which aims to determine whether or not the mean (μ) of the difference between the tau_b (tau_x) estimated conditioning the analysis to the global index and the tau_b (tau_x) estimated conditioning the analysis to the domestic index is (i) equal, (ii) lower, or, (iii) greater than 0. If the p-values are larger than the ten per cent level of significance and hence fail to reject the null hypothesis.

APPENDIX B

Additional material for Chapter 5

B.1 Robustness analysis based on MES and LRMES

As stated in Section 5.2, we conduct a robustness test for the herding analysis conditioned to different systemic states of the markets. In particular, we estimate Eq. (5.12) with the dummy variables D_1 and D_2 constructed with: i) the marginal expected shortfall (MES) introduced by Acharya, Pedersen, Philippon, and Richardson (2017);[1] and, ii) the long run MES ($LRMES$) of Brownlees and Engle (2016), which is the expected shortfall component of the $SRISK$.[2] The dummy variable D_1 takes the value of 1 if the systemic risk measure (SRM) lies above the 3^{rd} quartile (75^{th} quantile) of the empirical distribution and 0 otherwise; while, the dummy variable D_2 takes the value of 1 if the SRM lies below the 1^{st} quartile (25^{th} quantile) of the empirical distribution and 0 otherwise.

Tables B.1 and B.2 presents the estimates from Eq. (5.12), which is conditioned on different systemic risk circumstances of the market, which are measured with MES and $LRMES$, respectively. Eq. (5.12) allows to analyze herding in case of medium (γ_1), high

[1] A detailed description of MES can be found in Appendix A.1.2. For each country, we weight the MES at time t for the sum of the market capitalizations of the index constituents at time $t-1$.

[2] The $LRMES_{i,t}$ is estimated as $1 - exp(log(1-d) * \beta)$, where d is the six-month crisis threshold for the global market index decline and its default value is 40%, and β is the firm's beta coefficient (V-Lab: Systemic Risk Analysis (Global Dynamic MES) of World Financials). For each country, we weight the $LRMES$ at time t for the sum of the market capitalizations of the index constituents at time $t-1$.

(γ_2) and low (γ_3) systemic risk of the market.

Results are both quantitative and qualitative similar to the estimates disclosed in Section 5.3.3. In particular, again , the OLS and quantile regressions indicate positive estimates when systemic risk is medium (γ_1) or low (γ_3). This finding is consistent with the leak of herding behavior. On the other hand, the estimates conditioned on high systemic risk level of the market (γ_2) point out the presence of herding behavior and an increasing tendency of investors to herd in extreme tail events – i.e. in the higher quantiles, for both SRM. The results confirm and reinforce the state that high systemic risk is strongly related to herding behavior. Compared to the analysis conditioned to the $\Delta CoVaR$, the $LRMES$ points out exactly to the same conclusion – i.e., the same equity markets are found to herd in case of high systemic risk; while, under the MES only Germany and US markets are not found to herd in case of γ_2.

B.2 Further tests: variance decomposition

In order to better understand and investigate the relationship between systemic risk and herding behavior, we are motivated to study the relationship between the increases in the systemic risk level, which are measured as the logarithmic first difference of the $\Delta^{\$}CoVaR_{99^{th},i}$, and the return clustering measure (CSAD). To this end we proceed to the estimation of an unrestricted VAR model (the lag length is chosen based on the Akaike information criterion)[3] and present the results of the variance decomposition (with Monte Carlo standard errors based on 100 repetitions) of each variable for each country, in Tables B.3–B.5. In order to obtain a more comprehensive analysis we present the results related to the full sample period and seven sub-periods, which span: i) the period prior to the GFC; ii) the GFC; iii) the period subsequent the GFC and prior to the EZC; iv) the EZC; v) the period subsequent the EZC and prior to the China's market crash; vi) China's market crash;

[3] The Dickey-Fuller test (ADF) and KPSS tests indicate that the logarithmic first difference of $\Delta^{\$}CoVaR_{99^{th},i}$ and the CSAD are stationary for each country included in this study.

Table B.1: Estimates of herding behavior in global markets due to systemic risk (MES).

Asia Pacific		γ_1	γ_2	γ_3	$Adj.R^2$
Australia	*OLS*	0.011	-0.123***	-0.141***	32.29%
	$\tau=95^{th}$	0.052	-0.269*	-0.396***	28.14%
	$\tau=99^{th}$	-0.090***	-0.160***	-0.419***	28.10%
China	*OLS*	-0.015***	0.016***	0.015***	32.31%
	$\tau=95^{th}$	-0.014	0.040***	0.031	22.67%
	$\tau=99^{th}$	0.000	0.125***	0.113***	27.04%
Hong Kong	*OLS*	0.006	-0.018	-0.008	38.19%
	$\tau=95^{th}$	0.027	-0.036	-0.032	30.28%
	$\tau=99^{th}$	0.036***	-0.069***	-0.010	35.94%
India	*OLS*	0.018	-0.030**	0.039***	49.85%
	$\tau=95^{th}$	0.060**	-0.078***	0.009	29.67%
	$\tau=99^{th}$	0.065	-0.140	-0.007	40.97%
Indonesia	*OLS*	0.010	-0.053***	-0.003	69.20%
	$\tau=95^{th}$	0.021**	-0.062***	0.085***	49.88%
	$\tau=99^{th}$	0.048	-0.078*	0.088	58.36%
Japan	*OLS*	0.004	-0.031***	0.003	31.64%
	$\tau=95^{th}$	0.023	-0.052***	-0.040***	25.92%
	$\tau=99^{th}$	0.013	-0.062	-0.067**	33.38%
Malaysia	*OLS*	0.005	-0.098***	-0.016	40.81%
	$\tau=95^{th}$	0.041	-0.172***	-0.044	27.25%
	$\tau=99^{th}$	0.114	-0.199**	0.294	32.40%
Singapore	*OLS*	0.006	-0.090***	-0.007	34.16%
	$\tau=95^{th}$	0.036	-0.112***	-0.086***	25.90%
	$\tau=99^{th}$	0.102	-0.233***	-0.224***	33.30%
South Korea	*OLS*	-0.007**	-0.106***	0.021*	41.83%
	$\tau=95^{th}$	0.017	-0.110***	0.090*	31.19%
	$\tau=99^{th}$	0.032	-0.118**	0.074	39.41%
Taiwan	*OLS*	-0.026***	-0.017***	-0.036***	27.88%
	$\tau=95^{th}$	-0.047***	-0.042***	-0.006	20.51%
	$\tau=99^{th}$	-0.059***	-0.038***	0.043	15.79%
Thailand	*OLS*	0.008	-0.033***	0.029***	61.41%
	$\tau=95^{th}$	0.040	-0.077**	0.030	41.37%
	$\tau=99^{th}$	-0.008	-0.052***	0.058	49.58%

Latin America		γ_1	γ_2	γ_3	$Adj.R^2$
Argentina	*OLS*	-0.016*	-0.015**	0.037***	45.56%
	$\tau=95^{th}$	-0.006	-0.002	0.100	31.77%
	$\tau=99^{th}$	-0.008	0.031	0.226	37.15%
Brazil	*OLS*	0.016***	-0.041***	-0.009	35.73%
	$\tau=95^{th}$	0.064**	-0.079***	-0.044***	28.27%
	$\tau=99^{th}$	0.077	-0.099	0.107**	37.69%
Chile	*OLS*	0.001	-0.012	0.102***	35.33%
	$\tau=95^{th}$	0.029	-0.022	0.244***	28.42%
	$\tau=99^{th}$	0.023	0.189	0.310***	40.74%
Mexico	*OLS*	0.037***	-0.055***	0.002	40.42%
	$\tau=95^{th}$	0.098**	-0.132***	-0.065*	32.08%
	$\tau=99^{th}$	0.093**	-0.170***	0.136	38.36%

North America		γ_1	γ_2	γ_3	$Adj.R^2$
Canada	*OLS*	0.022	-0.096***	-0.023	46.42%
	$\tau=95^{th}$	0.148***	-0.215***	-0.193***	35.12%
	$\tau=99^{th}$	-0.036	-0.195***	-0.292***	38.30%
USA	*OLS*	-0.074***	0.018	0.078***	50.01%
	$\tau=95^{th}$	-0.088	0.039	0.111**	38.88%
	$\tau=99^{th}$	-0.099	0.048	0.104*	34.99%

Western Europe		γ_1	γ_2	γ_3	$Adj.R^2$
Austria	*OLS*	0.023***	-0.058***	0.869***	46.83%
	$\tau=95^{th}$	0.044***	-0.113***	1.453***	38.78%
	$\tau=99^{th}$	0.010	-0.118***	2.073***	42.19%
Belgium	*OLS*	0.035**	-0.085***	0.742***	42.48%
	$\tau=95^{th}$	0.045*	-0.154***	1.303***	33.73%
	$\tau=99^{th}$	0.292***	-0.330***	2.048***	36.99%
France	*OLS*	-0.001	-0.023**	0.816***	34.86%
	$\tau=95^{th}$	0.011	-0.019	1.525***	26.18%
	$\tau=99^{th}$	0.013	-0.019**	2.210***	20.71%
Germany	*OLS*	-0.066***	0.015	0.767***	38.88%
	$\tau=95^{th}$	-0.068	0.023	1.405***	29.94%
	$\tau=99^{th}$	0.008	-0.004	2.133***	28.64%
Ireland	*OLS*	-0.014	0.058*	1.376***	55.71%
	$\tau=95^{th}$	-0.008	-0.017	2.477***	41.35%
	$\tau=99^{th}$	-0.048	-0.071**	3.418***	45.05%
Netherlands	*OLS*	-0.031*	-0.013	0.829***	39.66%
	$\tau=95^{th}$	0.018*	-0.027***	1.616***	29.63%
	$\tau=99^{th}$	0.054***	-0.049***	2.461***	29.05%
Switzerland	*OLS*	-0.031*	-0.009	0.633***	45.79%
	$\tau=95^{th}$	-0.011	-0.004	1.272***	37.41%
	$\tau=99^{th}$	-0.022	-0.018	1.818***	41.09%
UK	*OLS*	0.030***	-0.060***	0.886***	39.73%
	$\tau=95^{th}$	0.078***	-0.139***	1.402***	30.39%
	$\tau=99^{th}$	0.037*	-0.140***	2.115***	30.46%

Northern Europe		γ_1	γ_2	γ_3	$Adj.R^2$
Denmark	*OLS*	0.045**	-0.083***	0.951***	37.05%
	$\tau=95^{th}$	0.097***	-0.148***	1.666***	27.07%
	$\tau=99^{th}$	0.236***	-0.280***	2.418***	39.22%
Finland	*OLS*	-0.022	0.002	1.231***	40.92%
	$\tau=95^{th}$	-0.006	-0.020**	1.808***	29.69%
	$\tau=99^{th}$	-0.026	-0.058	2.223***	29.17%
Norway	*OLS*	0.016	-0.033***	1.423***	39.31%
	$\tau=95^{th}$	0.046	-0.075	2.190***	31.16%
	$\tau=99^{th}$	0.247***	-0.217***	3.054***	39.61%
Sweden	*OLS*	-0.018**	-0.026**	0.813***	32.31%
	$\tau=95^{th}$	0.000	-0.015**	1.560***	25.51%
	$\tau=99^{th}$	0.003	-0.017***	2.195***	27.58%

Southern Europe		γ_1	γ_2	γ_3	$Adj.R^2$
Greece	*OLS*	0.019***	-0.021***	1.363***	47.74%
	$\tau=95^{th}$	0.055	-0.058	2.138***	36.61%
	$\tau=99^{th}$	0.070	-0.043**	2.700***	41.50%
Italy	*OLS*	0.010***	-0.031***	0.862***	34.67%
	$\tau=95^{th}$	0.023	-0.045*	1.452***	24.93%
	$\tau=99^{th}$	0.044	-0.067	1.987***	23.63%
Portugal	*OLS*	-0.008**	-0.017**	0.832***	33.79%
	$\tau=95^{th}$	-0.009	-0.015*	1.479***	21.69%
	$\tau=99^{th}$	-0.005	-0.033	1.981***	25.85%
Spain	*OLS*	0.009*	-0.021***	0.778***	32.67%
	$\tau=95^{th}$	0.034**	-0.044***	1.457***	23.30%
	$\tau=99^{th}$	0.088	-0.118	1.880***	30.73%

Notes: The table reports the estimated coefficients of Eq. (5.12): $CSAD_t = \alpha + \gamma_0|R_{m,t}| + \gamma_1 R^2_{m,t} + D_1\gamma_2 R^2_{m,t} + D_2\gamma_3 R^2_{m,t} + \varepsilon_t$, where $CSAD_t$ is the cross-sectional absolute deviation and $R_{m,t}$ is the market return. Dummy variable D_1 equals 1 if the MES_i lies in the upper 25% of the distribution and 0, otherwise; dummy variable D_2 equals 1 if the MES_i lies in the lower 25% of the distribution and 0, otherwise. A significant negative value of γ_1, γ_2, γ_3 suggest the presence of herding in case of medium, high and low systemic risk, respectively. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table B.2: Estimates of herding behavior in global markets due to systemic risk (LRMES).

Asia Pacific

		γ_1	γ_2	γ_3	$Adj.R^2$
Australia	*OLS*	0.010	-0.191***	-0.036	32.39%
	$\tau=95^{th}$	-0.027	-0.254***	-0.087***	26.80%
	$\tau=99^{th}$	-0.086***	-0.185***	-0.077***	26.65%
China	*OLS*	-0.014***	0.015***	-0.002	31.86%
	$\tau=95^{th}$	-0.006	0.030***	0.011	21.57%
	$\tau=99^{th}$	-0.003	0.090*	0.020	24.25%
Hong Kong	*OLS*	0.003	-0.062***	-0.010	38.88%
	$\tau=95^{th}$	0.009	-0.122***	-0.002	30.89%
	$\tau=99^{th}$	0.028	-0.143***	-0.017	35.85%
India	*OLS*	0.016	-0.058***	0.041***	49.08%
	$\tau=95^{th}$	0.059***	-0.130***	0.010	28.51%
	$\tau=99^{th}$	0.016	-0.104***	0.037	40.90%
Indonesia	*OLS*	-0.012	-0.155***	-0.022*	66.14%
	$\tau=95^{th}$	0.010	-0.162***	0.017	46.06%
	$\tau=99^{th}$	0.008	-0.208***	0.044	51.25%
Japan	*OLS*	0.005	-0.012	0.014	27.71%
	$\tau=95^{th}$	0.025	-0.026	-0.030***	21.39%
	$\tau=99^{th}$	-0.008	-0.027***	-0.042*	29.93%
Malaysia	*OLS*	-0.009	-0.155***	0.008	41.55%
	$\tau=95^{th}$	0.030	-0.165***	-0.022	27.32%
	$\tau=99^{th}$	0.118	-0.131**	-0.118**	32.46%
Singapore	*OLS*	0.009*	-0.115***	0.022	32.98%
	$\tau=95^{th}$	0.041	-0.172***	0.003	24.16%
	$\tau=99^{th}$	0.072	-0.203	0.324	28.94%
South Korea	*OLS*	-0.006*	-0.098***	0.018*	40.73%
	$\tau=95^{th}$	0.011	-0.113***	0.075	30.58%
	$\tau=99^{th}$	0.002	-0.113***	0.067	39.22%
Taiwan	*OLS*	-0.023**	0.002	-0.043***	20.46%
	$\tau=95^{th}$	-0.047***	-0.084***	-0.015	17.96%
	$\tau=99^{th}$	-0.076***	-0.045***	-0.036***	13.86%
Thailand	*OLS*	0.009	-0.045***	0.013	60.04%
	$\tau=95^{th}$	0.023	-0.086**	-0.037	41.00%
	$\tau=99^{th}$	0.052	-0.133	-0.106	49.33%

Latin America

		γ_1	γ_2	γ_3	$Adj.R^2$
Argentina	*OLS*	-0.017*	-0.010	0.039***	46.70%
	$\tau=95^{th}$	-0.010	-0.020**	0.080***	32.81%
	$\tau=99^{th}$	0.118	-0.134**	0.140	37.66%
Brazil	*OLS*	0.017***	-0.005	0.001	33.58%
	$\tau=95^{th}$	0.055**	-0.038**	-0.014	26.17%
	$\tau=99^{th}$	0.057	-0.044	0.107***	34.74%
Chile	*OLS*	0.001	-0.005	0.097***	35.41%
	$\tau=95^{th}$	0.030	-0.044	0.228***	28.85%
	$\tau=99^{th}$	-0.018	0.367***	0.317***	41.26%
Mexico	*OLS*	0.034***	-0.050**	0.050**	40.43%
	$\tau=95^{th}$	0.096*	-0.114***	0.112***	32.10%
	$\tau=99^{th}$	0.103**	-0.163***	0.324	39.96%

North America

		γ_1	γ_2	γ_3	$Adj.R^2$
Canada	*OLS*	0.025*	-0.075*	0.044	43.79%
	$\tau=95^{th}$	0.046	-0.139***	-0.053*	33.12%
	$\tau=99^{th}$	-0.053	-0.286***	-0.241***	37.22%
USA	*OLS*	-0.045***	-0.072***	0.049***	47.54%
	$\tau=95^{th}$	-0.050**	-0.085**	0.054***	36.37%
	$\tau=99^{th}$	-0.027	-0.069***	0.028***	35.13%

Western Europe

		γ_1	γ_2	γ_3	$Adj.R^2$
Austria	*OLS*	0.019***	-0.070***	-0.056**	45.32%
	$\tau=95^{th}$	0.041***	-0.142***	-0.183***	37.75%
	$\tau=99^{th}$	0.008	-0.184***	-0.288***	42.29%
Belgium	*OLS*	0.035**	-0.087***	0.008	42.20%
	$\tau=95^{th}$	0.057*	-0.158***	-0.006	33.61%
	$\tau=99^{th}$	0.289***	-0.331***	-0.211***	38.19%
France	*OLS*	0.010**	-0.030*	0.035***	35.82%
	$\tau=95^{th}$	0.004	-0.005	0.085***	25.52%
	$\tau=99^{th}$	0.017	-0.017	0.060**	20.44%
Germany	*OLS*	-0.020	-0.043*	0.031*	36.20%
	$\tau=95^{th}$	-0.014	-0.077**	0.047	27.48%
	$\tau=99^{th}$	-0.021	-0.027***	0.103	25.52%
Ireland	*OLS*	-0.012	0.101***	0.062***	55.75%
	$\tau=95^{th}$	0.006	0.061*	0.074	41.48%
	$\tau=99^{th}$	-0.002	0.096***	0.410	45.75%
Netherlands	*OLS*	-0.014	-0.025	0.049***	39.67%
	$\tau=95^{th}$	0.025***	-0.016***	0.116***	29.22%
	$\tau=99^{th}$	0.010	-0.015***	0.134**	29.83%
Switzerland	*OLS*	-0.004	-0.062***	0.032***	43.02%
	$\tau=95^{th}$	0.016	-0.069***	0.107***	34.82%
	$\tau=99^{th}$	-0.002	-0.066***	0.132***	36.12%
UK	*OLS*	0.025***	-0.113***	0.002	38.89%
	$\tau=95^{th}$	0.069***	-0.210***	-0.099***	29.00%
	$\tau=99^{th}$	0.045***	-0.194***	-0.088***	29.28%

Northern Europe

		γ_1	γ_2	γ_3	$Adj.R^2$
Denmark	*OLS*	0.044**	-0.085***	0.052**	37.10%
	$\tau=95^{th}$	0.098***	-0.147***	0.056	27.11%
	$\tau=99^{th}$	0.248***	-0.279***	0.014	40.13%
Finland	*OLS*	-0.044***	-0.026	0.054***	39.78%
	$\tau=95^{th}$	-0.014	-0.029***	0.148**	29.15%
	$\tau=99^{th}$	-0.015	-0.101	0.027	28.19%
Norway	*OLS*	0.011	-0.082***	0.014	39.88%
	$\tau=95^{th}$	0.025	-0.158***	0.006	31.65%
	$\tau=99^{th}$	0.278***	-0.254**	0.092	39.97%
Sweden	*OLS*	-0.017**	-0.019	0.031***	30.30%
	$\tau=95^{th}$	-0.001	-0.014*	0.147**	23.82%
	$\tau=99^{th}$	-0.015	-0.014	0.155	25.41%

Southern Europe

		γ_1	γ_2	γ_3	$Adj.R^2$
Greece	*OLS*	0.015***	-0.021***	0.002	46.51%
	$\tau=95^{th}$	0.047	-0.053	-0.008	36.48%
	$\tau=99^{th}$	0.070	-0.081**	-0.043	40.95%
Italy	*OLS*	0.004	-0.050***	0.013**	35.12%
	$\tau=95^{th}$	-0.010***	-0.074***	0.033	25.41%
	$\tau=99^{th}$	0.001	-0.083***	0.075	22.80%
Portugal	*OLS*	-0.010***	-0.002	-0.003	33.66%
	$\tau=95^{th}$	-0.011	-0.021***	0.036	22.12%
	$\tau=99^{th}$	-0.042***	-0.024***	0.131***	25.34%
Spain	*OLS*	0.003	-0.048***	0.033***	33.23%
	$\tau=95^{th}$	0.028**	-0.088***	0.059	23.42%
	$\tau=99^{th}$	0.042	-0.129**	0.038	29.97%

Notes: The table reports the estimated coefficients of Eq. (5.12): $CSAD_t = \alpha + \gamma_0|R_{m,t}| + \gamma_1 R^2_{m,t} + D_1\gamma_2 R^2_{m,t} + D_2\gamma_3 R^2_{m,t} + \varepsilon_t$, where $CSAD_t$ is the cross-sectional absolute deviation and $R_{m,t}$ is the market return. Dummy variable D_1 equals 1 if the $LRMES_i$ lies in the upper 25% of the distribution and 0, otherwise; dummy variable D_2 equals 1 if the $LRMES_i$ lies in the lower 25% of the distribution and 0, otherwise. A significant negative value of γ_1, γ_2, γ_3 suggest the presence of herding in case of medium, high and low systemic risk, respectively. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

and, finally, vii) the period after China's market crash, that concludes our sample period in January 2019.[4]

Analyzing the full sample period, the variance decomposition of the CSAD for all the markets analyzed indicates that, for one period (two periods), 100% (almost 100%), of the variance of the CSAD is idiosyncratic and 0% (approximately 0%) is due to increases in the systemic risk level of the market. A similar pattern is found for the variance decomposition of the systemic risk increases. However, in some cases, such as China and Brazil, the variance decomposition of the systemic risk shows that, for two periods, respectively, approximately 96% and 97.5% of the variance of the systemic risk increases is idiosyncratic and approximately 4% and 3.5% is due to the return clustering.

The analysis of the sub-periods highlights some interesting insight. Overall, the variance decomposition of the CSAD for all the markets analyzed indicates that the variance of the CSAD is almost idiosyncratic, being not due to increases in the systemic risk level of the market. Only in India, in the pre-EZC period, the variance decomposition of the CSAD indicates that almost 6% of the variance of the CSAD is due to systemic risk increases. However, excluding this case, the variance of the return clustering measure is almost always idiosyncratic.

A more interesting pattern is found analyzing the variance decomposition of the systemic risk increases. In particular, we find that for the European countries, the variance decomposition of the systemic risk increases indicates that no more than 10% of the variance of the systemic risk increases is due to the CSAD. This result is found for two periods for Italy during the China's market crash sub-period. In the Latin and North American countries, we find a similar results, with a maximum 7.5% of the variance of the systemic risk increases

[4]Our sub-periods are defined as follow: i) from the 1^{st} Jan. 2000 to the 8^{th} Aug. 2007; ii) from the 9^{th} Aug. 2007 to the 31^{st} March 2009; iii) from the 1^{st} April 2009 to the 1^{st} May 2010; iv) from the 2^{nd} May 2010 to the 31^{st} Dec. 2012; v) from the 1^{st} Jan. 2013 to the 11^{th} June 2015; vi) from the 12^{th} June 2015 to the 29^{th} Feb. 2016; vii) from the 1^{st} March 2016 to the 31^{th} Jan. 2019. We explain how we define a crisis period and how we defined the EZC and the China's market crash in Section 5.2.1. We use the same period identified by Galariotis, Rong, and Spyrou (2015) for the GFC. Major details for the usage of this period as proxy of the GFC can be found on the 79^{th} Annual Report of the Bank for International Settlements, (Bank for International Settlements, 2009).

Table B.3: Asia Pacific markets: variance decomposition of variables.

	Asia Pacific																			
	Australia		China		Hong Kong		India		Indonesia		Japan		Malaysia		Singapore		South Korea		Taiwan		Thailand	
	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk
Full sample period																						
	Variance decomposition of CSAD																					
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9994	0.0006	0.9990	0.0010	0.9993	0.0007	0.9969	0.0031	0.9997	0.0003	0.9978	0.0022	0.9996	0.0004	1.0000	0.0000	0.9987	0.0013	0.9991	0.0009	0.9994	0.0006
	Variance decomposition of Systemic Risk																					
Period 1	0.0001	0.9999	0.0085	0.9915	0.0007	0.9993	0.0004	0.9996	0.0004	0.9996	0.0028	0.9972	0.0000	1.0000	0.0001	0.9999	0.0002	0.9998	0.0010	0.9990	0.0001	0.9999
Period 2	0.0031	0.9969	0.0387	0.9613	0.0011	0.9989	0.0005	0.9995	0.0005	0.9995	0.0037	0.9963	0.0008	0.9992	0.0103	0.9897	0.0036	0.9964	0.0018	0.9982	0.0089	0.9911
Pre-Global financial crisis period																						
	Variance decomposition of CSAD																					
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	1.0000	0.0000	0.9999	0.0001	0.9967	0.0033	0.9959	0.0041	0.9996	0.0004	0.9988	0.0012	0.9992	0.0008	0.9999	0.0001	0.9966	0.0034	0.9983	0.0017	0.9978	0.0022
	Variance decomposition of Systemic Risk																					
Period 1	0.0035	0.9965	0.0024	0.9976	0.0008	0.9992	0.0002	0.9998	0.0022	0.9978	0.0004	0.9996	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0015	0.9985	0.0000	1.0000
Period 2	0.0186	0.9814	0.0090	0.9910	0.0009	0.9991	0.0002	0.9998	0.0024	0.9976	0.0025	0.9975	0.0012	0.9988	0.0108	0.9892	0.0008	0.9992	0.0019	0.9981	0.0022	0.9978
Global financial crisis period																						
	Variance decomposition of CSAD																					
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9982	0.0018	0.9987	0.0013	0.9987	0.0013	0.9999	0.0001	0.9898	0.0102	0.9977	0.0023	0.9996	0.0004	0.9999	0.0001	0.9963	0.0037	0.9981	0.0019	0.9999	0.0001
	Variance decomposition of Systemic Risk																					
Period 1	0.0012	0.9988	0.0340	0.9660	0.0069	0.9931	0.0034	0.9966	0.0009	0.9991	0.0000	1.0000	0.0349	0.9651	0.0025	0.9975	0.0011	0.9989	0.0015	0.9985	0.0021	0.9979
Period 2	0.0121	0.9879	0.1157	0.8843	0.0068	0.9932	0.0098	0.9902	0.0085	0.9915	0.0008	0.9992	0.0349	0.9651	0.0179	0.9821	0.0106	0.9894	0.0033	0.9967	0.0554	0.9446
Pre-Eurozone crisis period																						
	Variance decomposition of CSAD																					
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9971	0.0029	0.9753	0.0247	1.0000	0.0000	0.9407	0.0593	0.9999	0.0001	0.9898	0.0102	0.9982	0.0018	0.9934	0.0066	0.9994	0.0006	0.9563	0.0437	0.9974	0.0026
	Variance decomposition of Systemic Risk																					
Period 1	0.0032	0.9968	0.0029	0.9971	0.0002	0.9998	0.0020	0.9980	0.0209	0.9791	0.0102	0.9898	0.0000	1.0000	0.0024	0.9976	0.0017	0.9983	0.0301	0.9699	0.0113	0.9887
Period 2	0.0111	0.9889	0.2587	0.7413	0.0330	0.9670	0.0235	0.9765	0.0273	0.9727	0.0261	0.9739	0.0217	0.9783	0.0477	0.9523	0.0155	0.9845	0.0989	0.9011	0.0113	0.9887
Eurozone crisis period																						
	Variance decomposition of CSAD																					
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9816	0.0184	0.9973	0.0027	0.9896	0.0104	0.9999	0.0001	0.9809	0.0191	0.9845	0.0155	0.9988	0.0012	0.9982	0.0018	0.9980	0.0020	0.9977	0.0023	0.9980	0.0020
	Variance decomposition of Systemic Risk																					
Period 1	0.0151	0.9849	0.0037	0.9963	0.0246	0.9754	0.0172	0.9828	0.0107	0.9893	0.0466	0.9534	0.0028	0.9972	0.0067	0.9933	0.0041	0.9959	0.0261	0.9739	0.0101	0.9899
Period 2	0.0153	0.9847	0.1603	0.8397	0.0275	0.9725	0.0194	0.9806	0.0444	0.9556	0.0555	0.9445	0.0032	0.9968	0.0072	0.9928	0.0078	0.9922	0.0704	0.9296	0.0549	0.9451
Pre-China's stock market crash																						
	Variance decomposition of CSAD																					
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9992	0.0008	0.9530	0.0470	0.9948	0.0052	0.9908	0.0092	0.9965	0.0035	0.9861	0.0139	0.9961	0.0039	0.9945	0.0055	0.9997	0.0003	0.9976	0.0024	0.9981	0.0019
	Variance decomposition of Systemic Risk																					
Period 1	0.0002	0.9998	0.0838	0.9162	0.0016	0.9984	0.0009	0.9991	0.0097	0.9903	0.0097	0.9903	0.0028	0.9972	0.0047	0.9953	0.0095	0.9905	0.0034	0.9966	0.0001	0.9999
Period 2	0.0028	0.9972	0.1803	0.8197	0.0343	0.9657	0.0014	0.9986	0.0288	0.9712	0.0318	0.9682	0.0046	0.9954	0.0052	0.9948	0.0123	0.9877	0.0539	0.9461	0.0759	0.9241
China's stock market crash																						
	Variance decomposition of CSAD																					
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9827	0.0173	1.0000	0.0000	0.9991	0.0009	0.9837	0.0163	0.9994	0.0006	0.9884	0.0116	0.9881	0.0119	0.9994	0.0006	0.9924	0.0076	0.9909	0.0091	0.9978	0.0022
	Variance decomposition of Systemic Risk																					
Period 1	0.0009	0.9991	0.0096	0.9904	0.0385	0.9615	0.0343	0.9657	0.0206	0.9794	0.0007	0.9993	0.0012	0.9988	0.0024	0.9976	0.0362	0.9638	0.0393	0.9607	0.0038	0.9962
Period 2	0.0013	0.9987	0.1638	0.8362	0.0417	0.9583	0.0479	0.9521	0.0592	0.9408	0.0014	0.9986	0.0100	0.9900	0.0073	0.9927	0.1200	0.8800	0.1529	0.8471	0.1480	0.8520
Post crises period																						
	Variance decomposition of CSAD																					
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9989	0.0011	0.9977	0.0023	0.9935	0.0065	0.9886	0.0114	0.9978	0.0022	0.9837	0.0163	0.9999	0.0001	0.9998	0.0002	1.0000	0.0000	0.9965	0.0035	0.9661	0.0339
	Variance decomposition of Systemic Risk																					
Period 1	0.0025	0.9975	0.0000	1.0000	0.0001	0.9999	0.0092	0.9908	0.0015	0.9985	0.0468	0.9532	0.0001	0.9999	0.0007	0.9993	0.0115	0.9885	0.0034	0.9966	0.0153	0.9847
Period 2	0.0036	0.9964	0.0812	0.9188	0.0073	0.9927	0.0108	0.9892	0.0022	0.9978	0.0533	0.9467	0.0015	0.9985	0.0048	0.9952	0.0313	0.9687	0.0235	0.9765	0.0401	0.9599

Notes: The table presents the results for decomposing the variance of the variables, based on an unrestricted VAR model, for the Asia Pacific countries. $CSAD$ is the cross-sectional absolute deviation and $S.Risk$ indicates the systemic risk increased measured with the $\Delta CoVaR_{99^{th},i}$. Periods 1 and 2 indicate the lag structure test of one or two lags depending on the sample period.

Table B.4: Latin and Northern American markets: variance decomposition of variables.

	Latin America								Noth America			
	Argentina		Brazil		Chile		Mexico		Canada		USA	
	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk
Full sample period												
	Variance decomposition of CSAD											
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9997	0.0003	0.9984	0.0016	1.0000	0.0000	0.9979	0.0021	1.0000	0.0000	0.9984	0.0016
	Variance decomposition of Systemic Risk											
Period 1	0.0004	0.9996	0.0234	0.9766	0.0000	1.0000	0.0026	0.9974	0.0004	0.9996	0.0011	0.9989
Period 2	0.0007	0.9993	0.0234	0.9766	0.0001	0.9999	0.0027	0.9973	0.0035	0.9965	0.0018	0.9982
Pre-Global financial crisis period												
	Variance decomposition of CSAD											
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9997	0.0003	0.9978	0.0022	1.0000	0.0000	0.9941	0.0059	1.0000	0.0000	0.9936	0.0064
	Variance decomposition of Systemic Risk											
Period 1	0.0002	0.9998	0.0707	0.9293	0.0000	1.0000	0.0079	0.9921	0.0000	1.0000	0.0020	0.9980
Period 2	0.0003	0.9997	0.0706	0.9294	0.0003	0.9997	0.0079	0.9921	0.0002	0.9998	0.0055	0.9945
Global financial crisis period												
	Variance decomposition of CSAD											
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9999	0.0001	0.9957	0.0043	0.9963	0.0037	0.9984	0.0016	0.9996	0.0004	0.9972	0.0028
	Variance decomposition of Systemic Risk											
Period 1	0.0176	0.9824	0.0070	0.9930	0.0016	0.9984	0.0078	0.9922	0.0040	0.9960	0.0160	0.9840
Period 2	0.0188	0.9812	0.0072	0.9928	0.0016	0.9984	0.0173	0.9827	0.0167	0.9833	0.0199	0.9801
Pre-Eurozone crisis period												
	Variance decomposition of CSAD											
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9985	0.0015	0.9965	0.0035	1.0000	0.0000	1.0000	0.0000	0.9949	0.0051	0.9994	0.0006
	Variance decomposition of Systemic Risk											
Period 1	0.0069	0.9931	0.0053	0.9947	0.0028	0.9972	0.0034	0.9966	0.0007	0.9993	0.0002	0.9998
Period 2	0.0107	0.9893	0.0155	0.9845	0.0742	0.9258	0.0149	0.9851	0.0013	0.9987	0.0131	0.9869
Eurozone crisis period												
	Variance decomposition of CSAD											
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9998	0.0002	0.9905	0.0095	0.9854	0.0146	0.9989	0.0011	0.9896	0.0104	0.9965	0.0035
	Variance decomposition of Systemic Risk											
Period 1	0.0013	0.9987	0.0069	0.9931	0.0003	0.9997	0.0069	0.9931	0.0028	0.9972	0.0075	0.9925
Period 2	0.0014	0.9986	0.0069	0.9931	0.0038	0.9962	0.0070	0.9930	0.0068	0.9932	0.0092	0.9908
Pre-China's stock market crash												
	Variance decomposition of CSAD											
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9954	0.0046	0.9991	0.0009	0.9947	0.0053	0.9963	0.0037	0.9989	0.0011	0.9997	0.0003
	Variance decomposition of Systemic Risk											
Period 1	0.0001	0.9999	0.0051	0.9949	0.0001	0.9999	0.0193	0.9807	0.0009	0.9991	0.0011	0.9989
Period 2	0.0003	0.9997	0.0051	0.9949	0.0067	0.9933	0.0193	0.9807	0.0228	0.9772	0.0028	0.9972
China's stock market crash												
	Variance decomposition of CSAD											
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9970	0.0030	0.9992	0.0008	0.9999	0.0001	0.9976	0.0024	0.9998	0.0002	0.9993	0.0007
	Variance decomposition of Systemic Risk											
Period 1	0.0003	0.9997	0.0047	0.9953	0.0021	0.9979	0.0041	0.9959	0.0186	0.9814	0.0099	0.9901
Period 2	0.0295	0.9705	0.0165	0.9835	0.0052	0.9948	0.0067	0.9933	0.0187	0.9813	0.0425	0.9575
Post crises period												
	Variance decomposition of CSAD											
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9985	0.0015	0.9978	0.0022	0.9983	0.0017	0.9987	0.0013	0.9962	0.0038	0.9917	0.0083
	Variance decomposition of Systemic Risk											
Period 1	0.0001	0.9999	0.0006	0.9994	0.0330	0.9670	0.0018	0.9982	0.0002	0.9998	0.0193	0.9807
Period 2	0.0162	0.9838	0.0055	0.9945	0.0361	0.9639	0.0227	0.9773	0.0031	0.9969	0.0361	0.9639

Notes: The table presents the results for decomposing the variance of the variables, based on an unrestricted VAR model, for the Latin and Northern American markets. $CSAD$ is the cross-sectional absolute deviation and $S.Risk$ indicates the systemic risk increased measured with the $\Delta CoVaR_{99^{th},i}$. Periods 1 and 2 indicate the lag structure test of one or two lags depending on the sample period.

Table B.5: European markets: variance decomposition of variables.

	Western Europe															
	Austria		Belgium		France		Germany		Ireland		Netherlands		Switzerland		United Kingdom	
	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk
Full sample period																
	Variance decomposition of CSAD															
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9998	0.0002	0.9951	0.0049	0.9997	0.0003	0.9983	0.0017	0.9999	0.0001	0.9999	0.0001	0.9997	0.0003	0.9996	0.0004
	Variance decomposition of Systemic Risk															
Period 1	0.0001	0.9999	0.0009	0.9991	0.0032	0.9968	0.0000	1.0000	0.0001	0.9999	0.0007	0.9993	0.0001	0.9999	0.0002	0.9998
Period 2	0.0003	0.9997	0.0011	0.9989	0.0045	0.9955	0.0015	0.9985	0.0003	0.9997	0.0008	0.9992	0.0007	0.9993	0.0010	0.9990
Pre-Global financial crisis period																
	Variance decomposition of CSAD															
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9989	0.0011	0.9999	0.0001	1.0000	0.0000	0.9985	0.0015	1.0000	0.0000	1.0000	0.0000	0.9994	0.0006	0.9998	0.0002
	Variance decomposition of Systemic Risk															
Period 1	0.0002	0.9998	0.0021	0.9979	0.0066	0.9934	0.0016	0.9984	0.0003	0.9997	0.0002	0.9998	0.0002	0.9998	0.0014	0.9986
Period 2	0.0013	0.9987	0.0025	0.9975	0.0069	0.9931	0.0058	0.9942	0.0007	0.9993	0.0007	0.9993	0.0009	0.9991	0.0032	0.9968
Global financial crisis period																
	Variance decomposition of CSAD															
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9847	0.0153	0.9690	0.0310	0.9919	0.0081	0.9936	0.0064	0.9999	0.0001	0.9976	0.0024	1.0000	0.0000	0.9960	0.0040
	Variance decomposition of Systemic Risk															
Period 1	0.0001	0.9999	0.0097	0.9903	0.0140	0.9860	0.0165	0.9835	0.0000	1.0000	0.0150	0.9850	0.0031	0.9969	0.0004	0.9996
Period 2	0.0001	0.9999	0.0149	0.9851	0.0482	0.9518	0.0176	0.9824	0.0008	0.9992	0.0167	0.9833	0.0152	0.9848	0.0007	0.9993
Pre-Eurozone crisis period																
	Variance decomposition of CSAD															
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9879	0.0121	0.9883	0.0117	0.9993	0.0007	0.9861	0.0139	0.9959	0.0041	0.9873	0.0127	0.9984	0.0016	0.9942	0.0058
	Variance decomposition of Systemic Risk															
Period 1	0.0030	0.9970	0.0131	0.9869	0.0096	0.9904	0.0010	0.9990	0.0239	0.9761	0.0008	0.9992	0.0070	0.9930	0.0107	0.9893
Period 2	0.0088	0.9912	0.0192	0.9808	0.0120	0.9880	0.0250	0.9750	0.0439	0.9561	0.0103	0.9897	0.0092	0.9908	0.0442	0.9558
Eurozone crisis period																
	Variance decomposition of CSAD															
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9982	0.0018	0.9898	0.0102	0.9926	0.0074	0.9920	0.0080	0.9972	0.0028	0.9869	0.0131	0.9996	0.0004	0.9943	0.0057
	Variance decomposition of Systemic Risk															
Period 1	0.0144	0.9856	0.0100	0.9900	0.0006	0.9994	0.0146	0.9854	0.0015	0.9985	0.0027	0.9973	0.0000	1.0000	0.0072	0.9928
Period 2	0.0179	0.9821	0.0158	0.9842	0.0006	0.9994	0.0149	0.9851	0.0032	0.9968	0.0037	0.9963	0.0004	0.9996	0.0074	0.9926
Pre-China's stock market crash																
	Variance decomposition of CSAD															
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9996	0.0004	0.9998	0.0002	0.9980	0.0020	0.9943	0.0057	0.9996	0.0004	1.0000	0.0000	0.9984	0.0016	0.9972	0.0028
	Variance decomposition of Systemic Risk															
Period 1	0.0095	0.9905	0.0003	0.9997	0.0035	0.9965	0.0029	0.9971	0.0038	0.9962	0.0000	1.0000	0.0001	0.9999	0.0009	0.9991
Period 2	0.0094	0.9906	0.0012	0.9988	0.0064	0.9936	0.0034	0.9966	0.0040	0.9960	0.0000	1.0000	0.0210	0.9790	0.0009	0.9991
China's stock market crash																
	Variance decomposition of CSAD															
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9986	0.0014	0.9906	0.0094	0.9987	0.0013	0.9984	0.0016	1.0000	0.0000	0.9963	0.0037	0.9999	0.0001	0.9983	0.0017
	Variance decomposition of Systemic Risk															
Period 1	0.0081	0.9919	0.0356	0.9644	0.0100	0.9900	0.0306	0.9694	0.0153	0.9847	0.0344	0.9656	0.0006	0.9994	0.0177	0.9823
Period 2	0.0150	0.9850	0.0356	0.9644	0.0101	0.9899	0.0324	0.9676	0.0247	0.9753	0.0345	0.9655	0.0510	0.9490	0.0434	0.9566
Post crises period																
	Variance decomposition of CSAD															
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9978	0.0022	0.9996	0.0004	0.9974	0.0026	0.9993	0.0007	0.9994	0.0006	1.0000	0.0000	0.9981	0.0019	0.9996	0.0004
	Variance decomposition of Systemic Risk															
Period 1	0.0007	0.9993	0.0002	0.9998	0.0113	0.9887	0.0060	0.9940	0.0073	0.9927	0.0000	1.0000	0.0080	0.9920	0.0029	0.9971
Period 2	0.0027	0.9973	0.0192	0.9808	0.0230	0.9770	0.0241	0.9759	0.0391	0.9609	0.0080	0.9920	0.0128	0.9872	0.0151	0.9849

Notes: The table presents the results for decomposing the variance of the variables, based on an unrestricted VAR model, for the Western, Northern and Southern European markets. $CSAD$ is the cross-sectional absolute deviation and $S.Risk$ indicates the systemic risk increased measured with the $\Delta CoVaR_{99^{th},i}$. Periods 1 and 2 indicate the lag structure test of one or two lags depending on the sample period.

Table B.5: European markets: variance decomposition of variables. (*Continued*)

	Northern Europe								Southern Europe							
	Denmark		Finland		Norway		Sweden		Greece		Italy		Portugal		Spain	
	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk	CSAD	S. Risk
Full sample period																
	Variance decomposition of CSAD															
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9998	0.0002	0.9983	0.0017	0.9992	0.0008	0.9995	0.0005	1.0000	0.0000	0.9982	0.0018	0.9996	0.0004	0.9987	0.0013
	Variance decomposition of Systemic Risk															
Period 1	0.0000	1.0000	0.0005	0.9995	0.0000	1.0000	0.0027	0.9973	0.0020	0.9980	0.0053	0.9947	0.0012	0.9988	0.0009	0.9991
Period 2	0.0000	1.0000	0.0027	0.9973	0.0009	0.9991	0.0032	0.9968	0.0040	0.9960	0.0084	0.9916	0.0014	0.9986	0.0012	0.9988
Pre-Global financial crisis period																
	Variance decomposition of CSAD															
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9987	0.0013	0.9994	0.0006	0.9993	0.0007	1.0000	0.0000	0.9999	0.0001	0.9998	0.0002	0.9994	0.0006	0.9986	0.0014
	Variance decomposition of Systemic Risk															
Period 1	0.0000	1.0000	0.0002	0.9998	0.0000	1.0000	0.0060	0.9940	0.0002	0.9998	0.0028	0.9972	0.0002	0.9998	0.0001	0.9999
Period 2	0.0021	0.9979	0.0022	0.9978	0.0015	0.9985	0.0062	0.9938	0.0006	0.9994	0.0031	0.9969	0.0002	0.9998	0.0101	0.9899
Global financial crisis period																
	Variance decomposition of CSAD															
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9953	0.0047	0.9987	0.0013	0.9988	0.0012	0.9953	0.0047	1.0000	0.0000	0.9953	0.0047	0.9948	0.0052	0.9999	0.0001
	Variance decomposition of Systemic Risk															
Period 1	0.0051	0.9949	0.0089	0.9911	0.0004	0.9996	0.0015	0.9985	0.0013	0.9987	0.0206	0.9794	0.0009	0.9991	0.0070	0.9930
Period 2	0.0152	0.9848	0.0156	0.9844	0.0047	0.9953	0.0029	0.9971	0.0180	0.9820	0.0214	0.9786	0.0123	0.9877	0.0108	0.9892
Pre-Eurozone crisis period																
	Variance decomposition of CSAD															
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9953	0.0047	0.9968	0.0032	0.9990	0.0010	0.9962	0.0038	0.9966	0.0034	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
	Variance decomposition of Systemic Risk															
Period 1	0.0050	0.9950	0.0073	0.9927	0.0271	0.9729	0.0121	0.9879	0.0133	0.9867	0.0003	0.9997	0.0165	0.9835	0.0014	0.9986
Period 2	0.0249	0.9751	0.0504	0.9496	0.0290	0.9710	0.0320	0.9680	0.0136	0.9864	0.0028	0.9972	0.0177	0.9823	0.0017	0.9983
Eurozone crisis period																
	Variance decomposition of CSAD															
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9999	0.0001	0.9865	0.0135	0.9946	0.0054	0.9952	0.0048	0.9968	0.0032	0.9937	0.0063	0.9957	0.0043	0.9927	0.0073
	Variance decomposition of Systemic Risk															
Period 1	0.0052	0.9948	0.0099	0.9901	0.0074	0.9926	0.0099	0.9901	0.0004	0.9996	0.0063	0.9937	0.0133	0.9867	0.0078	0.9922
Period 2	0.0053	0.9947	0.0104	0.9896	0.0084	0.9916	0.0107	0.9893	0.0041	0.9959	0.0274	0.9726	0.0158	0.9842	0.0120	0.9880
Pre-China's stock market crash																
	Variance decomposition of CSAD															
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9998	0.0002	0.9963	0.0037	0.9980	0.0020	0.9999	0.0001	0.9993	0.0007	0.9882	0.0118	0.9999	0.0001	0.9908	0.0092
	Variance decomposition of Systemic Risk															
Period 1	0.0045	0.9955	0.0003	0.9997	0.0003	0.9997	0.0002	0.9998	0.0027	0.9973	0.0041	0.9959	0.0227	0.9773	0.0004	0.9996
Period 2	0.0052	0.9948	0.0058	0.9942	0.0003	0.9997	0.0014	0.9986	0.0052	0.9948	0.0064	0.9936	0.0231	0.9769	0.0006	0.9994
China's stock market crash																
	Variance decomposition of CSAD															
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9917	0.0083	0.9612	0.0388	0.9962	0.0038	0.9967	0.0033	0.9996	0.0004	0.9940	0.0060	0.9783	0.0217	0.9947	0.0053
	Variance decomposition of Systemic Risk															
Period 1	0.0694	0.9306	0.0370	0.9630	0.0003	0.9997	0.0211	0.9789	0.0380	0.9620	0.0771	0.9229	0.0038	0.9962	0.0198	0.9802
Period 2	0.0696	0.9304	0.0389	0.9611	0.0078	0.9922	0.0256	0.9744	0.0913	0.9087	0.0962	0.9038	0.0094	0.9906	0.0229	0.9771
Post crises period																
	Variance decomposition of CSAD															
Period 1	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
Period 2	0.9964	0.0036	0.9999	0.0001	1.0000	0.0000	0.9986	0.0014	0.9998	0.0002	1.0000	0.0000	0.9856	0.0144	0.9987	0.0013
	Variance decomposition of Systemic Risk															
Period 1	0.0002	0.9998	0.0011	0.9989	0.0011	0.9989	0.0066	0.9934	0.0011	0.9989	0.0001	0.9999	0.0014	0.9986	0.0032	0.9968
Period 2	0.0172	0.9788	0.0126	0.9874	0.0059	0.9941	0.0099	0.9901	0.0519	0.9481	0.0216	0.9784	0.0107	0.9893	0.0459	0.9541

Notes: The table presents the results for decomposing the variance of the variables, based on an unrestricted VAR model, for the Western, Northern and Southern European markets. $CSAD$ is the cross-sectional absolute deviation and $S.Risk$ indicates the systemic risk increased measured with the $\Delta CoVaR_{99^{th},i}$. Periods 1 and 2 indicate the lag structure test of one or two lags depending on the sample period.

due to the CSAD, in Chile for two periods during the period antecedent the EZC. In the Asia Pacific markets, the variance decomposition of the systemic risk increases shows that a higher percentage of variance of the systemic risk increases is due to the CSAD for almost all the countries analyzed. In particular, in the case of China, this percentage reach the value of approximately 26%. This implies that, while for European and American markets only a low percentage of the variance of the systemic risk increases is due to the return clustering measure, for the Asia Pacific markets, which include most of the emerging markets in our sample (7 out of 11),[19] an higher percentage of the variance of the systemic risk increases may be due to the return clustering, and so to herding behavior. This result confirm the view of herding as an ex-ante aspect of systemic risk (Acharya and Yorulmazer, 2008). Indeed, high percentage of the variance of the systemic risk increases due to the return clustering measure are found mainly in the antecedent periods of the main market downturns covered by our sample.

APPENDIX C

Additional material for Chapter 6

C.1 Robustness analysis based on short-selling bans during the crises

In both the GFC and the EZC, regulators imposed bans on short sales. These bans were aimed at preventing stock price turbulence from destabilizing financial stability. In order to test the robustness of our results in Section 6.4.2 and Section 6.4.5, we augment the Eq. (6.2), (6.12) and (6.13) with a dummy variable D^{Crisis} that takes the value 1 during the crisis period, excluding the periods of the short-selling bans, and 0 otherwise. We exclude the short-selling ban periods from the dummy variable in order to avoid uncertainty in our results.

We download the dates of the short-selling regimes from the web-sites of national regulatory bodies and of the Committee of European Securities Regulators. For the scope of our study, we do not distinguish between "naked" and "covered" bans because both types of ban can be used by regulators in order to prevent negative bubble or herding behavior. These bans are seen as a way to stabilize the fundamental value of the firm, and thus its share price (Beber and Pagano, 2013). During the GFC, the short-selling ban imposed in the U.S. covers the period from the 19^{th} of September 2008 to the 8^{th} of October 2008. In the Eurozone several bans have been imposed to different countries during the GFC. We consider the period that spans from the 19^{th} of September 2008 to the 31^{st} of July 2009.[1] During the EZC no ban have been imposed in the U.S.; while, in the Eurozone, we use the period from the 9^{th} of August 2011 to the 16^{th} of December 2012.[2]

Tables C.1 – C.4 confirm and reinforce the results discussed in Section 6.4.2 and Section 6.4.5. In particular, even considering the short-selling bans, we find evidence of herding during the GFC (Table C.1), with both OLS and quantile regressions, for the US and Eurozone equity markets and financial industries. In this case, we find herding also for banks in the Eurozone. Moreover, excluding the short-selling bans, herding behavior seems to be even more pronounced in the quantile tails. During the EZC (Table C.2), in the Eurozone, banks, diversified financials and real estate industries, are (again) found to herd.

Analyzing the case of "intentional" and "spurious" herding during the GFC (Table C.3), our results confirm the evidence that the herding behavior detected during this period was "spurious" more than "intentional"; while, herding was "intentional", during the EZC in the Eurozone (Table C.4).

[1] In particular, the 19^{th} of September 2008 the short-selling ban started in Luxembourg and Ireland. The end of the ban has been settled as the 31^{st} of July 2009, which represents the end of the ban in Italy. The bans imposed in the other Eurozone's countries are included into this period. Other countries like Germany, France and Ireland had a ban until the 31^{st} of January 2010, the 1^{st} of February 2011 and the 31^{st} of December 2011, respectively. However, such periods are not included into the period we define for the GFC.

[2] During the EZC, the end of the ban for the Eurozone coincides with the lift date of the ban in Spain. The bans imposed in the other Eurozone's countries are included into this period.

Table C.1: Estimates of herding behavior for the US and Eurozone equity markets and financial industries, during the GFC considering the short-selling bans.

	Panel A: United States						Panel B: Eurozone					
	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2
All Market Equities												
OLS	0.520***	0.001	-1.788***	4.846***	0.009***	61.16%	0.477***	0.181***	-5.875***	3.346***	0.009***	43.07%
Quantile Regression												
τ=10th	0.280***	0.084***	0.286	1.653***	0.006***	18.17%	0.271***	0.060***	-1.429	3.482***	0.007***	15.47%
τ=25th	0.376***	0.061***	-0.384	2.553***	0.007***	22.64%	0.376***	0.070***	-4.443***	3.968***	0.007***	18.69%
τ=50th	0.485***	0.041	-1.322**	3.894***	0.008***	30.36%	0.461***	0.075***	-5.973*	5.272***	0.008***	23.20%
τ=75th	0.674***	-0.009	-3.320***	6.929*	0.010***	41.00%	0.575***	0.127***	-7.072***	5.952***	0.009***	28.07%
τ=95th	0.938***	-0.270***	-5.695***	16.459***	0.014***	53.68%	0.759***	0.592***	-11.592***	-1.335	0.012***	30.67%
τ=99th	0.814***	-1.011	-5.229**	41.469	0.022***	49.08%	0.342	0.725***	-3.059	-4.859***	0.020***	32.31%
Banks												
OLS	0.431***	0.048**	-0.653**	1.956***	0.005***	61.36%	0.249***	0.237***	-0.668	1.658*	0.008***	45.10%
Quantile Regression												
τ=10th	0.201***	0.034***	-0.036	1.527***	0.003***	18.23%	0.212***	0.136***	-0.850	1.028***	0.004***	15.75%
τ=25th	0.267***	0.048***	-0.108	1.597***	0.003***	24.63%	0.276***	0.161***	-1.781**	1.490***	0.005***	18.8%
τ=50th	0.399***	0.066***	-0.645***	1.815***	0.004***	33.25%	0.273***	0.181***	-1.636**	2.272***	0.007***	22.23%
τ=75th	0.579***	0.070***	-1.111***	2.450***	0.006***	41.68%	0.271***	0.187**	-0.455	3.419*	0.009***	26.46%
τ=95th	1.095***	0.033	-3.450***	3.894	0.010***	55.97%	0.111	0.367***	3.113	3.811***	0.015***	33.55%
τ=99th	1.774***	-0.120	-6.754***	5.976	0.017***	57.47%	-0.233	0.613***	9.689	1.555*	0.025***	35.18%
Diversified Financials												
OLS	0.473***	0.026	-1.312***	3.272***	0.007***	58.31%	0.310***	0.192***	-1.965**	1.212***	0.007***	32.80%
Quantile Regression												
τ=10th	0.292***	0.062*	-0.513***	1.486	0.004***	19.17%	0.216***	0.056***	-1.821	1.725***	0.004***	9.85%
τ=25th	0.364***	0.040***	-0.878***	2.770***	0.005***	23.59%	0.261***	0.083***	-2.160	1.498***	0.005***	11.50%
τ=50th	0.463***	0.051*	-1.524***	2.763***	0.007***	30.31%	0.324***	0.099***	-2.876***	2.389***	0.007***	14.61%
τ=75th	0.573***	0.008	-1.726**	5.259***	0.009***	37.87%	0.445***	0.191***	-3.830***	1.937*	0.008***	18.68%
τ=95th	1.121***	-0.067	-5.193***	6.929***	0.013***	49.88%	0.432***	0.496***	-2.768**	-0.221	0.012***	26.63%
τ=99th	1.353***	-0.345	-6.358***	16.353	0.019***	50.72%	0.011	0.462	3.800	1.006	0.022***	27.05%
Insurance												
OLS	0.498***	0.063*	0.193	3.952***	0.006***	65.81%	0.343***	0.232***	-2.240***	1.981***	0.006***	46.86%
Quantile Regression												
τ=10th	0.188***	0.056***	1.822	1.556***	0.003***	17.92%	0.231***	0.060***	-1.235***	2.284***	0.004***	15.12%
τ=25th	0.231***	0.033	1.967***	3.061***	0.004***	23.70%	0.253***	0.056***	-1.694***	3.353***	0.004***	18.31%
τ=50th	0.407***	0.073***	0.984***	3.063***	0.005***	31.74%	0.302***	0.102***	-1.679	3.255***	0.005***	22.77%
τ=75th	0.609***	0.064	-0.023	4.401	0.006***	42.27%	0.394***	0.190***	-2.571***	3.149***	0.007***	27.85%
τ=95th	1.333***	-0.056	-4.637***	14.889***	0.010***	58.81%	0.730***	0.828***	-7.235***	-2.171***	0.009***	38.36%
τ=99th	2.510***	-0.411	-13.061***	32.734*	0.018***	62.04%	0.368	1.041***	-3.455	-4.191***	0.019***	37.88%
Real Estate												
OLS	0.361***	0.007	-0.487**	3.265***	0.006***	66.43%	0.476***	0.107**	-6.809***	3.294***	0.006***	28.31%
Quantile Regression												
τ=10th	0.208***	0.048***	0.133***	1.266***	0.004***	21.25%	0.241***	-0.005	-3.348**	3.145***	0.003***	7.32%
τ=25th	0.258***	0.068***	-0.124*	0.962***	0.005***	25.81%	0.365***	0.024*	-5.831***	3.035***	0.004***	10.48%
τ=50th	0.314***	0.047	-0.060	2.268	0.006***	33.06%	0.457***	0.042***	-6.686***	3.806***	0.005***	13.72%
τ=75th	0.425***	-0.001	-0.763***	4.350	0.007***	43.11%	0.625***	0.079**	-8.588***	4.670***	0.007***	17.71%
τ=95th	0.870***	-0.063*	-2.592***	6.375***	0.011***	58.39%	0.789***	0.353	-9.720***	5.297	0.012***	22.74%
τ=99th	1.343	-0.478	-4.982	31.752*	0.015***	59.70%	0.896***	0.485	-14.544***	6.520	0.022***	22.13%

Notes: The table reports the estimated coefficients for the augmented model (6.3): $CSAD_t = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1-D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R^2_{m,t} + \gamma_4(1-D^{Crisis})R^2_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation, $R_{m,t}$ is the market return and D^{Crisis} is a dummy variable that takes the value 1 during the period of the GFC, excluding the periods of the short selling bans, and the value 0 otherwise. West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table C.2: Estimates of herding behavior for Eurozone equity market and financial industries, during the EZC considering the short-selling bans.

	Eurozone					
	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2
All Market Equities						
OLS	0.195***	0.241***	0.895	2.619***	0.009***	42.66%
Quantile Regression						
τ=10th	0.147***	0.065***	1.251	3.426***	0.007***	14.01%
τ=25th	0.159***	0.093***	1.173*	3.713***	0.007***	16.42%
τ=50th	0.196***	0.121***	0.481	4.766***	0.008***	20.52%
τ=75th	0.249***	0.257***	-0.011	3.935***	0.009***	26.08%
τ=95th	0.169**	0.735***	3.219	-3.470***	0.012***	33.92%
τ=99th	-0.326***	0.895***	12.468***	-7.223***	0.019***	35.98%
Banks						
OLS	0.297***	0.213***	-0.380	2.074**	0.008***	45.53%
Quantile Regression						
τ=10th	0.192***	0.100***	0.581***	1.643***	0.005***	16.51%
τ=25th	0.280***	0.130***	-0.600	1.681***	0.006***	19.83%
τ=50th	0.311***	0.127**	-0.406**	3.383*	0.007***	23.46%
τ=75th	0.356***	0.124*	-0.862***	4.525**	0.009***	27.52%
τ=95th	0.344***	0.389***	-0.632	3.658***	0.015***	34.34%
τ=99th	-0.225	0.664***	7.276	1.180	0.025***	37.83%
Diversified Financials						
OLS	0.174***	0.220***	0.241	0.931**	0.007***	33.05%
Quantile Regression						
τ=10th	0.080***	0.062***	1.450***	1.686***	0.004***	9.06%
τ=25th	0.115***	0.104***	0.895*	1.363***	0.005***	10.56%
τ=50th	0.173***	0.149***	-0.118	1.784***	0.006***	13.72%
τ=75th	0.238***	0.256***	-0.849	1.334	0.008***	18.38%
τ=95th	0.328***	0.564***	-2.146*	-0.937	0.012***	27.45%
τ=99th	-0.630**	0.518	25.668***	-0.013	0.022***	29.34%
Insurance						
OLS	0.167***	0.275***	1.096	1.611***	0.006***	47.98%
Quantile Regression						
τ=10th	0.121***	0.070***	0.471	2.175***	0.004***	13.78%
τ=25th	0.135***	0.084***	0.702	3.123***	0.004***	17.59%
τ=50th	0.173***	0.136***	0.816	3.012***	0.005***	22.31%
τ=75th	0.226***	0.248***	0.336	2.701***	0.007***	27.83%
τ=95th	0.217***	0.883***	1.247***	-2.586***	0.010***	41.91%
τ=99th	-0.326	1.192***	11.793*	-5.216***	0.017***	42.03%
Real Estate						
OLS	0.131***	0.171***	-0.988	2.400***	0.006***	27.62%
Quantile Regression						
τ=10th	0.098***	0.008	-1.300*	3.006***	0.003***	6.76%
τ=25th	0.148***	0.058***	-1.865***	2.710***	0.003***	9.09%
τ=50th	0.145***	0.094***	-1.452	3.306***	0.005***	11.59%
τ=75th	0.141***	0.182***	-0.233	3.450***	0.007***	15.84%
τ=95th	0.181	0.626***	-0.816	-1.065	0.011***	23.53%
τ=99th	-0.335	0.770	14.242	-2.943	0.022***	24.51%

Notes: The table reports the estimated coefficients for the augmented model (6.3): $CSAD_t = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1 - D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R^2_{m,t} + \gamma_4(1 - D^{Crisis})R^2_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation, $R_{m,t}$ is the market return and D^{Crisis} is a dummy variable that takes the value 1 during the period of the EZC, excluding the periods of the short selling bans for the Eurozone's countries, and the value 0 otherwise. West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table C.3: Estimates of herding behavior due to non-fundamentals and fundamentals for the US and Eurozone equity markets and financial industries, during the GFC considering the short-selling bans.

	Panel A: United States				Panel B: Eurozone			
	$CSAD_{NONFUND,t}$		$CSAD_{FUND,t}$		$CSAD_{NONFUND,t}$		$CSAD_{FUND,t}$	
	γ_3	γ_4	γ_3	γ_4	γ_3	γ_4	γ_3	γ_4
All Market Equities								
OLS	0.113	-0.613*	-1.869***	5.636***	0.214	-0.106	-2.195**	6.258***
Quantile Regression								
τ=10th	-0.029	0.332***	-0.289	1.805***	0.213**	0.812***	1.072**	2.261**
τ=25th	1.295***	-3.742***	-1.040**	2.673**	2.297***	-0.580	-0.474	3.141***
τ=50th	-0.343**	-0.201*	-2.818***	4.880***	0.256	0.152	-2.415***	4.627***
τ=75th	-0.700***	-0.091	-2.995***	9.220*	-1.080***	0.115	-3.873***	7.437***
τ=95th	-0.330***	0.501	-3.997***	17.007***	-0.486***	0.671	-8.018***	12.167***
τ=99th	-0.134***	0.842***	-3.277	33.568***	-0.256***	0.908***	-13.163	21.573
Banks								
OLS	0.090	-0.694***	-0.695***	2.673***	0.136	-0.641***	0.628	2.475***
Quantile Regression								
τ=10th	-0.081	-0.965*	-0.368	1.562	-0.172***	-0.377	0.501***	1.384***
τ=25th	0.290*	-5.057**	-0.664**	1.827***	0.405**	-4.870***	-0.030	2.146***
τ=50th	0.176**	-0.454	-1.105***	2.268***	0.717**	-0.246***	-0.042	3.678***
τ=75th	-0.364***	-0.262***	-0.543***	5.798***	-0.734***	-0.099	1.056	4.632***
τ=95th	-0.159***	0.402	-2.620***	5.378	-0.320***	0.388	0.403	6.916**
τ=99th	-0.087***	0.592	-5.096	3.984	-0.146***	0.486***	-2.912	20.662
Diversified Financials								
OLS	0.030	-0.343***	-1.289***	3.721***	-0.012	-0.152	-0.565	4.211***
Quantile Regression								
τ=10th	-0.034	0.108**	-0.620***	1.345	0.062***	-0.249	0.213	2.238***
τ=25th	0.542***	-1.511***	-0.976***	3.038***	0.483***	-2.196***	-0.366	2.577***
τ=50th	-0.050	-0.251***	-1.800***	3.320**	0.000	0.138	-0.690	3.871***
τ=75th	-0.439***	-0.098	-0.970***	7.478***	-0.528***	0.157	-1.051***	3.907***
τ=95th	-0.196***	0.747	-3.866***	7.244***	-0.219***	0.770	-3.255***	13.634
τ=99th	-0.106***	0.820	-6.203***	9.232	-0.090*	0.951**	-2.655***	44.341***
Insurance								
OLS	0.113	-1.775***	0.088	5.818***	0.177	-0.351	-0.402	3.845***
Quantile Regression								
τ=10th	0.147**	0.153	-0.028	1.869***	0.006	0.615***	1.246***	1.662***
τ=25th	0.558***	-9.415***	0.183	3.128**	0.676***	-4.572***	0.249	2.225***
τ=50th	-0.306**	-1.059***	-0.482	4.421***	0.012	-0.204	-0.371	3.338***
τ=75th	-0.711***	-0.417*	1.069**	13.687*	-0.880***	-0.296**	-0.116	4.247***
τ=95th	-0.339***	0.776	-2.447**	19.051***	-0.229***	0.616	-5.071***	3.778***
τ=99th	-0.127***	1.295**	-11.649***	35.397	-0.097***	1.144**	-7.570	30.943
Real Estate								
OLS	0.101	-0.456	-0.597***	3.751***	0.334	-0.115	-1.522	5.404***
Quantile Regression								
τ=10th	0.057**	0.255**	-0.145	1.200***	-0.400	-0.072	-0.773	0.832
τ=25th	1.092***	-0.960***	-0.516***	1.017***	1.560***	-0.678***	-0.936	2.241
τ=50th	-0.087**	-0.071	-0.788***	2.650***	0.695***	-0.012	-2.518***	4.702***
τ=75th	-0.298***	-0.182	-0.747***	5.363**	-0.689***	0.042	-3.903***	5.085***
τ=95th	-0.131***	0.726	-1.640*	9.023	-0.192***	0.656	-4.854***	19.322***
τ=99th	-0.083***	1.253**	-3.597***	30.667*	-0.061*	0.720**	-9.476***	30.770

Notes: The table reports the estimated coefficients for the augmented models (6.12) and (6.13): $CSAD_{NONFUND,t} = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1-D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R^2_{m,t} + \gamma_4(1-D^{Crisis})R^2_{m,t} + e_t$, and $CSAD_{FUND,t} = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1-D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R^2_{m,t} + \gamma_4(1-D^{Crisis})R^2_{m,t} + e_t$; $CSAD_{NONFUND,t} = \varepsilon_t$, form regression (6.7): $CSAD_t = \alpha + \beta_1(R_{m,t} - R_f) + \beta_2 HML_t + \beta_3 SMB_t + \beta_4 MOM_t + \varepsilon_t$; $CSAD_{FUND,t} = CSAD_t$ - $CSAD_{NONFUND,t}$. D^{Crisis} is a dummy variable that takes the value 1 during the period of the global financial crisis, excluding the periods of the short selling bans, and the value 0 otherwise. West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table C.4: Estimates of herding behavior due to non-fundamentals and fundamentals for the Eurozone equity market and financial industries, during the EZC considering the short-selling bans.

	Eurozone			
	$CSAD_{NONFUND,t}$		$CSAD_{FUND,t}$	
	γ_3	γ_4	γ_3	γ_4
All Market Equities				
OLS	-2.642***	0.467*	4.171***	2.128***
Quantile Regression				
τ=10th	-10.794***	0.405***	3.324***	3.521***
τ=25th	-3.840***	2.088***	3.219***	3.473***
τ=50th	-1.691***	0.266***	3.133***	3.399***
τ=75th	-1.197***	0.653**	6.027***	1.615***
τ=95th	0.522	-0.401***	10.012***	-3.043***
τ=99th	1.092***	-0.158	14.016***	-5.206***
Banks				
OLS	-1.582***	-0.027	1.555**	2.205**
Quantile Regression				
τ=10th	-7.895***	0.198**	1.311***	1.371***
τ=25th	-7.662***	0.035	0.887***	1.598***
τ=50th	-1.312***	0.107	3.553***	3.898***
τ=75th	-0.886***	0.231*	3.198***	4.082***
τ=95th	0.294	-0.221***	1.382**	4.140***
τ=99th	0.878***	-0.026	8.730	0.655
Diversified Financials				
OLS	-1.791***	0.098	2.675***	0.836***
Quantile Regression				
τ=10th	-5.951***	0.082***	2.938***	1.502***
τ=25th	-4.165***	0.391***	2.508***	1.228***
τ=50th	-1.548***	0.078	2.641**	1.475**
τ=75th	-1.046***	0.239**	2.881**	0.997***
τ=95th	0.450	-0.207***	3.957	-0.318
τ=99th	1.378***	-0.046	28.149***	0.095
Insurance				
OLS	-2.305***	0.335	3.697***	1.246**
Quantile Regression				
τ=10th	-11.190***	0.301***	2.213***	1.880***
τ=25th	-9.338***	0.645***	3.111***	2.436***
τ=50th	-2.046***	0.250***	3.674***	1.591***
τ=75th	-1.597***	0.141	5.172**	1.642***
τ=95th	0.407	-0.170***	7.343	-2.184***
τ=99th	1.103***	-0.086***	14.364**	-4.878***
Real Estate				
OLS	-2.684***	0.460***	2.424*	1.922***
Quantile Regression				
τ=10th	-9.116***	0.277***	-0.079	2.818***
τ=25th	-2.513***	1.609***	-0.006	1.975***
τ=50th	-2.060***	0.373***	1.831*	1.976
τ=75th	-1.331***	0.617***	4.178***	1.732***
τ=95th	0.743**	-0.148**	9.149	-0.810
τ=99th	1.432***	-0.053	30.259	1.169

Notes: The table reports the estimated coefficients for the augmented models (6.12) and (6.13): $CSAD_{NONFUND,t} = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1-D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R^2_{m,t} + \gamma_4(1-D^{Crisis})R^2_{m,t} + e_t$, and $CSAD_{FUND,t} = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1-D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R^2_{m,t} + \gamma_4(1-D^{Crisis})R^2_{m,t} + e_t$; $CSAD_{NONFUND,t} = \varepsilon_t$, form regression (6.7): $CSAD_t = \alpha + \beta_1(R_{m,t} - R_f) + \beta_2 HML_t + \beta_3 SMB_t + \beta_4 MOM_t + \varepsilon_t$; $CSAD_{FUND,t} = CSAD_t$ - $CSAD_{NONFUND,t}$. D^{Crisis} is a dummy variable that takes the value 1 during the period of the Eurozone crisis, excluding the periods of the short selling bans for the Eurozone's countries, and the value 0 otherwise. West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.