Empirical Aspects of Financial Stability

Submitted by

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Abstract

This thesis discusses the empirical aspects of financial stability and presents evidence that suggests that stock market bubbles and volatility are related, and that financial crises are also triggered by events related to non-financial sectors. Financial crises are predominantly related to boom episodes and asset price bubbles, which can seriously impact the financial system when they burst. This thesis draws upon the findings of previous papers and argues that the risk of financial instability (systemic risk) is formed during the boom phase and materialises on the eruption of crisis. In so doing, this study considers stock market bubbles as a potential source of risk for financial stability.

The severe impact on the economy in the wake of the recent financial crisis has not only demonstrated the way in which trouble in a relatively small market can escalate into a serious crisis exerting economy-wide effects, but is also an example of the important role financial stability plays in the functioning of modern economies. Chapter 1 addresses factors that contribute to financial crises and policy tools to mitigate their effects. The Global Financial Stability Map (Map), summarising and graphically presenting underlying factors that may lead to a systemic threat, shows the complex interactions among different factors that affect each other and, in combination, are relevant to financial stability. In this connection, the importance of countercyclicality is addressed and the weaknesses of the Value at Risk (VaR) measure are discussed.

Chapter 2 examines whether longer periods of low volatility influence the formation of bubbles, which are defined as the difference between current prices and an adaptive moving average of an alternate history of asset prices, and whether stock market bubbles increase the likelihood of stock market crashes. The regression analysis employed confirms that longer episodes of low realised volatility exerts a significant influence on the formation of stock market bubbles, which, in turn, significantly increase the likelihood of stock market crises. This relationship is referred to as volatility paradox. Furthermore, the bubble is incorporated to inflate Value at Risk, in order to generate a countercyclical capital buffer for extreme events. It is shown that the inflated VaR covers the majority of the extreme negative returns. This leads to the conclusion that the information content of bubbles should be taken into account while measuring risk in stock markets.

The recent financial crisis revealed that even relatively small markets of the economy are capable of jeopardising financial stability, and the objective of Chapter 3 is to assess the contribution of both financial and non-financial sectors of an economy to systemic risk. For this purpose, the marginal systemic risk contribution, measured by ΔCoVaR of

10 sectors, is estimated for the US, the UK, and Germany, through the employment of quantile regressions. The estimated ΔCoVaRs are tested for significance and dominance in order to classify sectors as systemically relevant and to obtain a formal ranking of the sectors in terms of contribution to systemic risk. The outcomes reveal a weak link between VaR and ΔCoVaR and significant externalities of sectors. Chapter 3 discusses the role of low volatility in excessive risk–taking and lending behaviour during booms as well as the deleveraging behaviour during bust episodes. It argues that countercyclical tools, which reduce such behaviour, can successfully mitigate financial crises. This line of argumentation is related to the countercyclical capital buffer discussed in Chapter 2, which is aimed at dampening the upward movements of asset prices. Taking into account the finding that real economy sectors also have significant effects on systemic risk, Chapter 3 proposes the application of macroprudential policy tools individually to those sectors in which bubbles emerge.

Chapter 4 compares the realised volatility levels between international stock markets. Although the volatility patterns are fairly similar, the pairwise t-test reveals a significant difference between the volatility levels of national stock markets. A two component GARCH-MIDAS model is applied to decompose conditional volatility into a short-run and a long-run volatility component and to link macroeconomic variables directly with stock market volatility. The outcomes of the GARCH-MIDAS model indicate that stock market volatility is associated with macroeconomic variables, and that stock market volatility depends upon different variables in different countries. Realised volatility is found to explain a considerable proportion of conditional volatility. The Granger causality test reveals no significant causal relationship of volatility with illiquidity or with sentiment.

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List of Abbreviations

τ (tau)	Long-run volatility component
Δ	Inflator
ΔCoVaR	Delta CoVaR
μ_d	Benchmark on day d
ADF	Augmented Dickey-Fuller unit root test
ANFCI	Adjusted National Financial Conditions Index
AR(1)	First-order autoregressive model
B_d	Bubble on day d
BIS	Bank for International Settlement
B_t	Average of daily bubbles within month t
BuVaR	Bubble Value at Risk
CCI	Consumer confidence index
CoVaR	Conditional Value at Risk
CPI	Growth rate of consumer price index
C_t	Crisis indicator
DIP	Distress insurance premium
DP	Dividend yield
DTV	Debt-to-Income
ECB	European Central Bank
ERP	Equity risk premium
ES	Expected shortfall
FRED	Federal Reserve Economic Data
FXR	Exchange rate index
g	Short-run volatility component
GFSR	Global Financial Stability Reports
GSADF	Generalized sub ADF
ICB	Industry Classification Benchmark
IMF	International Monetary Fund
IPG	Growth rate of industrial production
IPO	Initial public offering
K	Number of variable lags

LR_{ind}	Likelihood-ratio test statistic for independence
LR_{uc}	Likelihood-ratio test statistic for unconditional coverage
LTV	Loan-to-Value
Map	Global Financial Stability Map
MES	Marginal expected shortfall
MIDAS	Mixed data sampling regression
MILL	Market illiquidity measure
MP	Growth rate of industrial production
M_t	Number of trading days in month t
NIPO	Number of IPOs
OECD	Organisation for Economic Co-operation and Development
PC1	First principal component
POF	Proportion of failures test
PP	Phillips-Perron unit root test
PPI	Growth rate of producer price
q	Quantile
q	Quarter
RIPO	Average first-day return on IPOs
RV	Realised volatility
SDSVaR	State-dependent sensitivity VaR
SENT	Sentiment index
SES	Systemic expected shortfall
SIFI	Systemically important financial institution
SPR	Term premium
SV	State variables
t12	12 months lagged variable
t24	24 months lagged variable
TARP	Troubled Asset Relief Program
TUFF	Time until first failure test
TURN	Market turnover

Unemp	Unemployment rate
UPR	Default premium
UTS	Term premium
VaR	Value at Risk
VAR	Vector autoregression model
VR	Variance ratio
θ	Slope parameter

Chapter 1 Introduction

'Der Kluge ist der, welchen die scheinbare Stabilität nicht täuscht und der noch dazu die Richtung, welche der Wechsel zunächst nehmen wird, vorhersieht.'

Arthur Schopenhauer (1788–1860)

Like many other quotes, there are surely numerous ways to interpret the quote by Schopenhauer (1851). Most may interpret the quote in the sense that individuals should not let the current, seemingly obvious, situation mislead them about the inherent jeopardies and that any situation draws to a close. This also implies that people should be vigilant regarding changing conditions and accordingly modify their behaviour. The consequences of activities should be borne in mind, and it is advisable to act diligently and with foresight. One might interpret that one should be prepared for sudden and unexpected events that pose significant risks to the conditions, which could be affected in the long-run. Metaphorically, this could mean that agents in financial markets must act deliberately and try to foresee the consequences of their decisions. Risk management strategies must account for the potential risks for wealth, which also implies that risk measures are modified according to the current conditions. A lack of appropriate risk management tools or an over-reliance on positive developments accompanied by excessive risk-taking behaviour can substantially threaten financial stability, i.e. according to Rosengren (2011), the financial system's ability to continuously provide credit intermediation and payment services that are needed in the real economy to grow. The definition of financial stability by Rosengren (2011) implies three key elements of financial instability: Financial system problems, damage of intermediation or the provision of it, and severe effects on the real economy.

In the governmental statement on 15th February 2008, the German Minister of Finance Peer Steinbrück considered the US mortgage market as the source of the financial crisis 2007–2009. Experts had long under-estimated or even neglected the potential strain it would place on the global financial system. The avarice for high returns motivated banks in the US to lower their requirements for creditors and lend credits on low securities. These bundled credit risks were sold to investors around the world and drove many banks to the brink of collapse when the boom ended. In his governmental statement, Peer Steinbrück also referred to the obvious infection risk of the financial crisis on the global economy and the global economic growth. Yet, the fundamental data did not indicate a massive downturn, or even a recession, of the German economy.

The German economy was considered to be robust, and the industrial production was expected to evolve positively (Steinbrück, 2008).

However, in October 2008, Steinbrück stated that the economy was confronted with substantial risks and that the financial crisis reinforced this negative trend. Steinbrück regarded the current financial crisis as the most dangerous financial market crisis since the Great Depression and predicted a very turbulent 2009 (Steinbrück, 2008a).

The international financial system was on the brink of collapse when the summer of 2008 came to an end. The real economy was severely affected by the financial market turbulences. The global growth suffered its most intense drop for decades and developed countries suffered an unexampled downturn in value added. Uncertainty surged, the confidence of market participants diminished, and they were unwilling to estimate risk. Consequently, risk premia rose to unprecedented levels. An extraordinary widening of bid-ask spreads over a spectrum of financial instruments and a four-fold rise of risk perception indicators in the equity markets, derived from option prices compared with pre-crisis levels, were observed. The overall level of activity had dramatically decreased in important economies and growth expectations were revised upwards from the third quarter of 2009 (Deutsche Bundesbank, 2009).

The recent financial crisis is one crisis among many that was triggered by an asset price collapse. Many crises have been related to problems in the real estate sector, usually following a period of rapid and sharp increases in values. Although two crises are never exactly alike, there are some elements that financial crisis episodes have in common, such as stock prices decreases, implied volatility increases and portfolio turnover from riskier asset classes toward low-risk asset classes. Additionally, trading activities reduced and market liquidity worsened (OECD, 2008).

Figure 1.1 illustrates the values of major stock market indices. Major volatility indices derived from option prices are demonstrated in Figure 1.2.

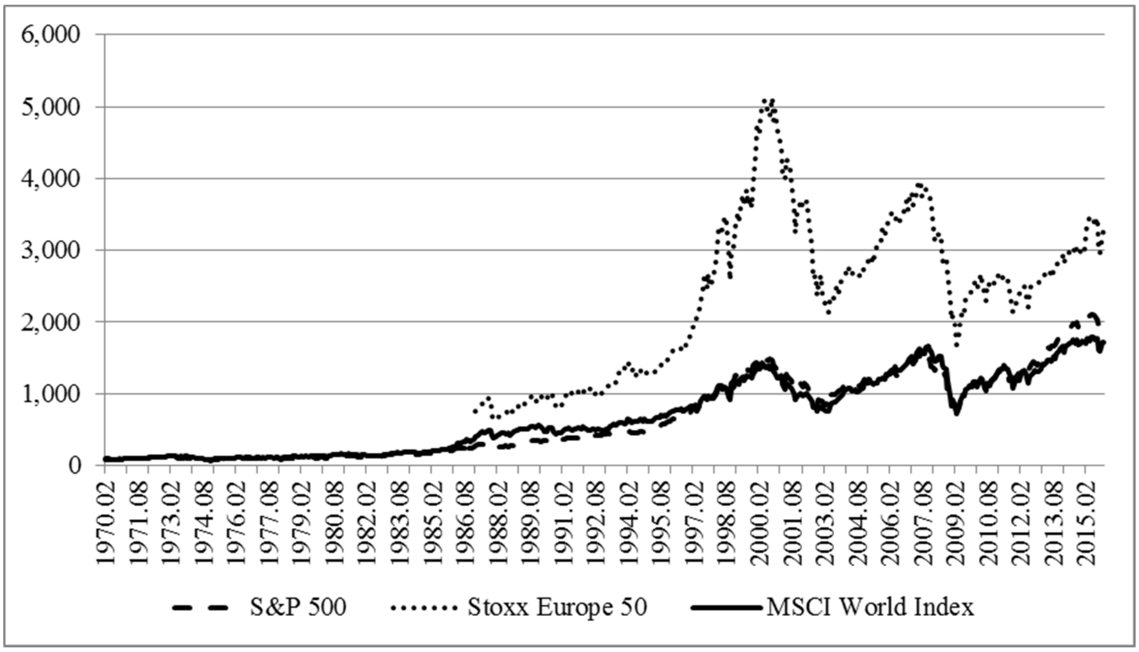

Figure 1.1: History of major stock market indices.
The index values are at monthly frequency and were taken from Datastream. The observation period ends in December 2015. S&P500 and the MSCI World Index are expressed in the US Dollar and the Stoxx Europe 50 is expressed in the Euro.

Equity returns outperformed those on bonds from 1974 to 1999 on an average of 15% per annum in those countries forming the euro area today. This is also the case for the US. As a consequence of the market crashes, which followed the dot.com bubble burst in 2000/2001 and the collapse of Lehman Brothers in 2008, the equity returns between 2000 and 2012 fell to levels of 3% and 2% per annum in the euro area and the US, respectively, and were below the returns on long-term government bonds. The evolution of the market indices in both economic areas from 2009 indicate that the development in the euro area has uncoupled from the US in wake of the European debt crisis (ECB, 2013).

Periods of stock price decreases tend to coincide with higher stock market volatility episodes. Figure 1.2 shows that after a period of low volatility index levels, the levels increased with the outburst of the financial crisis in the summer of 2007 and kept on high levels in the aftermath. Typically, during such periods, investors become more uncertain and require higher risk premia as compensation for holding equities (ECB, 2008). The equity risk premia (henceforth ERP) for major industrial countries are displayed in Figure 1.3.

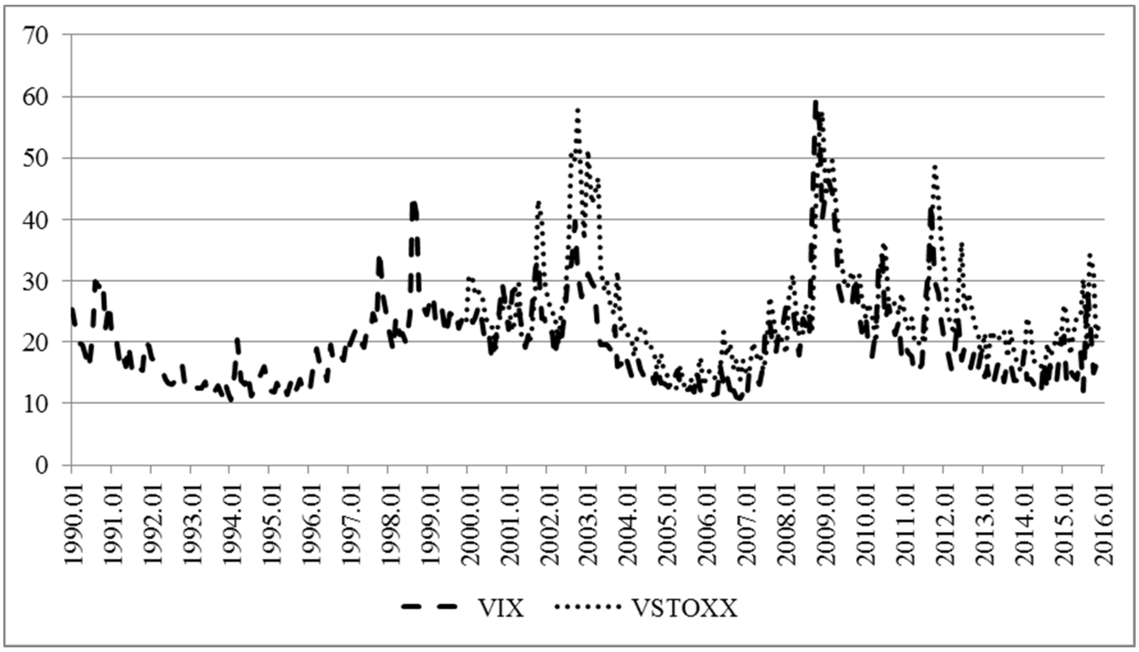

Figure 1.2: Historical volatility indices.
The VIX was taken from FRED database and the VSTOXX was taken from Datastream. The observation period ends in December 2015.

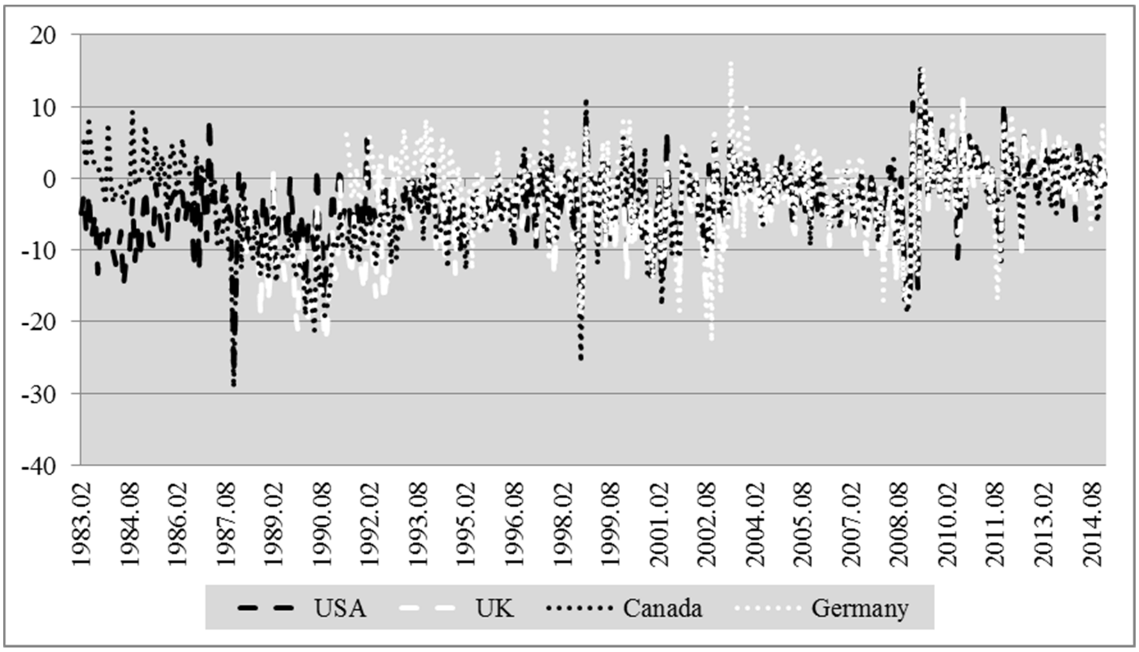

Figure 1.3: Historical equity risk premia for major industrial countries.
The ERP is considered as a proxy of the risk aversion. The equity risk premium was calculated by the author as difference between the stock market index return in month t and the 3-month riskless yield in the same month. These data were downloaded from Datastream.

Many factors contributed to the recent financial crisis, but the triggering event was the enormous underestimation of risk in the subprime residential mortgage loans in the US (OECD, 2008) preceded by a long period of low interest and inflation rates. As a result, the economic environment was highly optimistic, characterised by a rapid expansion of credit and large housing price increases. Loose lending standards and over-reliance on rating agencies, among other factors, gave rise to a more fragile financial system. The financial crises set in with rapidly decreasing housing prices in the US, severely affecting the economy (Wilkinson et al., 2010).

The importance of financial stability and the complexity of its underlying factors motivated the introduction of the Global Financial Stability Map (henceforth Map), which provides a summary and graphical presentation of four risks and two conditions that are relevant for financial stability. The idea behind the Map is to separate its underlying risks and conditions that may lead to a systemic threat rather than considering one single indicator. The risks and conditions are displayed on six axes, respectively, where the assessment of each axis is indicated by dots along the axis, i.e. dots closer to the centre represent lower risks, reduced risk appetite and tighter monetary and financial conditions. Figure 1.4 illustrates how the dots in the Map move from April 2007 to October 2009 (Dattels et al., 2010).

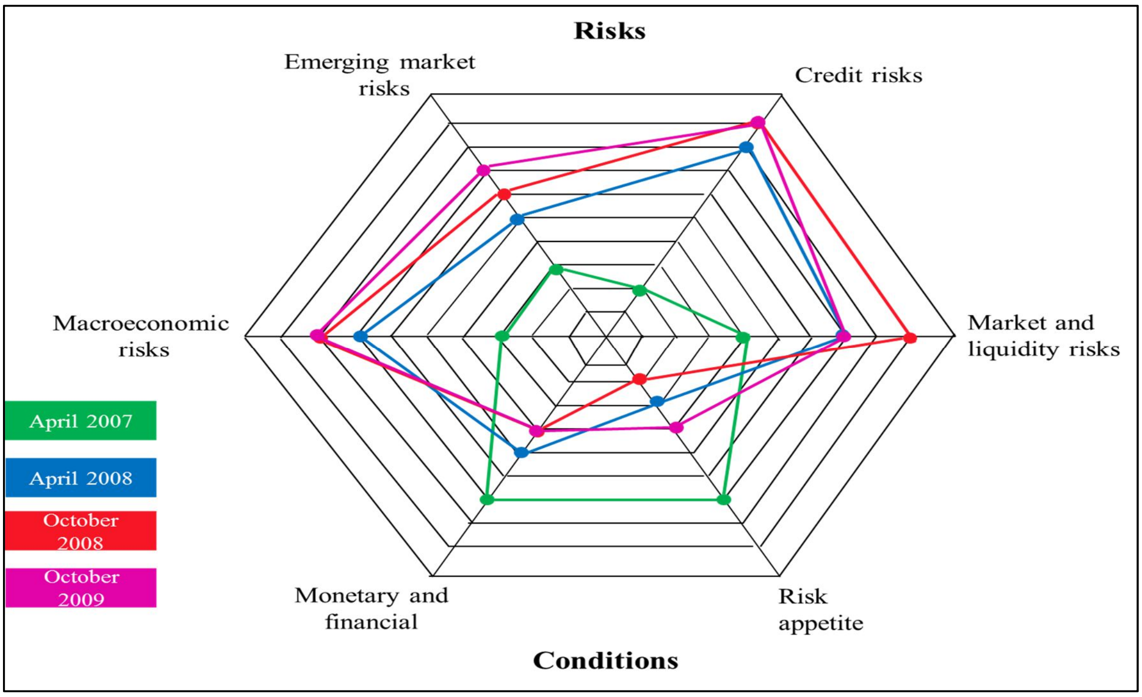

Figure 1.4: Changes in the Global Financial Stability Map over the financial crisis.
The two categories at the bottom represent the conditions and the remaining four categories are the risks. Dots closer to the centre represent tighter monetary and financial conditions and lower risk appetite or less risk. The Map was created based on Dattels et al. (2010) and various IMF Global Financial Stability Reports (henceforth GFSR). The dots for April 2007 were taken from the April 2007 GFSR (IMF, 2007). The dots for April 2008 and October 2008 were taken from the October 2008 GFSR (IMF, 2008). The dots for October 2009 were taken from the October 2009 GFSR (IMF, 2009a). The dots from April 2007 to April 2009 are also illustrated in Dattels et al. (2010).

The individual risk categories do not directly threaten the financial stability, but events affecting one risk category could affect others. Low interest rates and low volatility fostering risk-taking behaviour and leverage intensify the possibility of linkages between the risk categories (IMF, 2007).

A long period of easy macroeconomic and financial conditions had led to high risk appetite levels and large imbalances prior to the crisis. The Map indicated to a credit risk increase in October 2007 caused by declining US housing prices and a surge in credit risks because of the Lehman bankruptcy. Risk appetite sharply contracted prior to the crisis. Macroeconomic risk was low at the beginning of the crisis, but increased throughout the crisis. The similar pattern holds for market and liquidity risk, which reached its peak in the aftermath of the Lehman collapse (Dattels et al., 2010). This indicates a deterioration in macroeconomic risk brought on by the economic downturn. Credit risks also increased due to the uncertainty of the downturn and strains on the financial system (IMF, 2009). By April 2011, the conditions became easier than during the crisis and the risk appetite increased again, which encouraged risk assets to rally. Besides that, macroeconomic risks decreased because of an improved activity and lower deflation risks (IMF, 2011).

The Map can be altered by decomposing certain categories or adding further categories. The Map's ability to capture systemic risk is improved by constantly examining additional techniques and indicators (Dattels et al., 2010).

For example, history provides evidence that asset price bubbles pose significant risks to systemic stability. Financial systems tend to create boom-bust cycles in asset prices. These can take such systemic scales that they can contribute or even cause financial crises and recessions. Hence, bubbles are a potential risk to financial stability and contribute to building-up systemic risk in the background which materialises when the crisis erupts. As a result, the banking system can collapse along with severe impacts on the real economy (Tumpel-Gugerell, 2011).

The effect of bubble bursts on the economy and the financial system are most severe when market participants are highly leveraged and high bank-provided debt finance is involved, but is less dependent on the asset type (Brunnermeier and Schnabel, 2016).

The high costs associated with the recent financial crisis have stimulated the long-standing debate on how central banks should deal with asset price bubbles and raised the question of whether the associated costs would have been reduced if the monetary policy had accounted for the bubbles in asset prices. While an ex-post 'cleaning up the mess' policy, i.e. mitigating the effects of a bubble burst instead of preventing their build-up, is often costly, the prevention of bubbles by 'leaning against the wind' policy, i.e. reacting early to growing asset prices, can help deflate bubbles and alleviate economic crises and has sometimes succeeded (Brunnermeier and Schnabel, 2016). This 'leaning against the wind' attitude, which is involved in the ECB monetary analysis, was conducive to soften the economic consequences during the recent financial crisis. Additionally, macroprudential policy tools are acquired by regulators who aim at applying an 'ex-ante' policy to prevent the build-up of asset price bubbles and lower the procyclicality of the financial system. Two important preventative policy tools are countercyclical liquidity and capital buffers (Tumpel-Gugerell, 2011).

One such countercyclical method designed to address regulatory capital is the Bubble Value at Risk (henceforth BuVaR) approach proposed by Wong (2011, 2013).

As VaR is defined as the minimum loss that can happen to an asset in the (1-α)% worst cases it only considers the smallest loss of the (1-α)% possible losses and the potential amount of a loss is neglected. Consequently, two assets can have the same VaR, but inhere very different potential losses in extreme market movements since VaR does not describe the losses in the tails. Figure 1.5 graphically illustrates the failure of VaR in describing the tail of a distribution. Panel A (which represents asset A) depicts the (1-α)% VaR of a distribution and the returns below this level. In panel B (which represents asset B) the fraction below the VaR level is shifted to the left without affecting the (1-α)% VaR. The VaR remains unchanged, although the potential loss of asset B is much higher than that of asset A.

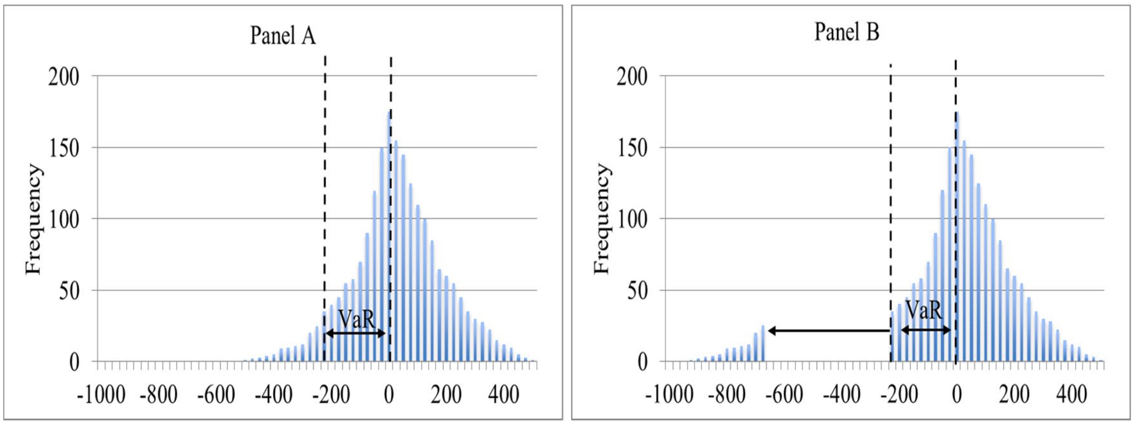

Figure 1.5: Same VaR despite different distributions
This is a theoretical example and reproduces the example shown in Leippold (2004)

The fact that potential losses are not considered can increase the risk to an entire institution, in the sense that risk managers who rely on VaR pay no attention to the potential losses as VaR is the same number no matter how large the potential loss actually is (Leippold, 2004).

Traders have an incentive to buy instruments that promise high profits, but contain low-probability large downside potential risks that are accepted as long as they meet the allowable VaR constraint. Besides that, the use of VaR might negatively impact the financial system when everyone in the system uses VaR. VaR users act like dynamic hedgers who adjust their positions according to the market prices, which leads to the danger of uncorrelated risks turning into correlated risks. As a result, the risk is larger than represented by the VaR models applied by institutions (Dowd, 2005). In short, VaR does not say anything about the potential loss in the worst cases and is, therefore, 'blind' to the sizes of tail losses without indicating how bad 'bad' might be (Dowd, 2010).

Accounting for the information content in price levels makes the expected loss dependent on the asset price level and poses an estimate of the expected loss between the minimum loss, represented by VaR and the maximum loss (Wong, 2013).

Given previous papers' findings, this thesis assigns an important role to bubbles and addresses the relationship between asset price bubbles and their effect on stock market crashes as well as financial system stability. It is common sense that the build-up of bubbles mostly occurs in a low volatility environment and easy monetary and financial conditions. Motivated by the countercyclical behaviour of stock market volatility and the volatility differences observed between major industrialised countries, the thesis further examines the time variation of volatility in stock markets by directly linking it with macroeconomic variables. In so doing, the thesis uses international data on stock markets and macroeconomic variables focusing on the G7 countries Canada, Germany, the UK and the US, respectively. Claessens and Kose (2013) regard crises as extreme demonstrations of the interplay between the real economy and the financial sector. From this perspective, it is imperative to understand macro-financial linkages to understand financial crises (Claessens and Kose, 2013). This is a complicated issue and this thesis' objective is more modest in that it examines the effect of real economy sectors on systemic risk. As such, the thesis extends the existing literature on systemic risk, which mostly considers the impacts of problems in the financial system on the real economy (see e.g. the definitions of systemic risk by The Group of Ten (2001) or ECB (2009)).

In considering the different aspects of financial stability, i.e. stock market bubbles, systemic risk and stock market volatility, this thesis points out that these aspects are not independent of each other, but are interlinked.

Historical data on financial markets provides evidence that bubbles, crashes and financial crises have been repetitive events from the beginning of financial markets up to today. Although boom and crisis phases have demonstrated common patterns and recurrent issues, each boom and crisis is individual regarding its details. Typically, in a financial crisis, a crash follows a boom period in asset prices so that, in almost all financial crises, a run-up phase and a crisis phase play a role (Brunnermeier and Oehmke, 2013).

Motivated by the literature on asset price bubbles and the consequences of bubble bursts, chapter 2 addresses the relationship between stock market bubbles and crashes in the US stock market during the post-World War II period. In this connection, bubble episodes in the US stock market are first identified, where bubbles are considered as explosive asset price bubbles and the AR(1) regression approach is adopted to detect periods of explosive asset price dynamics. The AR(1) coefficients allow timestamping bubbles' episodes and investors' behaviours once a bubble period has been detected. As we will see in chapter 2, the AR(1) coefficients in the post-World War II era indicate a deflationary behaviour rather than a sudden bubble burst. Further analysis accounts for the relationship between bubbles and crashes in the stock market and applies a logistic regression including the bubble, the realised volatility (RV) and macroeconomic state variables to predict the probability of stock market crises. In so doing, the bubble is considered as a deviation of the current price level from its long-term average irrespective of the fundamental value of the stock market index. The logistic regression analysis shows that bubbles increase the probability of stock market crashes and that the predictive power of bubbles, regarding stock market crises, only holds in the short run, i.e. around one year. The logistic regression results do not find a significant direct relationship between realised volatility and stock market crashes. Furthermore, chapter 2 takes the predictive power of bubbles, with respect to stock market crashes, into account in measuring downside risk and estimates BuVaR. It is shown that BuVaR estimates cover most of the extreme negative stock market returns in contrast to VaR. BuVaR thus acts as countercyclical buffer that protects against events in the fat-tail (Wong, 2013). In light of the logistic regression results, the BuVaR approach is modified with respect to the length of the rolling window referred to as the modified BuVaR. The visual inspection illustrates that the modified BuVaR is closer to extreme returns than BuVaR. The logistic regression results show a significant crisis effect for the bubble, but not for realised volatility. Further empirical examination using linear regression suggests that a long period of realised volatility is significantly related to the bubble with an increasing effect when the time horizon is longer. Given the bubble's significant effect on stock market crises, it is argued that realised volatility indirectly affects stock market crashes through the bubble as it significantly affects bubble formation, and bubbles increase the probability of stock market crashes. This phenomenon is henceforth referred to as the volatility paradox.

The recent financial crisis demonstrated that bubble bursts in a relatively small market of the economy can trigger a serious financial crisis with massive impacts on the real economy. That is, financial crises occur due to amplification effects, which are considerably important during a crisis phase, and spread out to other sectors in the economy significantly reducing economic activity (Brunnermeier and Oehmke, 2013). The Map assessed a spectrum of risks to financial stability by including macroeconomic risks such as economic activity. Chapter 3 extends the existing literature on systemic risk, i.e. the risk of financial instability that hampers a financial system's functioning, and discusses the contribution of real economy sectors to systemic risk based on their DeltaCoVaRs (henceforth ΔCoVaR). ΔCoVaR captures the marginal contribution of an economic sector to the entire systemic risk rather than measuring the risk of a sector. Chapter 3 considers ten economic sectors following the Industry Classification Benchmark (henceforth ICB) and classifies the sectors as being systemically important. The estimated ΔCoVaRs are tested for significance and dominance to obtain a formal ranking of the sectors in terms of systemic risk contribution to determine sectors that contribute more to systemic risk than others. Testing for significance suggests that all sectors significantly contribute to systemic risk, but differ in terms of their dominance. Chapter 3 will show that the financial sector affects systemic risk most, in all countries under examination, and that sector dominance changes over time. Unstable financial conditions, or the fear thereof, are essential for acute financial tensions and the impact on systemic risk. Further examination of the relationship between ΔCoVaR and VaR shows that ΔCoVaR is larger than VaR and that there is no one-to-one relationship between these measures. It is argued that ΔCoVaR takes significant externalities into account, which are neglected by VaR. The results show that the degree of externalities changes over time. Chapter 3 follows the line of argumentation of previous papers and distinguishes two phases of systemic risk. That is, systemic risk builds up in the background during a phase of rising asset prices and imbalances and materialises when a crisis sets in. Hence, the discussion on policy implications is based on the relationship between these two phases, which inhere within almost every financial crisis (Brunnermeier and Oehmke, 2013), and discusses two categories of policy instruments. The policy instruments depend on the phase and can be used ex-ante or ex-post, i.e. prior to a bubble burst or in the aftermath of a bubble burst when systemic risk materialises. The ex-post view has moved towards an ex-ante attitude, referred to as 'leaning against the wind' policy, which suggests an early reaction to upward movements in asset prices to prevent asset price bubbles. The policy tools are discussed in section 3.7, which concludes that it is reasonable to apply sectorally adjusted macroprudential tools to account for the systemic risk contribution of individual sectors. Although financial instability need not be implied by market volatility, higher market volatility nearly always accompanies periods of financial instability (IMF, 2003). As we will see in chapter 4, the realised volatility levels between the stock markets of four G7 countries significantly differ although their volatility patterns are fairly similar. The realised volatilities of the countries largely move together and reach their peaks simultaneously. When the uncertainty among stock market participants was high in the wake of the September 2008 events, the annualised monthly realised volatility in all observed countries peaked at around 80%. All the observed stock markets have in common that they decline to their pre-crisis levels from their peaks indicating countercyclicality in realised volatility. The countercyclical behaviour of stock market volatility fostered research on rational explanations and modelling the economic sources of volatility (Engle et al., 2013). Motivated by previous papers that stated that macroeconomic variables move stock market volatility, chapter 4 employs a two-component model referred to as the GARCH-MIDAS model, which consists of a short-run (GARCH) and a long-run (MIDAS) volatility component. In the past, realised volatility was used over some horizon to measure long-run volatility, and realised volatility is considered as natural candidate to model the long-run volatility component. Hence, the two-component volatility specification, based on realised volatility, is considered as the benchmark model. The GARCH-MIDAS model is employed to directly relate long-run stock market volatility with macroeconomic time series. The results suggest that the variables with the predictive ability for volatility vary between the countries, reflecting their different economic structures. The explanatory power of lagged macroeconomic variables with respect to long-run stock market volatility is relatively weak, whereas lagged realised volatility (RV) explains a considerable fraction of variation in conditional variance. It is reasonable to argue that RV already contains plenty of information on business conditions. Motivated by the observation that the short-run volatility component picks up the highs and lows in volatility, chapter 4 employs two-vector autoregression (henceforth VAR) systems to examine the drivers of the short-run volatility component. The two separate VAR systems employed include the short-run and the long-run component, respectively, as well as macroeconomic, firm-specific and financial market specific variables. The VAR results are reported from Granger-causality tests that reveal that neither illiquidity nor sentiment have a significant causal relationship with volatility.

The remainder of this thesis is organised as follows: Chapter 2 discusses methods of identifying bubble episodes and the information content of bubbles with respect to stock market crashes. Furthermore, the role of low volatility in bubble formation is addressed and BuVaR is estimated. Chapter 3 examines the contribution of real economy sectors to systemic risk. In this connection, chapter 3 addresses the role of asset price bubbles and provides policy implications about systemic risk. The volatility differences between international stock markets and the different effects of macroeconomic variables on conditional stock market volatility in developed countries are addressed in chapter 4. Chapter 5 summarises the thesis and concludes. Additionally, chapter 5 provides ideas about future research on financial stability.

Chapter 2 The relationship between low volatility, bubbles and stock market crises: Are bubbles related to crises in the US stock market?

2.1 Introduction

History has witnessed the boom and bust of bubbles in different asset classes. Literature refers to the Dutch tulip bubble (1634–1637) as the first known example of a bubble. Early examples of stock price bubbles are the South Sea bubble in the UK (1720) and the Mississippi bubble (1719–1720). Further bubbles had been observed thereafter in many countries, but the most devastating stock market collapse in October 1929 experienced by the US, and subsequently world stock markets, is known as the Great Depression. Further examples of stock market bubbles in more recent history is the internet bubble that started around 1995 and gradually deflated March 2000 onwards. The financial crisis 2008–2009 showed how a bubble in the real estate market can lead to severe stock market declines around the world, driving financial institutions to bankruptcy with severe systemic consequences. Empirical examples show that bubbles can either burst or deflate (e.g. the internet bubble), where Scherbina (2013) notes that a bubble takes more time to establish than to deflate. The focus of more recent papers has shifted towards explaining bubble initiation and the causes of their bursts relaxing the assumption of perfect rationality of agents (Scherbina, 2013).

Generally, a bubble refers to a situation where the asset's market price deviates significantly from its fundamental price determined by fundamental factors because of shareholders who believe that the asset can be sold at a higher price. Researchers have been long concerned with such price deviations and developed four groups of models to understand the preconditions of bubble formations. These models impose different assumptions and empirical tests, but cannot explain the beginning of bubbles. That is, the first two groups are based on the rational expectations paradigm, but are different in their assumptions. While the third group is about the interplay between non-rational and rational investors, according to the fourth group, the beliefs of investors are heterogeneous and agree in that they do not agree about the fundamental asset value, which may be a consequence of psychological biases. The first group model assumes the same information of investors in contrast to the second group model, which assumes asymmetric information between investors and the existence of bubbles need not be of common knowledge. Furthermore, despite the observation that bubbles seem to deflate over time, in reality, they burst in most models (Brunnermeier, 2008).

In recent years, researchers and practitioners have defined volatility as risk and introduced models to estimate the volatility of financial assets. Even though researchers have investigated the volatility-recession relationship, the paper by Danielsson et al. (2015) is, to their best knowledge, the first study on the volatility-crisis relationship. Danielsson et al. (2015) study the effect of volatility on the likelihood of financial crises, constructing a cross-country database and finding that volatility does not have a significant forecasting power of financial crises. Distinguishing between high and low levels of volatility, the authors support Minsky's (1992) hypothesis of changing risk-taking behaviour when market risk changes, and conclude that low volatility encourages investors to take more risk, which finally gives rise to high volatility and a crisis.

This chapter's objective is to extend Danielsson et al.'s (2015) study and to take another vantage point on the volatility-crisis relationship by including the concept of bubbles. Motivated by Brunnermeier and Oehmke (2013), who argue that bubbles and crises are two sides of the same coin, this chapter first timestamps the start and the end of a bubble period using the procedure proposed by Taipalus (2012). As will be shown, this procedure predicts downturns as well as upturns in the stock market. This method helps examine the bubble behaviour in more detail and identify an asymmetric pattern in bubble periods, i.e. if bubbles rise and/or fall rapidly or slowly (i.e. deflate) over time. That is, looking at the AR(1) coefficients provides information about the behaviour of investors and the stage of bubbles. Bubbles reach their peak of explosive behaviour fast and often deflate gradually over a longer horizon. The subsamples suggest that bubbles deflate over time as investors become aware of overvalued assets rather than a sudden burst. The results also show that the end of bubble behaviour is close to crisis periods in the stock market and that crises promptly follow bubble periods. It seems, therefore, reasonable to conclude that bubble periods and crisis periods are related, and simple lagged values, lagged by 12 and 24 months, are used in the logistic model framework to account for this prompt relationship.

Bubbles are subsequently defined as a deviation of the market price from a benchmark, which is calculated using Wong's (2013) proposed approach, and the analysis on this approach is run from 1945 to 2015. The bubble is interpreted as a result of a sequence of returns leading to a high asset price, which deviates from its benchmark. The argument of this chapter is as follows. The so-called volatility paradox is tested by testing the effect of realised volatility (henceforth RV) on the bubble measure and finds that a long period of volatility has a significant effect on the bubble. Furthermore, a logistic regression is run that finds that bubbles indeed increase the probability of stock market crises. Hence, if RV has a significant effect on bubble formation and bubbles significantly affect the probability of crises, it is argued that volatility influences stock market crises. Bubbles are applied to modify stock market risk measures following the Bubble Value at Risk (henceforth BuVaR) approach introduced by Wong (2011, 2013). BuVaR and VaR are compared with respect to their ability to capture extreme negative stock market returns. The backtest results indicate that BuVaR covers some extreme negative returns over a period from 1945 to 2015, but sometimes overestimates extreme returns.

The remainder of this chapter is organised as follows: Section 2.2 explores the methodology of timestamping bubbles and discusses the structure of bubbles in the post-World War II period. Section 2.3 describes the BuVaR model proposed by Wong (2011, 2013) as well as the logistic regression and the framework applied to detect a volatility paradox. The data used is discussed in section 2.4. Section 2.5 describes the logistic regression's empirical results and the relationship between volatility and the bubble. Section 2.6 concludes.

2.2 Detecting explosive bubbles in asset prices

Brunnermeier and Oehmke (2013) note that bubbles are followed by a crash that starts with a trigger event, which causes a bubble burst. They distinguish a phase in which bubbles emerge and a crisis phase, respectively, which must be seen in combination. However, due to lacking knowledge about the fundamental asset value, it is a challenge to identify bubble periods in the time series. This section addresses the observation that asset prices explosively evolve when investors are euphoric (Brunnermeier and Oehmke, 2013), and redefines the bubble as an explosive asset price bubble using econometric methods to detect periods in which asset prices inherit explosive dynamics. Diba and Grossman (1988) apply unit root tests to the gap between the asset prices and fundamental price to detect explosive asset price bubbles. In the aftermath of Diba and Grossman (1988), unit root tests have been widely used to test for explosiveness. However, Evans (1991) points out that unit root tests fail to identify explosive bubbles when bubbles periodically collapse unless there is a slow collapse frequency in the sample. Phillips et al. (2011) and Phillips et al. (2015) repeatedly implement a right-tailed ADF (Augmented Dickey-Fuller) test on a sequence of subsamples providing a bubble's starting and termination date.

Phillips et al. (2011) confirm Evans' (1991) criticism and apply the ADF against the alternative of an explosive root. The model is repeatedly estimated for subsets in the sample where each subsample's corresponding t-statistic is compared with a corresponding right-tailed critical value. Phillips et al. (2011) define the beginning and the end of explosive behaviour as

$$\begin{aligned} \hat{t}_e &= \inf_{s \geq t_0} \left\{ s : ADF_s > cv_{\beta_n}^{adf}(s) \right\} \\ \hat{t}_f &= \inf_{s \geq t_e} \left\{ s : ADF_s < cv_{\beta_n}^{adf}(s) \right\} \end{aligned} \tag{2.1}$$

with $\widehat{t_e}$ and $\widehat{t_f}$ as the origin date and the termination date of exuberance, respectively. ADF_s with $s \in [s_0, 1]$ represents the recursive test statistic and cv the critical value of ADF_s at significance level $ß_n$. The fraction of the total sample is t where $t_0 \leq t \leq 1$. Applying the test to the NASDAQ shows that periodically collapsing bubbles can be detected and confirms explosiveness in the index. In their recent paper, Phillips et al. (2015) develop a generalised version of the sub-ADF test, which significantly improves discriminatory power when multiple bubbles exist in the sample and is therefore, a more useful approach to timestamp subsequent bubbles. Phillips et al. (2015) show through simulations that the generalised sup ADF (GSADF) test is a remarkable improvement in detecting multiple bubble events.

Taipalus (2012) suggests estimating an AR(1) model over rolling data samples generating an AR(1) coefficient for each period and each new sample. In so doing, a coefficient of at least 1.0 signals a unit root and hence, indicates the possibility of a bubble, as autoregressive behaviour in asset prices are observed when bubbles exist in the markets. Taipalus (2012) also suggests applying an ADF test to a rolling window of a fixed size where the main focus is on the coefficient γ of the variable y_{t-1}. A value of $\gamma=0$ is consistent with a unit root. The suggested methods directly consider the coefficients rather than calculating the t-values where the regression is run over subsamples with a fixed size and rolls forward by one step until the end period is reached.

In what follows, the approach proposed by Taipalus (2012) is adopted and an AR(1) regression, on the seasonally adjusted S&P500 price level, is run using a rolling window of 36, 48 and 60 months. The seasonal adjustment performs the X11 adjustment procedure introduced by the US Census Bureau in 1965 and neither accounts for calendar effects nor for outliers.[1] The critical value of 1.0 is used for the AR(1) coefficient to define a unit root and define processes to be stationary if the coefficient is below 1.0. Figure 2.1 shows the distribution of the AR(1) coefficients from 1945 to 2015 based on a 36-month rolling window. Using a period from 1915 to 2015, the 95%-quantile returns a value of 1.0357 and the value is 1.0171 at the 90%-quantile. It seems justified to use a critical value of 1.0 as least squares regressions return downward biased estimates and therefore, a smaller value than the quantiles as critical value is applied (Taipalus, 2012).

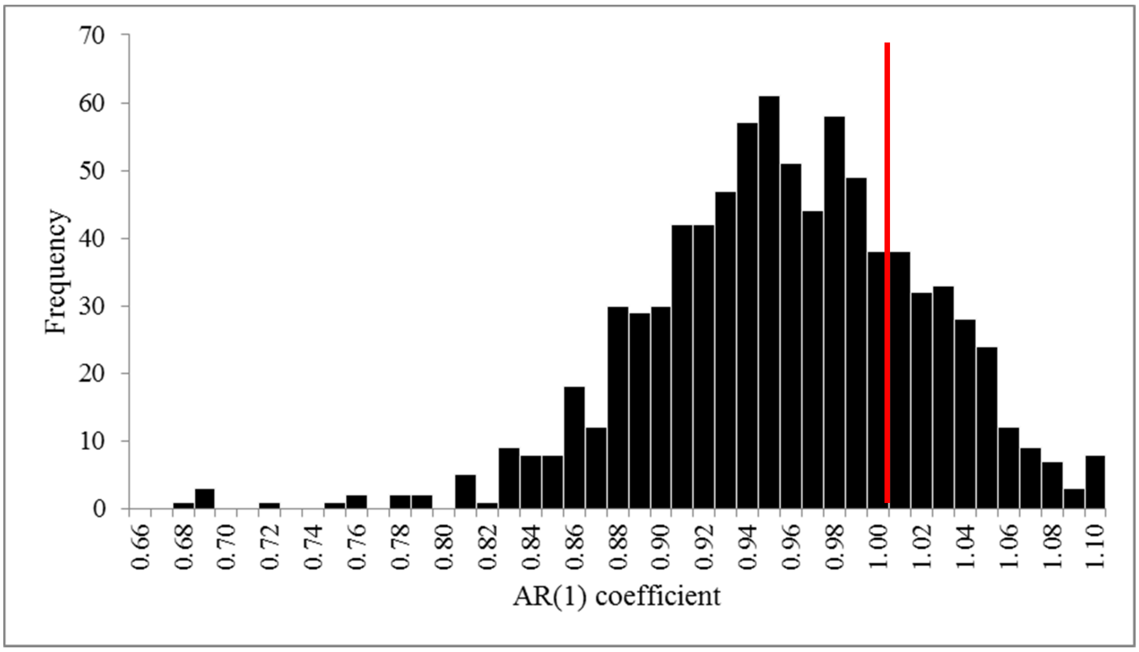

Figure 2.1: AR(1) coefficients from 1945 to 2015 using a 36-month rolling window.
The regression is applied to monthly S&P500 seasonally adjusted price levels using the X11 procedure for seasonal adjustments developed by the US Census Bureau. The raw S&P500 data are taken from Robert Shiller's webpage. The regression model is fit using OLS and the rolling window spans 36 months. Those AR(1) coefficients larger than 1.0 (vertical line) indicate a bubble.

2.2.1 Empirical results on explosive behaviour

The tests used to detect explosiveness in asset prices are applied to subsamples rather than to the full sample. This procedure allows to date the beginning and the end of a bubble as unit roots are tested at each point in time. In so doing, a bubble is identified as soon as the AR(1) coefficient exceeds the critical value of 1.0. Figure 2.2 illustrates the S&P500 price index from 1945 to 2015 where the shaded areas represent the bubble periods. It can be seen that the bubble detected by the AR(1) coefficients occurs prior to declines in stock market prices and, therefore, seems to be a good predictor of downturns, at least in the second half of the sample. The bubble periods for the 36-

[1] The AR(1) regression is also run using raw price levels and the price/dividend ratio and returns similar results as the regression based on seasonally adjusted price levels. The results are available upon request and not reported here.

month rolling window are consistent with those in Taipalus (2012). However, the internet bubble 1995–2000 is too short using a 36-month rolling window. Therefore, the AR(1) based on 60 months are run. The results are shown in Figure 2.3.

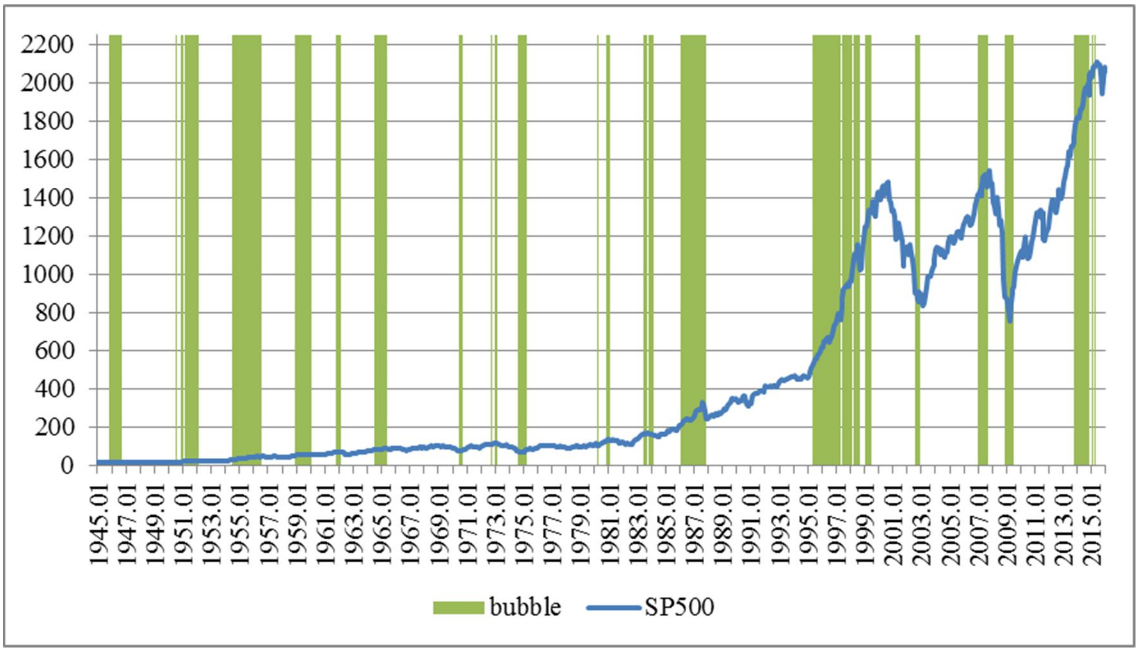

Figure 2.2: Historical S&P500 Index and bubbles using a 36-month rolling window.
The shaded areas represent the bubbles detected using AR(1) coefficients exceeding the critical value of 1.0. The AR(1) regression was applied to rolling windows covering 36 months. The bubbles are calculated using the S&P500 seasonally adjusted prices. The raw prices were taken from Robert Shiller's webpage and adjusted using the X11 procedure developed by the US Census Bureau without handling calendar effects or outliers.

The bubbles shown in Figure 2.2 and Figure 2.3 were calculated based on the adjusted S&P500 prices. Figure 2.3 illustrates the bubbles over a 60-month rolling window and the historical S&P500 Index. In the latter case, the end of the bubble almost coincides with the local peak of the index. This observation aligns with the logistic regression results, which will be shown in section 2.5 and suggests only a significant influence of the bubble in the short run, i.e. around 12-month lagged values.

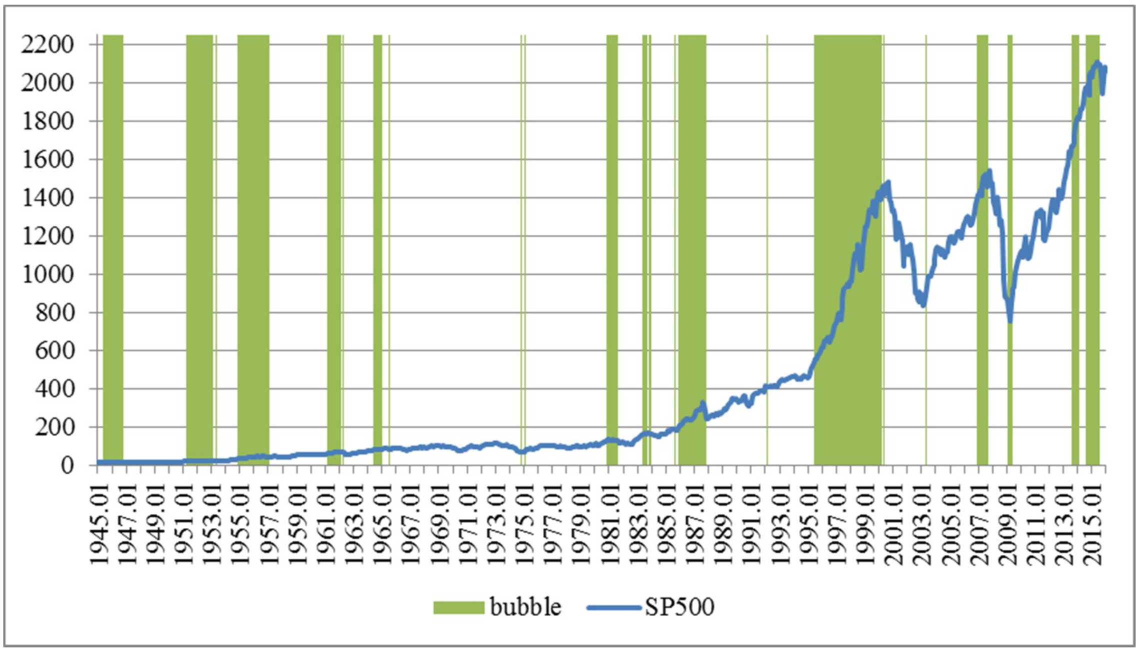

Figure 2.3: Historical S&P500 Index and bubbles using a 60-month rolling window.
The shaded areas represent the bubbles detected using AR(1) coefficients exceeding the critical value of 1.0. The AR(1) regression was applied to rolling windows covering 60 months. The bubbles are calculated using the S&P500 seasonally adjusted prices. The raw prices were taken from Robert Shiller's webpage and adjusted using the X11 procedure developed by the US Census Bureau without handling calendar effects or outliers.

Figure 2.2 and Figure 2.3 show that the S&P500 Index had risen by 11.4% during 2014 constituted by growing company profits and a strengthening US economy, before concerns about falling oil prices set in in the last days of December 2014 (Long, 2014). The downturn continued in 2015 because of worries about the oil prices, the economic slowdown in China as well as the speculations regarding the Fed's interest policy. With a loss of 0.7%, 2015 was the worst since the collapse in 2008 (Gillespie, 2015).

The shaded area at the beginning of 2009 indicates the financial crisis that reached its peak with the Lehman bankruptcy and the associated uncertainty in the wake of this event. That is, the AR(1) approach employed not just detects positive bubbles, but also negative bubbles when the stock market is oversold. Figure 2.3 demonstrates the occurrence of bubble periods in the stock market and their different lengths. Some bubbles gradually deflate over time, whereas others end suddenly followed by a severe downturn in stock prices. In general, Figure 2.3 supports the logistic regression's findings in that bubbles precede massive stock price downturns.

2.2.2 Asymmetry in bubbles

The panels of Figure 2.4 below represent the AR(1) coefficients during the individual bubble periods, which occurred between 1945 and 2015, where the horizontal axis shows the length of the bubbles. It is quite interesting to observe that the AR(1) coefficients rise quite fast once explosive behaviour has set in. That is, the coefficients reach their peak in the first half of the period and decline thereafter until the end of the bubble.

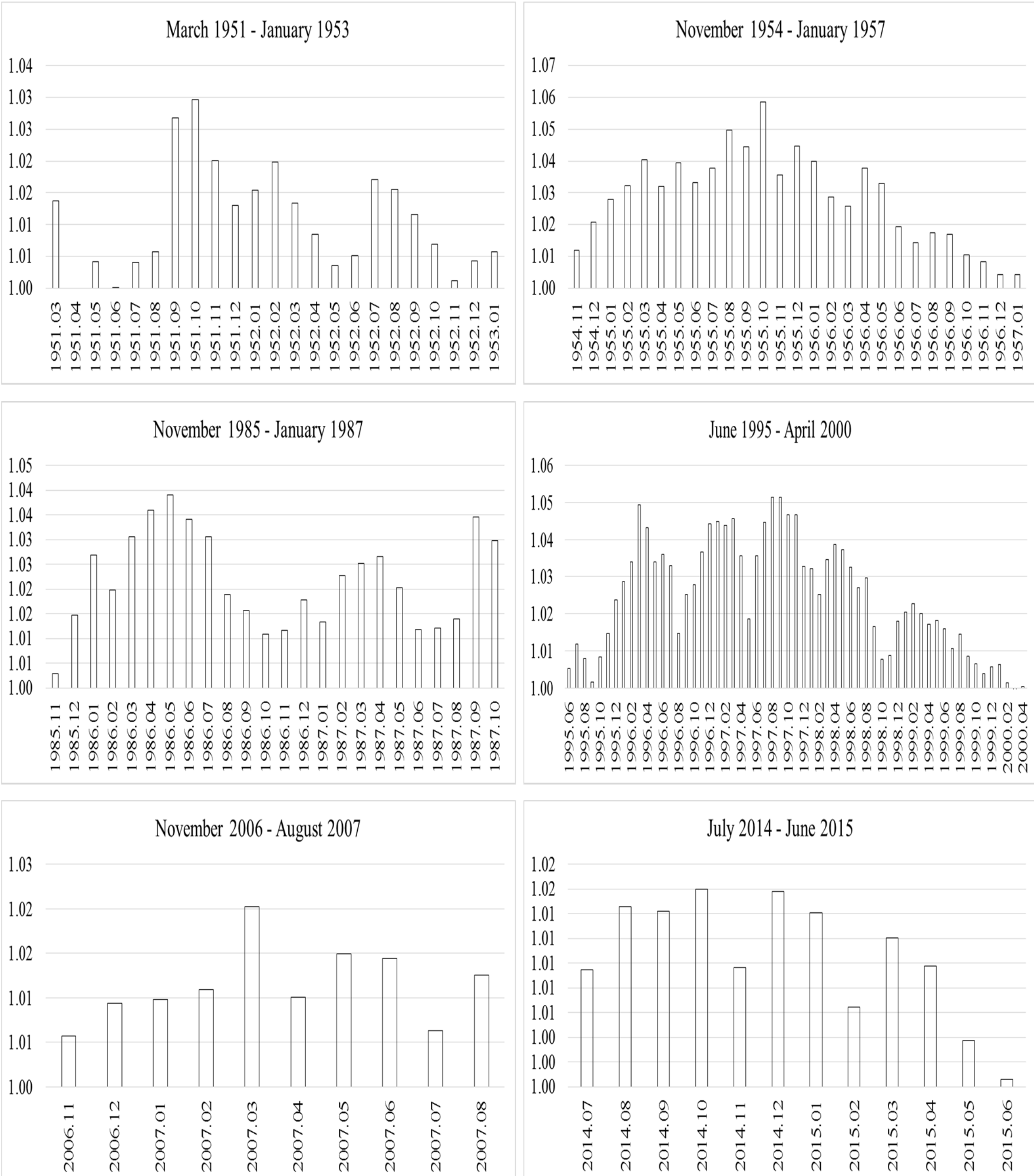

Figure 2.4: AR(1) coefficients during bubble periods in the post-World War II era.
The coefficients were calculated using an AR(1) regression based on seasonally adjusted S&P500 price levels. The seasonal adjustment performs the X11 adjustment procedure introduced by the US Census Bureau without accounting for calendar effects or outliers. The AR(1) regression was applied to rolling windows covering 60 months. Only AR(1) coefficients exceeding the critical value of 1.0 are considered as they indicate a bubble.

I conclude that investors react rapidly to market conditions and follow market trends very fast. That is, once a bubble begins, investors do not hesitate to get in or out of the market. So, when the market is going up, they decide to immediately buy stocks pushing the AR(1) coefficients up. Once they have bought the stocks of their interest, the AR(1) coefficients begin to decline as fewer investors are willing to buy further stocks. Scherbina (2013) provides a possible explanation for this observation. The trading volume is low in the early bubble stage of the life cycle and surges in the middle bubble stage as a wide cross-section of market participants note the past price increases and engage in speculative trading. As a result, the demand for the asset is high, which is mitigated through a higher supply of that asset leading to a drop in new capital inflow. The consequences are lower bubble growth rates and possibly a lower trading volume. As investors realise in the later stage that assets are overvalued, they sell them and the bubble begins to deflate. The panels of Figure 2.4 indicate such a deflationary behaviour of the AR(1) coefficients, and a sudden bubble burst for the S&P500 in the post-World War II period is not found except for the bubble from November 1985 to January 1987. Thus, Scherbina (2013) notes that the relationship between trading volume and returns is informative about the stage of a bubble. Given these results, it is concluded that the AR(1) coefficients provide useful information about bubble behaviour and the stage of a bubble period.

2.3 The bubble VaR approach by Wong

The most common risk measure used by financial institutions and fund managers is Value at Risk (VaR). Although relatively unknown in 1990, it rapidly became a well-known measure of risk because of the competition between leading financial institutions to construct methods to model daily VaR forecasts (Dowd, 2010).

Value at Risk is the predicted worst loss with a pre-specified probability or confidence level, which is mathematically expressed through formula (2.2)

$$\int_{-\infty}^{V_1} f(v)dv = 1 - \alpha = P(v \leq V_1) \tag{2.2}$$

where f(v) represents the density function of returns and α stands for the desired confidence level. V_1 denotes VaR, which is defined in a way that (1-α) equals the probability that a return below V_1 occurs. Hence, VaR considers the loss that could be suffered with a given probability and can be used to identify the level of serious losses of a portfolio. In this thesis, a confidence level of e.g. 99% means a 1% chance of obtaining a return below V_1 (Booth et al., 2005).

The ‘tail blindness’ and the lack of the subadditivity property gave rise to introducing expected shortfall (henceforth ES) as an alternative to VaR. ES has the subadditivity property and accounts for the average size of losses beyond a certain threshold, i.e. the (1-α)% lowest outcomes of the distribution. This means that ES measures the average size of losses greater than VaR and hence, entails information about the risk (Saita, 2007). That is, ES is the average of the c% worst cases of variable X, it can be expressed mathematically through

$$ES_c = -\frac{1}{c}\int_0^c X_q dp \tag{2.3}$$

where c $\in$ (0,1] represents the c% worst outcomes of the distribution (Acerbi, 2010).

That is, ES accounts for the loss beyond VaR and is absolutely essential for the effectiveness of ES to accurately estimate the tail of the distribution. It is difficult to accurately estimate a distribution’s tail through applying conventional estimation methods as the correlation among asset prices may change subject to the market situation, and distribution tail estimation using conventional simulation methods based on constant correlations would be impossible. The effectiveness of expected shortfall also depends on the stability of estimation and the efficiency of backtesting methods. Backtesting ES turns out to be a more difficult issue compared to backtesting VaR, as backtesting methods applying ES compare the estimated ES with the average of realised losses larger than VaR while backtesting using VaR compares the frequency of losses larger than the estimated VaR and the confidence level to test a model’s validity. Due to the infrequent loss beyond VaR, it is demanding to accurately estimate the average loss, and ES-based backtesting requires more data than VaR-based backtesting (Yamai and Yoshiba, 2002).

Yamai and Yoshiba (2002a) employ a Monte Carlo simulation to compare the estimation errors of VaR and ES. ES estimation error largely depends on the underlying distribution in that a fat-tailed distribution gives rise to larger estimation errors compared to VaR. In brief, the ES estimation error exceeds the VaR estimation error if the distribution is fat-tailed due to large, infrequent losses in the tail. On the other hand, in case of an approximately normal distribution, the estimation errors are pretty much the same. The authors argue that estimation errors are caused by limited sample size and scrutinise the sample size’s effect on estimation errors. The authors find that enlarging the sample size lowers the ES estimation error, and that ES requires a larger sample size than VaR to achieve the same level of accuracy (Yamai and Yoshiba, 2002a).

For these reasons, the subsequent analysis uses VaR instead of ES as risk measure and makes the expected loss dependent on the price level, particularly on a market cycle function. This achieves a countercyclical measure, so that the expected loss is somewhere between VaR and the maximum loss. Wong (2011, 2013) decomposes the time series of asset prices into three components, which describe the long-term trend, the cycle and the noise, respectively. Whilst the trend component is governed by real economic growth, the noise component reflects the realised trading activities under normal efficient market conditions.

Wong (2013) supposes that the cycle component, caused by speculative excess, explains phenomena such as fat tails or volatility clustering instead of the noise component, which is used by conventional VaR to model distributional properties. The cycle is combined with breaks, or a compression as well as a combination of both to explain phenomena in return series, and it is argued that the components of price series can model realistic market behaviours. The main objective is to use the cycle to inflate a tail measure e.g. VaR asymmetrically to hamper a market crash. The larger the price deviation from some benchmark level, i.e. the larger the bubble, the higher will be the risk of a crash. The inflation of the tail measure should be carried out to reflect this higher crash risk, which is achieved by multiplying the distribution of returns with a so-called inflator. The inflator depends on the bubble and adjusts every scenario of the return distribution to sanction longs and shorts conditional on the current price levels (Wong, 2013).

Wong (2011) defines the inflator as a response function that converts the bubble B_d to the inflator Δ_d at any given day d as follows

$$\Delta_d = \mathrm{Min}\left(\frac{\psi}{2\sigma_d}, \exp\left\{\left(\frac{\mathrm{Abs}(B_d)}{B_{max}}\right)^{\omega_2} \ln\left(\frac{\psi}{2\sigma_d}\right)\right\}\right) \tag{2.4}$$

where ω_2 is the curvature parameter of Δ determining the smoothness of variation in BuVaR as shown in Figure 2.5 for different values of ω_2.

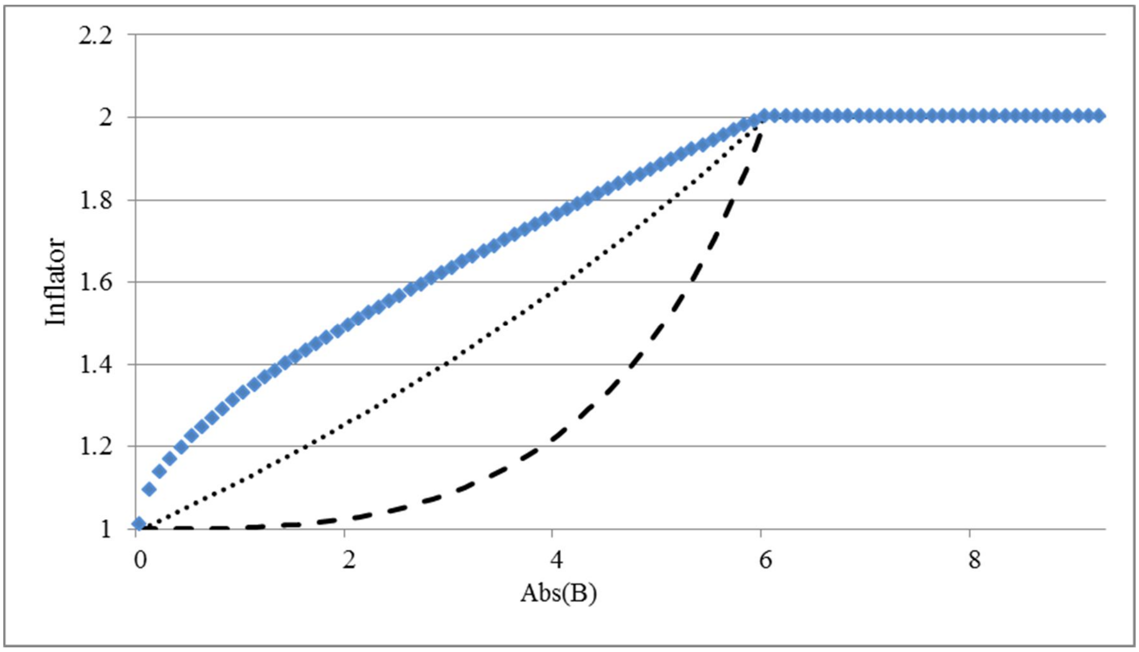

Figure 2.5: Inflator response function for different values of ω_2.
The dotted line is the inflator response function for $\omega_2 = 1$. The dashed line is the inflator response function for $\omega_2 = 3$ and the solid line represents the inflator response function for $\omega_2 = 0.49$. Abs(B) is the absolute bubble value. The inflator is capped at 2.0 and reaches its maximum at Abs(B) = 6. This example was reproduced from Wong (2013).

Figure 2.5 displays how the inflator grows with the bubble given a certain value of ω_2 where the inflator is capped, for example, at 2.0. That is, the inflator does not exceed the cap even if the bubble rises. The inflator is capped by $\psi/2\sigma_d$, which is the shift that brings $2\sigma_d$, representing an approximate of the current VaR, to ψ. This in turn denotes the average of the 5 largest profits and losses (in absolute terms) in the asset's history, which may be capped by a circuit-breaker. Although Wong uses $2\sigma_d$ as approximation of VaR, in this chapter $2\sigma_d$ is replaced by the VaR directly. B_{max} is the biggest absolute value of the bubble in the asset's history. That is, the inflator ranges between an upper limit and VaR and adjusts multiplicatively every scenario on one side of the return distribution so that the returns on day d are transformed according to

$$R_n \rightarrow \begin{cases} \Delta_d R_n \text{ if } \operatorname{sign}(R_n) \neq \operatorname{sign}(B_d) \\ R_n \text{ if } \operatorname{sign}(R_n) = \operatorname{sign}(B_d) \end{cases} \tag{2.5}$$

where $\Delta_d \geq 1$ and n is the number of the scenario. Hence, R_n denotes the return of scenario n. Wong (2013) multiplies the daily inflator Δ_d daily with every return scenario either on the negative or positive side of the return distribution and the bubble side is penalised such that the inflator $\Delta = 1$ if $B_d > 0$ for all returns on the positive side and vice versa if $B_d < 0$ for the negative side, i.e. if the bubble is positive, only the returns on the negative side are multiplied by the inflator $\Delta \neq 1$ and vice versa if the bubble is negative.

The intuition behind BuVaR is that crashes only occur downwardly and in the countertrend direction. Therefore, long positions are more vulnerable to massive downward movements than short positions at the peak of a bubble, whereas short positions are more prone to a bounce at the low of a downturn. Due to its countercyclicality, BuVaR helps build up a countercyclical capital buffer for market risk in advance of a crisis (Wong, 2014).

The idea of the transformation is to offset the asymmetric risk of a crash, which is not well considered in VaR. The inflation of one side depends on the current state in the boom-bust cycle. Note that the inflator is not a probability weight in the sense that the application of an inflator of size z to a side increases the likelihood of profits or losses by factor z (Wong, 2011).

2.3.1 Defining the bubble

In Wong's (2011, 2013) framework, the bubble used in the inflation of VaR is a price deviation from a benchmark level. Thus, the bubble grows larger as the price moves away from the benchmark indicating a higher crash risk. The bubble will be used to sanction longs if it is positive, and sanction shorts if it is negative. Wong (2013) argues that a moving average is not appropriate as a benchmark in a crash period. BuVaR could encourage investors to buy longs during a crash although it should penalise longs. Instead, a rank filtering process is proposed to derive a well-behaved measure for the benchmark. In doing so, the extreme price changes are eliminated, and alternative historical prices are computed whose adaptive moving average is defined as benchmark μ_d. Hence, the benchmark deviation

$$B_d = X_d / \mu_d - 1 \tag{2.6}$$

represents the bubble on day d. X_d denotes the starting price used to calculate the benchmark μ_d. That is, X_d represents the latest price of a vector of historical prices from X_{d-n} up to day d, where n is the number of days. μ_d is calculated over a past 1000-day rolling window. The adaptive moving average satisfies the criterion that, during a long-term growth period, investments are not penalised by the bubble. Due to the adaptive embracing, the bubble declines because of the sustainable growth trend and does not become negative during a crash. Instead, the benchmark point declines by the same size because of the fall of the starting price X_d. The bubble persists during a crash period and therefore, sanctions longs throughout a crash as well as during the emergence of a bubble. The inflator becomes negative when a crash has occurred, and a bearish bubble arises (Wong, 2013).

In addition to these properties, the bubble moves synchronously with the market cycle leading to its countercyclicality. Hence, BuVaR moves with the market and often leads crashes or rebounds (Wong, 2011).

2.3.2 The bubble-volatility relationship

Economic theory has recently emphasised the endogeneity of volatility, which goes down with rising asset valuations motivating financial intermediaries to accept more risk and pushing asset prices up. As agents lower their risk perceptions, they have an incentive to buy more risky assets and dampen volatility even further. Adrian and Brunnermeier (2016) empirically documented a build-up of systemic risk during times of low volatility, which is referred to as the volatility paradox. This phenomenon arises from increased positions in riskier asset classes encouraged by expected persistent low volatility and calm financial conditions. The widespread use of VaR is another source of the risk build-up in a low volatility environment as financial institutions can hold larger positions in risky assets given a certain VaR threshold (BIS, 2014).

Bhattacharya et al. (2015) argue that long periods of low uncertainty and high optimism about the economic future may lead to an economic system that is more prone to risks. The argument for this hypothesis is that optimism and leverage are interacted as agents invest a higher portion into riskier assets during periods of lower-than-expected financial risk.

Bookstaber (2011) defines the volatility paradox as endogenously determined by the behaviour of market participants, leading to a build-up of market risk during low volatility periods caused by higher leverage. That is, investors are highly leveraged, willing to take more risk without taking care about negative information, resulting in low volatility that, in turn, fosters more leverage decreasing the low volatility even more. Consequently, despite the low level of volatility the market is vulnerable, and a crisis may be triggered.

Subsequently, the bubble is considered as a result of a series of positive returns on the stock market index, resulting in a high index value and finally a bubble. As mentioned above, the bubble is transformed into the inflator. To detect the interaction between B_d and RV and to identify a possible volatility paradox, in the sense that a long period of low volatility gives rise to a bubble, a linear regression is run, and the bubble is set as a dependent variable. Motivated by Minsky (1992), Bookstaber (2011), Bhattacharya et al. (2015) and Adrian and Brunnermeier's (2016) findings, the volatility paradox is examined by applying the RV level proposed by Christiansen et al. (2012). Following Reinhart and Rogoff (2011), backward-looking moving averages from t-12 to t-L are employed. The linear regression model is defined as

$$B_t = \alpha_0 + \beta_1 RV_{[t\text{-}12 to. t\text{-}L]} + \beta_2 SV_{[t\text{-}12 to. t\text{-}L]} + \varepsilon_t. \tag{2.7}$$

In (2.7), RV denotes realised volatility and SV denotes the state variables where t refers to monthly values of the corresponding variables. Hence, [t-12 to t-L] is the one year lagged moving average over L months. L is chosen to take two, three and five years into account. The state variables (SV) include the growth rate of industrial production (MP), the term premium (UTS), the default premium (UPR) and the growth rate of producer price index (PPI), which are commonly used in financial studies. According to the financial theory, these factors are supposed to have an effect on stock market returns and were found by Chen et al. (1986) to significantly explain expected stock returns. Sohn (2009) uses these factors to examine their predictability relations with respect to stock market volatility and finds that PPI and MP contain information regarding future stock market volatility. B_t represents the average of the daily bubbles of month t where the variables RV and SV are observed in monthly frequency. The data used are described in more detail in the next section.

2.3.3 Logistic regression model

Prior to discussing the BuVaR estimates, it is of interest whether the bubble has predictive power regarding a stock market crash. In the model used here, the dependent variable is dichotomous where the independent variables are either continuous or categorical. A logistic regression is employed for predicting stock market crises using several variables such as the bubble, realised volatility and macroeconomic state variables leading to the logistic regression equation

$$P(y=1|x_1...,x_p)=\frac{1}{1+e^{-(\alpha+\beta_1 C_{t-p}+\beta_2 bubble_{t-p}+\beta_3 RV_{t-p}+\beta_4 SV_{t-p})}} \tag{2.8}$$

where the dependent variable y represents the crisis indicator C_t and the variables $x_1\ldots,x_p$ represent the independent variables, i.e. the bubble, RV and SV on the right-hand side of equation (2.8). As the crisis indicator from Reinhart and Rogoff (2011) is an annual indicator, it is directly converted to a monthly basis by putting 1 or 0 in all the months of the year. RV represents the realised volatility taken from Christiansen et al. (2012) and SV are the macroeconomic state variables. In model specification (2.8), the variables RV, bubble and SV are all in monthly frequency and the monthly averages of the daily calculated bubble are used. The independent variables are lagged by p months.

In addition to the logistic regression, a probit model was also employed that returns similar results as the logistic model. That is, the coefficient, which corresponds to the bubble, is also significant in the probit model and the RV is not significant in all the specifications. The standard errors are clustered at the year level. Given the similarity of both models' results, the logistic and the probit model, the logistic regression model is used for further analysis as it has certain advantages compared with the probit model.[2] The logistic coefficients represent the degree by which the log odds are increased, which can be transformed into odds ratios by exponentiating the logit coefficients. Hence, calculating the odds ratio shows the increase in the likelihood of the event y=1 when, ceteris paribus, a variable increases by one unit (Agresti, 2007).

2.4 Data

The logit regression analysis covers a period from 1950 to 2010 using monthly observations. The choice of state variables used in the regressions was motivated by Chen et al. (1986) who determine a set of economic state variables as possible sources of systematic asset risk. The variables of interest are the growth rate of industrial production (MP), the growth rate of producer price index (PPI), the default premium (UPR) and the term premium (UTS) defined as yield spread between long-term and one-year Treasury bond. UPR is defined as the yield spread between the Baa and Aaa corporate bond rated by Moody's. MP is calculated as log growth rate such that MP_t = log IP(t) – log IP(t-1), where IP denotes the industrial production index in month t. The data for MP, UPR and UTS were taken from Liu and Zhang (2008) who provide the

[2] The probit model results are shown in Appendix A.1.

original factors UI (unanticipated inflation) and DEI (change in expected inflation) used by Chen et al. (1986). Instead of working with those data, the producer price index time series is taken from FRED database at the Federal Reserve Bank of St. Louis. PPI is calculated as the log growth rate of producer price index. The variables and their definitions are summarised in Table 2.1.

	Definition	Calculation	Source
Crash	Stock market crisis, defined as cumulative decrease of at least 25% in real equity prices. The original data are available at annual frequency.	Variable takes either a value of 1 (crisis) or 0 (no crisis)	Reinhart and Rogoff (2011)
Bubble	Price deviation from a benchmark level calculated using a rank filtering process, which eliminates the extreme price changes and computes alternative historical prices. The benchmark is the adaptive moving average of alternative historical prices.	$B_d=X_d/\mu_d-1$	Bloomberg
MP	Log growth rate of industrial production, defined as difference between the log industry production index in month t and month t-1.	$MP_t=\log IP_t - \log IP_{t-1}$	Liu and Zhang (2008)
UTS	Term premium, defined as yield spread between the long-term and the one-year Treasury bonds.	UTS_t=20yr $yield_t$ – 1yr $yield_t$	Liu and Zhang (2008)
UPR	Default premium, defined as yield spread between Moody's Baa and Aaa corporate bonds.	UPR_t=Baa-rated $yield_t$ – Aaa-rated $yield_t$	Liu and Zhang (2008)
PPI	Log growth rate of producer price defined as difference between the log producer price index in month t and month t-1.	$PPI_t=\log PP_t - \log PP_{t-1}$	FRED database
RV	Realised volatility, defined as log of the square root of the sum of squared daily stock index returns within a month.	$RV_t = \ln\sqrt{\sum_{d=1}^{M_t} r_{d,t}^2}$	Christiansen et al. (2012)

Table 2.1: Summary of the independent variables used in the logistic regression.
All variables are calculated using monthly observations. The bubble and RV were calculated based on the S&P500 Index as proxy for the US stock market. The time horizon under examination spans from March 1950 to December 2010.

The data of the realised volatility were taken from Christiansen et al. (2012) who sum the squared daily S&P500 returns in month t using

$$\sum_{d=1}^{M_t} r_{d,t}^2 \tag{2.9}$$

with $r_{d,t}$ as the d-th daily return in month t and M_t as the number of trading days during month t. The realised volatility is defined as the log of the square root of (2.9) leading to

$$RV_t = \ln\sqrt{\sum_{d=1}^{M_t} r_{d,t}^2} \qquad (2.10)$$

where t = 1,…, T denotes the month. The variables are plotted in Figure 2.6.

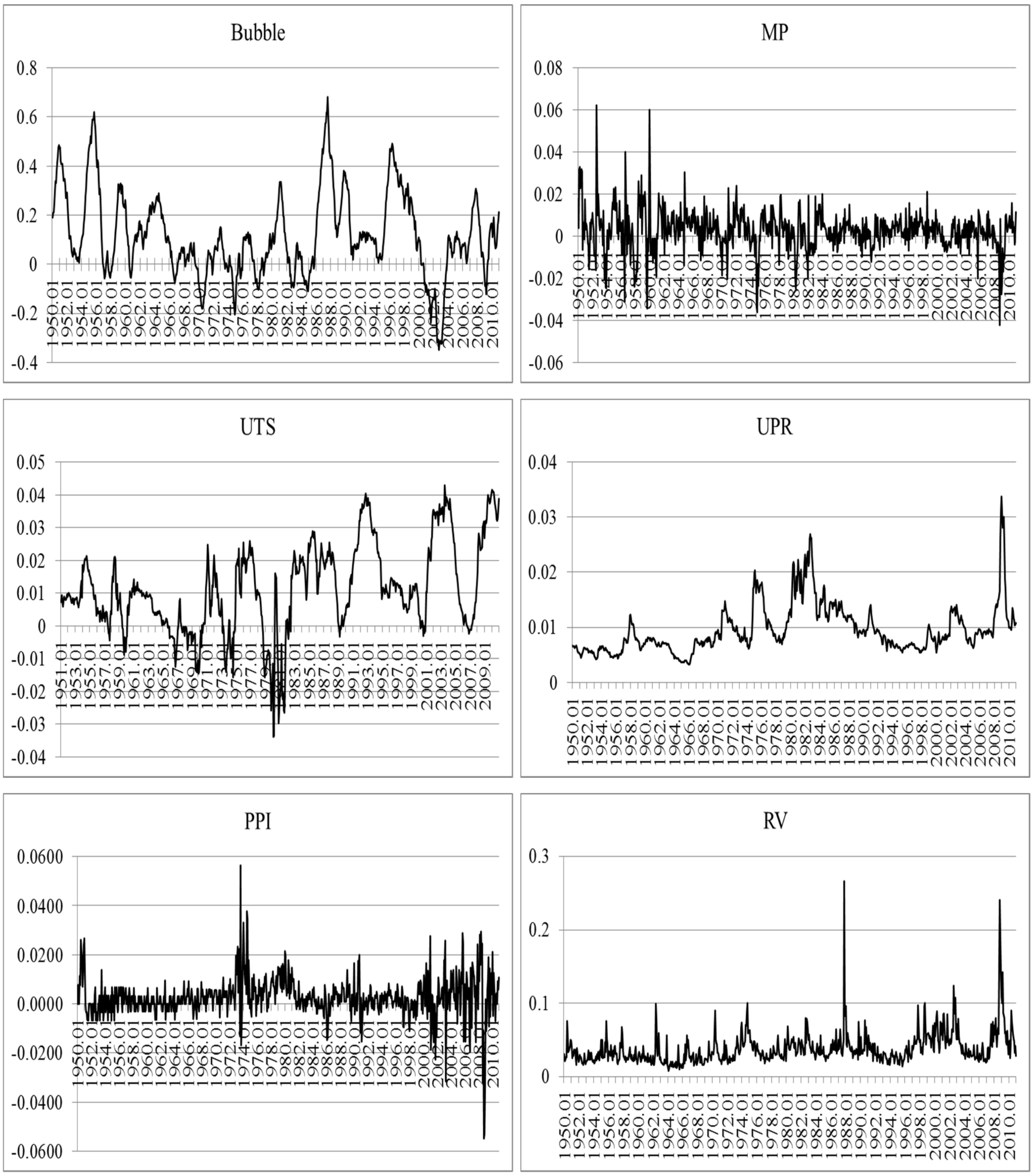

Figure 2.6: Plots of the bubble, state variables and realised volatility from 1950 to 2010.
Crash represents a stock market crisis indicator, defined as cumulative decrease of at least 25% in real equity prices. Bubble is a price deviation from a benchmark level calculated using a rank filtering process. MP is the log growth rate of industrial production, defined as difference between the log industry production index in month t and month t-1. UTS is the term premium, defined as yield spread between the long-term and the one-year Treasury bonds. UPR is the default premium, defined as yield spread between Moody's Baa and Aaa corporate bonds. PPI is the log growth rate of producer price, defined as difference between the log producer price index in month t and month t-1. RV is the realised volatility, defined as log of the square root of the sum of squared daily stock index returns within a month.

In this chapter, the S&P500 Index returns are considered as an approximation of the US stock market returns. The S&P500 Index levels, on daily and monthly frequency, were downloaded from Bloomberg. In what follows, a logistic regression is run with the stock market crisis indicator as a dependent variable. The annual crisis indicator is taken from Reinhart and Rogoff's (2011) database and is transformed to monthly frequency.

2.5 Empirical results

This section presents the empirical results of the previously discussed models. Section 2.5.1 discusses the results of the logistic regression and section 2.5.3 presents the results on the bubble-volatility relationship. BuVaR is backtested in section 2.5.2.

2.5.1 Empirical results on the relationship between bubble and stock market crises

Specification (2.8) shows the logistic regression on lagged variables, but the crisis indicator is often regressed on backward-looking moving averages of independent variables as this methodology reduces the multicollinearity and allows estimating the most relevant timescale (Danielsson et al., 2015).

Correlation *Probability*	Crash	Bubble	MP	UTS	UPR	PPI	RV
Crash	1.0000						

Bubble	-0.2394	1.0000					
	0.0000	-----					
MP	-0.2145	0.2265	1.0000				
	0.0000	*0.0000*	-----				
UTS	-0.2217	-0.0984	-0.0021	1.0000			
	0.0000	*0.0078*	*0.9548*	-----			
UPR	0.2530	-0.2851	-0.2654	0.2038	1.0000		
	0.0000	*0.0000*	*0.0000*	*0.0000*	-----		
PPI	0.1239	0.0113	0.0720	-0.1348	-0.0938	1.0000	
	0.0008	*0.7602*	*0.0517*	*0.0003*	*0.0112*	-----	
RV	0.2444	-0.0991	-0.1740	0.1787	0.4264	-0.1061	1.0000
	0.0000	*0.0074*	*0.0000*	*0.0000*	*0.0000*	*0.0041*	-----

Table 2.2: Correlation matrix from 1950 to 2010.

The coefficients were calculated using the ordinary Pearson method. The second line displays the probability. Crash represents a stock market crisis indicator, defined as cumulative decrease of at least 25% in real equity prices. Bubble is a price deviation from a benchmark level calculated using a rank filtering process. MP is the log growth rate of industrial production, defined as difference between the log industry production index in month t and month t-1. UTS is the term premium, defined as yield spread between the long-term and the one-year Treasury bonds. UPR is the default premium, defined as yield spread between Moody's Baa and Aaa corporate bonds. PPI is the log growth rate of producer price, defined as difference between the log producer price index in month t and month t-1. RV is the realised volatility, defined as log of the square root of the sum of squared daily stock index returns within a month. The period is from March 1950 to December 2010.

The correlation matrix in Table 2.2 demonstrates that multicollinearity is not a big issue, and the logistic and probit models are run in this chapter with simple lagged values, i.e. [t-12]. Table 2.3 plots the descriptive statistics of the monthly variables from 1950 to 2010 used in the regressions. Additionally, Table 2.3 presents the p-values of the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) unit root tests. It is important to note that the null hypothesis of both tests is that there is a unit root. That is, the alternative is that the time series is stationary. Given the small p-values of less than 0.05, both tests reject the null hypothesis of a unit root and suggest stationary time series.

	Bubble	**Crash**	**RV**	**MP**	**PPI**	**UPR**	**UTS**
Mean	0.1177	0.2959	0.0381	0.0026	0.0027	0.0096	0.0111
Median	0.0916	0.0000	0.0323	0.0029	0.0025	0.0082	0.0097
Maximum	0.6802	1.0000	0.2664	0.0623	0.0563	0.0338	0.0430
Minimum	-0.3485	0.0000	0.0085	-0.0421	-0.0548	0.0032	-0.0338
Std. Dev.	0.1709	0.4568	0.0225	0.0098	0.0084	0.0045	0.0135
Skewness	0.4944	0.8944	3.8970	0.2491	-0.1956	1.8182	0.0715
Kurtosis	3.4285	1.7999	30.4354	8.4690	12.6699	7.4069	3.1053
ADF test	0.0000	0.0028	0.0000	0.0000	0.0000	0.0033	0.0052
PP test	0.0010	0.0013	0.0000	0.0000	0.0000	0.0025	0.0084
Sum	85.8994	216.0000	27.7860	1.8839	1.9836	6.9899	8.0791
Sum Sq. Dev.	21.2870	152.0877	0.3706	0.0693	0.0513	0.0151	0.1327
Observations	730	730	730	730	730	730	730

Table 2.3: Descriptive statistics of the monthly variables from 1950 to 2010.
RV is the realised volatility and MP represents the industrial production growth. UTS is the term premium calculated as the yield spread between the long-term and the one-year Treasury bond and UPR is the default premium defined as yield spread between Baa and Aaa Moody's rated corporate bonds. Crash represents a stock market crisis indicator, defined as cumulative decrease of at least 25% in real equity prices. Bubble is a price deviation from a benchmark level calculated using a rank filtering process. MP is the log growth rate of industrial production, defined as difference between the log industry production index in month t and month t-1. UTS is the term premium, defined as yield spread between the long-term and the one-year Treasury bonds. UPR is the default premium, defined as yield spread between Moody's Baa and Aaa corporate bonds. PPI is the log growth rate of producer price, defined as difference between the log producer price index in month t and month t-1. RV is the realised volatility, defined as log of the square root of the sum of squared daily stock index returns within a month. The values in the two lines ADF test and PP test represent the p-values of the ADF and the PP unit root tests, respectively. The null hypothesis for the unit root tests is non-stationarity.

Table 2.4 presents the logistic regression results for the period from 1950 to 2010 and it is first considered how the probability of a crisis is related to the bubble. The period was determined by having data on stock market crises and the state variables. The results for 12-month lagged variables suggest significant influence of the bubble, whereas the RV has no significant coefficient. The significant influence of the bubble even survives the inclusion of state variables leading to the conclusion that the future crisis likelihood is not fully captured by state variables and RV. Table 2.4 also demonstrates the F-statistic and the Chi2, which are both significant at the 1% level.

Additionally, the logistic regression was run for 24-month lagged independent variables and the regression results indicate a significant influence of the bubble at the 5% level, which remains significant at the 10% level if the state variables are included. Again, the results indicate no significant effect of realised volatility. If the state variables are excluded, the F-statistic and the Chi2 are 1.46 and 4.38, respectively, but are not significant at the 10% level. Thus, it is concluded that the 24-month lagged logistic regression model does not provide a significant improvement in predicting stock market crises and there is no significant effect on the probability of stock market crises over a longer horizon than 12 months (Table 2.5). Consequently, this chapter concludes that variables promptly affect stock market crises, i.e. around a one-year period, but the influence declines over time.

The result that the coefficient of RV is not significant does not necessarily mean that RV has no effect on the crash. It is possible that RV is related to the bubble and that the regression results suggest that RV is causal to the bubble, which causes the crisis. That being the case, the logistic regression provides evidence of an indirect effect of RV on crashes through its effect on the bubble. However, the regression may be sensitive to such a relationship and another logistic regression is run without the bubble variable to check whether the RV coefficient becomes significantly negative. This is shown in the right panels of Table 2.4 and Table 2.5. Again, there is no significance of the RV coefficient. The linear regression results in Table 2.9, using backward-looking moving averages of RV, show that longer periods of RV significantly affect the formation of bubbles. Hence, this chapter interprets that volatility and the crash are connected through the bubble over longer periods of low volatility (see section 2.5.3).

12-month lagged value with bubble

	Dependent variable:	
	(1)	(2)
crash.t12	3.115***	2.916***
	(0.770)	*(0.846)*
bubble.t12	0.036**	0.031*
	(0.016)	*(0.017)*
MP.t12		0.119
		(0.135)
UTS.t12		-0.405*
		(0.238)
UPR.t12		-0.106
		(0.871)
PPI.t12		0.162
		(0.247)
RV.t12	-0.070	0.006
	(0.097)	*(0.104)*
Constant	-2.236***	-1.969***
	(0.626)	*(0.696)*
Observations	730	730
F-stat	*5.717****	*3.558****
Chi2	*17.151****	*24.909****
Note:	*p<0.1; **p<0.05; ***p<0.01	

12-month lagged value without bubble

	Dependent variable:	
	(1)	(2)
crash.t12	2.632***	2.546***
	(0.714)	(0.764)
MP.t12		0.180
		(0.130)
UTS.t12		-0.422*
		(0.219)
UPR.t12		-0.289
		(0.796)
PPI.t12		0.190
		(0.245)
RV.t12	-0.087	0.022
	(0.108)	(0.114)
Constant	-1.527***	-1.331**
	(0.468)	(0.594)
Observations	730	730
F-stat	*7.013****	*4.489****
Chi2	*14.026****	*26.933****
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 2.4: Logistic regression results for 12-month lagged variables.

The monthly bubble was estimated using the average of daily bubbles within the month. The crash represents a stock market crisis indicator, defined as cumulative decrease of at least 25% in real equity prices. Bubble is a price deviation from a benchmark level calculated using a rank filtering process. MP is the log growth rate of industrial production, defined as difference between the log industry production index in month t and month t-1. UTS is the term premium, defined as yield spread between the long-term and the one-year Treasury bonds. UPR is the default premium, defined as yield spread between Moody's Baa and Aaa corporate bonds. PPI is the log growth rate of producer price, defined as difference between the log producer price index in month t and month t-1. RV is the realised volatility, defined as log of the square root of the sum of squared daily stock index returns within a month. The ending 't12' to the independent variables refers to 12-month lagged observations. The independent variables were multiplied by 100 before the regression was run. The numbers in brackets are the robust standard errors clustered at the year level. The asterisks *** indicate the 1% significance level; ** indicate the 5% and * indicates the 10% significance level. The observation period is from March 1950 to December 2010.

24-month lagged value with bubble

	Dependent variable:	
	(1)	(2)
crash.t24	0.766	0.491
	(0.668)	*(0.726)*
bubble.t24	0.030**	0.030*
	(0.015)	*(0.016)*
MP.t24		0.168
		(0.113)
UTS.t24		-0.168
		(0.203)
UPR.t24		0.698
		(0.791)
PPI.t24		0.250
		(0.158)
RV.t24	0.037	0.037
	(0.086)	*(0.094)*
Constant	-1.649***	-2.170***
	(0.548)	*(0.724)*
Observations	730	730
F-stat	*1.462*	*1.516*
Chi2	*4.385*	*10.612*
Note:	$^{*}p < 0.1;^{**}p < 0.05;^{***}p < 0.01$	

24-month lagged value without bubble

	Dependent variable:	
	(1)	(2)
crash.t24	0.460	0.255
	(0.635)	(0.683)
MP.t24		0.233**
		(0.113)
UTS.t24		-0.198
		(0.181)
UPR.t24		0.469
		(0.719)
PPI.t24		0.242
		(0.159)
RV.t24	0.039	0.060
	(0.089)	(0.089)
Constant	-1.166***	-1.565**
	(0.417)	(0.651)
Observations	730	730
F-stat	*0.551*	*1.507*
Chi2	*1.103*	*9.043*
Note:	$^{*}p < 0.1;^{**}p < 0.05;^{***}p < 0.01$	

Table 2.5: Logistic regression results for 24-month lagged variables.
The monthly bubble was estimated using the average of daily bubbles within the month. The crash represents a stock market crisis indicator, defined as cumulative decrease of at least 25% in real equity prices. Bubble is a price deviation from a benchmark level calculated using a rank filtering process. MP is the log growth rate of industrial production, defined as difference between the log industry production index in month t and month t-1. UTS is the term premium, defined as yield spread between the long-term and the one-year Treasury bonds. UPR is the default premium, defined as yield spread between Moody's Baa and Aaa corporate bonds. PPI is the log growth rate of producer price, defined as difference between the log producer price index in month t and month t-1. RV is the realised volatility, defined as log of the square root of the sum of squared daily stock index returns within a month. The ending 't24' to the independent variables refers to 24-month lagged observations. The independent variables were multiplied by 100 before the regression was run. The numbers in brackets are the robust standard errors clustered at the year level. The asterisks *** indicate the 1% significance level; ** indicate the 5% and * indicates the 10% significance level. The observation period is from March 1950 to December 2010.

In addition to the logistic coefficients, Table 2.6 displays the average marginal effects of the model with clustered standard errors at the year level. The probability of a crisis in the stock market increases with a one-unit increase of the bubble for 12-month and 24-month lagged variables. In the first case, the significance of the bubble even survives the inclusion of the state variables.

Marginal effects 12-month lagged values

	Dependent variable:	
	(1)	(2)
crash.t12	0.5943***	0.5415***
	(0.1103)	*(0.1282)*
bubble.t12	0.0051*	0.0042*
	(0.0027)	*(0.0025)*
MP.t12		0.0159
		(0.0175)
UTS.t12		-0.0541
		(0.0369)
UPR.t12		-0.0142
		(0.1174)
PPI.t12		0.0216
		(0.0324)
RV.t12	-0.0098	0.0008
	(0.0142)	*(0.0138)*
Note:		*$^{*}p < 0.1$;$^{**}p < 0.05$;$^{***}p < 0.01$*

Marginal effects 24-month lagged values

	Dependent variable:	
	(1)	(2)
crash.t24	0.1571	0.0966
	(0.1386)	*(0.1463)*
bubble.t24	0.0058*	0.0056
	(0.0034)	*(0.0033)*
MP.t24		0.0317
		(0.0212)
UTS.t24		-0.0316
		(0.0390)
UPR.t24		0.1318
		(0.1512)
PPI.t24		0.0472
		(0.0304)
RV.t24	0.0072	0.0070
	(0.0169)	*(0.0178)*
Note:		*$^{*}p < 0.1$;$^{**}p < 0.05$;$^{***}p < 0.01$*

Table 2.6: Marginal effects for simple lagged variables logistic regression.
The marginal effects are calculated as average partial effects of the variables. The monthly bubble was estimated using the average of daily bubbles within the month. The crash represents a stock market crisis indicator, defined as cumulative decrease of at least 25% in real equity prices. Bubble is a price deviation from a benchmark level calculated using a rank filtering process. MP is the log growth rate of industrial production, defined as difference between the log industry production index in month t and month t-1. UTS is the term premium, defined as yield spread between the long-term and the one-year Treasury bonds. UPR is the default premium, defined as yield spread between Moody's Baa and Aaa corporate bonds. PPI is the log growth rate of producer price, defined as difference between the log producer price index in month t and month t-1. RV is the realised volatility, defined as log of the square root of the sum of squared daily stock index returns within a month. The endings 't12' and 't24' to the independent variables refer to 12-month and 24-month lagged observations, respectively. The independent variables were multiplied by 100 before the regression was run. The numbers in brackets are the robust standard errors clustered at the year level. The asterisks *** indicate the 1% significance level; ** indicate the 5% and * indicates the 10% significance level. The observation period is from March 1950 to December 2010.

The results lead to two conclusions. First, the bubble promptly affects the crash risk, and bubbles more than a year ago do not significantly affect crash risk. Second, the fact that bubbles exist does not mean that there is a risk of a sharp decline in stock prices. The next section incorporates the information content of bubbles into tail-risk measures and demonstrates that BuVaR covers some of the extreme returns in contrast to VaR.

2.5.2 Backtesting BuVaR and modified BuVaR

Backtesting is the quantitative evaluation of a model, which means comparing the risk model forecasts with subsequently realised profits and losses of the underlying random variable to determine the statistical compatibility of a risk forecasting model. Furthermore, backtesting helps detect potential weaknesses of a model and improve the model under consideration, as well as enables the user to rank alternative models of risk according to their forecast performance. As the assessment of model forecasts includes statistical hypothesis tests, a good risk model should further pass its applied statistical tests (Dowd, 2008).

Backtesting methods can be categorised as conditional and unconditional coverage tests. While the latter counts the number of VaR violations, which are compared with the confidence level to find out whether risk is over- or underestimated, conditional tests account for the temporal relationship between VaR exceedances.

Unconditional coverage tests count the number of losses that exceed the VaR. The VaR model is adequate if the observed number of exceedances does not deviate much from the expected number of VaR violations. For this purpose, a statistical test is needed that examines whether the rate of violations of a model statistically equals the expected failure rate (Angelidis and Degiannakis, 2008).

The first type of backtest belonging to unconditional methods is the Kupiec POF-test, which tests whether the observed frequency of VaR exceedances $\hat{p}$ is consistent with the predicted frequency of VaR exceptions $p=(1-\alpha)$ suggested by the confidence level α. Thus, the POF-test tests for the null hypothesis $H_0 := p = \hat{p} = \frac{\nu}{N}$ for N observations and ν exceedances. The best way to test this hypothesis is to apply a Likelihood-Ratio Test with following LR-statistic

$$LR_{POF} = -2\ln\left(\frac{p^{\nu}(1-p)^{N-\nu}}{\hat{p}^{\nu}(1-\hat{p})^{N-\nu}}\right). \tag{2.11}$$

This test follows an asymptotic Chi-squared distribution with one degree of freedom. The null hypothesis is accepted and the model is deemed as accurate if the LR-statistic value does not exceed the critical value related to the $(1-\alpha)$%-quantile of the Chi-squared distribution (Haas, 2001).

Kupiec also suggested the TUFF-test that is based on similar assumptions as the POF-test, but accounts for the time until the first violation occurs. The LR-statistic accounts for the time until the first violation and therefore takes the form

$$LR_{TUFF} = -2\ln\left(\frac{p(1-p)^{v-1}}{\hat{p}(1-\hat{p})^{v-1}}\right) \tag{2.12}$$

where v denotes the time until the first exception occurs. LR_{TUFF} follows an asymptotical Chi-squared distribution with one degree of freedom under the null hypothesis $H_0 = p = \hat{p} = 1/v$, which is accepted if LR falls below the critical value (Haas, 2001).

A shortcoming of unconditional coverage tests is that they do not include the independence of VaR violations from each other. Consequently, they may fail to reveal VaR measures whose VaR exceedances are dependent, in the sense that a VaR violation is followed by another. The fact that an accurate VaR measure must satisfy the unconditional coverage as well as the independence property has led to a number of tests examining the independence property of VaR violation series. A well-known test of this category is Chistoffersen's (1998) Markov test. Christoffersen (1998) examines whether a VaR exception is more likely if a VaR exception occurred the day before, i.e. whether exceptions are independent of each other in addition to unconditional coverage to form a complete conditional coverage test. If the model under consideration is accurate, a VaR violation occurred on the previous day does not influence the probability of a violation today, and the proportion of violations after a previous violation equals the proportion of violations without violation on the previous day (Angelidis and Degiannakis, 2008).

To obtain a complete test of conditional coverage, Christoffersen (1998) combines the tests of independence and unconditional coverage resulting in the test statistic

$$LR_{cc} = LR_{uc} + LR_{ind}, \tag{2.13}$$

which also follows a Chi-squared distribution with two degrees of freedom. In identity (2.13), LR_{uc} stands for the standard likelihood-ratio test statistic testing for unconditional coverage, and LR_{ind} is the test statistic for independence. Christoffersen's test is an appealing approach as it is possible to simultaneously test for coverage as well as independence hypotheses. Due to the fact that each hypothesis can be tested separately with this test, it is possible to find out whether a model failure arises from incorrect coverage or a lack of independence (Dowd, 2008).

The results of the bubble VaR approach, based on a daily calculation of VaR and BuVaR, are first visually illustrated in Figure 2.7. That is, the inflator is calculated daily and multiplied with the daily estimated VaR. The black line in Figure 2.7 represents the daily log returns of the stock market index. As the VaR and the BuVaR for long positions are expressed in positive terms, but the VaR for long positions is located on the negative side of the return distribution, the log returns were multiplied by -1 so that losses, i.e. negative returns appear as positive value in the Figures below. Therefore, the log returns are referred to as reverse log returns. Figure 2.7 shows that daily log returns exceed the VaR of long positions. Short positions are not considered as this analysis is interested in crashes. BuVaR covers some VaR exceedances, in that its value is closer to large daily returns on the negative side of the return distribution.

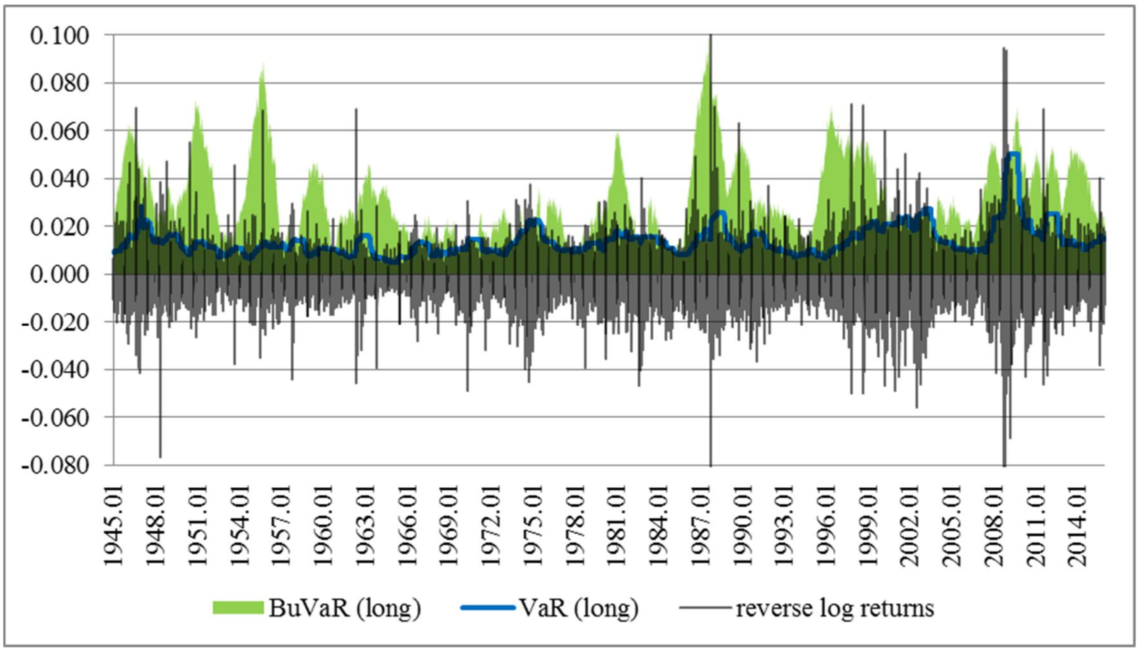

Figure 2.7: BuVaR and VaR for S&P500 Index estimated on daily basis.
VaR is calculated using daily S&P500 log returns, and the daily BuVaR is the multiplication of the daily inflator with the daily VaR. The S&P500 log returns are multiplied with -1 and represented by the black line. BuVaR is represented by the area in the figure. The historical VaR was calculated at the 5% quantile using a rolling window of 250 trading days. The confidence level is 95%.

However, the exceedances observed in Figure 2.7 are losses over one day rather than persistent losses over many days, which could be much higher than those over one day and therefore mean a higher risk. Hence, rolling returns including several days are calculated and the VaR is scaled to the longer horizon accordingly to backtest the adequacy of BuVaR in covering persistent losses. In doing so, 22 trading days are assumed per month and scale the daily estimated VaR to one-month VaR by multiplying it with the square root of 22.

The outcome is shown in Figure 2.8, and it can be seen that there are fewer BuVaR exceedances of 22-day rolling returns. Note that during the turbulences in late 1987 the 22-day rolling returns are about twice the VaR, but are covered by BuVaR.

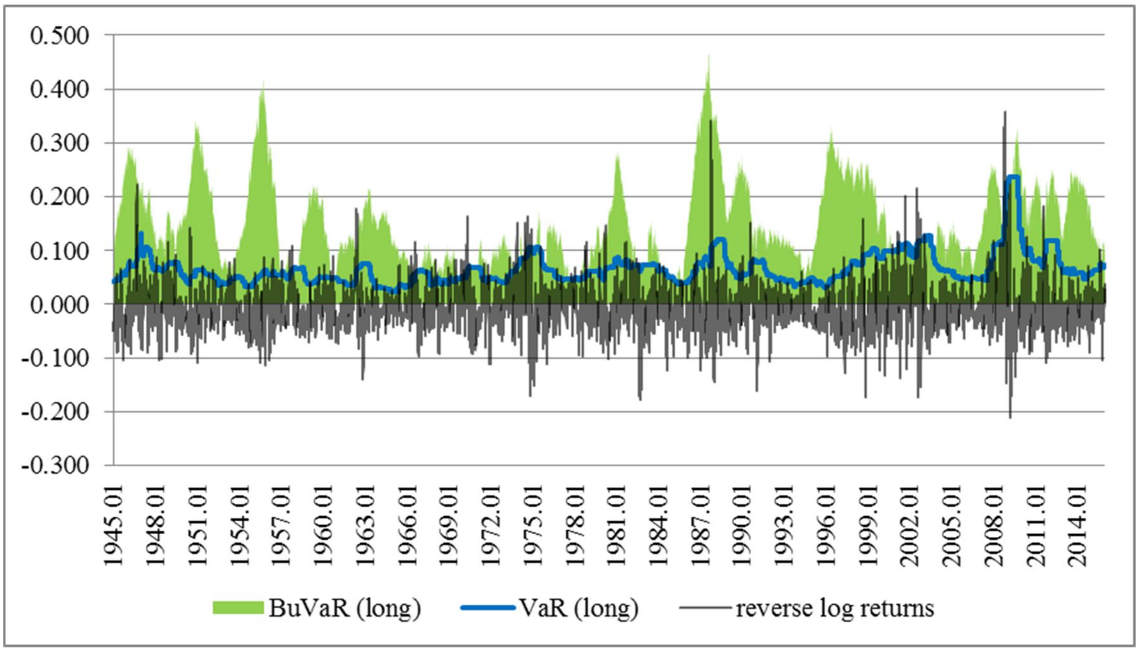

Figure 2.8: BuVaR, VaR and 22-day rolling S&P500 log returns.
VaR is calculated using daily S&P500 log returns, and the daily BuVaR is the multiplication of the daily inflator with the daily VaR. The S&P500 log returns are multiplied with -1 and represented by the black line. BuVaR is represented by the area in the figure. The daily VaR and the BuVaR were multiplied with the square root of 22. The 22 days log returns were calculated over a 22 trading-days rolling window. The historical VaR was calculated at the 5% quantile using a rolling window of 250 trading days. The confidence level is 95%.

For the sake of comparison, the rolling returns for 66 days were calculated as well, and the daily VaR was scaled to 66 days through multiplication with the square root of 66. This is shown in Figure 2.9.

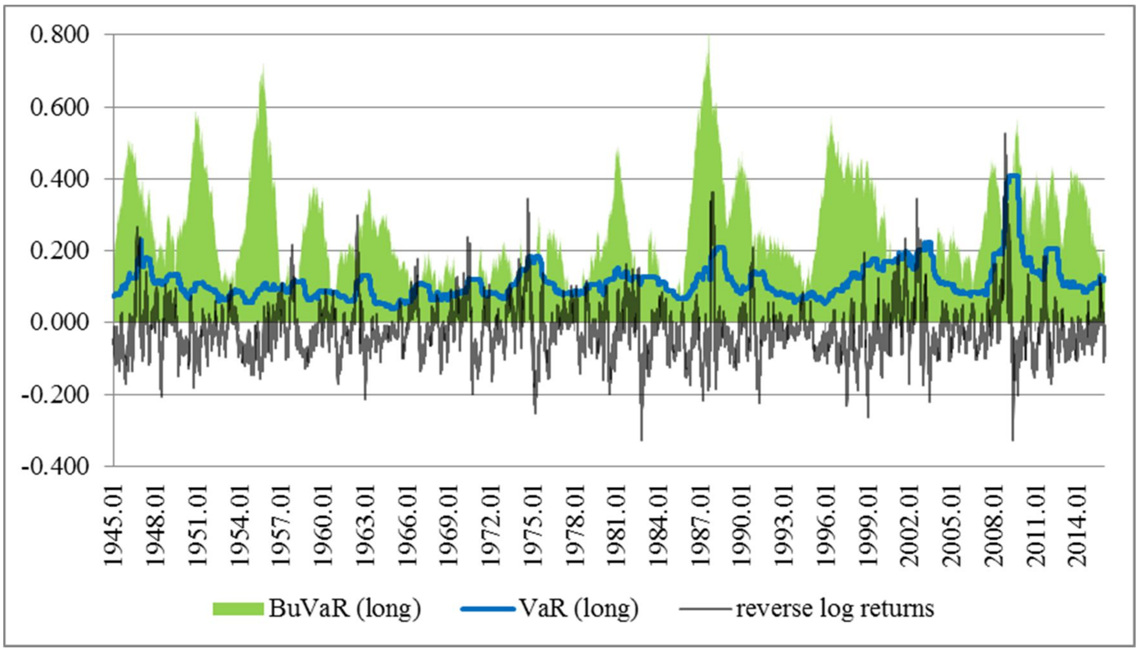

Figure 2.9: BuVaR, VaR and 66-day rolling S&P500 log returns.
VaR is calculated using daily S&P500 log returns, and the daily BuVaR is the multiplication of the daily inflator with the daily VaR. The S&P500 log returns are multiplied with -1 and represented by the black line. BuVaR is represented by the area in the figure. The daily VaR and the BuVaR were multiplied with the square root of 66. The 66 days log returns were calculated over a 66 trading-days rolling window. The historical VaR was calculated at the 5% quantile using a rolling window of 250 trading days. The confidence level is 95%.

BuVaR covers, or is at least close to, extreme rolling returns and increases often before a market slump is observed; whereas, VaR is exceeded remarkably because it rises with a market crash. However, the Figures above also show that BuVaR sometimes overestimates the risk of high negative returns, in that its value increases remarkably without a subsequent decline in stock market prices.

In this basic definition, Wong (2013) proposes to include the maximum stress, i.e. the largest positive or absolute negative daily returns and the maximum bubble in the history of the stock into the inflator. Given the logistic regression results and the short-run relationship between stock market crash and the bubble, it is debatable why the maximum overall history should be used as input in the inflator. As a consequence, a so-called modified BuVaR is proposed subsequently, which includes the maximum positive or negative (absolute) return as well as the maximum bubble over a 250 trading-days rolling window, respectively, in the calculation of the inflator. Figures 2.10 to 2.12 illustrate the outcomes of the modified BuVaR. The visual inspection illustrates that the modified BuVaR is closer to the extreme losses, in that it does not exceed the large losses as massively as the BuVaR proposed by Wong.

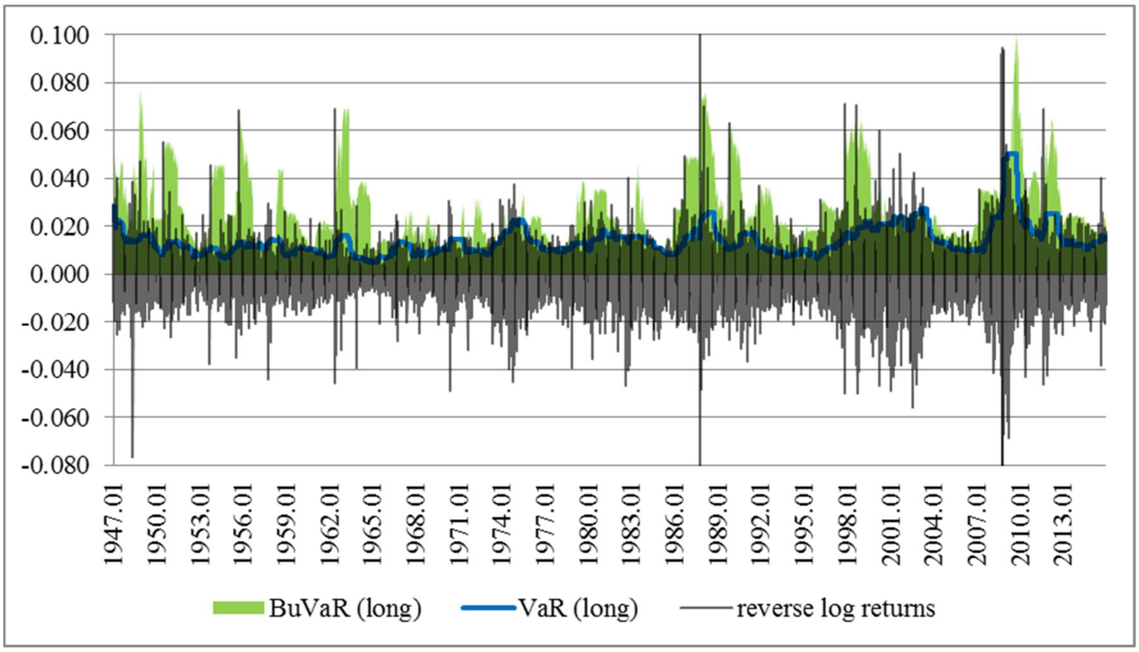

Figure 2.10: Modified BuVaR, VaR and S&P500 log returns estimated on daily basis.
VaR is calculated using daily S&P500 log returns, and the daily modified BuVaR is the multiplication of the daily modified inflator with the daily VaR. The S&P500 log returns are multiplied with -1 and represented by the black line. The modified BuVaR is represented by the area in the figure where the modified inflator includes the maximum positive or (absolute) negative log returns and the maximum bubble over a rolling window of 250 trading days. The historical VaR was calculated at the 5% quantile using a rolling window of 250 trading days. The confidence level is 95%.

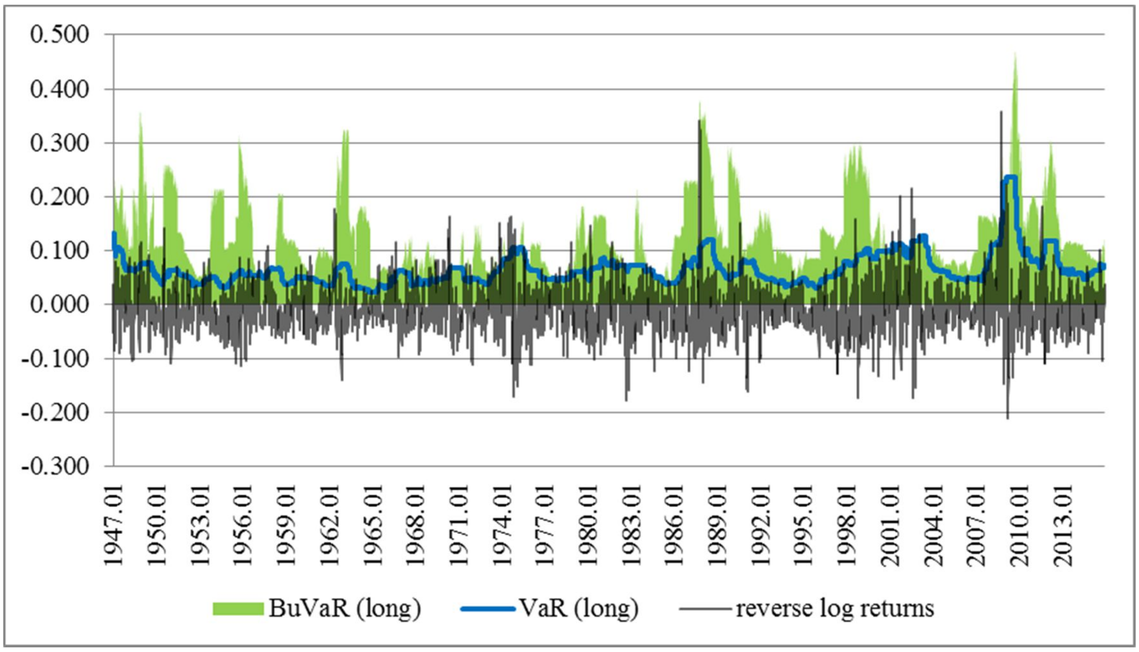

Figure 2.11: Modified BuVaR, VaR and 22-day rolling S&P500 log returns.
VaR is calculated using daily S&P500 log returns, and the daily modified BuVaR is the multiplication of the daily modified inflator with the daily VaR. The S&P500 log returns are multiplied with -1 and represented by the black line. The modified BuVaR is represented by the area in the figure where the modified inflator includes the maximum positive or (absolute) negative log returns and the maximum bubble over a rolling window of 250 trading days. The daily VaR and the modified BuVaR were multiplied with the square root of 22. The 22-day log returns were calculated over a 22 trading-days rolling window. The historical VaR was calculated at the 5% quantile using a rolling window of 250 trading days. The confidence level is 95%.

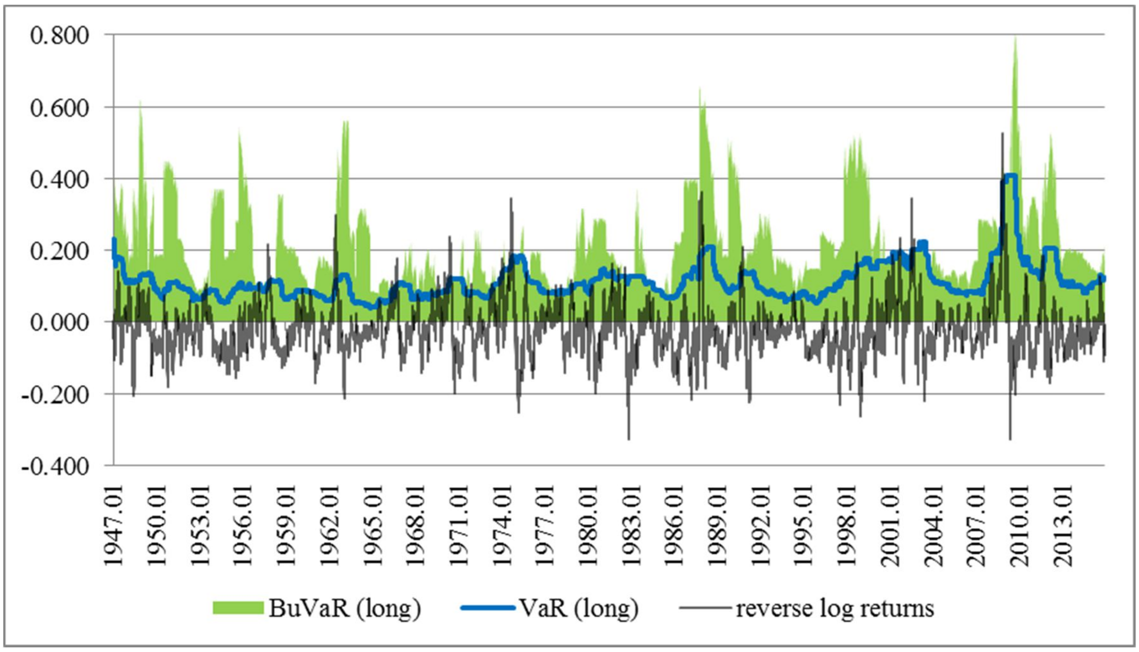

Figure 2.12: Modified BuVaR, VaR and 66-day rolling S&P500 log returns.
VaR is calculated using daily S&P500 log returns, and the daily modified BuVaR is the multiplication of the daily modified inflator with the daily VaR. The S&P500 log returns are multiplied with -1 and represented by the black line. The modified BuVaR is represented by the area in the figure where the modified inflator includes the maximum positive or (absolute) negative log returns and the maximum bubble over a rolling window of 250 trading days. The daily VaR and the modified BuVaR were multiplied with the square root of 66. The 66-day log returns were calculated over a 66 trading-days rolling window. The historical VaR was calculated at the 5% quantile using a rolling window of 250 trading days. The confidence level is 95%.

However, the modified BuVaR seems to increase more abruptly than BuVaR, which supports a longer rolling window. The results using a 500 trading-days rolling window (not reported here) show a slower build up and a slower decrease in BuVaR. BuVaR is longer lasting and indicates a higher risk. Given these outcomes, it is reasonable to interpret that the inflator should be calibrated according to the logistic regression results, and the outcomes of the logistic regression provide useful information for the calibration of BuVaR. That is, the optimal length of the rolling window appears to be roughly between 250 trading days and 500 trading days. The results are backtested for the correct number of exceedances with the unconditional coverage test. Table 2.7 and Table 2.8 summarise the results of the Kupiec backtest for the historical VaR and the Monte Carlo VaR at the 1% and 5% quantile.

Historical 1% quantile	Daily		22 days		66 days	
	VaR	BuVaR	VaR	BuVaR	VaR	BuVaR
exceedances expected	178	178	178	178	178	178
exceedances actual	90	39	167	103	74	47
LR statistic	54.2322	161.5369	0.7713	38.0936	79.3582	138.6128
critical value	3.8414	3.8414	3.8414	3.8414	3.8414	3.8414
p-value	0.0000	0.0000	0.3798	0.0000	0.0000	0.0000
Historical 5% quantile	**Daily**		**22 days**		**66 days**	
	VaR	**BuVaR**	**VaR**	**BuVaR**	**VaR**	**BuVaR**
exceedances expected	892	892	892	892	892	892
exceedances actual	410	156	715	359	576	315
LR statistic	341.0281	960.7784	39.8618	430.0354	134.5733	518.6666
critical value	3.8414	3.8414	3.8414	3.8414	3.8414	3.8414
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 2.7: Unconditional backtest results for the historical VaR and the modified BuVaR.
The backtest follows the Kupiec coverage test, where VaR is calculated at the 1% and 5% quantile. The confidence level at which the null hypothesis is evaluated is 95%. The VaR was calculated based on a rolling window of 250 trading days and accordingly scaled by the square root of time rule. The modified BuVaR uses the maximum positive and absolute negative returns as well as the maximum bubble from a 250 trading-rolling window.

Monte Carlo 1% quantile	Daily		22 days		66 days	
	VaR	BuVaR	VaR	BuVaR	VaR	BuVaR
exceedances expected	178	178	178	178	178	178
exceedances actual	179	73	289	154	129	78
LR statistic	0.0011	81.1453	58.1321	3.5759	15.3742	72.4779
critical value	3.8414	3.8414	3.8414	3.8414	3.8414	3.8414
p-value	0.9730	0.0000	0.0000	0.0586	0.0001	0.0000
Monte Carlo 5% quantile	**Daily**		**22 days**		**66 days**	
	VaR	**BuVaR**	**VaR**	**BuVaR**	**VaR**	**BuVaR**
exceedances expected	892	892	892	892	892	892
exceedances actual	179	73	289	154	129	78
LR statistic	881.8434	1312.932	576.8246	967.9523	1062.285	1287.758
critical value	3.8414	3.8414	3.8414	3.8414	3.8414	3.8414
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 2.8: Unconditional backtest results for the Monte Carlo VaR and the modified BuVaR.
The backtest follows the Kupiec coverage test where VaR is calculated at the 1% and 5% quantile. The confidence level at which the null hypothesis is evaluated is 95%. The VaR was calculated based on a rolling window of 250 trading days and accordingly scaled by the square root of time rule. The modified BuVaR uses the maximum positive and absolute negative returns as well as the maximum bubble from a 250 trading-rolling window.

This leads to the conclusion that BuVaR covers most extreme negative returns in contrast to VaR, but partially exceeds the negative returns massively. The backtesting results in Table 2.7 and Table 2.8 demonstrate that the number of actual exceedances of BuVaR is much lower than expected. The null hypothesis of correct exceedances is rejected.

2.5.3 Empirical results bubble-volatility relationship

Table 2.9 illustrates the simple regression results applied to analyse the relationship between the bubble and the realised volatility. The regression model is defined as

$$B_t = \alpha_0 + \beta_1 RV_{[t\text{-}12 to. t\text{-}L]} + \beta_2 SV_{[t\text{-}12 to. t\text{-}L]} + \varepsilon_t, \tag{2.14}$$

where t denotes monthly values of the corresponding variables.

Volatility paradox

	Dependent variable:		
	(2y)	(3y)	(5y)
crash.MA	-0.092*	-0.061	-0.001
	(0.053)	*(0.056)*	*(0.056)*
MP.MA	-19.895***	-17.407*	-6.239
	(7.100)	*(8.975)*	*(12.103)*
UTS.MA	4.017**	6.730***	12.773***
	(1.796)	*(1.921)*	*(1.662)*
UPR.MA	-0.749	5.137	25.240***
	(5.943)	*(7.198)*	*(6.462)*
PPI.MA	-4.173	-6.016	-13.625**
	(5.789)	*(6.590)*	*(6.712)*
RV.MA	-4.888**	-7.603***	-12.131***
	(1.970)	*(2.004)*	*(1.897)*
Constant	0.345***	0.352***	0.241**
	(0.093)	*(0.111)*	*(0.096)*
Observations	695	695	695
F-stat	*2.486***	*4.158****	*15.625****
Chi2	*14.917***	*24.951****	*93.749****
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 2.9: Linear regression results to test for the volatility paradox.
The variables are at a monthly frequency. The independent variables are backward-looking moving averages over two, three and five years, i.e. 24, 36 and 60 months lagged by 12 months, which is expressed by the ending ‘MA’ to the variables. The bubble is the monthly average of daily bubbles within that month. Crash represents a stock market crisis indicator, defined as cumulative decrease of at least 25% in real equity prices. Bubble is a price deviation from a benchmark level calculated using a rank filtering process. MP is the log growth rate of industrial production, defined as difference between the log industry production index in month t and month t-1. UTS is the term premium, defined as yield spread between the long-term and the one-year Treasury bonds. UPR is the default premium, defined as yield spread between Moody’s Baa and Aaa corporate bonds. PPI is the log growth rate of producer price, defined as difference between the log producer price index in month t and month t-1. RV is the realised volatility, defined as log of the square root of the sum of squared daily stock index returns within a month. The numbers in brackets are the robust standard errors clustered at the year level. The asterisks *** indicate the 1% significance level; ** indicate the 5% and * indicates the 10% significance level. The observation period is from February 1953 to December 2010.

L is chosen to take two, three and five years into account, and backward-looking moving averages of the independent variables are used instead of simple lags. That is, as the variables are observed monthly, 24, 36 and 60 lagged months are considered. In all three cases, RV has a highly significant negative influence on the bubble which indicates a so-called volatility paradox. In addition, the influence increases with the length of the moving average indicating that longer lasting periods of low realised volatility have more effect on the bubble than short periods. The line of argumentation is that low realised volatility increases the bubble which has a significant effect on crash risk. This context is interpreted as volatility paradox and complements the findings of the logistic regressions which are based on simple lagged variables and indicate a significant effect of the bubble on crash risk. A low volatility environment is an optimal precondition for the run-up phase of asset price bubbles and a slow build-up of imbalances in the background as well as higher risks that materialise when the bubble bursts (Brunnermeier and Oehmke, 2013). The finding that the RV coefficients increase with the length of the moving averages confirms the slow build-up of imbalances when volatility is low. That is, the longer the period of low volatility, the larger the bubble that grows during low volatility periods.

This phenomenon was observed in the 1990s when better economic stability during that period led to higher optimism and increased the willingness of stock market participants to take more risks. Because of the optimism about higher stability, prices of stocks increased to economically unsupportable levels by the end of the 1990s (Greenspan, 2002).

2.6 Conclusion

This chapter analyses the informative content of stock market bubbles with respect to stock market crises in the US over a period from 1950 to 2010 using monthly data for all variables. The results indicate that bubbles significantly affect the likelihood of stock market crashes where the influence loses its significance when a two-year period is assumed, giving rise to the conclusion that bubbles lead to a higher probability of crises in the short-run. Given these results, the relationship between bubbles and realised volatility is modelled, and realised volatility has a significant effect on bubbles which increases with the length of the realised volatility period. Therefore, this chapter argues that longer periods of realised volatility foster the formation of bubbles which in turn increase the crash risk in stock markets significantly.

The information content of bubbles is used to modify VaR to cover events in the fat tail, which exceed the VaR measures. This is done by the BuVaR framework proposed by Wong (2011, 2013), which is applied, and the inclusion of bubbles leads to a risk measure, which covers some of the extreme returns that exceed VaR. Furthermore, the bubble size moves with explosive behaviour detected by a simple AR(1) regression over a rolling window, which indicates the beginning and the termination of a bubble. The AR(1) coefficients are used to investigate the behaviour of a bubble where bubbles in the post-World War II era seemed to reach their maximum in the first half of the bubble period and deflate in the aftermath. That is, investors and risk managers should consider the structure of a bubble period when making their decisions as the highest returns are generated in the first two quarters of the bubble period. The results lead to the conclusion that AR(1) coefficients are informative about the stage of a bubble.

The results of this chapter are in line with previous papers, which find a relationship between bubble episodes and crash phases. The predictive power of bubbles with respect to stock market crises should be considered while measuring risk. The BuVaR approach as a countercyclical measure is one step toward this direction. However, it sometimes overestimates the risk in terms of extreme returns. Future research should therefore take advantage of the predictive content of bubbles in measuring risk and also consider the structure of bubbles to develop more accurate risk measures.

Chapter 3 Measuring the contribution to systemic risk of sectors in the US, the UK and Germany using ΔCoVaR

3.1 Introduction

Modern economies require a stable financial system to work smoothly and generate economic growth. The way a working financial system can contribute to economic growth (Levine, 1997) can fatally impact the economy. This was shown by the recent financial crisis in the wake of the burst of the subprime housing bubble in the US (Brunnermeier et al., 2017), which demonstrated how trouble in a comparatively small market niche of the economy can escalate into a serious financial crisis with significant impacts on the entire economy. The recent crisis drove large financial institutions to the brink of bankruptcy. Other large and traditional institutions such as Bear Stearns and Lehman Brothers, whose bankruptcy shook the capital market in the US and around the globe, required government intervention or even collapsed (Bullard et al., 2009).

Financial crises are frequently associated with episodes of booms and busts. Systemic financial crises can be triggered by bubble bursts that can seriously affect the financial system (Brunnermeier et al., 2017). Brunnermeier and Oehmke (2013) determined two elements of systemic risk. First, it forms during the run-up or bubble phase, and second, it materialises when the crisis breaks out. Such asset bubbles are most dangerous when they are fuelled by a credit boom and high leverage of market participants and give rise to more deleveraging and amplification mechanisms (Brunnermeier and Oehmke, 2013). Against this background, Brunnermeier et al. (2017) argue that policy instruments that prevent the build-up of risks should be employed early, when bubbles are already emerging. Following this argument, the analysis conducted in this chapter is related to the discussion on BuVaR in chapter 2, in that BuVaR can be considered as a countercyclical capital buffer, which is aimed at dampening the upward movements in asset prices.

Even though there is no generally accepted definition, any kind of risk that jeopardises the entire financial system's functioning is, in its broad sense, understood as a systemic risk. In a narrow sense, systemic risk points out how a banking crisis impacts the real economy (Bijlsma et al., 2010).

Literature distinguishes the debate on financial (in)stability in two dimensions. The time series dimension describes the build-up of a systemic risk over time and focuses on the common behaviour rather than the behaviour of individual institutions. That is, feedback effects, leverage and risk underestimation during boom phases and deleveraging and risk overestimation during recessions give rise to procyclicality as Smaga (2014) notes. The cross-section dimension describes the allocation of the risk in the financial system at a point in time and includes risks that arise from particular institutions, similar risk exposures, the links between financial institutions as well as structure and level of concentration of the financial system (BIS, 2010).

Smaga (2014) notes that both dimensions are closely related. Increased risk taking during boom phases fostered by exorbitant lending (time dimension), can result in accumulated risk exposures of banks and a concentration in market segments (cross-section dimension) at the micro level. Institutions tend to overreact and deleverage in phases of recessions and underestimate the risk of a burst in boom phases without setting up adequate capital buffers. This leads to procyclicality (Smaga, 2014).

According to Bijlsma et al. (2010) procyclicality refers to feedback mechanism, that links the financial sector and the real economy strengthening a financial crisis once it has set in. The credit expansion and enhanced risk-taking behaviour of banks during a boom results in asset price bubbles. When bubbles burst, asset markets collapse and credit losses as well as liquidity problems arise within the interbank market followed, with some time lag, by a banking crisis (Bijlsma et al., 2010).

Motivated by Schwaab et al. (2011), who note that business cycle downturns and financial sector problems have occurred simultaneously – given that the business cycle and financial problems significantly influence each other, and the Group of Ten (2001), which note that financial institutions and financial markets are affected not only by shocks coming from the financial industry or financial markets, but also from real sector shocks – this chapter's objective is to extend the empirical studies on systemic risk by measuring the systemic risk contribution of real economy sectors to the financial system. This is done by measuring the sector's marginal contribution to the entire systemic risk using Delta CoVaR (henceforth ΔCoVaR). Capturing the degree of a sector's contribution to the entire financial system with CoVaR, ΔCoVaR is the difference between CoVaR conditional on an awkwardly situated sector and the CoVaR when the sector is in the median, i.e. normal, state.

This study considers systemic risk as the risk of financial instability, which is so widespread that it hampers the functioning of the financial system (ECB, 2009) and uses the procyclical connection between the real economy and financial sector (Bijlsma et al., 2010) as motivation to analyse whether real economic sectors contribute to systemic risk. With this in mind, the ΔCoVaR concept is applied to the empirical study conducted in this work because (i) it can be used to estimate the magnitude of negative events within a particular sector that are transmitted to the system and (ii) it is a highly reactive measure of systemic risk because it relies on high-frequency financial market data (Bernal et al., 2014). Furthermore, ΔCoVaR can be used as a measure for ranking financial institutions and gauging the interconnectedness in the financial system (Castro and Ferrari, 2014).

The study that is closely related to this chapter's ideas is the one conducted by Bernal et al. (2014), which examines the contribution of individual financial sectors to systemic risk in the US and Europe and whether one particular sector (i.e. the banking, insurance, and financial services sector) is riskier than another. However, this chapter differs from Bernal et al. (2014) in several aspects. First, this chapter examines the contribution of real sectors to systemic risk. Second, this chapter focuses on individual countries such as the US, the UK and Germany.

The remainder of this chapter is organised as follows. Section 3.2 discusses various definitions of systemic risk and provides a brief review of systemic risk measures. The ΔCoVaR approach is described in section 3.3. Section 3.4 describes the data and methodology used in this chapter. The empirical results of the quantile regression for all countries under investigation and the analysis of the $\widehat{\mathrm{VaR}} - \widehat{\Delta\mathrm{CoVaR}}$ relationship is discussed in section 3.5. The time variation of $\widehat{\Delta\mathrm{CoVaR}}$ for each country and the consequences of shock events on ΔCoVaR are discussed in section 3.6. Section 3.7 discusses policy implications and section 3.8 concludes this chapter.

3.2 Definitions and measures of systemic risk

This section discusses the definitions of systemic risk in section 3.2.1. Some of the measures of systemic risk proposed in the literature are discussed in section 3.2.2.

3.2.1 Definitions of systemic risk

Despite its relevance, no definition of systemic risk is commonly accepted. The European Central Bank defines systemic risk as the risk of financial instability so widespread that it hampers the functioning of a financial system to such an extent that it substantially impacts economic growth and welfare (ECB, 2009).

The Group of Ten (2001) proposes another definition of systemic risk. According to this definition, systemic risk is the risk that a trigger event causes a loss in confidence or economic value and that problems in the financial system have significant impacts on the real economy. The Group of Ten's definition of systemic risk emphasises the effects of a systemic financial risk event on the real economy. A financial event is regarded as impacting the real economy through three channels, such as disruptions in the payment system that lead to the illiquidity of firms and disorders in credit flows that lead to fewer investments in opportunities. Third, economic activity is reduced through lower wealth and higher uncertainty because of the collapses in asset prices caused by a substantial reduction of the aggregate money supply (Group of Ten, 2001).

Hansen (2014) considers systemic risk to be a risk of dysfunction or a breakdown in financial markets that necessitates monitoring, intervening, and regulating financial markets, whereas Billio et al. (2012) define systemic risk as a number of circumstances that jeopardise the stability of the financial system or the public's confidence in it.

Schwarcz (2008) notes that the various definitions of systemic risk share a trigger event such as an economic shock or an institutional failure that leads to a series of negative consequences in the economy that may result in institution or market failures or high losses to financial firms and/or a dramatic volatility in financial market prices.

This chapter follows the definition of ECB (2009), and defines systemic risk as the risk of financial instability, which is so widespread that the financial system is affected and considers the role of asset price bubbles with respect to policy implications following Brunnermeier and Oehmke (2013).

3.2.2 Measures of systemic risk

Many authors have focused on the magnitude that a single financial institution contributes to systemic risk and, for this purpose, have proposed different methods such as the Systemic Expected Shortfall (SES) indicator proposed by Acharya et al. (2017), which represents the magnitude of a negative effect that an institution imposes on the system at large. Acharya et al. (2017) find that the components of the SES, the marginal expected shortfall (MES) and leverage explain a significant proportion of realised returns between July 2007 and December 2008 and show that equity and CDS data can be applied to estimate a cross-sectional measure of systemic risk.

However, the SES is static and unable to measure systemic risk ex ante, given that it requires data from actual financial crises. An alternative dynamic reduced form estimation of capital shortages is provided by Brownlees and Engle (2017), who introduce the SRISK index to measure the systemic risk contribution of a financial firm and the financial system's aggregate overall systemic risk. The index is composed of a firm's leverage, size and expected equity loss conditional on the market decline referred to as LRMES (long run marginal expected shortfall), which together determine the expected capital shortage that a financial institution would suffer if a systemic event were to occur. Institutions with higher SRISK values are at a higher risk and contribute more to the financial sector undercapitalisation in a crisis (Brownlees and Engle, 2017).

Huang et al. (2009) use data on the CDS of financial institutions to derive the probability of default (PD) of individual firms. In constructing their systemic risk measure, called the distress insurance premium (DIP), the second risk parameter, the stock return correlations among financial firms, is estimated based on the co-movements in equity prices. This risk measure represents a hypothetical insurance premium against systemic distress in the financial sector that increases in both the PD and equity return correlations. This approach can be applied to firms with CDS and equity contracts that are publicly tradeable, and it does not rely on accounting or balance sheet information (Huang et al., 2009).

The DIP and MES quantify the contagion effects from negative extreme events but have the weakness that calculating the DIP includes simulating rare events, whereas the MES is conditional on a rare event and thus is affected by scarce data (Chao et al., 2012).

The above-mentioned risk measures estimate the magnitude of losses that an institution would experience during a market crisis and only capture systemic exposures to the degree that historical data well represents systemic losses. However, during periods of rapid financial innovation, extreme losses in one financial sector need not coincide with simultaneous losses in another financial sector even though their connectedness implies higher systemic risk (Billio et al., 2012).

With an analysis focused on the spillover effects among financial firms, Adams et al. (2014) suggest state-dependent sensitivity VaR (SDSVaR), which measures the spillover effects, depending on the state of financial markets. Using a system of quantile regressions of financial institutions such as commercial banks, investments banks, hedge funds and insurance companies, the authors find a remarkable change in the spillover effects among financial firms from normal periods to volatile times and conclude that equivalent shocks have remarkable spillover effects during crisis periods compared with tranquil episodes (Adams et al., 2014).

Empirical studies on systemic risk measures are based on different data. Some analyses focus on the market equity data and balance sheet data of individual banks (e.g. Adrian and Brunnermeier, 2016; López-Espinosa et al., 2012; López-Espinosa et al., 2012a;

Brownlees and Engle, 2017), whereas other researchers use equity price data and CDS data (e.g. Huang et al., 2009; Acharya et al., 2017).

3.3 The ΔCoVaR approach

Adrian and Brunnermeier (2016) take a perspective similar to that of Acharya et al. (2017) and Brownlees and Engle (2017); they capture the degree of contribution of a single institution to the entire financial system with a measure called CoVaR. Adrian and Brunnermeier (2016) interpret the difference between CoVaR conditional on an awkwardly situated financial firm and the CoVaR, when the institution is in the median state as the institution's marginal contribution to the entire systemic risk, referred to as ΔCoVaR. That is, ΔCoVaR measures the contribution of a single institution to systemic risk rather than the risk of individual institutions in isolation, enabling regulators to impose stricter rules on institutions with a higher contribution to systemic risk even when their VaRs do not differ from firms with a lower systemic risk contribution. Furthermore, ΔCoVaR accounts for the risk spillovers between institutions across the financial network in that it captures the risk increase of an institution when another firm is in a stressed state. Although GARCH models can be used in estimating ΔCoVaR, Adrian and Brunnermeier (2016) prefer to use quantile regressions based on weekly changes in the market-valued total assets of publicly traded financial firms.

The VaR of institution j conditional on institution's i event $C(X^i)$ is represented by $CoVaR_q^{j|i}$, which is defined by quantile q of the conditional probability distribution, where

$$q = P\left(X^j \leq CoVaR_q^{j|C(X^i)} \middle| C(X^i) \right). \tag{3.1}$$

The CoVaR measures the risk spillover and is a low (i.e. large negative) number, the higher the potential loss to the system with a probability q (Roengpitya and Rungcharoenkitkul, 2010).

Adrian and Brunnermeier (2016) consider a single firm's contribution to systemic risk and therefore attribute j to the system and analyse the case when the portfolio return of all financial institutions is at its VaR level. Letting $\hat{X}_q^{system,i}$ denote the predicted value for a quantile conditional on firm i, the qth-quantile is defined as $\hat{X}_q^{system,i} = \hat{\alpha}_q^i + \hat{\beta}_q^i X^i$, and the relationship $VaR_q^{system} \left| X^i = \hat{X}_q^{system,i}\right.$ is derived from the definition of VaR. In words, the financial system's VaR conditional on X^i is given by the predicted value from the quantile regression of the system on firm i, given that the conditional quantile is the VaR_q given X^i.

The $CoVaR_q^i$ measure is obtained using a particular value of $X^i = VaR_q^i$, where the CoVaR measure is represented by

$$CoVaR_q^{system|X^i=VaR_q^i} := VaR_q^{system} \left| VaR_q^i = \hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i \right. . \tag{3.2}$$

The $\Delta CoVaR_q^i$ is then calculated by using

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i=VaR_q^i} - CoVaR_q^{j|X^i=median^i} \tag{3.3}$$

which is the difference between j's CoVaR, when i is at its VaR level and in its median state. Given that this study focuses on the systemic risk contribution of sectors, i represents a sector instead of a firm or institution, as in Adrian and Brunnermeier (2016).

The ΔCoVaR measure has been used to identify and rank systemically important institutions by developing a significance test and a test of dominance, as in Castro and Ferrari (2014), who demonstrate the importance of statistical testing when ΔCoVaR is being used to gauge interconnectedness and rank systematically important financial institutions (SIFIs). By deriving two hypothesis tests and their test statistics within a linear quantile regression framework, Castro and Ferrari (2014) have developed a significance test that makes it possible to determine whether a financial firm is systemically important in terms of its contribution to systemic risk and a test of dominance that aims to determine whether one financial firm contributes more to systemic risk than another. They conclude that a larger ΔCoVaR makes a significant contribution to systemic risk more likely, but does not necessarily imply that an institution's contribution is significant and that the results of pairwise tests of dominance should also be considered.

Despite its prominence, the ΔCoVaR risk measure has faced critiques in the literature. Danielsson et al. (2016) argue that ΔCoVaR does not bring any advantages to VaR, given that both measures convey a similar signal. Furthermore, it is not possible to identify the systemically riskier institution (or sector).

In the same vein, Jäger-Ambroźewicz (2013) notes that ΔCoVaR may give rise to an incorrect ranking of systemic risk in the sense that it attributes a lower systemic risk where a higher systemic risk should be detected.

In coping with the absence of a formal test to compare each financial sector's relative contribution, a bootstrap Kolmogorov-Smirnov test is implemented that makes it possible to rank the individual financial sectors according to their relative contribution to systemic risk.

The concept of CoVaR is a type of correlation and is, therefore, a measure of co-dependence that is based on a quantile regression and does not explain the channel by which an institution's risk impacts the risk measurement of another institution. The ΔCoVaR is sensitive to changing VaR estimates, which is the reason why institutions with higher changes in portfolio returns seem to contribute more to systemic risk than entities with larger engagements in these investments but fewer changing returns, as Arias et al. (2011) concluded for Colombian financial institutions.

As a distribution-based statistical measure, CoVaR is mostly based on equity return data and only measures physical systemic risk. It does not ex ante take the size of an institution into account (Black et al., 2013).

Boucher et al. (2013) argue that main systemic risk measures are highly sensitive to measurement errors. These authors claim that the systemic rankings are arbitrary and random, and they propose a corrected version of CoVaR that systemically highlights institutions that differ from the non-corrected CoVaR. Hence, the calculation of CoVaR and other systemic risk measures such as the MES and SRISK should also account for model risk (Boucher et al., 2013).

López-Espinosa et al. (2012a) show that the asymmetric effect of positive and negative shocks to bank balance sheets on the financial system may result in an underestimation of systemic risk when markets are declining. These authors extend the model proposed by Adrian and Brunnermeier (2016)[3] by allowing the functional form that characterises the conditional quantile of the system to be non-linearly dependent on positive and negative individual returns. That is, the original CoVaR model is supplemented by the terms $\delta_{1,i}X^{-}_{t,i}$ and $\delta_{2,i}X^{+}_{t,i}$, where $\delta_{1,i}$ and $\delta_{2,i}$ capture the co-movements between the system portfolio and the individual portfolio, when it is declining or increasing, is represented by $X^{-}_{t,i}$ and $X^{+}_{t,i}$, respectively. Hence, if $(\delta_{1,i}, \delta_{2,i}) > 0$, then a sudden

[3] This assumes a linear relationship between system and individual returns.

individual asset change will non-linearly transmit into the system (López-Espinosa et al., 2012a).

3.4 Data and Methodology

The objective of this section is to investigate the contribution of sectors in the economy to systemic risk in the investigated countries. In doing so, the influences of the 10 ICB industry-level sectors on systemic risk are examined and ranked according to their $\widehat{\Delta \mathrm{CoVaR}}$.

3.4.1 Data and sectors

Based on the empirical studies by Bernal et al. (2014), Castro and Ferrari (2014) and Girardi and Ergün (2013), this study's objective is to determine which sectors can be classified as being important to systemic risk and ranking them by their systemic risk contribution.

The sectors follow the Industry Classification Benchmark (ICB), categorising companies into 10 industries, 19 supersectors and 41 sectors, with the financial industry comprising banking, insurance and other financial services.

Following Bernal et al. (2014), Castro and Ferrari (2014) and Girardi and Ergün (2013), national stock market indices are considered as a proxy to represent the system for the countries under investigation. To that end, the S&P500 Index is used for the US, whereas the UK uses the FTSE All-Share Index. Germany uses the CDAX Index as a proxy for their system. From these indices, those companies that belong to the sector under examination are excluded so that shocks to a certain sector do not mechanically affect the index, despite the lack of spillover effects between the sector and the global index. Therefore, the system is represented by so-called ex indices. Given that 10 sectors are considered in this study, there are 10 ex indices, namely, the ex Consumer Goods index, the ex Consumer Services index, the ex Energy index, the ex Financials index, the ex Healthcare index, the ex Industrials index, the ex Technology index, the ex Basic Materials index, the ex Telecommunication index and the ex Utilities index. These indices are obtained from Bloomberg using the CIX function and are based on ICB.

Additionally, economic state variables that represent market states are incorporated into the analysis to estimate the time-varying CoVaR_t and VaR_t at time t, which capture the time-varying dynamics of expected returns and/or the conditional volatility, as in Adrian and Brunnermeier (2016). Furthermore, the return of the market portfolio (represented by the equity index returns), the liquidity spread and the yield spread change, which is defined as the difference between the 10-year bond rate and the 3-month bond rate of a country, are included. Furthermore, the credit spread change is incorporated, in addition to the difference between a country's 3-month bond rate in time t and the 3-month bond rate in time t-1, represented by the 3-month T-bill spread variation. Finally, real estate returns and the implied volatility in the stock market, represented by a volatility index, are taken into account. The usage of the state variables for the US is supported by Hautsch et al. (2015) and Fan et al. (2013).

Following empirical studies such as those by Chao et al. (2012) and Hautsch et al. (2015), the volatility index is used instead of the volatility index returns to represent the volatility in the markets. Whaley (2000) considers the VIX as a measure of fear that spikes during turbulent periods. A rise in volatility causes stock prices to fall, and high levels of VIX coincide with high degrees of market turbulence (Whaley, 2000). Other papers argue that the higher uncertainty estimated by VIX leads to a downturn in economic activity and output. Bloom (2009) finds important implications of the VIX levels for all asset class return expectations.

Following Ali (2012), who suggested using VSTOXX when the portfolio is composed of European stocks, given that VSTOXX measures the core European market, here, VIX is only used to gauge uncertainty in the US, whereas, for the UK, the FTSE 100 volatility index is considered the most accurate volatility measure. The VDAX New Index is used for Germany to account for the volatility of each geographical area.

In the subsequent analysis, the sample period is divided into four periods, which are referred to as difficult, calm, crisis and the recovery period as shown in Table 3.1.

Difficult period	8th November 1999–30th April 2003
Calm period	1st May 2003–31st July 2007
Crisis period	1st August 2007–30th October 2009
Recovery period	1st November 2009–9th August 2013

Table 3.1: Definition of periods for the US and Germany

The periods are similarly defined for the UK, with the difference that the difficult period begins on 5th January 2000 and the recovery period ends on 31st December 2012.

The analysis uses daily observations for a time horizon that spans from November 1999 to August 2013, resulting in 3,435 daily observations for the US and 3,486 for Germany. For the UK, the period spans from January 2000 to December 2012, leading to 3,244 observations. The stock market indices are summarised in Table 3.2 for each country under investigation. Also, the corresponding state variables used in the quantile regression analysis are summarised in Table 3.3.

Variables US		Variables UK		Variables Germany	
Variable	**Source of Data**	**Variable**	**Source of Data**	**Variable**	**Source of Data**
R: Daily market returns of the sectors and the system		*R: Daily market returns of the sectors and the system*		*R: Daily market returns of the sectors and the system*	
System	S&P500 Index excluded the sector under investigation	System	FTSE All Share Index excluded the sector under investigation	System	CDAX Index excluded the sector under investigation
Cons. Goods	S&P500 Cons. Goods Index	Cons. Goods	FTSE ALL-Share Cons. Goods Index	Cons. Goods	CDAX Cons. Goods Index
Cons. Services	S&P500 Cons. Services Index	Cons. Services	FTSE ALL-Share Cons. Services Index	Cons. Services	CDAX Cons. Services Index
Energy	S&P500 Energy Index	Energy	FTSE ALL-Share Oil & Gas Index	Energy	CDAX Energy Index
Financials	S&P500 Financials Index	Financials	FTSE ALL-Share Financials Index	Financials	CDAX Financials Index
Health Care	S&P500 Health Care Index	Health Care	FTSE ALL-Share Health Care Index	Health Care	CDAX Health Care Index
Industrials	S&P500 Industrials Index	Industrials	FTSE ALL-Share Industrials Index	Industrials	CDAX Industrials Index
IT	S&P500 IT Index	IT	FTSE ALL-Share IT Index	IT	CDAX IT Index
Basic Materials	S&P500 Basic Mat. Index	Basic Materials	FTSE ALL-Share Basic Mat. Index	Basic Materials	CDAX Basic Mat. Index
Telecomm.	S&P500 Telecomm. Index	Telecomm.	FTSE ALL-Share Telecomm. Index	Telecomm.	CDAX Telecomm. Index
Utilities	S&P500 Utilities Index	Utilities	FTSE ALL-Share Utilities Index	Utilities	CDAX Utilities Industry Index

Table 3.2: Indices of the considered countries.
To be correct, the tables show the 10 industries of the ICB that can be decomposed into supersectors such as banks and insurance companies. The subsequent analysis considers these industries as sectors so that, in the empirical study below, the industries are referred to as sectors. The data were taken from Bloomberg. The indices without the sector under investigation (referred to as ex index) were obtained from Bloomberg using the CIX function based on the ICB. IT denotes the Technology sector and the abbreviation Cons. stands for consumer.

M: State variables		*M: State variables*		*M: State variables*	
VIX	Volatility index	FTSE100 Vola Index	Volatility index	VDAX	Volatility index
Liquidity Spread	Difference between the 3-month repo rate and the 3-month T-Bill rate	Liquidity Spread	Difference between the 3-month repo rate and the 3-month UK nominal spot curve	Liquidity Spread	Difference between the 3-month repo rate and the 3-month German bond rate
3-month T-bill spread variation	Difference between the 3-month T-Bill rate in time t and the 3-month T-Bill rate in time t-1	3-month T- bill spread variation	Difference between the 3-month UK nominal spot curve in time t and the 3-month UK nominal spot curve in time t-1	3-month T-bill spread variation	Difference between the 3-month German bond rate in time t and the 3-month German bond rate in time t-1
Yield spread change	Difference between the 10-year Treasury Bonds rate and the 3-month T-Bill rate	Yield spread change	Difference between the 10-year Treasury Bonds rate and the 3-month UK nominal spot curve	Yield spread change	Difference between the 10-year German bond rate and the 3-month German bond rate
Credit spread change	Difference between the 10-year Macrobond BBB US corporate bonds rate and the 10-year US Treasury Bonds rate	Credit spread change	Difference between the 10-year Macrobond BBB UK corporate bonds rate and the 10-year UK Treasury Bonds rate	Credit spread change	Difference between the 10-year Macrobond BBB German corporate bonds rate and the 10-year German bond rate
Market return	S&P 500 Index return	Market return	FTSE All-Share Index return	Market return	CDAX Index return
Real estate returns	Return generated by the Dow Jones U.S. Real Estate index	Real estate returns	Daily return of the FTSE Real Estate Index	Real estate returns	Daily returns of DIMAX index interpolated from weekly values
Period	8/11/1999 – 9/8/2013	Period	5/1/2000 – 31/12/2012	Period	10/11/1999 – 9/8/2013

Table 3.3: State variables of the considered countries.

The 3-month T-bill rate for the UK is not available on a daily basis for the entire period. For this reason, the 3-month UK nominal spot curve is used as a proxy for the T-bill rate. The state variables are defined as in Table 3.3 and are included in the quantile regressions. They are considered to represent the market states and were taken from Bloomberg and Macrobond. The real estate index values for Germany were taken from Bankhaus Ellwanger & Geiger at weekly frequency and interpolated to daily frequency before the daily index returns were calculated. The daily real estate returns for the US were downloaded from the webpage www.djindexes.com.

3.4.2 Methodology

The empirical analysis is conducted in a six-step procedure that begins with the τ%-quantile regression:

$$R_t^i = \alpha^i + \gamma^i M_t + \varepsilon_t^i \tag{3.4}$$

with the daily market return of sector i at time t (R^i_t) as the dependent variable and a vector of state variables M_t, where, in this analysis τ is 2.5%[4]. Thus, (3.4) represents the 2.5%-quantile regression. The error term ε_t^i is assumed to be independent of M_t and iid with a mean 0 and a unit variance. The symbols α^i and γ^i denote the constant and the parameter vector, respectively. The quantile regression can be seen as a linear programming problem, which can be solved using linear programming methods such as the simplex algorithm (Koenker and Hallock, 2001). Koenker (2015) proposes to use the Frisch-Newton algorithm for problems with a few thousand observations and a Frisch-Newton algorithm, after preprocessing, for extremely large problems. This chapter uses the Barrodale and Roberts simplex algorithm as a fitting method in the quantile regression as it is a moderate sized problem.

The estimation of this linear model using a quantile regression provides the coefficients $\hat{\alpha}^i$ and $\hat{\gamma}^i$ (ε_t^i is assumed to be 0), which are used in step 2 to compute the predicted τ% VaR for each sector i. That is, the predicted VaR (τ%) of sector i is:

$$\widehat{VaR_t^i} = \hat{\alpha}^i + \hat{\gamma}^i M_t \tag{3.5}$$

with M_t representing the vector of the state variables.

Step 3 models the system returns R_t^{system} as a linear function of state variables M_t and sector return i. Thus,

$$R_t^{system} = \alpha^{system|i} + \beta^{system|i} R_t^i + \gamma^{system|i} M_t + \varepsilon_t^{system|i} \tag{3.6}$$

[4] Adrian and Brunnermeier (2016) use a vector of lagged state variables M_{t-1}.

with R_t^i as the return of sector index i and a vector of state variables M_t. Again, the employment of the 2.5%-quantile regression provides the estimates of $\alpha^{system|i}$, $\beta^{system|i}$ and $\gamma^{system|i}$.

Step 4 calculates the VaR of the system conditional on distress in sector i. In doing so, the VaR estimated in step 2 is included in the estimation of $\widehat{CoVaR_t^{system}}$, in addition to the vector of state variables M_t. That is, the coefficients $\widehat{\alpha^{system|i}}$, $\widehat{\beta^{system|i}}$ and $\widehat{\gamma^{system|i}}$, estimated in step 3, are applied and the predicted CoVaR of the system is represented by:

$$\widehat{CoVaR}^{system|i} = \hat{\alpha}^{system|i} + \hat{\beta}^{system|i}\widehat{VaR_t^i} + \hat{\gamma}^{system|i}M_t. \tag{3.7}$$

Adrian and Brunnermeier (2016) define ΔCoVaR as the difference between the system's VaR conditional on distress in sector i and the VaR of the same system conditional on the normal situation (i.e. the median state) of sector i.

Therefore, step 5 computes the contribution of sector i to systemic risk as the difference between the predicted CoVaR at the τ%-quantile CoVaR and the 50%-quantile CoVaR, which is mathematically expressed as:

$$\widehat{\Delta CoVaR_t}(\tau)^{system|i} = \widehat{CoVaR_t}(\tau\%)^{system|i} - \widehat{CoVaR_t}(50\%)^{system|i} \tag{3.8}$$

The 50%-quantile CoVaR is determined by conducting steps 1 to 4 for a 50%-quantile, i.e. by applying the same methodology with τ=0.5. It is important to note that sectors with larger absolute $\widehat{\Delta CoVaR}$ contribute relatively more to systemic risk in turbulent periods.

The ΔCoVaR approach is extended by the Kolmogorov-Smirnov test (KS) based on bootstrapping that makes it possible to check whether a certain sector significantly contributes to systemic risk. This significance test is supplemented by a test of dominance to evaluate whether a certain sector's contribution to systemic risk is larger than that of another. It is important to note that $\widehat{VaR}$ and $\widehat{\Delta CoVaR}$ denote the predicted values of VaR and ΔCoVaR, which are obtained by applying the procedure discussed above. However, VaR and ΔCoVaR without the bar only describe the VaR and ΔCoVaR in general. Thus, the subsequent discussion uses the notation with bars to refer to the values of VaR and ΔCoVaR, which were estimated by the author in the context of this study by using the five steps discussed so far. The same applies to CoVaR.

Step 6 has the objective of ranking the sectors concerning their contribution to systemic risk by testing the significance and stochastic dominance of the $\widehat{\Delta \text{CoVaRs}}$ estimated in the previous step. To find a systemically risky sector, whether the $\widehat{\Delta \text{CoVaR}}$ conditional on sector i is significantly different from zero is checked by using the bootstrap Kolmogorov-Smirnov test. Abadie (2002) notes that two distributions can be compared by testing the hypothesis of equality as well as the first-order or second-order stochastic dominance. Using two empirical distribution functions, the Kolmogorov-Smirnov statistic is a natural way to test the hypothesis of equal distributions (Abadie, 2002). In so doing, it is tested whether the CDFs of the 2.5%-quantile $\widehat{\text{CoVaRs}}$ and the 50%-quantile $\widehat{\text{CoVaRs}}$ are different from each other, where the 50%-quantile $\widehat{\text{CoVaR}}$ represents the VaR of the system in a normal situation. Thus, the $\widehat{\Delta \text{CoVaR}}$ is tested, whether it statistically equals 0, which would suggest that the corresponding sector is not statistically risky. Therefore, the null hypothesis H_0 is:

$$H_0 : \widehat{\text{CoVaR}}_t(2.5\%)^{\text{system}|i} = \widehat{\text{CoVaR}}_t(50\%)^{\text{system}|i} \tag{3.9}$$

and the alternative hypothesis H_1 is:

$$H_1 : \widehat{\text{CoVaR}}_t(2.5\%)^{\text{system}|i} < \widehat{\text{CoVaR}}_t(50\%)^{\text{system}|i}. \tag{3.10}$$

The null hypothesis is rejected if the p-value lies below a significance level of 5%. To obtain a formal ranking of the sectors, according to their contribution to systemic risk, and to check whether sector i contributes less (i.e. its $\widehat{\Delta \text{CoVaR}}$ is smaller) to systemic risk than sector j, a dominance test is conducted. In this case, the $\widehat{\Delta \text{CoVaRs}}$ related to each sector are bootstrapped, and the CDFs of two sectors are compared to test whether one sector has a higher systemic risk contribution than another sector.

Using a bootstrap strategy is also supported by Abadie (2002), who notes that the test statistic's asymptotic distributions are, in general, unknown under the null and proposes a bootstrap strategy as a solution.

To determine the alternative hypothesis that both sectors have an equal systemic risk contribution, the following two null hypotheses are tested:

$$H_0 : \widehat{\Delta \text{CoVaR}}_t(\tau)^{\text{system}|i} < \widehat{\Delta \text{CoVaR}}_t(\tau)^{\text{system}|j} \tag{3.11}$$

and

$$H_0 : \widehat{\Delta \text{CoVaR}}_t(\tau)^{\text{system}|j} < \widehat{\Delta \text{CoVaR}}_t(\tau)^{\text{system}|i} \tag{3.12}$$

That is, it is tested whether sector i contributes less to systemic risk and whether sector j contributes less to systemic risk, which means that the alternative hypothesis

$$H_1 : \widehat{\Delta \text{CoVaR}}_t(\tau)^{\text{system}|j} = \widehat{\Delta \text{CoVaR}}_t(\tau)^{\text{system}|i} \tag{3.13}$$

of non-dominance can be accepted if both null hypotheses are rejected (Castro and Ferrari, 2014). The test statistic for the dominance test equals that for the significance test, with the difference that the CDFs of the $\widehat{\Delta \text{CoVaR}}$ relate to two sectors (Bernal et al., 2014). Again, the p-value is compared to a significance level α, as discussed above.
Both statistical tests occur in a two-sample treatment control setting where 10,000 bootstraps are performed; these are actually Monte Carlo simulations, which are conducted to ascertain the proper p-value based on the empirical data (Sekhon, 2013).

3.5 Empirical results

This section presents the quantile regression results in section 3.5.1 and the statistical test results in section 3.5.2.

3.5.1 Regression results

The results of the quantile regressions for the US are shown in the following Tables, where the variables defined in Table 3.2 and Table 3.3 are regressed on each sector index. The regression results of each regression are presented in one table, respectively. The tables represent the sector index return regressions, and the ex sector index returns regressions at the 2.5% and 50%-quantiles.
The volatility index VIX has a negative and significant impact on the 2.5%-quantile sector index returns of all sectors during the difficult period, except for the Basic Materials, Consumer Services, Healthcare and Technology sectors (Table 3.4).

2.5%-quantile sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-1.6749	-0.7822	-0.1334	-0.5463	-1.4930	-2.4473	-0.8146	-3.4525	-0.2865	0.7157
	0.1024	*0.0000*	*0.7968*	*0.0886*	*0.0060*	*0.0042*	*0.2784*	*0.0010*	*0.7311*	*0.1071*
VIX	-0.0331	-0.0153	-0.0625	-0.0378	-0.0043	0.0054	-0.0831	-0.0344	-0.0835	-0.1464
	0.3922	*0.0148*	*0.0015*	*0.0019*	*0.8354*	*0.8665*	*0.0035*	*0.3849*	*0.0082*	*0.0000*
Liquidity spread variation	-0.0006	-0.0004	-0.0060	-0.0046	-0.0039	-0.0008	-0.0097	-0.0140	-0.0074	-0.0070
	0.9437	*0.7528*	*0.1348*	*0.0647*	*0.3542*	*0.9034*	*0.0944*	*0.0836*	*0.2490*	*0.0398*
T-bill spread variation	0.0291	0.0022	-0.0307	0.0234	0.0321	0.1461	-0.0709	0.0276	0.0816	-0.0015
	0.5857	*0.7959*	*0.2560*	*0.1614*	*0.2560*	*0.0010*	*0.0703*	*0.6129*	*0.0606*	*0.9490*
Yield spread change	-0.0006	0.0136	-0.0237	-0.0043	-0.0157	0.0675	-0.0654	0.0233	0.0409	-0.0099
	0.9888	*0.0480*	*0.2700*	*0.7492*	*0.4848*	*0.0560*	*0.0359*	*0.5912*	*0.2369*	*0.5920*
Credit spread change	0.0711	0.0180	-0.0299	0.0284	-0.0467	0.0742	-0.0609	-0.1396	0.0838	0.0782
	0.3511	*0.1451*	*0.4375*	*0.2342*	*0.2461*	*0.2417*	*0.2761*	*0.0729*	*0.1770*	*0.0180*
Return S&P 500	0.5352	0.7384	0.8141	0.4860	0.6764	0.4617	0.6795	1.7401	0.2382	0.2954
	0.0018	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0012*	*0.0000*	*0.0000*	*0.0865*	*0.0001*
Return real estate	0.0538	0.1499	0.3037	0.0765	0.2800	0.3427	0.3345	-0.9037	0.4874	-0.0986
	0.8508	*0.0013*	*0.0360*	*0.3927*	*0.0644*	*0.1500*	*0.1112*	*0.0020*	*0.0366*	*0.4264*

Table 3.4: 2.5%-quantile regression results for the US over the difficult period.

The daily market returns of the sectors are used as dependent variable in the linear quantile regression, which uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The difficult period ranges from 8th November 1999 to 30th April 2003. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta \text{CoVaR}}$.

2.5%-quantile ex sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-0.3524	-0.8182	-0.4785	-0.5611	-1.1805	-0.3154	-0.5355	-0.1398	-0.5050	-0.5315
	0.3484	*0.0086*	*0.0214*	*0.3226*	*0.0020*	*0.2568*	*0.3382*	*0.6428*	*0.2031*	*0.0390*
VIX	-0.0549	-0.0201	-0.0487	-0.0447	-0.0147	-0.0511	-0.0487	-0.0552	-0.0572	-0.0503
	0.0001	*0.0867*	*0.0000*	*0.0373*	*0.3082*	*0.0000*	*0.0214*	*0.0000*	*0.0001*	*0.0000*
Liquidity spread variation	-0.0037	-0.0033	-0.0048	-0.0034	-0.0003	-0.0029	0.0001	0.0004	-0.0005	0.0001
	0.2003	*0.1681*	*0.0026*	*0.4311*	*0.9264*	*0.1727*	*0.9844*	*0.8802*	*0.8650*	*0.9798*
T-bill spread variation	0.0101	0.0263	0.0404	-0.0122	0.0383	0.0356	0.0113	0.0183	0.0249	0.0201
	0.6054	*0.1040*	*0.0002*	*0.6794*	*0.0539*	*0.0138*	*0.6957*	*0.2424*	*0.2225*	*0.1312*
Yield spread change	-0.0005	0.0090	0.0271	-0.0160	0.0247	0.0211	0.0078	0.0158	0.0248	0.0195
	0.9738	*0.4827*	*0.0014*	*0.4925*	*0.1143*	*0.0639*	*0.7342*	*0.2034*	*0.1252*	*0.0653*
Credit spread change	-0.1013	-0.0459	-0.0398	-0.1195	0.0005	-0.0384	-0.0756	-0.0428	-0.0977	-0.0930
	0.0003	*0.0470*	*0.0102*	*0.0046*	*0.9853*	*0.0622*	*0.0684*	*0.0568*	*0.0009*	*0.0000*
Return real estate	0.4118	0.3085	0.2510	0.3945	0.4179	0.4064	0.4991	0.3813	0.4636	0.4887
	0.0001	*0.0005*	*0.0000*	*0.0105*	*0.0001*	*0.0000*	*0.0007*	*0.0000*	*0.0000*	*0.0000*
Return sector i	0.2004	0.5921	0.2770	0.4304	0.4473	0.2532	0.1515	0.0787	0.1319	0.0614
	0.0001	*0.0000*	*0.0000*	*0.0001*	*0.0000*	*0.0000*	*0.0115*	*0.0000*	*0.0166*	*0.0510*

Table 3.5: 2.5%-quantile ex sector index regression results for the US over the difficult period.
The system returns, used as dependent variables in the linear quantile regression, are approximated by the ex sector index returns, which exclude the sector under examination. The regression uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The difficult period ranges from 8th November 1999 to 30th April 2003. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta \text{CoVaR}}$.

50%-quantile sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-0.0383	0.2017	0.0695	-0.0142	-0.0434	0.1830	-0.0890	-0.2804	0.4963	-0.1594
	0.8681	*0.0723*	*0.6245*	*0.9104*	*0.8184*	*0.3644*	*0.7399*	*0.5372*	*0.0297*	*0.5568*
VIX	0.0026	-0.0060	-0.0023	0.0012	0.0042	-0.0038	0.0008	0.0098	-0.0203	0.0080
	0.7681	*0.1599*	*0.6729*	*0.8086*	*0.5602*	*0.6174*	*0.9337*	*0.5684*	*0.0189*	*0.4358*
Liquidity spread variation	-0.0005	0.0009	0.0003	0.0006	0.0001	0.0015	-0.0064	-0.0029	0.0004	0.0030
	0.7903	*0.3139*	*0.8138*	*0.5577*	*0.9538*	*0.3487*	*0.0019*	*0.4015*	*0.8293*	*0.1553*
T-bill spread variation	0.0109	0.0050	-0.0128	0.0149	0.0053	0.0156	0.0172	-0.0042	-0.0173	0.0054
	0.3652	*0.3885*	*0.0849*	*0.0230*	*0.5904*	*0.1368*	*0.2177*	*0.8600*	*0.1460*	*0.7003*
Yield spread change	0.0069	0.0052	-0.0123	0.0025	0.0010	0.0085	0.0165	0.0067	-0.0035	0.0225
	0.4694	*0.2655*	*0.0375*	*0.6321*	*0.9024*	*0.3079*	*0.1383*	*0.7237*	*0.7136*	*0.0457*
Credit spread change	-0.0082	0.0018	-0.0085	0.0193	0.0033	0.0230	0.0042	-0.0483	0.0104	0.0133
	0.6341	*0.8291*	*0.4193*	*0.0393*	*0.8143*	*0.1261*	*0.8341*	*0.1527*	*0.5410*	*0.5088*
Return S&P 500	0.6614	0.8395	0.8897	0.5825	0.7967	0.6369	0.8088	1.8088	0.3112	0.5256
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return real estate	0.3098	0.1389	0.2446	0.1383	0.0515	0.1814	0.1960	-0.2961	0.1810	0.1136
	0.0000	*0.0000*	*0.0000*	*0.0001*	*0.3292*	*0.0013*	*0.0090*	*0.0198*	*0.0046*	*0.1338*

Table 3.6: 50%-quantile regression results for the US over the difficult period.

The 50%-quantile represents the median state, and the daily market returns of the sectors are used as dependent variables in the linear quantile regression, which uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The difficult period ranges from 8th November 1999 to 30th April 2003. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta \mathrm{CoVaR}}$.

50%-quantile ex sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	0.2316	0.0114	0.2086	0.2368	0.3249	0.2813	0.3301	0.2798	0.2493	0.1460
	0.1675	*0.9373*	*0.2580*	*0.1560*	*0.0139*	*0.1470*	*0.1430*	*0.1096*	*0.2752*	*0.5027*
VIX	-0.0114	-0.0007	-0.0079	-0.0111	-0.0151	-0.0151	-0.0142	-0.0115	-0.0120	-0.0077
	0.0712	*0.9008*	*0.2552*	*0.0788*	*0.0025*	*0.0395*	*0.0954*	*0.0820*	*0.1644*	*0.3509*
Liquidity spread variation	-0.0008	-0.0001	0.0019	0.0004	0.0009	0.0003	0.0029	0.0024	0.0006	0.0001
	0.5573	*0.9478*	*0.1911*	*0.7346*	*0.4017*	*0.8530*	*0.1006*	*0.0808*	*0.7254*	*0.9552*
T-bill spread variation	0.0329	0.0093	0.0272	0.0135	0.0107	0.0228	0.0263	0.0247	0.0382	0.0493
	0.0002	*0.2177*	*0.0043*	*0.1187*	*0.1198*	*0.0237*	*0.0245*	*0.0064*	*0.0012*	*0.0000*
Yield spread change	0.0253	0.0028	0.0233	0.0242	0.0151	0.0266	0.0260	0.0165	0.0363	0.0356
	0.0003	*0.6401*	*0.0020*	*0.0004*	*0.0053*	*0.0008*	*0.0049*	*0.0225*	*0.0001*	*0.0001*
Credit spread change	-0.0267	-0.0128	-0.0325	-0.0343	-0.0215	-0.0313	-0.0363	-0.0046	-0.0432	-0.0301
	0.0320	*0.2367*	*0.0179*	*0.0057*	*0.0288*	*0.0296*	*0.0300*	*0.7261*	*0.0107*	*0.0624*
Return real estate	0.4964	0.1857	0.2801	0.3812	0.3851	0.5216	0.6060	0.6537	0.7159	0.7207
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return sector i	0.4094	0.7795	0.5236	0.7233	0.6506	0.4465	0.2611	0.1308	0.2003	0.2020
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*

Table 3.7: 50%-quantile ex sector index regression results for the US over the difficult period.
The 50%-quantile represents the median state, and the system returns, used as dependent variables in the linear quantile regression, are approximated by the ex sector index returns, which exclude the sector under examination. The regression uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The difficult period ranges from 8th November 1999 to 30th April 2003. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta \text{CoVaR}}$.

2.5%-quantile sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-1.2255	-0.5089	-0.5777	-0.4176	-0.9661	-0.5753	0.6808	-0.2969	-0.6703	-2.8564
	0.0044	*0.0223*	*0.0001*	*0.0108*	*0.0087*	*0.0046*	*0.1453*	*0.4481*	*0.0196*	*0.0008*
VIX	-0.0133	-0.0102	-0.0087	-0.0117	0.0014	-0.0288	-0.1337	-0.0924	-0.0282	0.0405
	0.6267	*0.4693*	*0.3574*	*0.2611*	*0.9537*	*0.0259*	*0.0000*	*0.0002*	*0.1225*	*0.4526*
Liquidity spread variation	0.0029	-0.0028	0.0091	-0.0003	0.0066	0.0052	-0.0051	0.0091	-0.0082	0.0050
	0.7270	*0.5123*	*0.0015*	*0.9275*	*0.3452*	*0.1834*	*0.5646*	*0.2213*	*0.1361*	*0.7595*
T-bill spread variation	-0.0266	0.0007	0.0055	-0.0079	0.0030	-0.0124	-0.0343	-0.0280	-0.0171	-0.0363
	0.4016	*0.9650*	*0.6214*	*0.5138*	*0.9123*	*0.4089*	*0.3217*	*0.3342*	*0.4196*	*0.5626*
Yield spread change	-0.0268	0.0077	0.0000	-0.0042	-0.0009	0.0074	-0.0012	0.0133	-0.0297	-0.0141
	0.1378	*0.4112*	*0.9960*	*0.5373*	*0.9527*	*0.3849*	*0.9534*	*0.4194*	*0.0137*	*0.6915*
Credit spread change	-0.0569	-0.0260	0.0023	-0.0164	-0.0071	0.0363	0.0035	-0.0290	-0.0505	-0.0084
	0.2043	*0.2634*	*0.8808*	*0.3375*	*0.8529*	*0.0867*	*0.9424*	*0.4780*	*0.0919*	*0.9248*
Return S&P 500	1.2994	0.9941	0.9118	0.8639	0.8860	1.0674	0.7120	1.5339	0.5045	1.1006
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return real estate	0.0610	0.0632	0.1739	0.0655	0.0874	0.0045	-0.0811	-0.1419	0.2798	-0.0294
	0.5113	*0.1892*	*0.0000*	*0.0641*	*0.2722*	*0.9175*	*0.4221*	*0.0937*	*0.0000*	*0.8725*

Table 3.8: 2.5%-quantile regression results for the US over the calm period.
The daily market returns of the sectors are used as dependent variable in the linear quantile regression, which uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The calm period ranges from 1st May 2003 to 31st July 2007. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta \text{CoVaR}}$.

2.5%-quantile ex sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-0.3846	-0.3408	-0.2297	-0.3041	-0.5521	0.0826	-0.2330	0.1142	0.2338	-0.3187
	0.0053	*0.0411*	*0.0826*	*0.0000*	*0.0009*	*0.6561*	*0.3853*	*0.4282*	*0.1703*	*0.1495*
VIX	-0.0248	-0.0164	-0.0369	-0.0258	-0.0173	-0.0625	-0.0499	-0.0679	-0.0809	-0.0525
	0.0048	*0.1230*	*0.0000*	*0.0000*	*0.1009*	*0.0000*	*0.0035*	*0.0000*	*0.0000*	*0.0002*
Liquidity spread variation	0.0060	0.0040	-0.0047	0.0037	0.0034	0.0060	0.0049	0.0058	-0.0008	0.0126
	0.0220	*0.2120*	*0.0619*	*0.0037*	*0.2771*	*0.0896*	*0.3438*	*0.0357*	*0.7993*	*0.0028*
T-bill spread variation	0.0102	0.0003	-0.0046	0.0093	-0.0245	0.0269	0.0092	0.0253	0.0129	0.0210
	0.3164	*0.9835*	*0.6364*	*0.0591*	*0.0459*	*0.0501*	*0.6442*	*0.0179*	*0.3086*	*0.1989*
Yield spread change	-0.0013	-0.0009	-0.0028	0.0112	-0.0042	0.0121	0.0098	0.0087	0.0161	0.0121
	0.8176	*0.9002*	*0.6102*	*0.0001*	*0.5498*	*0.1183*	*0.3823*	*0.1512*	*0.0252*	*0.1888*
Credit spread change	-0.0070	0.0069	-0.0568	-0.0221	-0.0220	-0.0335	-0.0159	-0.0016	-0.0183	-0.0140
	0.6240	*0.6922*	*0.0000*	*0.0015*	*0.2056*	*0.0846*	*0.5700*	*0.9178*	*0.3057*	*0.5425*
Return real estate	0.2457	0.1892	0.1369	0.1613	0.3185	0.2504	0.3175	0.2921	0.3024	0.3345
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return sector i	0.4009	0.6351	0.5798	0.7945	0.5248	0.4789	0.2108	0.2863	0.3186	0.2100
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0001*	*0.0000*	*0.0000*	*0.0000*

Table 3.9: 2.5%-quantile ex sector index regression results for the US over the calm period.
The system returns, used as dependent variables in the linear quantile regression, are approximated by the ex sector index returns, which exclude the sector under examination. The regression uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The calm period ranges from 1st May 2003 to 31st July 2007. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta \text{CoVaR}}$.

50%-quantile sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	0.4820	0.1476	0.0212	-0.0152	0.0366	0.0860	0.0099	-0.0285	0.1785	0.4193
	0.0026	*0.0373*	*0.6845*	*0.8159*	*0.6744*	*0.3573*	*0.9323*	*0.8548*	*0.0747*	*0.0271*
VIX	-0.0282	-0.0059	-0.0026	0.0026	-0.0027	-0.0036	-0.0002	0.0052	-0.0098	-0.0221
	0.0057	*0.1921*	*0.4360*	*0.5274*	*0.6250*	*0.5439*	*0.9743*	*0.6032*	*0.1225*	*0.0667*
Liquidity spread variation	-0.0022	-0.0029	0.0008	-0.0003	-0.0006	-0.0013	0.0011	-0.0018	-0.0019	0.0004
	0.4789	*0.0312*	*0.4248*	*0.8413*	*0.7429*	*0.4706*	*0.6146*	*0.5537*	*0.3131*	*0.9022*
T-bill spread variation	0.0032	-0.0004	0.0024	-0.0084	0.0035	-0.0088	-0.0111	0.0019	-0.0143	0.0014
	0.7899	*0.9351*	*0.5374*	*0.0828*	*0.5844*	*0.2018*	*0.2016*	*0.8679*	*0.0539*	*0.9222*
Yield spread change	0.0097	0.0019	0.0021	-0.0083	0.0049	-0.0018	-0.0053	0.0179	-0.0303	-0.0217
	0.1508	*0.5304*	*0.3487*	*0.0026*	*0.1773*	*0.6422*	*0.2804*	*0.0062*	*0.0000*	*0.0064*
Credit spread change	-0.0070	-0.0120	0.0020	-0.0183	-0.0090	-0.0039	-0.0132	0.0045	-0.0309	-0.0111
	0.6761	*0.1047*	*0.7134*	*0.0074*	*0.3238*	*0.6919*	*0.2797*	*0.7828*	*0.0031*	*0.5756*
Return S&P 500	1.1242	1.0473	0.8481	0.8250	0.8343	0.8945	0.7262	1.3500	0.5615	0.9625
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return real estate	0.0923	0.0186	0.1943	0.0706	0.0503	0.0199	0.0265	-0.0088	0.1880	-0.0280
	0.0077	*0.2244*	*0.0000*	*0.0000*	*0.0077*	*0.3250*	*0.2948*	*0.7948*	*0.0000*	*0.4940*

Table 3.10: 50%-quantile regression results for the US over the calm period.

The 50%-quantile represents the median state, and the daily market returns of the sectors are used as dependent variables in the linear quantile regression, which uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The calm period ranges from 1st May 2003 to 31st July 2007. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta \text{CoVaR}}$.

50%-quantile ex sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	0.0376	0.0446	0.1486	0.1749	0.1801	0.1627	0.2419	0.2433	0.2350	0.1205
	0.6565	*0.4848*	*0.0208*	*0.0089*	*0.0221*	*0.0761*	*0.0167*	*0.0033*	*0.0097*	*0.2463*
VIX	-0.0017	-0.0042	-0.0072	-0.0124	-0.0115	-0.0126	-0.0166	-0.0157	-0.0141	-0.0090
	0.7490	*0.3014*	*0.0773*	*0.0035*	*0.0217*	*0.0303*	*0.0097*	*0.0029*	*0.0143*	*0.1728*
Liquidity spread variation	0.0004	0.0011	0.0004	0.0004	0.0022	0.0019	0.0014	0.0003	0.0001	0.0038
	0.7956	*0.3804*	*0.7533*	*0.7303*	*0.1485*	*0.2774*	*0.4841*	*0.8371*	*0.9589*	*0.0551*
T-bill spread variation	-0.0066	-0.0054	-0.0075	0.0033	-0.0094	0.0130	0.0001	-0.0007	0.0111	0.0016
	0.2938	*0.2551*	*0.1131*	*0.5113*	*0.1059*	*0.0554*	*0.9943*	*0.9145*	*0.0978*	*0.8330*
Yield spread change	0.0010	-0.0027	0.0054	0.0113	0.0064	0.0096	0.0094	0.0032	0.0218	0.0142
	0.7790	*0.3164*	*0.0447*	*0.0001*	*0.0535*	*0.0120*	*0.0258*	*0.3629*	*0.0000*	*0.0011*
Credit spread change	-0.0126	-0.0032	-0.0172	0.0064	0.0026	-0.0055	-0.0086	-0.0098	-0.0061	-0.0278
	0.1519	*0.6327*	*0.0103*	*0.3615*	*0.7511*	*0.5698*	*0.4156*	*0.2581*	*0.5231*	*0.0104*
Return real estate	0.2331	0.1433	0.0337	0.1194	0.2269	0.2688	0.3722	0.2892	0.2897	0.4143
	0.0000	*0.0000*	*0.0260*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return sector i	0.3980	0.7056	0.7520	0.8570	0.6080	0.5779	0.3451	0.2958	0.3778	0.1549
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*

Table 3.11: 50%-quantile ex sector index regression results for the US over the calm period.

The 50%-quantile represents the median state, and the system returns, used as dependent variables in the linear quantile regression, are approximated by the ex sector index returns, which exclude the sector under examination. The regression uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The calm period ranges from 1st May 2003 to 31st July 2007. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta \mathrm{CoVaR}}$.

2.5%-quantile sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-0.4955	0.0866	-0.1603	-0.5053	-0.5736	0.0952	-0.9704	-0.5796	-1.3814	-1.6376
	0.2928	*0.8042*	*0.6224*	*0.0231*	*0.0000*	*0.6647*	*0.0000*	*0.0335*	*0.0139*	*0.0391*
VIX	-0.0896	-0.0451	-0.0514	-0.0205	-0.0339	-0.0511	-0.0269	-0.0294	-0.0225	-0.0344
	0.0000	*0.0000*	*0.0000*	*0.0010*	*0.0000*	*0.0000*	*0.0000*	*0.0001*	*0.1503*	*0.1206*
Liquidity spread variation	-0.0318	-0.0031	0.0007	0.0014	0.0053	-0.0035	0.0074	-0.0107	-0.0006	-0.0289
	0.0000	*0.5272*	*0.8738*	*0.6505*	*0.0024*	*0.2619*	*0.0008*	*0.0054*	*0.9394*	*0.0098*
T-bill spread variation	-0.0800	-0.0220	0.0270	-0.0069	-0.0111	-0.0157	0.0077	-0.0198	-0.0224	-0.0917
	0.0016	*0.2394*	*0.1210*	*0.5626*	*0.0902*	*0.1809*	*0.3524*	*0.1748*	*0.4557*	*0.0308*
Yield spread change	-0.0161	-0.0062	0.0094	-0.0163	-0.0225	-0.0120	-0.0119	-0.0171	-0.0046	-0.0330
	0.4236	*0.6756*	*0.5001*	*0.0856*	*0.0000*	*0.1993*	*0.0723*	*0.1425*	*0.8469*	*0.3293*
Credit spread change	-0.0835	-0.0596	-0.0124	-0.0170	-0.0192	0.0054	0.0055	-0.0203	-0.0760	-0.0972
	0.0189	*0.0238*	*0.6121*	*0.3078*	*0.0382*	*0.7431*	*0.6358*	*0.3215*	*0.0719*	*0.1036*
Return S&P 500	1.2113	0.8928	0.7989	0.6919	0.6578	0.8192	0.8657	1.0717	0.6376	1.4315
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0011*	*0.0000*
Return real estate	-0.0431	-0.0059	0.4312	0.0540	0.1373	-0.0902	-0.0034	-0.0810	-0.0326	-0.1576
	0.5511	*0.9122*	*0.0000*	*0.1134*	*0.0000*	*0.0077*	*0.8877*	*0.0531*	*0.7051*	*0.1956*

Table 3.12: 2.5%-quantile regression results for the US over the crisis period.

The daily market returns of the sectors are used as dependent variable in the linear quantile regression, which uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The crisis period ranges from 1st August 2007 to 30th October 2009. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta \mathrm{CoVaR}}$.

2.5%-quantile ex sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-0.0622	-0.0852	0.3137	-0.6986	-0.3812	-0.0700	-0.3066	-0.0236	0.0619	-0.1770
	0.8004	*0.5634*	*0.0792*	*0.0000*	*0.0211*	*0.7070*	*0.4269*	*0.8902*	*0.8003*	*0.5474*
VIX	-0.0366	-0.0296	-0.0605	-0.0189	-0.0320	-0.0497	-0.0364	-0.0434	-0.0582	-0.0419
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0008*	*0.0000*	*0.0000*	*0.0000*
Liquidity spread variation	-0.0061	-0.0026	-0.0101	-0.0040	-0.0070	-0.0069	-0.0005	-0.0068	0.0032	-0.0008
	0.0794	*0.2121*	*0.0001*	*0.0141*	*0.0030*	*0.0091*	*0.9291*	*0.0048*	*0.3545*	*0.8515*
T-bill spread variation	0.0158	0.0020	-0.0092	0.0013	0.0109	0.0287	0.0357	0.0323	0.0327	0.0262
	0.2257	*0.7947*	*0.3315*	*0.8320*	*0.2077*	*0.0034*	*0.0804*	*0.0004*	*0.0120*	*0.0958*
Yield spread change	0.0023	-0.0017	-0.0186	0.0150	0.0166	0.0086	0.0202	0.0110	0.0077	0.0040
	0.8312	*0.7905*	*0.0147*	*0.0025*	*0.0180*	*0.2743*	*0.2185*	*0.1341*	*0.4616*	*0.7528*
Credit spread change	-0.0235	-0.0011	-0.0263	-0.0574	-0.0455	-0.0161	-0.0424	-0.0057	-0.0147	-0.0583
	0.2038	*0.9193*	*0.0497*	*0.0000*	*0.0003*	*0.2520*	*0.1445*	*0.6598*	*0.4273*	*0.0087*
Return real estate	0.2470	0.1501	0.0918	0.1841	0.2221	0.3729	0.2665	0.2412	0.3439	0.3396
	0.0000	*0.0000*	*0.0091*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return sector i	0.3175	0.6958	0.3433	0.7194	0.5432	0.2584	0.4229	0.4321	0.2510	0.1866
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0001*

Table 3.13: 2.5%-quantile ex sector index regression results for the US over the crisis period.
The system returns, used as dependent variables in the linear quantile regression, are approximated by the ex sector index returns, which exclude the sector under examination. The regression uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The crisis period ranges from 1st August 2007 to 30th October 2009. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta \text{CoVaR}}$.

50%-quantile sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	0.0778	0.0600	-0.1285	0.1034	-0.0030	0.1746	-0.0525	0.1659	0.1484	0.0126
	0.6700	*0.4477*	*0.1613*	*0.0580*	*0.9779*	*0.0644*	*0.6737*	*0.0620*	*0.3060*	*0.9332*
VIX	-0.0014	-0.0025	0.0043	-0.0024	0.0016	-0.0050	-0.0002	-0.0030	-0.0081	0.0023
	0.7851	*0.2499*	*0.0959*	*0.1196*	*0.6029*	*0.0595*	*0.9523*	*0.2348*	*0.0454*	*0.5783*
Liquidity spread variation	0.0031	0.0014	-0.0004	-0.0010	-0.0016	0.0010	0.0006	-0.0020	0.0036	0.0021
	0.2332	*0.2171*	*0.7504*	*0.1931*	*0.3007*	*0.4756*	*0.7356*	*0.1133*	*0.0801*	*0.3316*
T-bill spread variation	0.0081	-0.0053	0.0072	-0.0024	-0.0036	-0.0134	-0.0036	0.0031	0.0054	0.0119
	0.4067	*0.2077*	*0.1403*	*0.4178*	*0.5436*	*0.0080*	*0.5922*	*0.5138*	*0.4899*	*0.1380*
Yield spread change	0.0139	0.0008	0.0019	0.0029	-0.0002	-0.0123	-0.0077	0.0025	-0.0017	0.0166
	0.0749	*0.8034*	*0.6208*	*0.2080*	*0.9589*	*0.0023*	*0.1477*	*0.5147*	*0.7842*	*0.0098*
Credit spread change	0.0135	-0.0027	-0.0020	0.0057	-0.0040	-0.0200	0.0034	0.0030	0.0085	0.0092
	0.3274	*0.6477*	*0.7730*	*0.1647*	*0.6289*	*0.0049*	*0.7212*	*0.6533*	*0.4339*	*0.4174*
Return S&P 500	1.4642	1.0433	0.8785	0.8207	0.8190	0.7674	1.0049	0.9706	0.9051	1.4348
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return real estate	-0.0852	-0.0134	0.4149	0.0074	0.0684	-0.0430	-0.0679	0.0055	-0.1408	-0.1839
	0.0025	*0.2700*	*0.0000*	*0.3752*	*0.0001*	*0.0031*	*0.0004*	*0.6886*	*0.0000*	*0.0000*

Table 3.14: 50%-quantile regression results for the US over the crisis period.

The 50%-quantile represents the median state, and the daily market returns of the sectors are used as dependent variables in the linear quantile regression, which uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The crisis period ranges from 1st August 2007 to 30th October 2009. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta \text{CoVaR}}$.

50%-quantile ex sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	0.1176	0.0866	0.3498	0.0553	0.3588	0.1095	0.2708	0.0880	0.2313	0.2271
	0.1269	*0.1952*	*0.0028*	*0.4755*	*0.0020*	*0.2718*	*0.0028*	*0.3556*	*0.0187*	*0.0129*
VIX	-0.0040	-0.0020	-0.0109	-0.0021	-0.0123	-0.0033	-0.0080	-0.0042	-0.0059	-0.0063
	0.0650	*0.2759*	*0.0009*	*0.3387*	*0.0002*	*0.2366*	*0.0016*	*0.1137*	*0.0320*	*0.0135*
Liquidity spread variation	-0.0011	-0.0010	0.0022	0.0006	0.0006	-0.0016	-0.0013	0.0001	-0.0018	-0.0015
	0.3095	*0.2813*	*0.1784*	*0.5642*	*0.7016*	*0.2580*	*0.3234*	*0.9506*	*0.2006*	*0.2520*
T-bill spread variation	0.0158	0.0108	0.0199	0.0111	0.0153	0.0210	0.0184	0.0110	0.0154	0.0204
	0.0001	*0.0026*	*0.0014*	*0.0068*	*0.0120*	*0.0001*	*0.0001*	*0.0303*	*0.0032*	*0.0000*
Yield spread change	0.0065	0.0017	0.0122	0.0049	0.0127	0.0187	0.0140	0.0097	0.0099	0.0097
	0.0511	*0.5460*	*0.0147*	*0.1375*	*0.0101*	*0.0000*	*0.0003*	*0.0174*	*0.0179*	*0.0140*
Credit spread change	-0.0087	-0.0041	-0.0154	-0.0119	-0.0033	-0.0130	-0.0188	-0.0159	-0.0094	-0.0118
	0.1345	*0.4208*	*0.0792*	*0.0410*	*0.7021*	*0.0847*	*0.0058*	*0.0273*	*0.2039*	*0.0852*
Return real estate	0.2704	0.1280	0.0036	0.1437	0.1740	0.3067	0.2390	0.2283	0.3513	0.3221
	0.0000	*0.0000*	*0.8757*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return sector i	0.3426	0.7313	0.4524	0.9160	0.6494	0.5482	0.5436	0.5544	0.4243	0.2926
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*

Table 3.15: 50%-quantile ex sector index regression results for the US over the crisis period.
The 50%-quantile represents the median state, and the system returns, used as dependent variables in the linear quantile regression, are approximated by the ex sector index returns, which exclude the sector under examination. The regression uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The crisis period ranges from 1st August 2007 to 30th October 2009. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta \text{CoVaR}}$.

2.5%-quantile sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-0.7115	-0.3599	-0.0240	-0.3743	-0.2203	-0.7239	-1.8233	-0.8252	-0.8791	-1.0098
	0.0000	*0.0000*	*0.7128*	*0.0000*	*0.0670*	*0.0010*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
VIX	-0.0318	-0.0147	-0.0302	-0.0129	-0.0366	-0.0127	0.0278	-0.0145	-0.0052	-0.0094
	0.0000	*0.0000*	*0.0000*	*0.0003*	*0.0000*	*0.2070*	*0.0271*	*0.0685*	*0.5668*	*0.3145*
Liquidity spread variation	0.0164	0.0025	0.0163	-0.0164	-0.0095	-0.0089	0.0047	-0.0017	-0.0195	0.0086
	0.1176	*0.6159*	*0.0001*	*0.0010*	*0.2249*	*0.5350*	*0.7945*	*0.8839*	*0.1328*	*0.5191*
T-bill spread variation	-0.0250	-0.0012	-0.0149	0.0113	-0.0353	0.0182	-0.0680	-0.0760	-0.0778	0.0319
	0.5650	*0.9521*	*0.3948*	*0.5839*	*0.2756*	*0.7587*	*0.3583*	*0.1044*	*0.1469*	*0.5629*
Yield spread change	-0.0122	-0.0122	0.0030	-0.0015	0.0160	0.0257	-0.0047	-0.0265	-0.0142	-0.0008
	0.2079	*0.5642*	*0.4411*	*0.7382*	*0.0268*	*0.0525*	*0.7760*	*0.0113*	*0.2371*	*0.9518*
Credit spread change	0.0297	0.0023	0.0012	-0.0379	0.0544	0.0227	0.0143	-0.0149	-0.0167	0.0088
	0.1093	*0.7939*	*0.8705*	*0.0000*	*0.0001*	*0.3687*	*0.6501*	*0.4552*	*0.4639*	*0.7075*
Return S&P 500	1.4098	1.1189	0.8598	0.8443	0.8211	1.0302	0.6616	1.5532	0.5896	1.3717
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return real estate	-0.1430	-0.0079	0.2445	0.0446	0.0149	-0.1689	0.0475	-0.3101	0.0865	-0.1166
	0.0181	*0.7776*	*0.0000*	*0.1191*	*0.7399*	*0.0405*	*0.6440*	*0.0000*	*0.2461*	*0.1286*

Table 3.16: 2.5%-quantile regression results for the US over the recovery period.

The daily market returns of the sectors are used as dependent variable in the linear quantile regression, which uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The recovery period ranges from 1st November 2009 to 9th August 2013. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta \mathrm{CoVaR}}$.

2.5%-quantile ex sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-0.0648	-0.3409	0.1746	-0.1837	-0.4282	-0.1414	-0.1492	-0.1511	0.1060	-0.2143
	0.7052	*0.0000*	*0.3744*	*0.1227*	*0.0011*	*0.0444*	*0.4226*	*0.3528*	*0.6410*	*0.2383*
VIX	-0.0342	-0.0123	-0.0512	-0.0260	-0.0215	-0.0320	-0.0353	-0.0305	-0.0519	-0.0271
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0003*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0012*
Liquidity spread variation	-0.0049	0.0044	-0.0119	0.0022	0.0191	0.0016	-0.0149	0.0034	-0.0192	-0.0011
	0.6614	*0.1448*	*0.3561*	*0.7758*	*0.0244*	*0.7244*	*0.2224*	*0.7516*	*0.1983*	*0.9299*
T-bill spread variation	0.0082	0.0563	-0.0137	0.0780	0.0300	0.0075	0.0155	0.0006	-0.0097	0.0137
	0.8588	*0.0000*	*0.7960*	*0.0148*	*0.3890*	*0.6923*	*0.7581*	*0.9895*	*0.8740*	*0.7814*
Yield spread change	0.0242	0.0121	0.0161	0.0190	0.0233	0.0288	0.0327	0.0190	0.0322	0.0253
	0.0139	*0.0000*	*0.1657*	*0.0059*	*0.0016*	*0.0000*	*0.0015*	*0.0416*	*0.0104*	*0.0162*
Credit spread change	0.0173	0.0251	0.0526	0.0166	-0.0007	0.0348	0.0364	-0.0063	0.0371	0.0275
	0.3821	*0.0000*	*0.0201*	*0.2243*	*0.9644*	*0.0000*	*0.0900*	*0.7387*	*0.1576*	*0.1897*
Return real estate	0.3672	0.2638	0.1755	0.3222	0.3309	0.4030	0.4153	0.4127	0.4525	0.3514
	0.0000	*0.0000*	*0.0406*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return sector i	0.3208	0.5715	0.5374	0.5505	0.4290	0.4267	0.4228	0.3193	0.3226	0.3343
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0025*	*0.0000*

Table 3.17: 2.5%-quantile ex sector index regression results for the US over the recovery period.
The system returns, used as dependent variables in the linear quantile regression, are approximated by the ex sector index returns, which exclude the sector under examination. The regression uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The recovery period ranges from 1st November 2009 to 9th August 2013. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta \text{CoVaR}}$.

50%-quantile sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-0.1821	-0.0719	-0.0317	0.0713	0.2034	0.0038	-0.0978	-0.0511	-0.0642	0.0156
	0.0150	*0.2712*	*0.3687*	*0.1840*	*0.0047*	*0.9590*	*0.2050*	*0.4753*	*0.4058*	*0.8240*
VIX	0.0089	0.0038	-0.0005	-0.0027	-0.0068	0.0013	0.0075	0.0036	0.0029	-0.0008
	0.0091	*0.2030*	*0.7484*	*0.2670*	*0.0375*	*0.6919*	*0.0329*	*0.2673*	*0.4099*	*0.8075*
Liquidity spread variation	-0.0023	-0.0011	0.0058	-0.0027	-0.0054	0.0032	-0.0061	0.0001	0.0041	-0.0053
	0.6384	*0.8053*	*0.0119*	*0.4434*	*0.2504*	*0.5050*	*0.2262*	*0.9820*	*0.4116*	*0.2478*
T-bill spread variation	-0.0025	-0.0145	0.0095	-0.0150	-0.0188	-0.0149	-0.0073	-0.0017	-0.0068	0.0206
	0.9014	*0.4084*	*0.3165*	*0.3004*	*0.3306*	*0.4493*	*0.7253*	*0.9289*	*0.7454*	*0.2754*
Yield spread change	-0.0007	0.0050	0.0071	0.0006	-0.0011	-0.0005	-0.0047	-0.0024	-0.0015	-0.0028
	0.8854	*0.1995*	*0.0008*	*0.8633*	*0.8018*	*0.9016*	*0.3119*	*0.5756*	*0.7408*	*0.5082*
Credit spread change	0.0005	-0.0001	-0.0011	0.0014	0.0091	0.0108	-0.0057	-0.0039	0.0005	0.0049
	0.9530	*0.9945*	*0.7876*	*0.8233*	*0.2718*	*0.1986*	*0.5228*	*0.6331*	*0.9512*	*0.5384*
Return S&P 500	1.2247	1.0900	0.7678	0.8620	0.8950	0.9378	0.6388	1.1606	0.5460	1.2964
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return real estate	0.0382	0.0402	0.3635	0.0376	0.0274	-0.0412	0.0485	-0.0912	0.1085	-0.1039
	0.1721	*0.1001*	*0.0000*	*0.0611*	*0.3078*	*0.1314*	*0.0934*	*0.0007*	*0.0002*	*0.0001*

Table 3.18: 50%-quantile regression results for the US over the recovery period.

The 50%-quantile represents the median state, and the daily market returns of the sectors are used as dependent variables in the linear quantile regression, which uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The recovery period ranges from 1st November 2009 to 9th August 2013. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta \text{CoVaR}}$.

50%-quantile ex sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	0.2088	0.1395	0.1346	0.0614	0.0603	0.0228	0.2932	0.1189	0.2353	0.1310
	0.0000	*0.0000*	*0.0304*	*0.0965*	*0.2282*	*0.6682*	*0.0000*	*0.0016*	*0.0018*	*0.0367*
VIX	-0.0084	-0.0056	-0.0045	-0.0030	-0.0038	-0.0009	-0.0129	-0.0041	-0.0096	-0.0049
	0.0001	*0.0001*	*0.1158*	*0.0728*	*0.0995*	*0.7036*	*0.0000*	*0.0183*	*0.0056*	*0.0892*
Liquidity spread variation	-0.0026	-0.0011	-0.0060	0.0002	-0.0018	-0.0044	-0.0055	-0.0047	-0.0057	-0.0009
	0.3868	*0.6071*	*0.1420*	*0.9302*	*0.5809*	*0.2072*	*0.1887*	*0.0586*	*0.2503*	*0.8265*
T-bill spread variation	0.0463	0.0224	0.0031	0.0323	0.0285	0.0170	0.0519	-0.0026	0.0331	-0.0137
	0.0002	*0.0099*	*0.8551*	*0.0012*	*0.0331*	*0.2339*	*0.0027*	*0.7972*	*0.1035*	*0.4202*
Yield spread change	0.0255	0.0071	0.0182	0.0190	0.0299	0.0272	0.0467	0.0246	0.0479	0.0210
	0.0000	*0.0002*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Credit spread change	0.0166	0.0040	0.0113	0.0008	0.0010	0.0009	0.0110	0.0069	0.0129	0.0064
	0.0017	*0.2762*	*0.1133*	*0.8544*	*0.8652*	*0.8882*	*0.1348*	*0.1103*	*0.1372*	*0.3780*
Return real estate	0.3438	0.1727	0.0331	0.2029	0.3407	0.3675	0.4908	0.3820	0.5145	0.3672
	0.0000	*0.0000*	*0.2213*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return sector i	0.3744	0.6693	0.7044	0.7562	0.5603	0.5533	0.3215	0.4538	0.2891	0.3875
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*

Table 3.19: 50%-quantile ex sector index regression results for the US over the recovery period.
The 50%-quantile represents the median state, and the system returns, used as dependent variables in the linear quantile regression, are approximated by the ex sector index returns, which exclude the sector under examination. The regression uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The recovery period ranges from 1st November 2009 to 9th August 2013. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta \text{CoVaR}}$.

Interestingly, its effect is negative and significant only for the Healthcare, Telecommunication and Technology sectors during the calm period (Table 3.8) and affects all sectors, except the Energy and Utilities sectors, significantly during the crisis period, as shown in Table 3.12. Except for the Healthcare, Utilities, and Energy sectors, the influence of the VIX index remains significant during the recovery period (Table 3.16). During the difficult period (Table 3.4), all sectors are significantly positively affected by the equity returns represented by the S&P500 returns, also revealing the largest coefficient. This observation remains valid for the other periods. The situation is different with regard to the liquidity spread, which only has a significant negative effect on the Consumer Goods, Telecommunication, Technology and Energy sectors during the difficult period and a positive effect on the Financials sector index return when the situation is calm, whereas in the crisis period (Table 3.12), the 2.5%-quantile Basic Materials, Technology and Energy sector index returns are negatively influenced. When the economy is recovering, Table 3.16 shows that the liquidity spread significantly influences the Consumer Goods and Financials sector index returns, where the effect is negative and positive, respectively. Changes in the T-bill spread and yield spread show a significantly negative impact of the yield spread changes on the 2.5%-quantile Telecommunication index sector returns but positive coefficients for the Industrials and Healthcare sectors; whereas, changes in the T-bill spread affects the Healthcare and Utilities sector index returns positively and the Telecommunication sector index returns negatively during the difficult period as shown in Table 3.4.

Furthermore, as shown in Table 3.8, changes in the T-bill spread and yield spread do not significantly influence the 2.5%-quantile sector index returns during the calm period, except for the Utilities sector index returns, which are negatively affected by the yield spread changes. This observation changes slightly when the economy is in a state of crisis, in the sense that changes in the T-bill spread have a significant impact on the returns of the Basic Materials, Consumer Services and Energy sectors, whereas yield spread changes significantly impact the Consumer Goods, Consumer Services and Telecommunication sector index returns (Table 3.12). In contrast to the T-bill spread changes, which do not affect the sector index returns at the 2.5%-quantile during the recovery period, changes in the yield spread have a significant effect on the sector index returns of the Consumer Services, Healthcare and Technology sectors during this period (Table 3.16). During the difficult period, credit spread changes significantly influence the Technology sector index returns and the Energy sector index returns, where the effect for the latter sector's returns is positive. When the economy is in a calm state, this state variable is related to significant coefficients for the Healthcare and Utilities sector index returns (Table 3.8), whereas changes in the credit spread significantly impact the 2.5%-quantile sector index returns of the Basic Materials, Industrials, Consumer Services and Utilities sectors during the period of crisis (Table 3.12). This significant influence remains concerning the Consumer Goods and Consumer Services sector index returns during the recovery period, where the influence for the former is negative.

The 2.5%-quantile regression results show a significant effect of real estate returns during the difficult period for five sector index returns; it is negative only for the Technology sector, which is also significantly negatively affected during the calm and crisis periods. During the crisis period, we find significant coefficients for the Financials, Consumer Services, Healthcare and Technology sector index returns, where the effect on the Financials and Consumer Services sectors is positive. During the recovery period, real estate returns significantly negatively impact the sector index returns of the Basic Materials, Healthcare and Technology sectors (Table 3.16).

As discussed above, the system returns are approximated by ex sector indices that exclude the sector under investigation to obtain the effect of one particular sector on the system, resulting in 10 ex sector quantile regressions. The state variables are the same as before without the S&P500 returns including the sector i returns.

This similarity is shown for the ex sector 2.5%-quantile index returns, which are affected by real estate returns and the returns of sectors i over all four periods. That is, both state variables have a positive influence on all ex sector 2.5%-quantile index returns over all periods. Except for the ex Consumer Services sector returns, volatility has a significant negative influence on all ex sector indices during the difficult period, whereas its impact is significantly negative on all ex sector 2.5%-quantile sector returns when the economy is in a crisis state (Table 3.13). Excluding the Industrials and Consumer Services sectors, volatility does not have a significant influence on ex sector index returns during the calm period, but it affects all ex sector 2.5%-quantile index returns significantly when the financial market is recovering (Table 3.17).

During the difficult period, excluding the Financials sector, changes in the liquidity spread have a significant impact on ex sector returns as shown in Table 3.5. Table 3.9 shows the significant coefficients of this state variable for the ex Basic Materials, Financials, Healthcare, Consumer Goods, Technology and Energy sector returns for the calm period, and except for the ex Industrials, Telecommunication, Utilities and Energy sector returns, its significant effect remains during the crisis period (Table 3.13). When the financial market is recovering, excluding the Consumer Services sector, the regression results return a significant coefficient (Table 3.17).

Excluding the Financials and Healthcare sectors, changes in the T-bill spread and the yield spread both significantly influence the ex sector index return. Also, the yield spread changes alone impact the ex Energy sector index returns only during the difficult period. Similarly, excluding the Consumer Services sector, the ex sector index regression returns a significant T-bill spread variation coefficient for the same period (Table 3.5). Both state variables together have a significant coefficient for the ex Consumer Goods sector index returns in a calm state. Also, the T-bill spread changes significantly affect the ex Healthcare, ex Consumer Services and ex Technology sector index returns, whereas, excluding the Utilities sector, the yield spread changes have a significant positive effect (Table 3.9). Running the 2.5%-quantile regression for the crisis period returns insignificant coefficients for the T-bill spread variable except for the ex Utilities, ex Telecommunication, ex Technology, ex Healthcare and ex Energy sector index returns. Furthermore, excluding the Financials, Consumer Goods and Consumer Services sectors, we obtain significant coefficients for the yield spread change variable (Table 3.13). During the recovery period, only the ex Industrials and ex Consumer Goods sector index returns are significant and positively influenced by T-bill spread changes, whereas, except for the ex Financials sector index returns, changes in the yield spread are related to significant coefficients (Table 3.17). The regression results also show that, during difficult times, except for the ex Consumer Services sector index returns, the ex sector index returns are significantly affected by credit spread changes (Table 3.5). The influence of credit spread changes still exists in calm times with respect to the ex Financials, ex Healthcare, and ex Consumer Goods sector index returns (Table 3.9). For the crisis period, excluding the Financials, Consumer Goods, Consumer Services and Energy sectors, the regression results return significant coefficients for the ex sector index returns, whereas during the recovery period, the ex Basic Materials, ex Consumer Goods, ex Consumer Services, ex Technology, ex Utilities and ex Energy sector index returns are not significantly affected by credit spread changes (Table 3.17).

In contrast to the 2.5% regression results, the results for the 50%-quantile regression show that volatility has a negative influence only on the Utilities 50%-quantile returns when the economy is in a difficult state as shown in Table 3.6, whereas its influence on the Energy and Basic Materials 50%-quantile returns during calm times is significant as shown in Table 3.10. When the economy enters a crisis state, the volatility index has a significant impact on the Financials, Healthcare and Utilities' 50%-quantile sector index returns (Table 3.14). The effect during the recovery period with regard to the Basic Materials, Consumer Services and Telecommunication sector index returns is significant at the 50%-quantile as shown in Table 3.18.

The 50%-quantile sector index regressions return a significant coefficient of the liquidity spread with respect to the Telecommunication sector during the difficult state and the Industrials sector when the situation is calm (Table 3.6 and Table 3.10). When the economy is in a stress period, we find a significant impact on the Utilities' 50%-quantile sector index returns. The liquidity spread significantly influences the Financials sector index returns at the 50%-quantile when the economy is recovering (Table 3.18).

Both state variables, equity returns and real estate returns, together have a significant effect on all 50%-quantile sector index returns during the difficult period, except in the case of the Consumer Services and Energy sector index returns, which are significantly influenced by the S&P500 returns only (Table 3.6). This observation holds during the calm period, where the 50%-quantile returns are not significantly affected by real estate returns with regard to the Industrials, Healthcare, Telecommunication, Technology and Energy sector index returns (Table 3.10). When the financial market is in a crisis situation, both state variables together have significant coefficients on all 50%-quantile sector index returns, except in the case of the Industrials, Consumer Goods and Technology sectors, which are only significantly affected by equity returns as shown in Table 3.14. Equity returns affect all 50%-quantile sector index returns significantly at the 1% level during the recovery period, whereas real estate returns have a significant impact on the Financials, Consumer Goods, Telecommunication, Technology, Utilities and Energy sector index returns at the 50%-quantile as is shown by Table 3.18.

Changes in the T-bill spread affect the Financials and Consumer Goods sector's 50%-quantile index returns significantly during difficult times, whereas yield spread changes coefficients are significant concerning the Financials and Energy sector index returns (Table 3.6). When the situation is calm, variations in the T-bill spread significantly affect the Consumer Goods and Utilities sector index returns at the 50%-quantile, whereas changes in the yield spread significantly influence the Consumer Goods, Technology, Utilities and Energy's 50%-quantile sector index returns as shown in Table 3.10. In times of the crisis, the T-bill spread changes significantly influence the 50%-quantile sector index returns related to Healthcare, whereas changes in the yield spread have a significant effect on the Basic Materials, Healthcare and Energy sector index returns (Table 3.14). The significant influence diminishes during the recovery period in the sense that changes in the yield spread solely affect the Financials' 50%-quantile sector index returns, whereas changes in the T-bill spread have no significant effect at all as shown in Table 3.18.

The 50%-quantile regression returns a significant coefficient for the credit spread change with respect to the Consumer Goods sector index returns during difficult times and for the Consumer Goods and Utilities sector index returns during the calm period as Table 3.10 illustrates. When the financial market is in crisis, Table 3.14 shows that credit spread changes significantly affect the 50%-quantile returns related to the Healthcare sector, but its significant effect disappears when the financial market is recovering, and we find no significant effect of this state variable (Table 3.18).

The ex sector 50%-quantile index returns are not significantly influenced by the VIX index during the difficult period when the Industrials, Financials, Utilities and Energy sectors are excluded (Table 3.7). Volatility has no significant impact on the ex Energy, ex Basic Materials and ex Industrials 50%-quantile sector index returns when the economy is in a calm state (Table 3.11), and its influence remains insignificant during the crisis period with respect to the ex Industrials, ex Healthcare, ex Consumer Goods and ex Technology 50%-quantile sector index returns (Table 3.15). Except for the ex Financials and ex Healthcare sector index returns at the 50%-quantile, the VIX index has a significant effect on all ex sectors' 50%-quantile index returns when the financial market is recovering (Table 3.19). Examining the liquidity spread, we find a significant effect on the ex Technology 50%-quantile sector index returns during the difficult period (Table 3.7) and a significant impact during the calm period when the Energy sector is excluded (Table 3.11). Although the liquidity spread has no significant effect at all in the crisis period, it affects the ex Technology 50%-quantile sector index returns when the financial market is recovering as shown in Table 3.19.

During the difficult state, all 50%-quantile ex sector index returns are significantly positively influenced by sector i returns and real estate returns. This observation holds for the other periods, except in the case of the ex Financials 50%-quantile sector index returns, which are not significantly affected by real estate returns during the crisis and recovery period (Table 3.15 and Table 3.19). The ex Industrials 50%-quantile sector index returns are not significantly affected by changes in yield spread when the situation is difficult (Table 3.7), and in the calm state, excluding the Basic Materials, Industrials and Technology sectors, we find no significant influence on the 50%-quantile ex sector returns as shown in Table 3.11. When the financial market is in a crisis state, excluding the Industrials and Consumer Goods sectors, the regression results at the 50%-quantile return an insignificant coefficient of the yield spread change variable (Table 3.15). Changes in the yield spread have a significant impact on all 50%-quantile ex sector index returns during the recovery period. The ex Industrials and ex Technology 50%-quantile sector index returns are not significantly affected by credit spread changes in a difficult state (shown in Table 3.7), whereas during the calm period, excluding the Financials and Energy sectors, changes in the credit spread significantly influence the 50%-quantile ex sector index returns (Table 3.11). In turbulent times, credit spread changes do not significantly affect the ex Basic Materials, ex Industrials, ex Consumer Services and ex Utilities 50%-quantile sector index returns (Table 3.15) and have a significant effect only on the ex Basic Materials 50%-quantile sector index returns during the recovery period as shown in Table 3.19.

Excluding the Industrials, Consumer Services and Consumer Goods sectors, we find no significant effect of T-bill spread changes on the 50%-quantile ex sector index returns during the difficult period (Table 3.7). Changes in the T-bill spread influence the ex Healthcare and ex Utilities sector index returns at the 50%-quantile when the economy is in a calm state (Table 3.11), whereas all 50%-quantile ex sector index returns are significantly influenced by variations in the T-bill spread during the crisis period as shown in Table 3.15. During the recovery period, the influence of T-bill spread changes is equated in the sense that five of the ten 50%-quantile ex sector index returns are significantly influenced, namely, the 50%-quantile ex sector index returns excluding the Basic Materials, Industrials, Consumer Goods, Consumer Services and Telecommunication sectors as shown in Table 3.19.

Due to the number of tables showing the regression results, the regression results for the UK and Germany are not reported here, and the interested reader is referred to the Appendix B. The regression results for the UK are shown in Tables B.1–B.16 and those for Germany are shown in Tables B.17–B.32. The interpretation of the quantile regression results for the UK and Germany follows the same manner as described above for the US. The regression results contain all state variables of interest. The insignificant state variables are sequentially eliminated, and the quantile regressions are re-run until only significant explanatory variables remain. The remaining significant variables were used to estimate the $\widehat{\Delta \text{CoVaR}}\text{s}$. At the 2.5%-quantile, this method faced no problems, and only significant coefficients, after a number of regressions, were obtained in case of the US and the UK. As shown, excluding the Healthcare, Telecommunication and Energy sectors, the ex sector index regressions return no significance at the 2.5%-quantile during the calm period for Germany (Table B.22), and no significance of the ex

Basic Materials 2.5%-quantile sector index returns for the second regression was obtained. In these cases, the regressions were started with one variable and kept if there was significance at the 10% level. Then, the second variable was added, and the regression was re-run with two variables. The insignificant variables were eliminated, and the third variable was added before the regression was re-run with only the significant variables of the previous regression. This procedure was followed until all state variables were included in the quantile regression. This method returned significant variables for the remaining ex sector index returns.

The same issue arose for the difficult period of the ex Technology 2.5%-quantile sector returns regression, and the state variables were added to the quantile regression in a stepwise manner, as described above (Table B.18). However, no significance regarding the ex Healthcare sector index return regressions at the 2.5%-quantile were found.

3.5.2 Statistical test results

Following the definition of Adrian and Brunnermeier (2016), ΔCoVaR measures the marginal contribution of a sector to systemic risk. Hence, $\widehat{\Delta\text{CoVaR}}$ is used to assess each sector's contribution to systemic risk in the sense that $\widehat{\Delta\text{CoVaR}} \neq 0$ means that a particular sector is systemically relevant. In doing so, the significance test is conducted under the null hypothesis of equal CDFs of the $\widehat{\text{CoVaRs}}$ at the 2.5% and 50%-quantile, i.e. $\widehat{\Delta\text{CoVaR}} = 0$. The resulting bootstrapped p-values for all the US sectors indicate that the null hypothesis could be rejected at the 1% significance level for all periods. Testing for the significance of the examined sectors for the UK and Germany signals that, during all periods, all sectors have a significant impact on the economy, as indicated by the p-values of the bootstrap Kolmogorov-Smirnov test.

The stochastic dominance test tests the null hypothesis that sector i contributes less to systemic risk than sector j. The implication is that the sectors are compared in a pairwise manner in the dominance test (Castro and Ferrari, 2014).

Using a matrix, we observe the p-values of the dominance test, indicating if sector i's ΔCoVaR in absolute terms is smaller than that of sector j and hence contributes less to the risk of the real economy than sector j. The resulting p-values can be shown in a matrix, with the column representing sector i and the line representing sector j. However, in some cases the ΔCoVaR CDFs of two sectors either overlap or are very close to each other, meaning that there is no significant difference between them.

Hence, I conclude that there is a non-dominance between the pair under investigation. Given that the $\widehat{\Delta \text{CoVaRs}}$ are estimated at the 2.5% quantile, we obtain negative $\widehat{\Delta \text{CoVaRs}}$ and $\widehat{\text{VaRs}}$. The subsequent interpretation centres on absolute $\widehat{\Delta \text{CoVaR}}$ values, i.e. more negative $\widehat{\Delta \text{CoVaRs}}$ are referred to as larger $\widehat{\Delta \text{CoVaRs}}$.

Table 3.20 summarises the number of dominated sectors per period and the median $\widehat{\Delta \text{CoVaRs}}$ for the US. As shown, the dominant sectors differ between periods. That is, in turbulent times, the Consumer Services sector dominates most sectors, indicating its strong effect on systemic risk during such periods, and it is of less systemic relevance during the calm and recovering periods. By contrast, the Utilities sector dominates all other sectors during the calm period, and its dominance remains the highest during the crisis period. The Industrials sector represents little contribution to systemic risk, and therefore, it seems to be of little systemic relevance, given that it dominates five sectors only in the difficult period. It is interesting to observe that the Financials sector dominates no sectors during calm and growing periods but only during turbulent periods.

	Difficult period		Calm period		Crisis period		Recovery period	
	ΔCoVaR	**dominated sectors**	**ΔCoVaR**	**dominated sectors**	**ΔCoVaR**	**dominated sectors**	**ΔCoVaR**	**dominated sectors**
Consumer Services	-2.5037	9	-1.3240	4	-2.1605	7	-1.2466	5
Healthcare	-2.3368	8	-1.4625	7	-2.0548	4	-1.1942	3
Consumer Goods	-2.2647	7	-1.1173	2	-1.9967	3	-1.1088	2
Financials	-2.1869	5	-0.9029	0	-1.9934	4	-1.1230	0
Industrials	-2.1735	5	-1.0563	0	-1.5960	0	-0.9485	0
Basic Materials	-1.8843	4	-1.2682	3	-1.9724	3	-1.2328	5
Telecommunication	-1.6901	2	-1.2068	1	-1.7755	1	-1.3955	7
Technology	-1.6637	2	-1.3474	5	-2.1172	6	-1.0416	1
Energy	-1.4965	1	-1.5078	8	-1.7919	1	-1.2104	3
Utilities	-1.4805	0	-1.6932	9	-2.1331	8	-1.2165	4

Table 3.20: Number of dominated sectors in the US.

The number of dominated sectors was estimated using the bootstrap Kolmogorov-Smirnov test with 10,000 bootstraps. The sectors were compared in a pairwise manner and the resulting p-values indicate whether sector i contributes less to systemic risk than sector j. The ordering of the sectors follows the number of dominated sectors during the difficult period. The $\widehat{\Delta \text{CoVaRs}}$ represent the median $\widehat{\Delta \text{CoVaRs}}$ of the daily $\widehat{\Delta \text{CoVaRs}}$ over the sub-periods as defined in Table 3.1.

The scatter plots in Figures 3.1 to 3.4 graphically show the link between the sector risk in isolation, $\widehat{\mathrm{VaR}}$, and the sector contribution to systemic risk represented by $\widehat{\Delta\mathrm{CoVaR}}$ for the four periods.

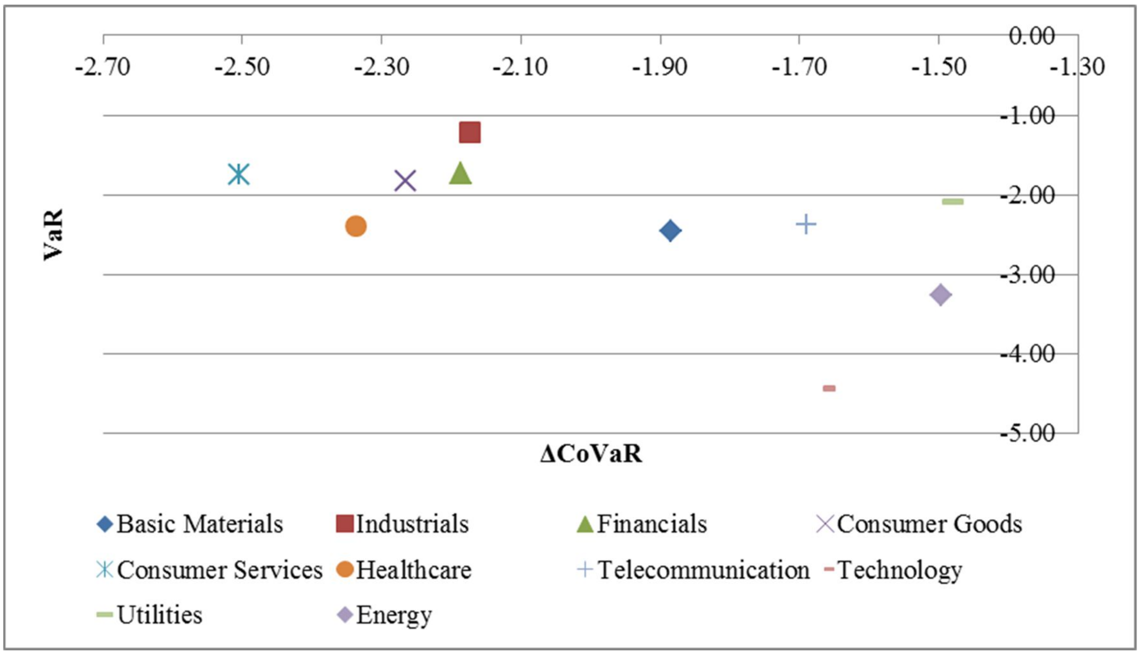

Figure 3.1: Scatter plot for the difficult period in the US.
The $\widehat{\Delta\mathrm{CoVaR}}$s and the $\widehat{\mathrm{VaR}}$s represent the median values of the daily $\widehat{\Delta\mathrm{CoVaR}}$s and $\widehat{\mathrm{VaR}}$s over the difficult period as defined in Table 3.1. The values for the $\widehat{\Delta\mathrm{CoVaR}}$s and $\widehat{\mathrm{VaR}}$s are negative as they are estimated at the 2.5% quantile.

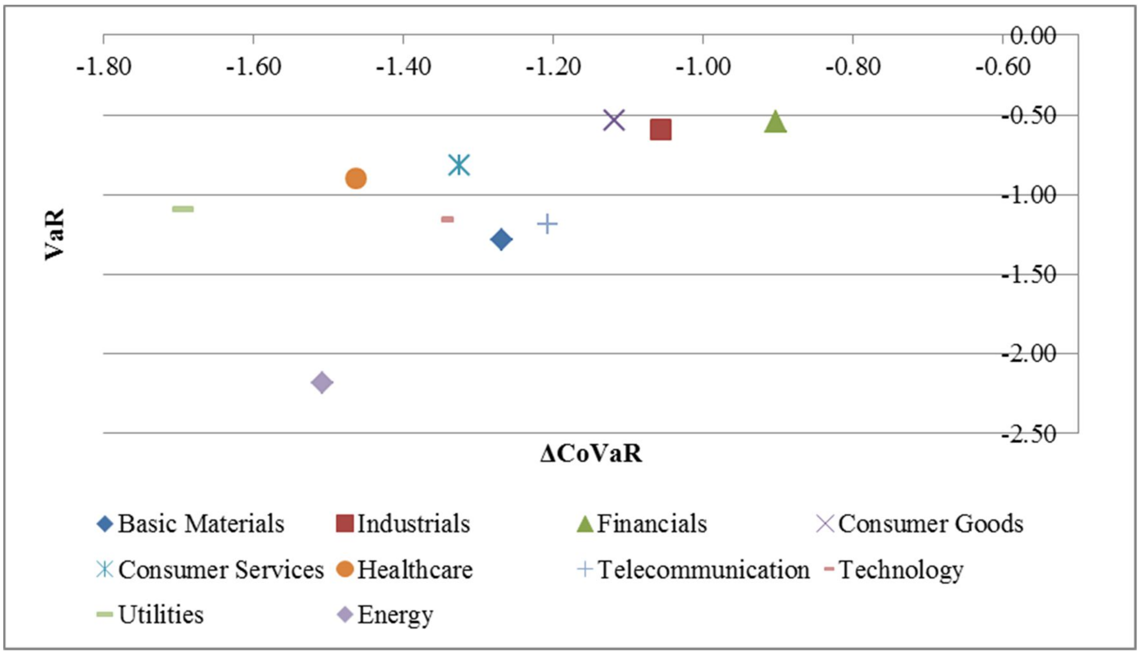

Figure 3.2: Scatter plot for the calm period in the US.
The $\widehat{\Delta\mathrm{CoVaR}}$s and the $\widehat{\mathrm{VaR}}$s represent the median values of the daily $\widehat{\Delta\mathrm{CoVaR}}$s and $\widehat{\mathrm{VaR}}$s over the calm period as defined in Table 3.1. The values for the $\widehat{\Delta\mathrm{CoVaR}}$s and $\widehat{\mathrm{VaR}}$s are negative as they are estimated at the 2.5% quantile.

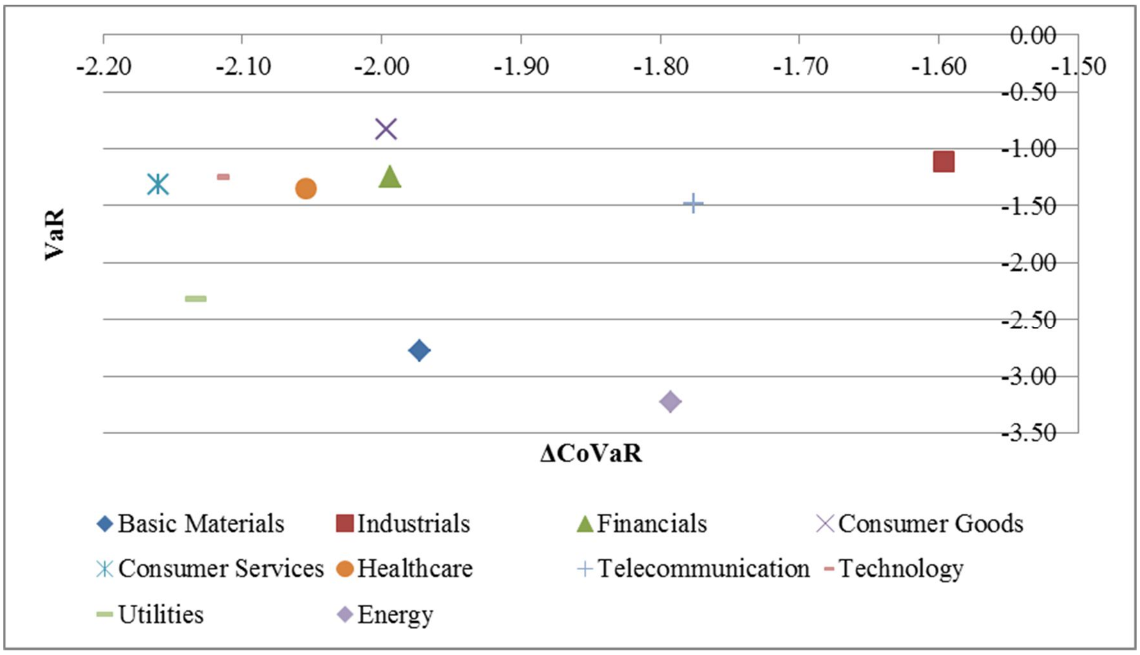

Figure 3.3: Scatter plot for the crisis period in the US.
The $\widehat{\Delta\text{CoVaR}}$s and the $\widehat{\text{VaR}}$s represent the median values of the daily $\widehat{\Delta\text{CoVaR}}$s and $\widehat{\text{VaR}}$s over the crisis period as defined in Table 3.1. The values for the $\widehat{\Delta\text{CoVaR}}$s and $\widehat{\text{VaR}}$s are negative as they are estimated at the 2.5% quantile.

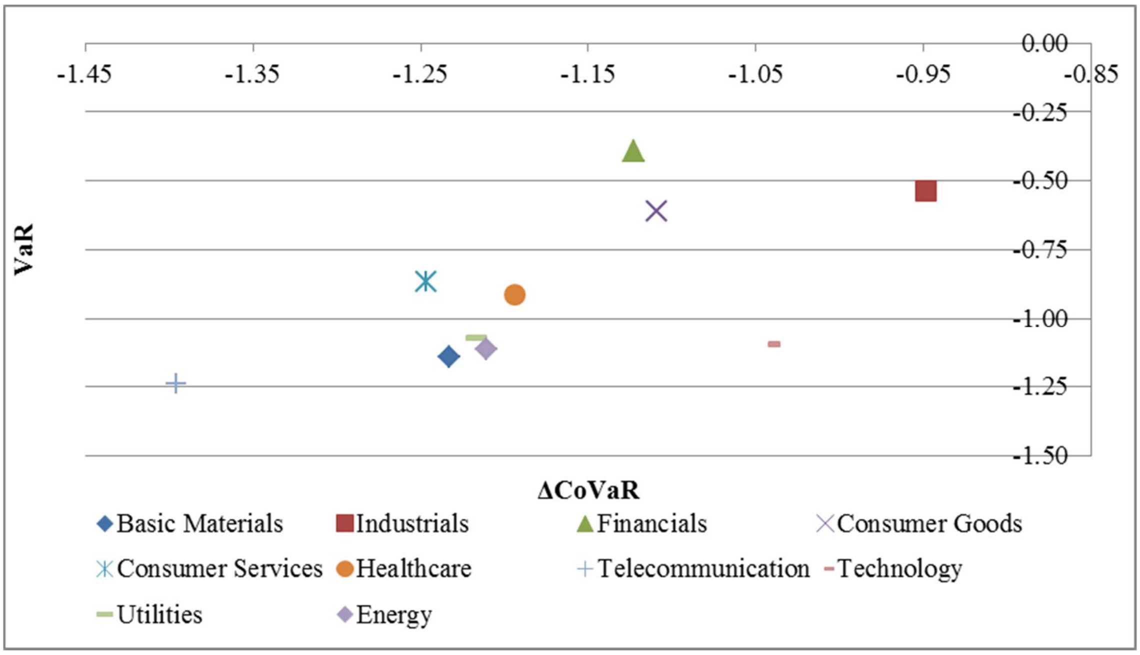

Figure 3.4: Scatter plot for the recovery period in the US.
The $\widehat{\Delta\text{CoVaR}}$s and the $\widehat{\text{VaR}}$s represent the median values of the daily $\widehat{\Delta\text{CoVaR}}$s and $\widehat{\text{VaR}}$s over the recovery period as defined in Table 3.1. The values for the $\widehat{\Delta\text{CoVaR}}$s and $\widehat{\text{VaR}}$s are negative as they are estimated at the 2.5% quantile.

The $\widehat{\Delta\text{CoVaR}}$ and the $\widehat{\text{VaR}}$ plotted in the scatter plots represent the median measure over the respective period. Comparing the scatter plots shows that the levels of the median $\widehat{\Delta\text{CoVaR}}$ change across periods. Also, the sectors with the highest (i.e., most negative) $\widehat{\Delta\text{CoVaR}}$ differ across periods. That is, the Consumer Services sector reveals the highest $\widehat{\Delta \mathrm{CoVaR}}$ in the crisis and difficult periods, whereas its $\widehat{\Delta \mathrm{CoVaR}}$ ranks fifth in the calm period. By contrast, the Telecommunication sector turns out to be the systemically most relevant sector over the recovery period, given that its median $\widehat{\Delta \mathrm{CoVaR}}$ is the highest compared to the remaining sectors and has the seventh highest $\widehat{\Delta \mathrm{CoVaR}}$ in calm times, whereas it ranks ninth in the crisis period. Surprisingly, the systemic risk contribution of the Financials sector is the sixth highest during the crisis period and declines in relation to the other sectors when the situation is recovering. The $\widehat{\Delta \mathrm{CoVaR}}$ is even the smallest during the calm period. The systemic risk contribution of the Industrials sector is relatively low over different periods; that is, its $\widehat{\Delta \mathrm{CoVaR}}$ is high regarding the median $\widehat{\Delta \mathrm{CoVaR}}$ and compared to the other sectors in the difficult period but low in the crisis and recovery periods and thus can be considered to be of relatively little systemic relevance. The dots do not lie on a straight diagonal line for all the scatter plots, which means that the $\widehat{\Delta \mathrm{CoVaRs}}$ do not go hand in hand with the $\widehat{\mathrm{VaRs}}$, and the $\widehat{\Delta \mathrm{CoVaR}} / \widehat{\mathrm{VaR}}$ ratios were calculated to underpin the weak link between these measures, as shown in Table 3.21.

	Difficult	Calm	Crisis	Recovery
Basic Materials	0.7646	0.9863	0.7090	1.0798
Industrials	1.7943	1.7916	1.4430	1.7725
Financials	1.2641	1.6638	1.5999	2.8490
Consumer Goods	1.2358	2.0731	2.4218	1.8215
Consumer Services	1.4284	1.6129	1.6427	1.4418
Healthcare	0.9778	1.6218	1.5283	1.3072
Telecommunication	0.7103	1.0127	1.1950	1.1279
Technology	0.3754	1.1619	1.7059	0.9525
Utilities	0.7112	1.5534	0.9203	1.1356
Energy	0.4591	0.6888	0.5543	1.0879

Table 3.21: $\widehat{\Delta \mathrm{CoVaR}} / \widehat{\mathrm{VaR}}$ ratios per period in the US.
The ratios represent the median $\widehat{\Delta \mathrm{CoVaR}}$ divided by the median $\widehat{\mathrm{VaR}}$ of the corresponding period as defined in Table 3.1. Values greater than 1 are those where the value of $\widehat{\Delta \mathrm{CoVaR}}$ exceeds that of $\widehat{\mathrm{VaR}}$.

Values greater than 1 are those where the value of $\widehat{\Delta \mathrm{CoVaR}}$ exceeds that of $\widehat{\mathrm{VaR}}$, meaning that there is not a one-to-one relationship between them. Hence, a high ratio can be the result of either a high value of $\widehat{\Delta \mathrm{CoVaR}}$ and/or a low value of $\widehat{\mathrm{VaR}}$. For instance, the Consumer Goods sector reveals the highest ratio during the calm period even though its $\widehat{\Delta \mathrm{CoVaR}}$ is only the third lowest due to the low $\widehat{\mathrm{VaR}}$. Surprisingly, the Consumer Goods and Technology sectors reveal the highest ratio during the crisis period, given that their $\widehat{\Delta\text{CoVaRs}}$ increase disproportionately compared to their $\widehat{\text{VaRs}}$. During the recovery period, the Financials sector again shows the highest ratio due to the strong decline in $\widehat{\text{VaR}}$ relative to the decline of $\widehat{\Delta\text{CoVaR}}$. Summarising the observations of Table 3.21, we observe that the increases in the $\widehat{\Delta\text{CoVaR}}$ between the periods exceed those of the $\widehat{\text{VaR}}$ and that the ratios of the sectors change between periods, which means that the degree of externalities seems to change from period to period. These results suggest that, for some sectors, significant externalities exist that are not considered by $\widehat{\text{VaR}}$, which leads to the weak observed relationship. This interpretation is consistent with Roengpitya and Rungcharoenkitkul (2010) who plotted the average ΔCoVaRs and average VaRs of Thai banks and concluded that significant externalities may be present.

Examining the UK, Table 3.22 demonstrates the number of dominated sectors according to the dominance test and the respective median $\widehat{\Delta\text{CoVaR}}$. The Financials sector dominates most sectors only in the difficult period and only five sectors in the crisis period, whereas the Utilities sector dominates most sectors in the crisis and the recovery periods. Similar to the results for the US, the value of the median $\widehat{\Delta\text{CoVaR}}$ does not necessarily reveal the degree of dominance over other sectors, which justifies the application of a statistical dominance test to rank the sectors by their dominance.

	Difficult period		Calm period		Crisis period		Recovery period	
	ΔCoVaR	dominated sectors	ΔCoVaR	dominated sectors	ΔCoVaR	dominated sectors	ΔCoVaR	dominated sectors
Financials	-1.9101	9	-0.9798	5	-2.2330	5	-1.2815	6
Industrials	-1.6745	6	-0.8983	3	-1.3467	0	-1.1190	0
Technology	-1.6701	6	-0.7414	1	-1.8459	4	-1.3444	7
Telecommunication	-1.2658	2	-1.0576	9	-1.5889	2	-1.0259	0
Consumer Goods	-1.3395	2	-0.9068	3	-1.3969	1	-1.1937	4
Utilities	-1.3248	2	-0.9634	5	-1.9582	7	-1.4962	9
Energy	-1.3420	2	-0.6802	0	-1.8527	3	-1.1723	3
Healthcare	-1.1873	0	-0.8659	2	-1.9429	6	-1.3839	6
Consumer Services	-1.1641	0	-1.0379	8	-1.8649	6	-1.1894	3
Basic Materials	-0.9446	0	-1.0186	5	-1.6519	2	-1.1162	2

Table 3.22: Number of dominated sectors in the UK.
The number of dominated sectors was estimated using the bootstrap Kolmogorov-Smirnov test with 10,000 bootstraps. The sectors were compared in a pairwise manner, and the resulting p-values indicate whether sector i contributes less to systemic risk than sector j. The ordering of the sectors follows the number of dominated sectors during the difficult period. The $\widehat{\Delta \text{CoVaRs}}$ represent the median $\widehat{\Delta \text{CoVaRs}}$ of the daily $\widehat{\Delta \text{CoVaRs}}$ over the sub-periods as defined in Table 3.1. The difficult period is from January 2000 to April 2003. The calm period is from May 2003 to July 2007. The crisis period is from August 2007 to October 2009, and the recovery period is from November 2009 to December 2012.

Figures 3.5 to 3.8 also show a weak relationship between the $\widehat{\Delta \text{CoVaR}}$ of the sectors and their $\widehat{\text{VaR}}$s.

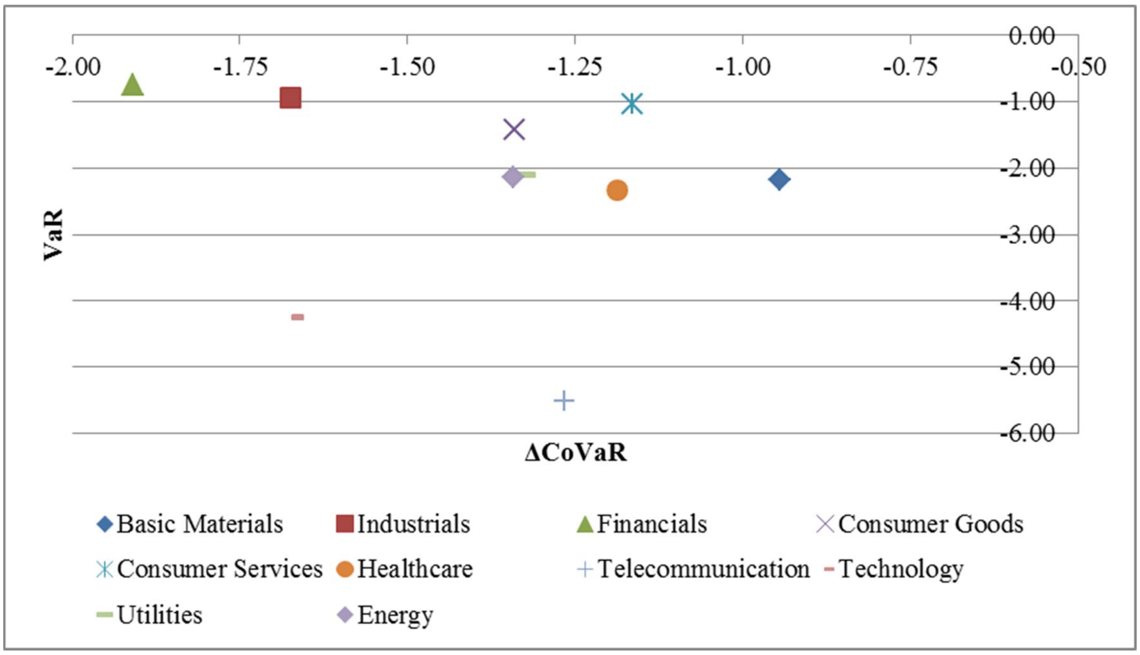

Figure 3.5: Scatter plot for the difficult period in the UK.

The $\widehat{\Delta \text{CoVaR}}$s and the $\widehat{\text{VaR}}$s represent the median values of the daily $\widehat{\Delta \text{CoVaR}}$s and $\widehat{\text{VaR}}$s over the difficult period from January 2000 to April 2003. The values for the $\widehat{\Delta \text{CoVaR}}$s and $\widehat{\text{VaR}}$s are negative as they are estimated at the 2.5% quantile.

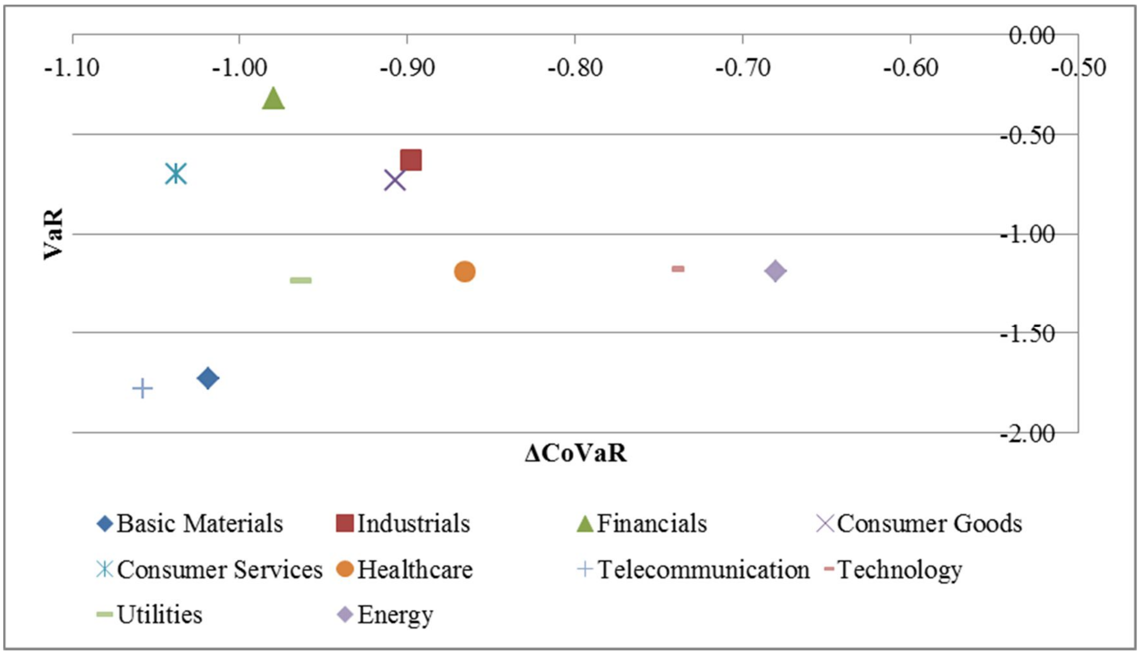

Figure 3.6: Scatter plot for the calm period in the UK.

The $\widehat{\Delta \text{CoVaR}}$s and the $\widehat{\text{VaR}}$s represent the median values of the daily $\widehat{\Delta \text{CoVaR}}$s and $\widehat{\text{VaR}}$s over the calm period from May 2003 to July 2007. The values for the $\widehat{\Delta \text{CoVaR}}$s and $\widehat{\text{VaR}}$s are negative as they are estimated at the 2.5% quantile.

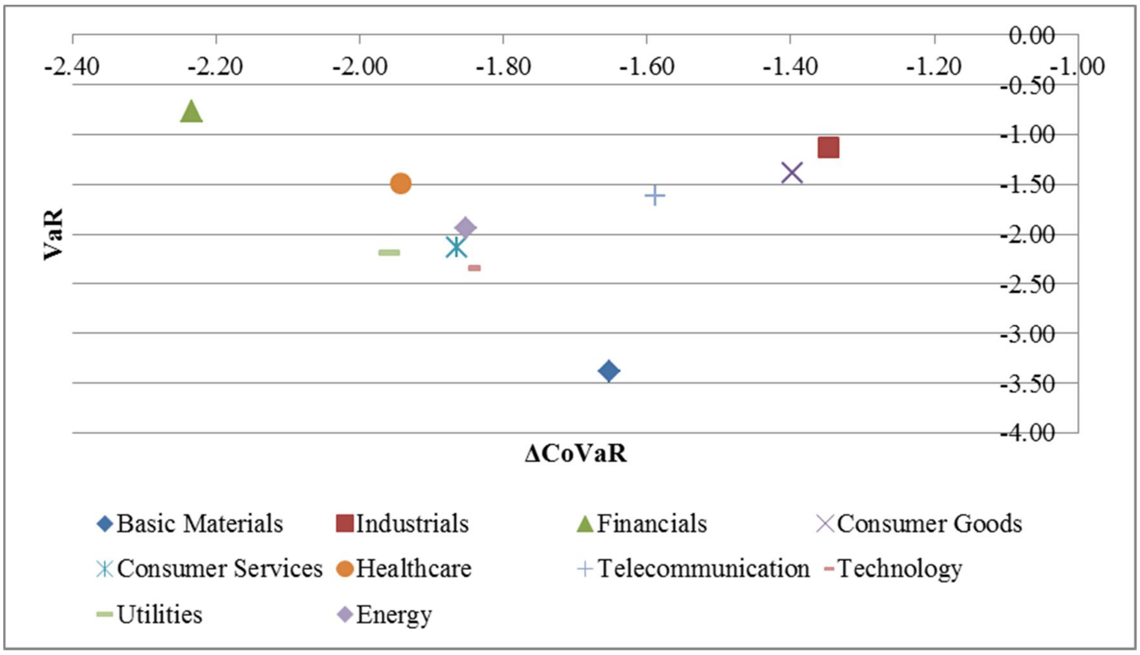

Figure 3.7: Scatter plot for the crisis period in the UK.

The $\widehat{\Delta\text{CoVaR}}$s and the $\widehat{\text{VaR}}$s represent the median values of the daily $\widehat{\Delta\text{CoVaR}}$s and $\widehat{\text{VaR}}$s over the crisis period from August 2007 to October 2009. The values for the $\widehat{\Delta\text{CoVaR}}$s and $\widehat{\text{VaR}}$s are negative as they are estimated at the 2.5% quantile.

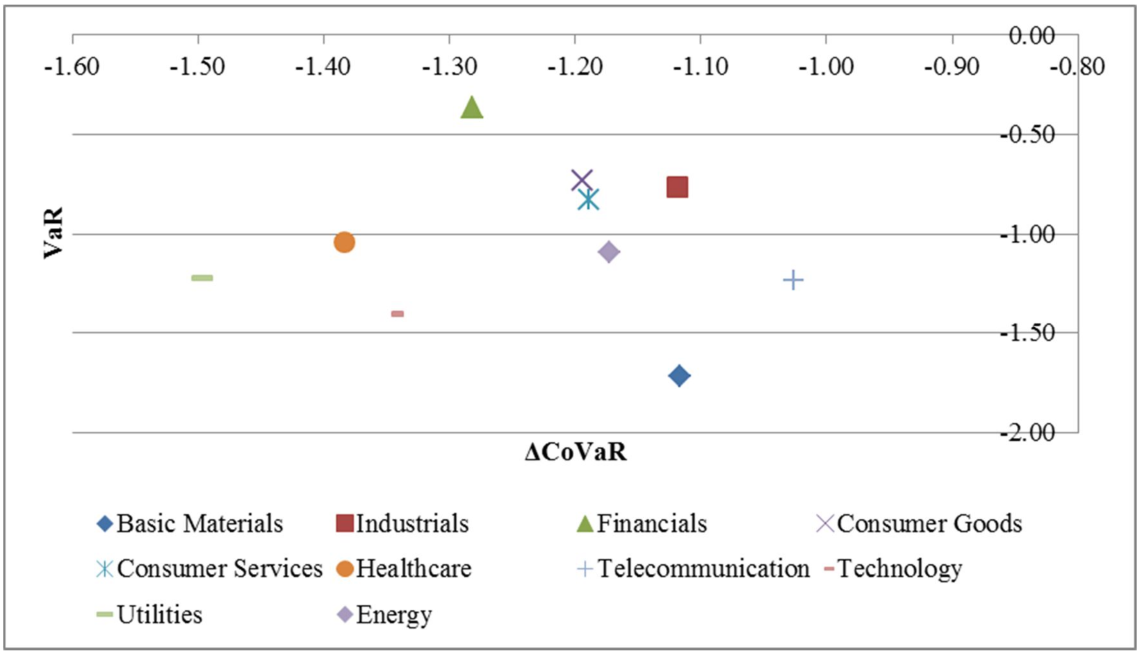

Figure 3.8: Scatter plot for the recovery period in the UK.

The $\widehat{\Delta\text{CoVaR}}$s and the $\widehat{\text{VaR}}$s represent the median values of the daily $\widehat{\Delta\text{CoVaR}}$s and $\widehat{\text{VaR}}$s over the recovery period from November 2009 to December 2012. The values for the $\widehat{\Delta\text{CoVaR}}$s and $\widehat{\text{VaR}}$s are negative as they are estimated at the 2.5% quantile.

In contrast to the US, the Financials sector has the largest $\widehat{\Delta\text{CoVaR}}$ in the difficult and crisis periods; it remains among the four highest $\widehat{\Delta\text{CoVaR}}$s during the calm and recovering periods. The Industrials sector seems to contribute the least to systemic risk during the crisis period, and its contribution remains low during the recovery period.

Examining the plots, the levels of the $\widehat{\Delta \mathrm{CoVaR}}$ seem to be higher on average in the US, and the $\widehat{\Delta \mathrm{CoVaR}} / \widehat{\mathrm{VaR}}$ ratios are smaller for the UK during the difficult and calm periods, indicating higher externalities in the US during these periods. This observation holds for the crisis period. The high ratios for the Financials sector in the UK over all periods leads to the conclusion that, for the Financials sector, significant externalities may exist, indicating that this sector is the systemically riskiest sector in the UK. This is shown in Table 3.23.

	Difficult	**Calm**	**Crisis**	**Recovery**
Basic Materials	0.4331	0.5887	0.4878	0.6512
Industrials	1.7747	1.4291	1.1963	1.4644
Financials	2.5619	3.0829	2.8992	3.5103
Consumer Goods	0.9477	1.2374	1.0076	1.6342
Consumer Services	1.1328	1.4870	0.8754	1.4321
Healthcare	0.5105	0.7267	1.3020	1.3281
Telecommunication	0.2293	0.5938	0.9842	0.8326
Technology	0.3931	0.6295	0.7878	0.9575
Utilities	0.6334	0.7806	0.8967	1.2254
Energy	0.6308	0.5731	0.9553	1.0729

Table 3.23: $\widehat{\Delta \mathrm{CoVaR}} / \widehat{\mathrm{VaR}}$ ratios per period in the UK.

The ratios represent the median $\widehat{\Delta \mathrm{CoVaR}}$ divided by the median $\widehat{\mathrm{VaR}}$ of the corresponding period. Values greater than 1 are those where the value of $\widehat{\Delta \mathrm{CoVaR}}$ exceeds that of $\widehat{\mathrm{VaR}}$. The difficult period is from January 2000 to April 2003. The calm period is from May 2003 to July 2007. The crisis period is from August 2007 to October 2009 and the recovery period is from November 2009 to December 2012.

Table 3.24 presents the number of dominated sectors for Germany. The Industrials sector dominates most sectors over all periods except for the crisis period, during which the Utilities sector seems to be systematically risky. The Financials sector contributes more to systemic risk during the difficult and calm periods whereas its contribution drops in the crisis period and remains low thereafter.

	Difficult period		Calm period		Crisis period		Recovery period	
	ΔCoVaR	**dominated sectors**	**ΔCoVaR**	**dominated sectors**	**ΔCoVaR**	**dominated sectors**	**ΔCoVaR**	**dominated sectors**
Industrials	-4.8265	8	-2.8232	9	-3.1913	5	-3.1187	7
Basic Materials	-4.2393	7	-1.8566	4	-3.1054	5	-2.8275	6
Financials	-4.2958	7	-2.7062	8	-2.1025	1	-1.5574	1
Telecommunication	-3.8267	6	-1.8140	2	-3.1737	5	-2.5056	3
Utilities	-3.2612	4	-1.8934	2	-3.9654	9	-1.9242	2
Consumer Services	-3.1601	2	-2.3695	6	-1.9851	0	-3.0166	7
Energy	-3.1601	2	-1.2301	0	-2.7889	3	-2.5567	3
Consumer Goods	-3.3117	1	-1.4347	1	-2.1582	1	-1.1365	0
Technology	-2.5490	1	-2.3625	6	-2.8097	3	-3.1472	8
Healthcare	0.1798	0	-1.8399	3	-3.2426	6	-2.6227	5

Table 3.24: Number of dominated sectors in Germany.
The number of dominated sectors was estimated using the bootstrap Kolmogorov-Smirnov test with 10,000 bootstraps. The sectors were compared in a pairwise manner and the resulting p-values indicate whether sector i contributes less to systemic risk than sector j. The ordering of the sectors follows the number of dominated sectors during the difficult period. The $\widehat{\Delta \mathrm{CoVaRs}}$ represent the median $\widehat{\Delta \mathrm{CoVaRs}}$ of the daily $\widehat{\Delta \mathrm{CoVaRs}}$ over the sub-period as defined in Table 3.1.

Again, in examining Figures 3.9 to 3.12, we observe a weak link between $\widehat{\Delta \text{CoVaR}}$ and $\widehat{\text{VaR}}$.

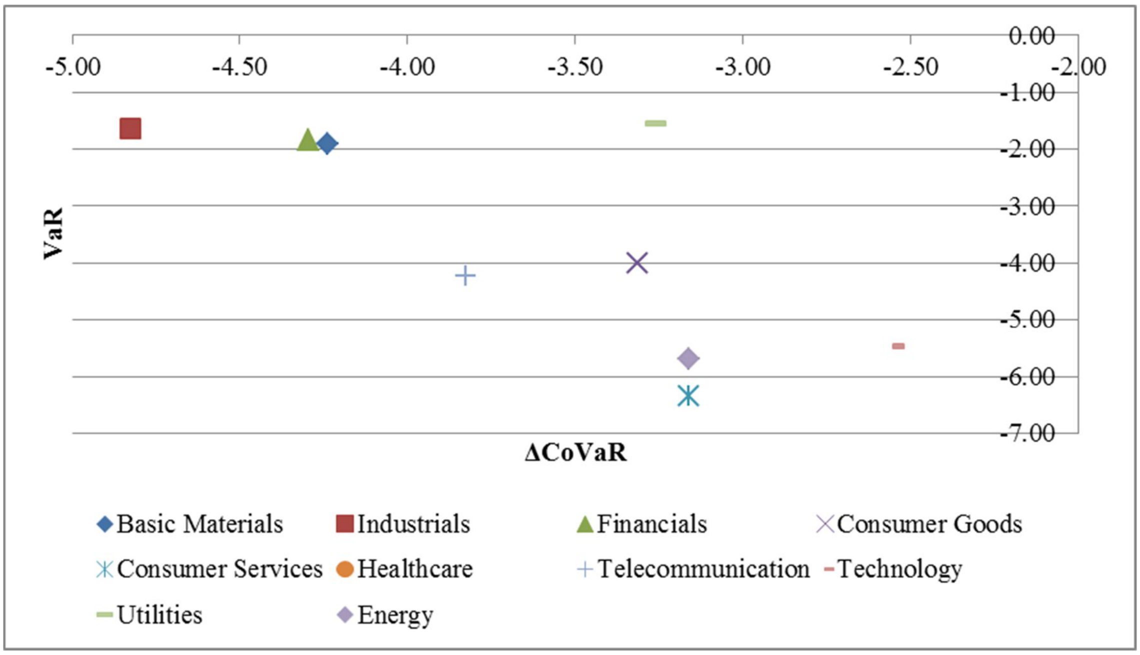

Figure 3.9: Scatter plot for the difficult period in Germany.
The $\widehat{\Delta \text{CoVaR}}$s and the $\widehat{\text{VaR}}$s represent the median values of the daily $\widehat{\Delta \text{CoVaR}}$s and $\widehat{\text{VaR}}$s over the difficult period as defined in Table 3.1. The values for the $\widehat{\Delta \text{CoVaR}}$s and $\widehat{\text{VaR}}$s are negative as they are estimated at the 2.5% quantile.

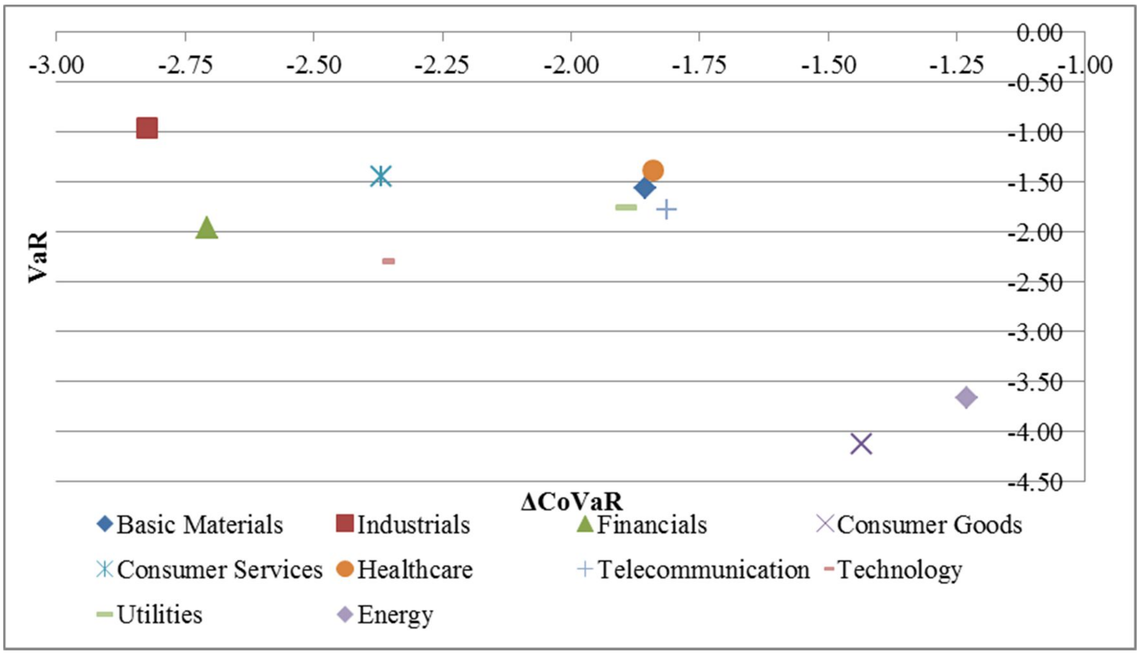

Figure 3.10: Scatter plot for the calm period in Germany.
The $\widehat{\Delta \text{CoVaR}}$s and the $\widehat{\text{VaR}}$s represent the median values of the daily $\widehat{\Delta \text{CoVaR}}$s and $\widehat{\text{VaR}}$s over the calm period as defined in Table 3.1. The values for the $\widehat{\Delta \text{CoVaR}}$s and $\widehat{\text{VaR}}$s are negative as they are estimated at the 2.5% quantile.

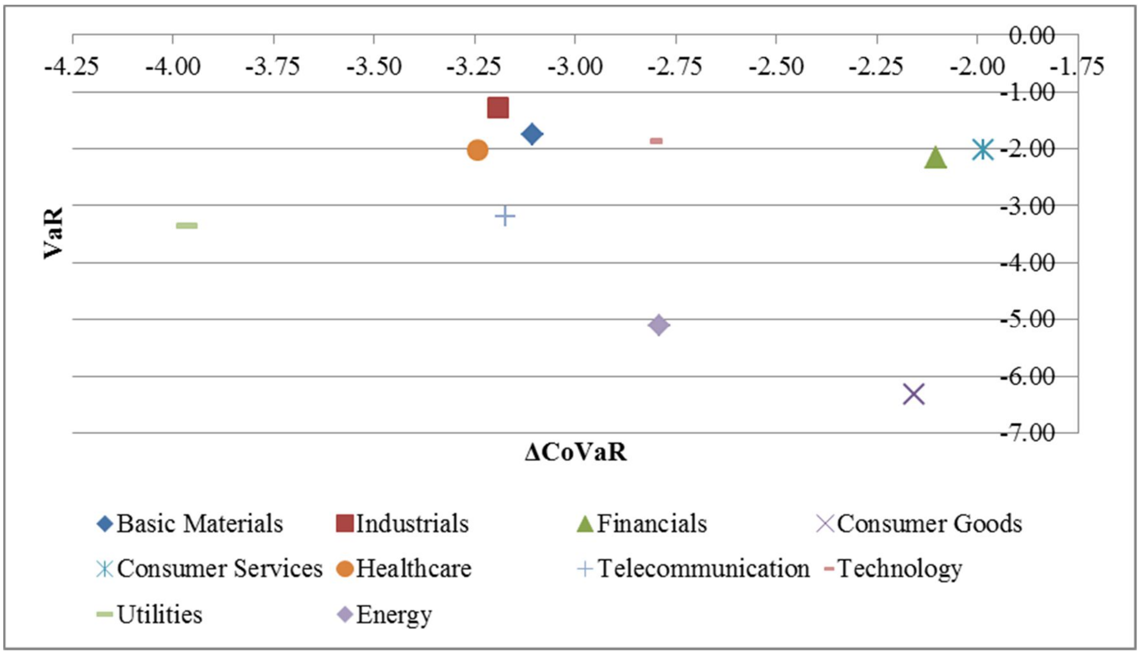

Figure 3.11: Scatter plot for the crisis period in Germany.

The $\widehat{\Delta CoVaR}$s and the $\widehat{VaR}$s represent the median values of the daily $\widehat{\Delta CoVaR}$s and $\widehat{VaR}$s over the crisis period as defined in Table 3.1. The values for the $\widehat{\Delta CoVaR}$s and $\widehat{VaR}$s are negative as they are estimated at the 2.5% quantile.

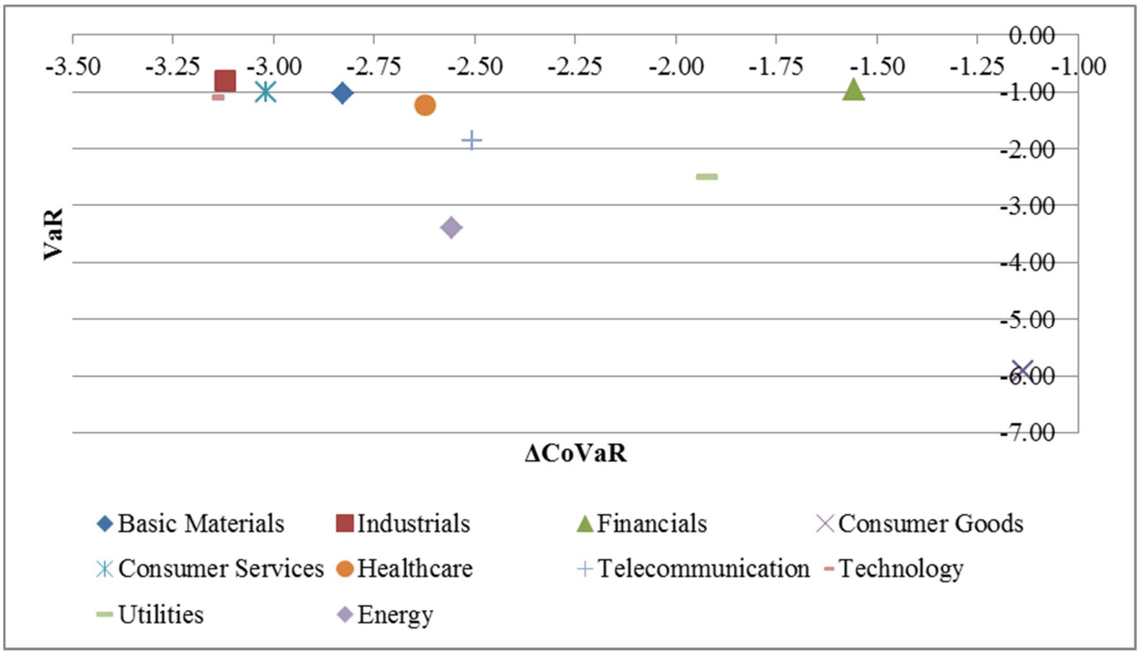

Figure 3.12: Scatter plot for the recovery period in Germany.

The $\widehat{\Delta CoVaR}$s and the $\widehat{VaR}$s represent the median values of the daily $\widehat{\Delta CoVaR}$s and $\widehat{VaR}$s over the recovery period as defined in Table 3.1. The values for the $\widehat{\Delta CoVaR}$s and $\widehat{VaR}$s are negative as they are estimated at the 2.5% quantile.

The Industrials sector reveals a high median $\widehat{\Delta CoVaR}$ in absolute terms during the first two observation periods, whereas its $\widehat{VaR}$ is low compared to the other sectors. This observation also holds for the recovery period, indicating high externalities related to this sector. Table 3.25 confirms this observation in the sense that the Industrials sector exhibits the highest $\widehat{\Delta \text{CoVaR}} / \widehat{\text{VaR}}$ ratios in all periods. By contrast, the Consumer Goods sector is related to high $\widehat{\text{VaR}}$ values (in three periods, even the highest value) but a low $\widehat{\Delta \text{CoVaR}}$ in absolute terms, indicating that this sector may be risky in isolation but contributes little to systemic risk and hence is less risky for the real economy. The ratios presented in Table 3.25 underpin this observation. Note that the negative ratio for Healthcare during the difficult period arises from the positive median $\widehat{\Delta \text{CoVaR}}$ value for this period, given that no significance at the 2.5% quantile is found. Therefore, the results for the Healthcare sector during the difficult period should be treated with caution.

	Difficult	**Calm**	**Crisis**	**Recovery**
Basic Materials	2.2260	1.1876	1.7808	2.7544
Industrials	2.9345	2.9438	2.4845	3.9413
Financials	2.3477	1.3852	0.9795	1.6067
Consumer Goods	0.8263	0.3477	0.3408	0.1919
Consumer Services	0.4984	1.6339	0.9815	3.0184
Healthcare	-0.0329	1.3291	1.6030	2.1157
Telecommunication	0.9070	1.0214	0.9967	1.3456
Technology	0.4652	1.0337	1.5111	2.8997
Utilities	2.1232	1.0811	1.1814	0.7749
Energy	0.5554	0.3357	0.5454	0.7509

Table 3.25: $\widehat{\Delta \text{CoVaR}} / \widehat{\text{VaR}}$ ratios per period in Germany.
The ratios represent the median $\widehat{\Delta \text{CoVaR}}$ divided by the median $\widehat{\text{VaR}}$ of the corresponding period as defined in Table 3.1. Values greater than 1 are those where the value of $\widehat{\Delta \text{CoVaR}}$ exceeds that of $\widehat{\text{VaR}}$.

The results observed for the cases presented above are consistent with those of Adrian and Brunnermaier (2016) in the sense that there is no one-to-one relationship between $\widehat{\Delta \text{CoVaR}}$ and $\widehat{\text{VaR}}$ and that high $\widehat{\Delta \text{CoVaR}}$ sectors may contribute more to systemic risk. Roengpitya and Rungcharoenkitkul (2010) define systemic risk as a micro risk with large macro implications, which is akin to the notion of externalities. Given this definition, I interpret that a more systemically important sector can be considered as a sector with higher externalities on the system.

3.6 Changes in ΔCoVaR over time

Movements in equity markets are accompanied by movements in the daily $\widehat{\Delta \text{CoVaR}}$s, as illustrated for each country in Figures 3.13 to 3.15.

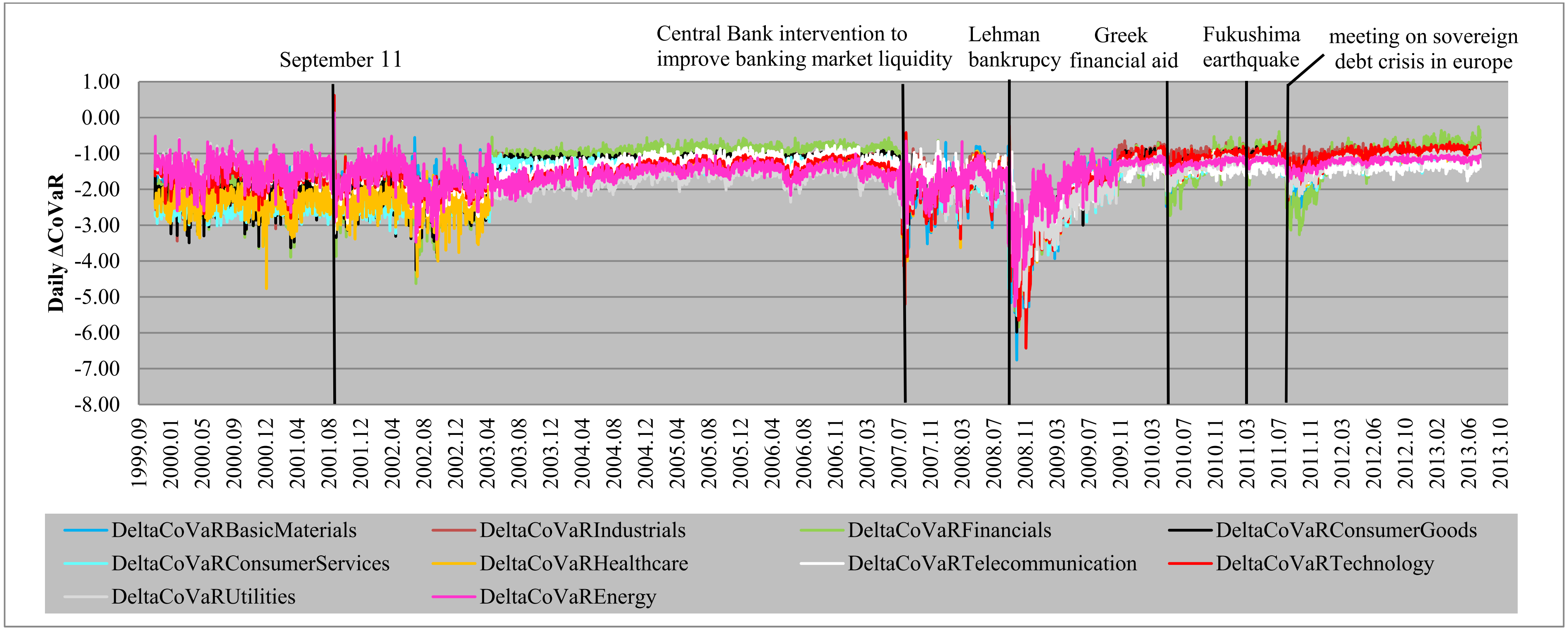

Figure 3.13: Daily estimated $\widehat{\Delta\text{CoVaRs}}$ for the US.

The $\widehat{\Delta\text{CoVaRs}}$ were estimated individually for each sub-period and were finally put together to generate a history of the $\widehat{\Delta\text{CoVaRs}}$ over the entire period from November 1999 to August 2013. The $\widehat{\Delta\text{CoVaRs}}$ are estimated at the 2.5% quantile using quantile regressions. The $\widehat{\Delta\text{CoVaRs}}$ are estimated at a daily frequency and expressed as negative values.

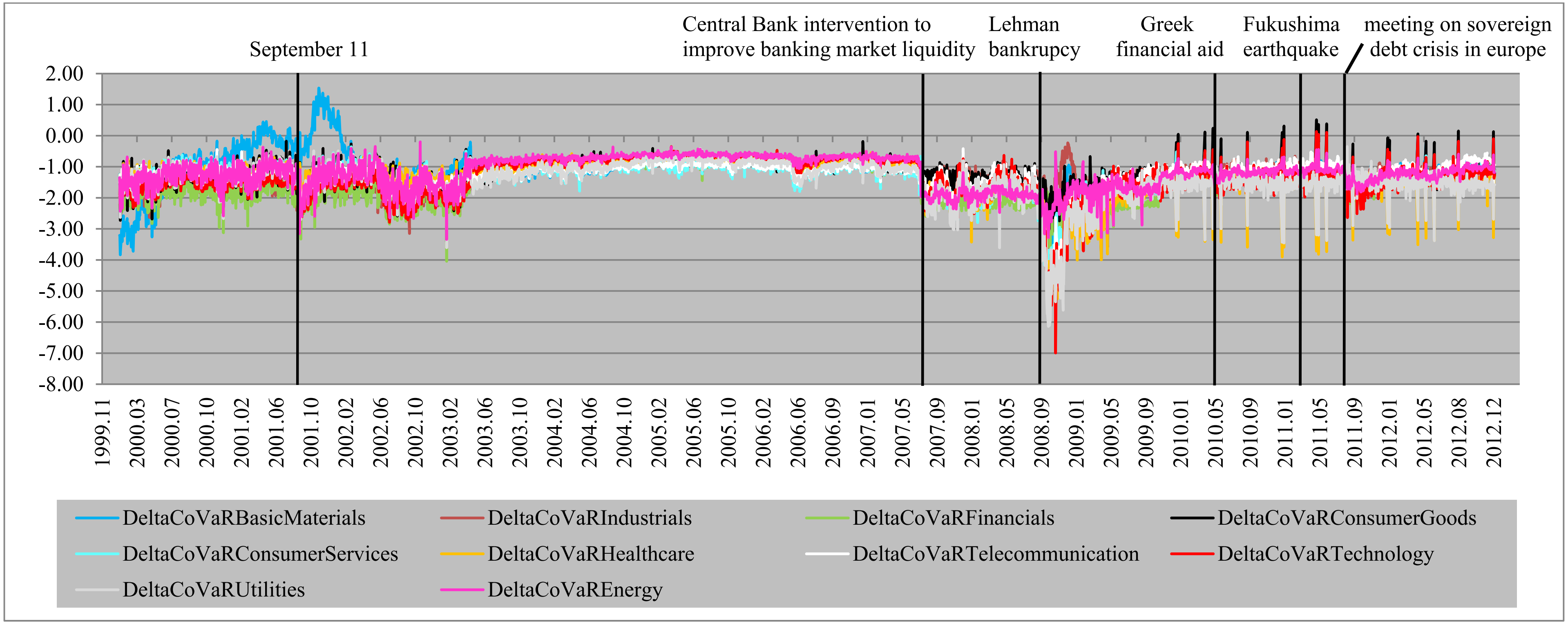

Figure 3.14: Daily estimated $\widehat{\Delta \text{CoVaRs}}$ for the UK.

The $\widehat{\Delta \text{CoVaRs}}$ were estimated individually for each sub-period and were finally put together to generate a history of the $\widehat{\Delta \text{CoVaRs}}$ over the entire period from January 2000 to December 2012. The $\widehat{\Delta \text{CoVaRs}}$ are estimated at the 2.5% quantile using quantile regressions. The $\widehat{\Delta \text{CoVaRs}}$ are estimated at a daily frequency and expressed as negative values.

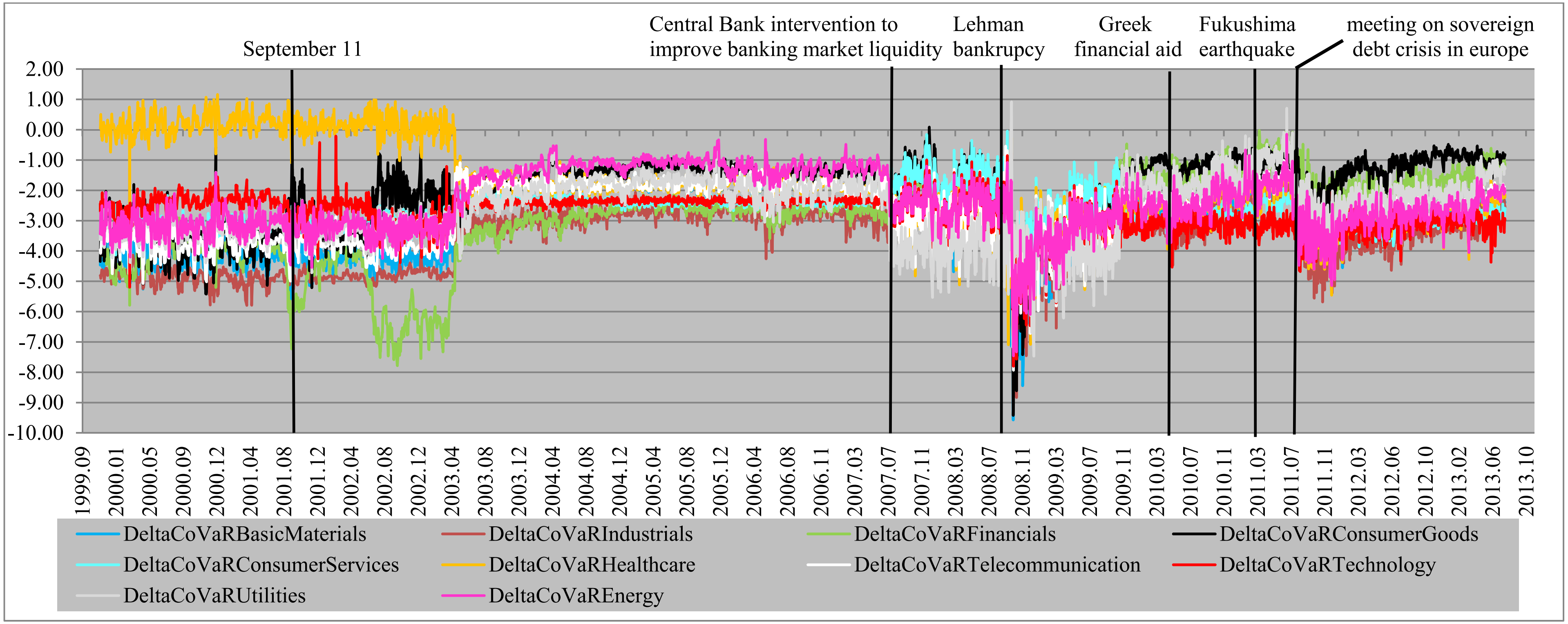

Figure 3.15: Daily estimated $\widehat{\Delta \text{CoVaRs}}$ for Germany.

The $\widehat{\Delta \text{CoVaRs}}$ were estimated individually for each sub-period and were finally put together to generate a history of the $\widehat{\Delta \text{CoVaRs}}$ over the entire period from November 1999 to August 2013. The $\widehat{\Delta \text{CoVaRs}}$ are estimated at the 2.5% quantile using quantile regressions. The $\widehat{\Delta \text{CoVaRs}}$ are estimated at a daily frequency and expressed as negative values.

The period between 2003 and mid-2007 was characterised by relatively low $\widehat{\Delta \text{CoVaRs}}$ for all the investigated countries.

The massive change in $\widehat{\Delta \text{CoVaRs}}$ that followed the Lehman collapse misleads many people into believing that the financial crisis was caused by the Lehman bankruptcy, and the sharp drop in the S&P500 Index and the downturn in output and the massive capital injection to save the financial system would have been avoided if Lehman had been rescued. However, according to Cochrane and Zingales (2009), this belief is not correct because the Lehman failure was only one event that did not occur in isolation from other preceding and subsequent failures, such as the AIG bailout. The main risk indicators, i.e. bank CDS spreads and the Libor-OIS spread, did not soar after the Lehman bankruptcy, but they did in the wake of the TARP (Troubled Asset Relief Program) speeches by Henry Paulson and Ben Bernanke on September 23 and 24 in which they vented that the financial system would be at the brink of a collapse without knowing the reason (Cochrane and Zingales, 2009).

The conclusion of Cochrane and Zingales (2009) permits the conclusion that even the collapse of large financial institutions, such as Lehman Brothers, need not trigger a widespread financial crisis but that unstable financial conditions play an essential role in acute financial tensions and higher risk levels. These factors are a feature of the 2008 financial crisis and the turmoil in the wake of the sovereign debt crisis that set in in 2010, with Greece at the centre of the crisis. The fear of an uncontrolled default by Greece prompted policymakers to act to avoid financial turmoil and a major crisis. The situation in Greece raised concerns about the ability of banks to suffer losses on Greek bonds and the transmission of the crisis to the European financial sector, which would have increased its instability (Nelson et al., 2011).

The $\widehat{\Delta \text{CoVaRs}}$ did not slump in the aftermath of the devastating earthquake that hit Japan in March 2011, despite the concern that the high public debt to finance the reconstruction could drive Japan into a sovereign debt crisis similar to that in Greece. The negative effects of the earthquake and the nuclear crisis on Japan's economy had a lesser impact on financial markets and global GDP (Nanto et al., 2011). The global financial markets were very stable during this period even though the Japanese financial system was surrounded by high uncertainty about future developments such as the European debt crisis. The CoVaR and the MES measure had been decreasing since their highs and rose only temporarily after this event in March 2011. Additionally, in 2011, the Financial Cycle Indices, represented by the leading index and the lagging index, did not indicate either instability in the Japanese financial system or in the near future (Bank of Japan, 2012).

Dovern and van Roye (2013) noted the quick transmission of financial stress shocks from the US to other countries. Their analysis comprises 20 countries in Asia, America and Europe over a sample period from 1970 to 2012. The authors computed a cross-country correlation for all countries that showed an increasing correlation over the sample period. This observation indicates rising international financial integration and tendentially more co-moving financial cycles. The respective pairwise correlation between Germany, the UK and the US is high, where the US financial stress is generally highly correlated with all other countries, leading to the assumption that the US is a very important source of financial stress in the UK and Germany. Dovern and van Roye (2013) identified the financial openness of a country as an important factor that explains the differences in exposure to financial stress. It turns out that the degree of financial openness is positively correlated with the correlation of financial stress and that countries such as the UK, the US and Germany reveal a high correlation with other countries' financial stress indices and are highly financially integrated. The correlation of financial stress among countries is time-varying and is particularly strong during episodes of global financial stress (Dovern and van Roye, 2013).

Balakrishnan et al. (2009) note that transmission can occur through common or country-specific channels, depending on country-specific financial and trade linkages as well as other factors, and they ascribe the co-movement of financial stress indices to the existence of common factors.

Motivated by the findings of Dovern and van Roye (2013), the US is assumed to be an important source of financial stress in an international setting. Next, a pooled OLS regression is implemented to identify the main drivers of systemic risk contribution measured by $\widehat{\Delta \mathrm{CoVaR}}$. In doing so, the individual quarterly median $\widehat{\Delta \mathrm{CoVaRs}}$ of the sectors are regressed on quarterly observations of independent variables that account for sector-specific and market-related characteristics. Following Borri et al. (2012), the independent variables include VaR, size, leverage, volatility and financial stress. To identify the sources of risk in a more granular manner, the pooled OLS is run for all sectors and for the six most dominant and four least dominant sectors according to their $\widehat{\Delta \mathrm{CoVaR}}$. The correlation between VaR and volatility is high in all cases and is maximum when the most dominant sectors are considered. Also, volatility is most correlated with $\widehat{\Delta \mathrm{CoVaR}}$, especially when considering the least dominant sectors. On average, the correlation between $\widehat{\text{VaR}}$ and $\widehat{\Delta\text{CoVaR}}$ is weak, which is consistent with the discussion above (the correlation results are shown in Appendix B.3). The results of the pooled OLS panel regression are reported in Table 3.26 with the quarterly median $\widehat{\Delta\text{CoVaR}}$ as the dependent variable, where the regression includes robust standard errors. Panel A shows the results for all 10 sectors. All variables included have a significant effect, and the adjusted R^2 is 52.9%. Columns (2) and (4) indicate that the size effect increases when leverage is introduced. Size and leverage seem to strengthen each other, given that both variables together yield a higher coefficient than each variable individually. The introduction of leverage does not contribute much more to the explanatory power than the $\widehat{\text{VaR}}$ and volatility variables alone as shown in column (3).

To answer the question why some sectors are systemically more relevant, the 10 sectors are divided into two groups of sectors, where the first group contains the six most dominant sectors. The second group consists of the four remaining sectors. Leverage has a smaller coefficient than size but seems to have more explanatory power than size, given that leverage has more effect on the adjusted R^2 in the most dominant sectors. In none of the scenarios in Panel B of Table 3.26 does $\widehat{\text{VaR}}$ significantly influence the risk contribution of the most dominant sectors. A significant effect of the financial conditions on the most dominant sectors is found to be relatively small regarding its coefficient but increases the adjusted R^2 by more than 4% as shown in column (5). Panel C represents the results for the least dominant sectors, which show a low but significant coefficient of $\widehat{\text{VaR}}$ compared with volatility and size. Again, larger sectors, in terms of their log of book value of equity, increase the explanatory power in terms of adjusted R^2, whereas leverage does not improve the explanatory power much when compared to $\widehat{\text{VaR}}$ and volatility. The ANFCI index has a negative and significant coefficient, indicating a significant relationship between the systemic risk contribution of the least dominant sectors and the financial conditions that are weaker compared to Panels A and B and does not increase the adjusted R^2 compared to column (4). Brave and Butters (2011) show that the financial crises are closely linked to tightness peaks, i.e. financial conditions associated with higher risks and lower credit and leverage than average and that financial condition indices contain future economic activity information and can forecast GDP growth.

The regression results indicate that the most dominant sectors depend more on financial conditions than the least dominant sectors and are therefore more prone to financial crises. Furthermore, the findings underpin that $\widehat{\text{VaR}}$ seems to play a minor role in explaining $\widehat{\Delta\text{CoVaR}}$. $\widehat{\text{VaR}}$ has a significant impact on the least dominant sectors in contrast to the most dominant sectors. That is, in Panel A, the regression that includes only $\widehat{\text{VaR}}$ and volatility yields an adjusted R^2 of 39.2%. The regression in Panel C yields an adjusted R^2 of 67.6% with volatility and $\widehat{\text{VaR}}$ as the only independent variables. By contrast, we obtain an adjusted R^2 of 26.2% when volatility and $\widehat{\text{VaR}}$ are the only explanatory variables for the most dominant sectors, which increases to 48% when all other independent variables are included.

Panel A: All sectors					
	1	2	3	4	5
Intercept	-0.1783*	-1.6054***	-0.1396	-1.9683***	-2.3156***
VaR	0.1445***	0.0812***	0.1648***	0.1088***	0.1330***
Volatility	-0.5242***	-0.6163***	-0.4964***	-0.5800***	-0.4533***
Size		0.7727***		1.0188***	1.0574***
Leverage			-0.0191***	-0.0450***	-0.0476***
ANFCI					-0.1528***
Observations	540	540	540	540	540
adj. R-squared	0.3924	0.4569	0.4002	0.4968	0.5291
Panel B: Six most dominant sectors					
	1	2	3	4	5
Intercept	-0.3885***	-2.4125***	0.5449***	-1.0372***	-1.5015***
VaR	0.0404	-0.0164	0.0453	0.0048	0.0356
Volatility	-0.5088***	-0.5693***	-0.6014***	-0.6269***	-0.4918***
Size		1.0302***		0.7192***	0.7850***
Leverage			-0.2596***	-0.2126***	-0.1951***
ANFCI					-0.1597***
Observations	324	324	324	324	324
adj. R-squared	0.2624	0.3578	0.3983	0.4393	0.4803
Panel C: Four less dominant sectors					
	1	2	3	4	5
Intercept	0.0483	-0.6772***	0.0722	-2.0952***	-2.2511***
VaR	0.4022***	0.3175***	0.4189***	0.2265***	0.2288***
Volatility	-0.4930***	-0.6155***	-0.4647***	-0.7242***	-0.6785***
Size		0.4563***		1.4288***	1.4558***
Leverage			-0.0129**	-0.0699***	-0.0716***
ANFCI					-0.0554*
Observations	216	216	216	216	216
adj. R-squared	0.6756	0.6951	0.6788	0.7745	0.7741

Table 3.26: Regression results pooled OLS for the US.

The dependent variable is the median $\widehat{\Delta \text{CoVaR}}$ of daily $\widehat{\Delta \text{CoVaRs}}$ within a quarter q. The independent variables are VaR, volatility, size, leverage and ANFCI. VaR is defined as the median of daily 2.5%-$\widehat{\text{VaRs}}$ of sector i within quarter q. Size is defined as sector market value at quarter q. Leverage is the average ratio of the total assets to equity in sector i at quarter q, and volatility of sector i is the realised volatility calculated from daily squared sector returns within a quarter following Christiansen et al. (2012). Christiansen et al. (2012) estimate the realised volatility by summing the squared daily returns in month t using $\sum_{d=1}^{M_t} r_{d,t}^2$ with $r_{d,t}$ as the d-th daily return in month t and M_t as the number of trading days during month t. The realised volatility is defined as the log of the square root leading to $RV_t = \ln\sqrt{\sum_{d=1}^{M_t} r_{d,t}^2}$. In our case, $r_{d,t}$ is the daily return within quarter q. The ANFCI is defined as financial market stress index as provided by the Federal Reserve Bank of St. Louis at a quarterly frequency. Positive values of ANFCI indicate tighter financial conditions than average, and negative values indicate looser financial conditions than average. Tight financial conditions mean higher risk and lower credit and leverage (see Brave and Kelley (2017) for details). Size and leverage were taken from Bloomberg at a quarterly frequency. The regression was run over the period from November 1999 to August 2013. The asterisks *** indicate significance at the 1% level. The asterisks ** indicate significance at the 5% level, and the asterisk * indicates significance at the 10% level.

3.7 Policy implications

The recent financial crisis demonstrates the important role played by financial stability and shows that price stability, as the primary goal of monetary policy, is not a sufficient condition to ensure financial stability. The introduction of macroprudential policy in the wake of the financial crisis has also been led by the insight that a systemic approach is needed to maintain financial stability. Although financial stability is the goal of macroprudential policy tools, monetary policy authorities should bear financial stability in mind (Smets, 2014).

The need for different policy tools or a combination thereof is influenced by the dimensions and development phases of systemic risk. When systemic risk materialises, the focus is on preventing the escalation of elements of instability and reducing the negative impacts of worsened conditions. Once a systemic crisis has set in, it may be necessary to implement a range of monetary and macroprudential instruments such as tools for crisis management or built-in stabilisers. Communicating with the financial market to reduce concerns about the stability of the financial sector is also included. In the preventive phase, the target should be constraining the contribution of different sectors to systemic risk by reducing the contributions of sectors or imposing a limit on them. For this purpose, countercyclical buffers serve as an important macroprudential instrument (Frait and Komárková, 2011).

The high costs in association with the recent crisis have triggered off a debate on the 'cleaning up the mess' policy, i.e. to mitigate the consequences of bubble bursts, and if bubbles should be considered in policy decisions. The view has moved towards the ex ante view that policy should react early to upward movements in asset prices and prevent the build-up of bubbles, which is referred to as 'leaning against the wind policy' (Brunnermeier and Schnabel, 2016).

Against this background, the following discussion distinguishes between policy instruments, which aim at preventing the build-up of bubbles, and the occurrence of crises (ex ante instruments) and mitigating the economic consequences of bubble bursts (ex post instruments).

3.7.1 Ex post policy instruments

Monetary authorities changed monetary policy behaviour during financial crises. Martin and Milas (2013) found that UK's monetary policy can be described by a simple Taylor rule in the pre-financial crisis period. When the financial crisis set in, the Taylor rule no longer prevailed, in the sense that there was no significant link between the policy rate and inflation but a very strong reaction to financial stress measures. Thus, Martin and Milas (2013) distinguished between a no-crisis regime and a financial crisis regime over the period 1992–2010. Although the no-crisis regime was a simple Taylor rule, the interest rate fell sharply during the financial crisis, reflecting the necessity of responding to the crisis (Martin and Milas, 2013).

Empirically estimated time-varying monetary policy rules note the changing behaviour of central banks when they are confronted with financial stress. This reaction is mainly inherent in decreasing policy rates, where the size fluctuates over time and from country to country as noted by Baxa et al. (2013) who have analysed the response of central banks in the US and the UK over a 28-year period. They have found an effect of financial stress on the interest rate that is insignificant when financial stress is low but that becomes significant during financial stress. Financial stability concerns account for approximately 50% of the policy rate decline in the UK during the financial crisis, whereas in the US, the majority of the policy rate decrease is driven by low inflation and an output that is below its potential (Baxa et al., 2013).

In the aftermath of the Lehman collapse, the ECB applied the full range of its policy tools. Lending to financial institutions in the Euro area was doubled within weeks, and interest rates were reduced. Such ex post policies were crucial to maintain the confidence in the financial system and to avoid an economic collapse. The moderate downturn in real GDP between the years 2007 and 2009 compared with that during the Great Depression 1929-1933 shows that ex post policies successfully soften the effects on the real economy but is substantially costly (Tumpel-Gugerell, 2011).

3.7.2 Ex ante policy instruments

Financial institutions base their decisions on current stability but disregard future stability. The excessive lending and risk-taking behaviour during booms contribute to a build-up of risks and asset price bubbles. Conversely, the overreaction and deleverage during recessions in combination with a lack of adequate capital buffers lead to procyclicality and the evolution of risk over time. In this case, countercyclical tools, which reduce the exorbitant risk-taking behaviour during booms and the scale of deleveraging behaviour during recessions seem natural (Smaga, 2014).

Policy reactions aimed at dampening the build-up of bubbles are referred to as ‘leaning’, which involve the leaning interest rate policy (i.e. increases in interest rates) or macroprudential instruments. Leaning instruments try to reduce lending behaviour in boom phases and include loan-to-value ratios and credit restrictions for banks as well as leaning interest rate policies (Brunnermeier and Schnabel, 2016).

The macroprudential policy aims at achieving greater financial system stability and assists in reducing the systemic risk that evolves over the financial cycle by applying regulatory instruments to counteract an exorbitant rise in leverage and credit and growth in asset prices (Reserve Bank of New Zealand, 2015).

Various papers have focused on countercyclical capital buffers as a policy response to reduce the likelihood of a financial crisis rather than considering the role of debt financing that applies not only to banks but also across the financial system. Schoenmaker and Wierts (2015) suggest using the leverage ratio as a basis for a maximum debt financing requirement in the system and show that a countercyclical leverage ratio stabilises the financial cycle. Introducing a minimum leverage ratio prevents the endogenous creation of financial imbalances and dampens the financial cycle (Schoenmaker and Wierts, 2015).

Lim et al. (2011) find that countries use credit-, liquidity-, and capital-related macroprudential policies, which are often adjusted countercyclically, to address systemic risk. Further macroprudential tools are caps on the loan-to-value (LTV) ratio, caps on the debt-to-income (DTI) ratio, ceilings on credit growth or credit, countercyclical capital requirements and reserve requirements (for a comprehensive list of macroprudential instruments and how they are used, see Lim et al. (2011)). Procyclicality can be reduced by using tools such as caps, reserve and countercyclical capital requirements and ceilings on credit growth or credit, where the type of shocks affect the effectiveness of the tools. Using panel regressions, the authors found that capital-related tools, such as LTV or DTI caps, reduce the procyclicality of leverage whereas credit growth-limiting measures (e.g., ceilings on credit growth) also affect leverage growth (Lim et al., 2011).

History provides evidence that macroprudential instruments can successfully attenuate crises. They can be directly employed to those sectors where bubbles emerge and are more focused than monetary policy tools. Timing and scope of the tools are essential when implementing macroprudential policy so that they are effective (Brunnermeier and Schnabel, 2016).

However, the macroprudential policy cannot fully compensate for financial imbalances or shocks and faces constraints that attribute a greater role to monetary policy in saving financial stability. Executing both policies requires a consideration of the mutual effects, given that it is rarely optimal to compensate for weaknesses in monetary policy through macroprudential policies (IMF, 2013).

Given the empirical results of this chapter, it is reasonable to use sectorally adjusted macroprudential instruments to address the financial stability concerns associated with sectors. That is, sectoral tools, such as sectoral capital requirements, are more appropriate than aggregate tools if systemic risk stems from a particular sector and can have an effect on the credit demand-side or the credit supply-side (IMF, 2013a).

3.8 Conclusions

This chapter investigates the contribution of sectors in an economy to systemic risk using the ΔCoVaR introduced by Adrian and Brunnermeier (2016). The economies of the US, the UK and Germany are divided into 10 different sectors. The estimated $\widehat{\Delta \text{CoVaRs}}$ of these sectors are tested for statistical significance and dominance to classify sectors as systemically relevant and to rank the sectors with respect to their systemic risk contribution. The empirical results show that systemic risk is affected by real economy sectors, where the most dominant sectors differ between countries and the state of the economy concerning statistical dominance.

The movements of $\widehat{\Delta \text{CoVaRs}}$ over time suggest that $\widehat{\Delta \text{CoVaRs}}$ rose remarkably when the financial system was confronted with difficulties and was considered to be unstable. Hence, even financial shocks or shocks to the real economy need not impact systemic risk if the financial system is stable. The $\widehat{\Delta \text{CoVaRs}}$ of the analysed countries seem to be positively correlated, and we find a weak relationship between the $\widehat{\text{VaR}}$ and $\widehat{\Delta \text{CoVaRs}}$ for all the countries and all sub-periods. The $\widehat{\Delta \text{CoVaRs}}$ increase disproportionately compared to their $\widehat{\text{VaRs}}$ between the sub-periods. Surprisingly, the pooled OLS regression for the US indicates that those sectors which influence the most systemic risk over the entire period are not significantly influenced by $\widehat{\text{VaR}}$ in contrast to less dominant sectors. The time element of systemic risk is driven by the financial cycle, and the macroprudential policy tools help reduce the build-up of systemic risk, which evolves over the financial cycle. Regulators need to be aware of the current state of the economy and adjust their tools accordingly rather than implementing standard aggregate tools if systemic risk stems from a particular sector and the economic situation changes. The empirical results support the use of sectorally adjusted macroprudential instruments to account for financial stability concerns associated with sectors. Furthermore, procyclicality is an important factor that must be considered while implementing macroprudential policy instruments effectively.

Previous papers, such as Brunnermeier and Schnabel (2016) and Jordà et al. (2015), provide evidence that the severity of financial crises in the wake of bubble bursts is dependent on the amount of credit lending involved in the boom episode. The increased risk-taking behaviour during episodes of stability is significantly driven by low volatility leading to riskier investments and a higher likelihood of a financial crisis (Danielsson, 2015). This relationship was reflected by Janet Yellen in the press conference on June 18, 2014, when she mentioned that the volatility level is at such a low level that it may lead to certain circumstances that pose risks to financial stability (Yellen, 2014). This highlights the crucial role of volatility in the build-up of asset price bubbles and a higher likelihood of financial crises. The next chapter decomposes conditional volatility into a short-run and a long-run component and examines the drivers of the volatility components, especially how macroeconomic variables affect the long-run volatility component.

Chapter 4 How do macroeconomic variables affect differences in stock market volatility in developed countries?

4.1 Introduction

Academic researchers and practitioners have long been concerned with financial market volatility and introduced models to estimate the volatility of financial assets.

Schwert (1989) analysed why stock market volatility varies over time using monthly data on the US stock market from 1857 to 1987 and found a correlation between stock market volatility and the volatility of several economic variables, such as interest rates and corporate bond returns. Furthermore, stock market volatility is higher when economic growth is negative and financial leverage accounts just for a small portion of movements in stock market volatility. Macroeconomic data can explain changes in stock market volatility over time if they contain information about future expected cash flows or discount rates. Hence, stock return volatility movements would be caused by changing uncertainties about future macroeconomic states (Schwert, 1989).

There is broad agreement that stock market volatility is higher in times of recessions and lower in times of expansions and consequently has a countercyclical pattern, which can be largely explained by macroeconomic factors as shown by Corradi et al. (2013). Using a no-arbitrage model, which relates stock market volatility to numerous unobservable and macroeconomic factors, the authors find that industrial production growth contributes approximately 73% to stock volatility and is responsible for over 90% of the variation in stock volatility if some so-called unobserved factor is taken into account which contributes about 17% to stock market volatility. Furthermore, Corradi et al. (2013) find evidence that countercyclical volatility risk premiums are associated with the business cycle and more countercyclical than stock volatility itself and largely drive fluctuations of the VIX index which was observed during the financial crisis from 2007 to 2009 (Corradi et al., 2013).

Using a broad set of potential risk drivers, Mittnik et al. (2015) employ componentwise gradient boosting techniques to assess the effect of risk drivers on the S&P500 volatility and predict monthly volatility. Mittnik et al. (2015) identify VIX as an important factor to predict realised volatility signalling changes in future S&P500 volatility in positive and negative direction and is one of few variables which is able to forecast a decrease in realised volatility along with log realised volatility, new orders of consumer goods and illiquidity, which is measured as Libor minus T-Bill rate (Mittnik et al., 2015).

The numerous studies on the relationship between volatility and macroeconomic factors are difficult to delineate due to the different variables and econometric frameworks employed. One alternative was introduced by Engle et al. (2008) who used a GARCH-MIDAS framework to decompose conditional volatility into a short-run and a long-run component. The appealing characteristic of this approach is that the macroeconomic factors can be applied to model the long-run volatility component (Paye, 2012).

Previous studies largely employed the GARCH-MIDAS model to the US stock market. This chapter extends existing papers, in that the GARCH-MIDAS model is applied to international stock market indices as the volatility-macroeconomic data relationship in different countries is the matter of interest. That is, it is supposed that macroeconomic factors determine the long-run component and a unit GARCH process specifies the short-run volatility component, which evolves around the long-term trend. Using a MIDAS filter, the long-term volatility is modelled as a weighted average of lagged values of macroeconomic variables, which are observed at different frequencies (Conrad and Loch, 2015). In the light of the model used in this chapter and the assumption that macroeconomic variables impact the volatility, the GARCH-MIDAS model may also help explain the differences in volatility levels between international stock market indices and their similar pattern, i.e. movements.

The objective of this chapter is therefore threefold. First, it investigates the sources of conditional volatility and examines the differences between developed countries. One paper closely associated to the ideas discussed in this chapter is by Sohn (2009) in that it also uses a GARCH-MIDAS model to derive a short-run and a long-run volatility component and includes both components in a VAR model. The second objective is to compare different GARCH-MIDAS specifications, i.e. GARCH-MIDAS models with different variables and assess their performance in terms of their variance ratio (VR). The third objective is to include the impact of commonly assumed drivers of volatility in a VAR model and to test their relationship with the long-run and short-run component of conditional volatility.

The results show that some variables are related to volatility where those variables are different among the countries under examination. However, macroeconomic variables alone explain only a marginal proportion of the variation in long-run volatility whereas the realised volatility contributes considerably to long-run volatility variation. In all model specifications, the short-run volatility picks up the highs and lows in volatility. This observation is the motivation to examine the drivers of the short-run volatility component in more detail by using a Granger-causality test on variables, which are considered to be related to volatility. Generally speaking, the results suggest that market liquidity and sentiment changes have no significant causal relationship neither with volatility levels nor with changes in volatility.

This chapter is organised as follows. Section 4.2 provides a literature review of studies that examine the relationship between macroeconomy and volatility. The data used in the GARCH-MIDAS model are described in section 4.3. Section 4.4 presents the historical realised volatility levels of Canada, Germany, the UK and the US and analyses if there is actually a significant difference. Section 4.5 describes the GARCH-MIDAS model, which is empirically employed to the countries to identify the effect of macroeconomic variables on expected stock market volatility. Section 4.5 also describes the VAR model. The empirical results are discussed in section 4.6, and section 4.7 concludes this chapter.

4.2 Literature review

Davis and Kutan (2003) extend Schwert (1989) and find a weak impact of movements in real output and inflation on stock market volatility when analysing 13 developed and developing countries. In general, the empirical evidence that macroeconomic volatility causes stock market volatility is rather weak with only few exceptions concerning European countries. In the light of these weak findings, Arnold and Vrugt (2008) relate stock market volatility with macroeconomic uncertainty instead of volatility. They show a significant relationship between volatility in the stock market and economic forecast dispersion from SPF (Survey of Professional Forecasters) participants. Macroeconomic uncertainty outperforms macroeconomic volatility in that it rises more massively during recessions and is more probable to gather economic reality. Thus, Arnold and Vrugt (2008) can reduce Schwert's (1989) volatility puzzle to the period since 1997.

Gerlach et al. (2006) support these results in that they find no robust relationship between financial market volatility and macroeconomic volatility and argue that this observation could be justified by the omission of financial crises or eras of political instability from the analysis. Using a time span of up to 150 years, remarkable variations of volatility have been observed, which were massively influenced by periods of economic and political turbulence. Volatility across countries has increased since around 1970 despite more stable economic aggregates in G7 countries since the 1980s, which is expected to have a positive effect on stock return volatility. Hence, there seems to be an inverse linkage between stock return volatility and macroeconomic volatility (Gerlach et al., 2006).

Differences in stock market volatility have been observed by previous studies e.g. Bekaert and Harvey (1997), Griffin and Karolyi (1998) or Aggarwal et al. (1999). Bekaert and Harvey (1997) show that lower volatility characterises more open economies and that capital market liberalisations significantly reduce volatility in emerging markets whilst Griffin and Karolyi (1998) find little explanatory power of industrial structure with respect to country index return variation. Aggarwal et al. (1999) examine volatility shifts of emerging stock market returns and find that large shifts in volatility are caused by local events rather than global events (except for the stock market crash in October 1987) during the 1985–1995 period.

Xing (2004) analyses differences in stock market volatility using equity price indices of 37 developed (21 countries) and emerging (16 countries) countries and identifies the market concentration as a significant factor of volatility differences, which on the other hand are negatively associated with relative market size. Nevertheless, the most important factor negatively affecting volatility differences across countries is the average education level of investors, which is proxied by school life expectancy in a country, that accounts for 36% of the cross-country market volatility difference[5]. Hence, collective characteristics of investors in a market can be considered to have a significant effect on market volatility (Xing, 2004).

Christiansen et al. (2012) models realised volatility using conventional linear approaches with lagged volatility and macroeconomic variables as predictors but, in addition to stock market volatility, includes other asset classes. Christiansen et al. (2012) find that variables capturing funding illiquidity, time-varying risk premia and leverage effects are common predictive factors of financial volatility across asset classes (Christiansen et al., 2012).

Aggregate stock return volatility is found to be persistent and countercyclical moving closely with empirical business condition measures. Macroeconomic data must contain information additional to that provided by lagged volatility to improve volatility forecasts. Paye (2012) finds only little forecasting gains by including macroeconomic data and argues that plenty of information about business conditions is included in lagged volatility itself (Paye, 2012).

In the light of the countercyclical behaviour of stock market return volatility, it is reasonable to examine the relationship between macroeconomic variables and expected

[5] See Xing (2004) for the definition of school life expectancy.

volatility. This chapter argues that the buy and sell decisions of stock market participants causes volatility as a consequence of their changing expectations or uncertainty about future developments. That is, investors are guided by macroeconomic data, which are the basis of sales and dividends. This chapter assumes, therefore, macroeconomic conditions to be important drivers of changes in the stock market volatility.

Engle and Rangel (2008) relax the assumption of GARCH models that volatility reverts to a constant level and introduce a spline-GARCH model to link macroeconomic conditions to stock volatility. In doing so, the volatility process is separated into a high-frequency and a low-frequency component where the low-frequency component is described by the trend in the volatility process related to slowly moving deterministic economic conditions. Engle and Rangel (2008) empirically identify the determinants of this low-frequency volatility by considering international markets and find that low-frequency market volatility is primarily caused by GDP and interest rates. Market size relative to GDP as well as the number of companies listed both have a negative effect on low-frequency volatility and emerging markets reveal higher low-frequency market volatilities. The GARCH-MIDAS model used here is motivated by Engle and Rangel (2008) in that it uses macroeconomic variables such as interest rates and growth in industrial production among others as discussed in section 4.3. Engle and Rangel (2008) use nearly 50 countries of different sizes and a different number of listed companies in an index. Larger countries are found to be more volatile and more listed companies mean more diversification opportunities. This chapter uses four G7 countries, which are comparable in terms of their level of development, and the indices used comprise approximately the same number of stocks. Furthermore, the study of Engle and Rangel (2008) does not include the recent financial crisis and the effects it could have on their findings. It would also be interesting to examine how the macroeconomic variables together affect the low-frequency volatility, e.g. by using the first principal component.

4.3 Data

The empirical analysis is based on macroeconomic data observed at a daily as well as monthly frequency. The observation period was guided by having a complete set of data for all countries and variables under investigation. Motivated by Chen et al. (1986) and Asgharian et al. (2013), the variables of interest are the growth rate of industrial production (IPG), the growth rate of consumer price (CPI) and the term premium (SPR) defined subsequently as the difference between the long-term interest rates and the short-term interest rates. The long-term interest rates refer to government bonds with a 10-year maturity. Short-term interest rates are rates at which short-run government bonds are issued or rates at which short-run borrowings between financial institutions are effected. These data are taken from OECD webpage. Following Conrad and Loch (2015), IPG is calculated as monthly growth rate of the industrial production index in month t. In the same vein, CPI is the growth rate of consumer price index. These data were taken from FRED database at the Federal Reserve Bank of St. Louis. These data are available on a monthly basis from the Liu and Zhang (2008) website for the US. As four countries are considered, the data from Liu and Zhang (2008) are not used and the equations used here to calculate these variables were applied to the corresponding data for the countries under investigation. Also, the consumer confidence index (CCI), the unemployment rate (Unemp) and the exchange rate index (FXR) are included in the analysis. The first two data sets were taken from the OECD webpage, and the exchange rate index was downloaded from the Bank of England webpage for all countries.

In the MIDAS regression, 22 trading days per month and 36 lags (given that a monthly frequency is used) are assumed following previous papers such as Engle et al. (2013) and Asgharian et al. (2013), which use three MIDAS lag years and show that the optimal lag weights approach zero after approximately 30 months. The volatility in the national stock markets is estimated using daily stock market returns where large national stock market indices are used as proxy of the national stock market. The analysis comprises Canada, Germany, the UK and the US.

4.4 Cross-country volatility levels

Prior to decomposing conditional volatility into its short-run and long-run components, the historical volatility across countries is considered. Following Schwert (1989), realised volatility (henceforth RV) is defined as monthly standard deviation calculated as the sum of squared daily stock returns within that month leading to

$$\hat{\sigma}_t^2 = \sum_{d=1}^{N_t} r_{dt}^2, \tag{4.1}$$

where N_t is the number of daily returns within month t and r_{dt} is the return on day d within month t after subtraction of the average daily return in month t.

Figure 4.1 plots the monthly annualised realised volatility of the investigated countries. One empirical observation is that realised volatility spikes simultaneously. Germany's stock market volatility moves largely with that of other countries but appears to fluctuate more than the other countries. All countries showed a dramatic increase in realised volatility in 2008 when the annualised monthly volatility rose to over 80% in the US. Similarly, the other countries reached a volatility of slightly less than 80%, which is not surprising given the high uncertainty among stock market participants caused by the events in September 2008. However, it can be observed that after each volatility peak the volatility declines to a moderate level and approaches its pre-increase level settling down between 5% and 15%. The most obvious observation from Figure 4.1 is the similarity in the volatility pattern. The countries show a fairly similar behaviour in stock market volatility with Germany as the exception, which peaked more often and more massively than the remaining countries.

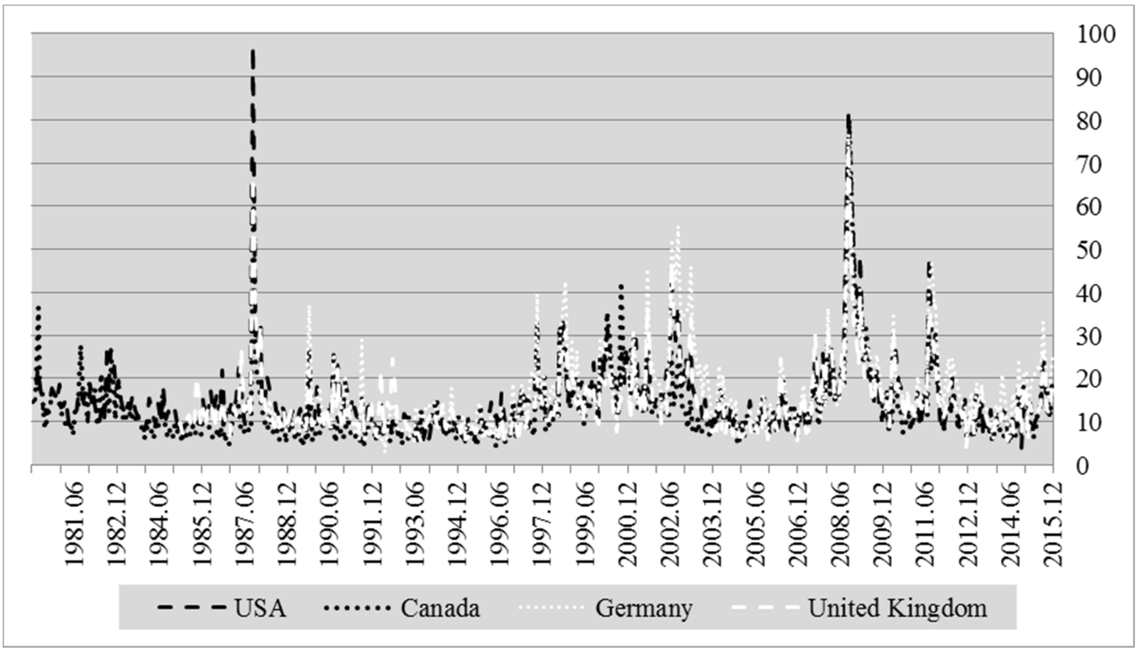

Figure 4.1: Annualised monthly realised volatility in international stock markets.
The monthly realised volatilities were calculated using daily returns of the stock market index for each country following Schwert (1989) and annualised by multiplying with the square root of 12. The stock market indices used are CDAX for Germany, the S&P/TSX for Canada, the FTSE All-Share for the UK and the S&P500 for the US. The observation period starts in January 1980 for Canada and the US. The observation period for Germany starts in April 1988 and that for the UK starts in February 1985. The observation period ends in December 2015 for all countries. Data were taken from Bloomberg.

Table 4.1 summarises the median and mean levels for the full observation period and the sub-periods, respectively. The median and mean values confirm our observation that Germany deviates from the other countries in that both measures are the highest over the full sample as well as over the sub-samples. During the period from 2000 to 2015, when stock return volatility is low across the countries, Germany's volatility remained higher compared to those of other industrialised countries (lowest panel in Table 4.1).

	1980-2015	1980-1989	1990-1999	2000-2009	2010-2015
Median					
Canada	10.6107	9.8190	8.4752	13.4955	10.8135
Germany	14.6453	9.4423	11.4150	17.8982	16.7693
UK	11.8212	10.9888	10.3112	14.3692	13.0444
US	12.8462	12.7976	11.1851	15.6294	12.0136
Mean					
Canada	12.7248	11.5875	9.8961	17.1353	11.9837
Germany	17.0697	11.8467	13.2736	21.1983	18.0388
UK	14.0561	13.4202	11.4962	16.9903	13.9532
US	15.0708	14.6294	12.6777	18.5468	14.0018
High					
Canada	80.2598	65.3657	32.0516	80.2598	31.2072
Germany	76.6101	37.0349	42.7238	76.6101	46.8180
UK	74.1094	66.8583	30.8976	74.1094	35.7474
US	97.1438	97.1438	33.9761	81.8313	48.2941
Low					
Canada	4.2995	4.3619	4.2995	4.6212	4.9850
Germany	3.0509	7.2201	3.0509	7.3575	5.6928
UK	4.0790	6.7779	5.1259	5.7750	4.0790
US	3.7754	7.4274	4.9758	6.4643	3.7754

Table 4.1: Summary of annualised monthly realised volatilities.
The total period was determined by having data on stock market index returns. The categorisation of the sub-periods was guided by the burst of stock market bubbles so that each sub-period contains one stock market crash and a boom phase to avoid any biases. The stock market indices used are CDAX for Germany, the S&P/TSX for Canada, the FTSE All-Share for the UK and the S&P500 for the US. The observation period starts in January 1980 for Canada and the US. The observation period for Germany starts in April 1988 and that for the UK starts in February 1985. The observation period ends in December 2015 for all countries. Data were taken from Bloomberg.

Even though Figure 4.1 illustrates a fairly similar volatility pattern, the volatility levels are different between the countries. The annualised monthly realised volatility for Germany stands on average at 17.07% over the full period whereas that of Canada is at 12.72% over the full sample and also has a higher mean during the sub-periods.

Table 4.2 summarises the results of the pairwise t-test over an observation period from April 1988 to December 2015. The first line of the cells represents the hypothesis test result h, which is a logical value of either 0 or 1. That is, a value of 1 indicates that the null hypothesis that the mean of the pairwise difference between the RVs is equal to zero is rejected. Hence, a value of 0 indicates that the null hypothesis cannot be rejected, i.e. is accepted at the 10% significance level. The corresponding p-values query whether the null hypothesis is valid. The low p-values of less than 0.01 indicate that there is a significant difference in volatility between the countries. Hence, it is interpreted that the RVs significantly differ between the four countries under investigation.

	Canada	**Germany**	**UK**	**US**
Canada		1 (0.0000)	1 (0.0001)	1 (0.0000)
Germany	1 (0.0000)		1 (0.0000)	1 (0.0000)
UK	1 (0.0001)	1 (0.0000)		1 (0.0000)
US	1 (0.0000)	1 (0.0000)	1 (0.0000)	

Table 4.2: Results of the pairwise sample t-test of realised volatility at the 10% significance level. The first lines in the cells denote the hypothesis test result were 1 and 0 indicate the rejection and the acceptance of the null hypothesis that the mean of the pairwise difference between the RVs equals zero, respectively. The corresponding p-value is shown in parentheses. The observation period for all countries ranges from April 1988 to December 2015.

The findings are consistent with Grouard et al. (2003) who compare the volatility patterns in industrialised countries and find that the correlation between the stock market indices has risen over time and that the volatility patterns are quite similar. Japan is one exception whose equity returns are less correlated with those in Europe and the US. However, the volatility level of indices differ greatly across countries due to the combined factors in association with the composition of indices such as the number of stocks included or the degree of diversification.

Numerous papers starting with Merton (1980) and Schwert (1989) use realised volatility over some single horizon (e.g. month or quarter) to measure volatility in the long-run. On the contrary, in the GARCH-MIDAS model, the long-run volatility component is a filtered process of RV as the RV-GARCH-MIDAS specification smooths the realised volatility by employing a GARCH filtering and in this way specifies the long-run component τ (Engle et al., 2013). Realised volatility is consequently a natural candidate to model the long-run component of the two-component volatility specification. The long-run component based on RV is used as the benchmark GARCH-MIDAS model following previous papers such as Conrad and Loch (2015) and Engle et al. (2013). The next section introduces the GARCH-MIDAS model and is focused on the decomposition of conditional volatility into a short-run and long-run volatility component in order to identify how macroeconomic variables affect volatility.

4.5 Decomposing stock market volatility and sources of volatility

The next section describes the GARCH-MIDAS model and focuses on the decomposition of conditional volatility into a short-run and long-run volatility component in order to identify how macroeconomic variables affect volatility. This is done in section 4.5.1. Section 4.5.2 discusses the VAR and the variables used in the model.

4.5.1 GARCH-MIDAS model

The GARCH-MIDAS model makes an insight into the relationship between the macroeconomic factors and stock market volatility possible and was inspired by the work on mixed data sampling (MIDAS). The GARCH-MIDAS model uses a MIDAS polynomial, which applies to macroeconomic variables measured at different frequencies (e.g. monthly or quarterly) and a daily GARCH process so that a short-run and a long-run volatility component can be estimated and is used to examine the relationship between economic activity and volatility in the stock market.
Assuming that a two-component volatility model models daily unexpected returns such that

$$r_{d,t} - E_{d-1,t}(r_{d,t}) = \sqrt{\tau_t g_{d,t}} Z_{d,t} \tag{4.2}$$

accounts for the idea that the effect of the same news on unexpected returns differs in dependence on the economic state, i.e. the level of τ. In equation (4.2), the volatility has a short-run component, g, and a long-run component τ where $E_{d,t}$ denotes the expectation conditional on the information set up to day d-1 and $Z_{d,t} \sim (0,1)$ (Engle et al., 2013).
Whilst the short-run volatility component g is related to daily liquidity concerns and other short-run factors, the long-term component τ is related to the future expectations regarding cash flows and discount rates whereas it is assumed that macroeconomic variables contain information about this source of volatility in the stock market (Sohn, 2009).
The short-run conditional volatility g is assumed to follow a unit GARCH (1,1) process

$$g_{d,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{d-1,t} - \mu)^2}{\tau_t} + \beta g_{d-1,t} \tag{4.3}$$

where $r_{d-1,t}$ is the market return on day d-1 in month t and τ_t the long-run volatility component in t, respectively.

Engle and Rangel (2008) note that the conditional variance reverts to its mean when $\alpha+\beta < 1$ and that for a long period, the volatility forecast will have the same constant regardless of the point in time when the forecast is made. The GARCH (1,1) model can, therefore, capture more permanent or slow-moving volatility patterns to a limited extent. This contrasts with the observed stock market volatilities, which can be enormously high or low over a long-time horizon.

Engle et al. (2008) estimate the long-run component of stock market volatility by using either a direct approach based on macroeconomic data or a filtered realised variance approach and conclude that macroeconomic variables have a significant influence on volatility predictions at short horizons.

In contrast to a long history of papers using RV over some horizon to measure long-run volatility, in the GARCH-MIDAS framework, RV is smoothed through MIDAS filtering to estimate the long-run component, i.e.

$$\tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) RV_{t-k} \tag{4.4}$$

with RV_t as the sum of squared daily returns within month t. N_t denotes the number of days in month t, thus

$$RV_t = \sum_{d=1}^{N_t} r_{dt}^2 \tag{4.5}$$

Following Conrad and Loch (2015), the RV-GARCH-MIDAS model (4.4) is considered as the benchmark model that the macroeconomic GARCH-MIDAS specifications are compared to.

The long-term component in month t based on past macroeconomic variables is defined as

$$\tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) X_{t-k}^{(i)} \tag{4.6}$$

where m denotes the constant and $X_t^{(i)}$ is the monthly macroeconomic variable of interest. φ denotes the weighting scheme and will be used henceforth to refer to the functional constraint. To accommodate economic sources of volatility, the long-term component is estimated by taking macroeconomic variables into account. That is, the MIDAS scheme allows assessing whether an economic variable helps predict the long-term component τ by linking τ directly to macrovariables (Engle et al., 2008).

K denotes the number of variable lags. Parameters ω_1 and ω_2 can generate various shapes of the weighting scheme, which can decrease fast or slowly with the lag depending on the value of ω_2 where the rate of decline determines the number of lags in the weighting scheme (Ghysels et al., 2007). The slope parameter θ reveals the impact that past behaviour of a macroeconomic variable has on the long-run volatility component (Nieto et al., 2015).

The application of a parsimonious data-driven polynomial weight is the key feature of MIDAS models, and various versions of polynomial weighting schemes have been discussed by Ghysels et al. (2007). The weighting scheme in (4.4) and (4.6) can be either an unrestricted MIDAS polynomial (U-MIDAS), an exponential almon lag or a beta lag structure.

This chapter uses the beta lag polynomial, which is based on the beta function and is defined as

$$\varphi(k;\omega) = \frac{(k/K)^{\omega_1-1}(1-k/K)^{\omega_2-1}}{\sum_{k=1}^{K}(k/K)^{\omega_1-1}(1-k/K)^{\omega_2-1}} \tag{4.7}$$

with two parameters ω_1 and ω_2. The beta lag polynomial (also referred to as beta lag) can take various shapes depending on the values of ω_1 and ω_2. The weights are equal for $\omega_1 = \omega_2 = 1$ and can decline slowly or fast where the weights decline faster as ω_2 increases. In specification (4.7), the number of lags included is determined by the rapidity of weight decrease. The beta lag has the property that it sums to unity and yields positive weights (Ghysels et al., 2007).

Following Engle et al. (2008) who distinguished between the level and volatility of $X_t^{(i)}$, the macroeconomic variable of interest used in here relates to its changes of the level rather than its volatility. Asgharian et al. (2013) note the complexity of GARCH-MIDAS models and the convergence problems as a result of including several variables in one model. For this reason, this analysis follows Asgharian et al. (2013) and constructs the first principal component (henceforth PC1) to incorporate the information content of several macroeconomic variables as one variable in the GARCH-MIDAS model.

4.5.2 Drivers of stock market volatility components

As discussed above, the short-run component is assumed to be related to short-lived factors and worries about the liquidity (Sohn, 2009). It is argued that volatility, generally, is a result of uncertain future cash flows and discount rate, which arise from factors at the macro level, such as GDP volatility or uncertain economic conditions. In addition, the financial markets structure like market liquidity and firm-specific factors may influence volatility as well where countercyclical volatility variations can be predicted by leverage and profitability effects (BIS, 2006). Other papers find that liquidity fluctuates over time and document its effect on stock returns (e.g. Amihud, 2002).

It has also been demonstrated by Acharya and Pedersen (2005) as well as Pastor and Stambaugh (2003) that liquidity variation is an underlying stock market risk factor. The effect of liquidity on volatility is discussed in Chordia et al. (2002) who find a negative influence on contemporaneous volatility, which retains a significant explanatory variable of one day ahead volatility in the stock market even after controlling for order imbalance, lagged volatility and dollar volume. However, little is known regarding the drivers of liquidity variation. Liu (2015) fills this gap and finds a higher stock market liquidity when survey-based measures of investor sentiment increase (i.e. investors are more bullish) and that investor sentiment Granger causes liquidity when examining a period from 1976 to 2007. Given the results in Liu (2015) in combination with those in Chordia et al. (2002), in this chapter, it is assumed that investor sentiment is an interesting candidate in explaining the volatility components.

This point of view is supported by Lee et al. (2002) who find that sentiment is a priced risk and show that conditional volatility is revised downwards as a consequence of bullish changes in sentiment and vice versa. Hence, sentiment shifts and market volatility are negatively correlated in US stock markets where sentiment has the biggest effect on the NASDAQ index. The authors argue that shifts in sentiment influence future excess returns through their impact on conditional volatility (Lee et al., 2002). This is in line with Brown and Cliff (2004) who find a weak correlation between near-term future returns and sentiment but a strong predictability of sentiment for long-horizon returns. Lee et al. (2002) use the Investors' Intelligence (II) sentiment index provided by Investors' Intelligence of New Rochelle, NY, whereas Brown and Cliff (2004) and Liu (2015) take the II and the American Association of Individual Investors

(AAII) into consideration. In so doing, II is interpreted as a proxy for institutional investor sentiment and AAII is interpreted as a proxy for individual investor sentiment.[6]
In what follows, sentiment indices are necessary, not just for the US but also for the other countries like Canada, Germany and the UK, and some of those survey-based measures are only available for a relatively short time period. Moreover, the use of surveys has also been criticised in the literature, and market variables were suggested as sentiment proxies instead of surveys to measure sentiment indirectly (Finter et al., 2012).
Baker and Wurgler (2006) note that although a number of sentiment proxies have been suggested in the literature, none of them is uncontroversial and therefore construct a composite sentiment index. This index condenses six sentiment proxies in one index by extracting their first principal component where the sentiment index is a linear function of its underlying standardised proxies[7] (Baker and Wurgler, 2006).
For the reasons mentioned above, the subsequent analysis uses the strategy proposed by Baker et al. (2012) to estimate a sentiment index based on sentiment proxies, which contain some information about sentiment. The proxies are first orthogonalised to eliminate idiosyncratic variations that are unrelated to sentiment before they are used to form their first principal component. Hence, this strategy provides a single total sentiment index for each country. The orthogonalisation is applied to the macroeconomic variables discussed in section 4.3, which are used in the GARCH-MIDAS model, i.e. SPR, CCI, CPI, Unemp, IPG and FXR. The proxies are regressed on these variables, and the resulting residuals are considered as cleaner sentiment proxies entering the index estimation. The residuals from those regressions are standardised before the principal components are estimated. This procedure is also proposed by Baker and Wurgler (2006). Following Baker et al. (2012), the sentiment index is estimated using the volatility premium (PVol), the number of IPOs (NIPO), the average first-day return on IPOs (RIPO) and the market turnover (TURN). The definitions of those variables follow Baker et al. (2012), and the interested reader is referred to this paper for more information on those variables.[8] The data required to calculate the

[6] For details on the two surveys measuring the sentiment directly and why they are interpreted as proxy for individual and institutional investor sentiment see Brown and Cliff (2004).
[7] For details on the sentiment index, its properties and its construction see Baker and Wurgler (2006).
[8] Baker et al. (2012) use annual data and therefore refer to yearend data or values over a year. As this chapter uses monthly data, the definitions in Baker et al. (2012) are applied to monthly data. Furthermore, in this chapter, equally weighted averages are used instead of value-weighted averages. For the market turnover, first differences are employed as the level of TURN contains a unit root for all countries except Canada for which TURN is not included due to the lack of data prior to 1998 and hence its short time period. As a result, Canada's sentiment index is estimated based on NIPO, RIPO, and PVol.

variables were downloaded at a monthly frequency from Datastream. The data on IPO, NIPO and RIPO, were kindly provided by Jay Ritter on an annual basis. The annual IPO data were, therefore, converted to monthly frequency using a cubic spline interpolation method, which matches each value of the annual data to the last monthly observation in association with the annual frequency period. The points in between are then placed on a natural cubic spline, which links all the points (see description on frequency conversion in Eviews).

To take the effect of liquidity on volatility into account found by Chordia et al. (2002), the VAR model used here includes a liquidity measure as further variable following the definition in Amihud (2002). To be correct, Amihud (2002) proposes a measure of illiquidity, which is defined as the average ratio between the daily absolute return and the trading volume on the same day expressed in monetary terms, i.e. $\frac{\left|R_{d,t}^{i}\right|}{TVOL_{d,t}^{i}}$ where $\left|R_{d,t}^{i}\right|$ represents stock's i return on day d of month t (Amihud (2002) uses the return on day d of the year y rather than month, but as this chapter is dealing with monthly data, y is replaced by t). $TVOL_{d,t}^{i}$ denotes the corresponding trading volume of stock i on day d expressed in monetary terms. To obtain a monthly measure of illiquidity for each stock, the daily measure is averaged within its respective month leading to

$$ILL_t^i = \frac{1}{D_t^i} \sum_{d=1}^{D_t^i} \frac{\left|R_{d,t}^{i}\right|}{TVOL_{d,t}^{i}} \tag{4.8}$$

with D_t^i as the number of days with available data for stock i within that month.

The illiquidity measure ILL_t^i for individual stocks of month t are used to calculate the average market illiquidity across stocks as follows

$$MILL_t = \frac{1}{S_t} \sum_{i=1}^{S_t} ILL_t^i \tag{4.9}$$

where S_t denotes the number of stocks in month t (Amihud, 2002).

To be consistent with the GARCH-MIDAS model, the $MILL_t$ measure is calculated for the S&P500, CDAX, FTSE ALL-Share and the S&P/TSX, respectively based on the stocks included in those indices. That is, MILL is calculated similarly as in Amihud

(2002), but, instead of using data for individual stocks, the monthly absolute return of the market index is divided by the volume of the market index. The subsequent analysis uses the logarithmic transformation of the illiquidity measure $MILL_t$ following Amihud (2002) and Liu (2015).

BIS (2006) notes that financial volatility did not follow the long-run decrease in macroeconomic volatility and allege, as a possible explanation, that risk aversion may not be dependent on macroeconomic volatility and therefore remains volatile even under macroeconomically stable conditions. Macroeconomic volatility fluctuations were found to not completely explain the changes in stock return volatility over the business cycle, which suggests that risk aversion changes also have an impact (BIS, 2006).

Following Damodaran (2017), risk aversion in the market is interpreted as the main driver of equity risk premium (ERP), which increases when investors are more risk averse and ERP is used as a proxy of the risk aversion. The equity risk premium in this chapter is calculated as the difference between the return of the stock market index in month t and the 3-month riskless yield in the same month.

Volatility is a result of uncertainty concerning future cash flows, which may be affected by factors on the macroeconomic level and the financial market structure. Also, firm-specific factors may also be a source of volatility. Whilst leverage was found to be poorly associated with volatility, profitability of firms is negatively related to stock returns volatility. The increased profitability and the decline in the uncertainty on profitability of firms affected the financial volatility decline observed in many industrial countries (BIS, 2006).

This latter possibility is taken into account by including the dividend-price ratio (DP), also referred to as dividend yield, into the VAR model. The question that rises is how the volatility components are related to the different firm-specific and macroeconomic factors and the financial market structure. The variables discussed above are included in two VAR models, which include the volatility components separately and are defined as

$$y_t^{(1)} = \begin{bmatrix} DP_t \\ MILL_t \\ ERP_t \\ SENT_t \\ g_t \end{bmatrix} \quad \text{and} \quad y_t^{(2)} = \begin{bmatrix} DP_t \\ MILL_t \\ ERP_t \\ SENT_t \\ tau_t \end{bmatrix} \tag{4.10}$$

The two VAR systems include macroeconomic variables on one hand and firm- and financial market-specific variables on the other. The VAR analysis results are reported from Granger-causality tests, and the number of lags are chosen based on the Schwarz criterion.

4.6 Empirical results

This section presents the results of the GARCH-MIDAS model in section 4.6.1. The results from the Granger-causality tests are reported in section 4.6.2.

4.6.1 GARCH-MIDAS results

The parameter estimations from the GARCH-MIDAS specifications are summarised in Table 4.3 and Table 4.4 for all countries, respectively. The key question is how macroeconomy is related to stock market volatility, and the parameter outcomes of the GARCH-MIDAS specifications tell something about the relationship between a variable and volatility by looking at the parameter estimates. In what follows the variables are changes and the interpretation refers to changes in variables.

The slope parameter θ is the most interesting parameter of the MIDAS filter as it indicates the relationship between the specific variable and volatility. Its parameter estimates range from 0.1626 to -0.0748 over the full observation period for Germany. That means that high changes in realised volatility lead to high stock market volatility, and changes in the unemployment rate reduce volatility. Both parameter estimates are significant at the 5% level as the second line of each variable suggests. Consumer confidence seems to be the only variable that is not significantly related to stock market volatility. The restricted weighting function imposed by the MIDAS assumptions puts 6.15 on the weighting parameter ω_2 for the rolling RV and almost 1.00 for SPR. The value of above 1 for ω_2 (ω_1 is set to 1 in the restricted version and is therefore not reported) ensures a decaying pattern so that the first lag has the largest weight (Asgharian et al., 2013).

Germany							
	μ	α	β	θ	ω	m	BIC
Rolling RV	0.0006	0.1009	0.8502	0.1626	6.1506	0.0069	-37576.70
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	
CCI	0.0006	0.0911	0.8894	0.0133	1.0084	0.0001	-37537.80
	0.0000	*0.0000*	*0.0000*	*0.2077*	*0.0000*	*0.0000*	
CPI	0.0006	0.0909	0.8857	-0.0219	1.0033	0.0002	-37545.00
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	
FXR	0.0006	0.0916	0.8884	-0.0057	3.4227	0.0001	-37543.30
	0.0000	*0.0000*	*0.0000*	*0.0311*	*0.0187*	*0.0000*	
IPG	0.0006	0.0915	0.8895	0.0136	1.0954	0.0001	-37554.30
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	
SPR	0.0006	0.0926	0.8883	-0.0499	1.0010	0.0001	-37557.20
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	
Unemp	0.0006	0.0938	0.8851	-0.0748	1.9569	0.0001	-37568.70
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	
PC1	*0.0006*	*0.0918*	*0.8882*	*-0.0049*	*3.6861*	*0.0001*	-37542.10
	0.0000	*0.0000*	*0.0000*	*0.0532*	*0.0446*	*0.0000*	
Canada							
	μ	α	β	θ	ω	m	BIC
Rolling RV	0.0005	0.1325	0.7895	0.1749	15.5790	0.0049	-55387.30
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	
CCI	0.0005	0.1046	0.8855	-0.0196	5.5364	0.0001	-55354.70
	0.0000	*0.0000*	*0.0000*	*0.0071*	*0.0039*	*0.0000*	
CPI	0.0005	0.1056	0.8806	-0.0062	1.0081	0.0001	-55350.00
	0.0000	*0.0000*	*0.0000*	*0.0091*	*0.0000*	*0.0000*	
FXR	0.0005	0.1051	0.8806	0.0033	1.2488	0.0001	-55350.40
	0.0000	*0.0000*	*0.0000*	*0.0037*	*0.0360*	*0.0000*	
IPG	0.0005	0.1044	0.8826	0.0012	1.0376	0.0001	-55346.50
	0.0000	*0.0000*	*0.0000*	*0.5202*	*0.1387*	*0.0000*	
SPR	0.0005	0.1046	0.8818	-0.0149	1.1590	0.0001	-55350.50
	0.0000	*0.0000*	*0.0000*	*0.0011*	*0.0027*	*0.0000*	
Unemp	0.0005	0.1041	0.8823	-0.0202	6.4910	0.0001	-55358.90
	0.0000	*0.0000*	*0.0000*	*0.0005*	*0.0054*	*0.0000*	
PC1	*0.0005*	*0.1052*	*0.8806*	*0.0031*	*1.3660*	*0.0001*	-55350.20
	0.0000	*0.0000*	*0.0000*	*0.0058*	*0.0613*	*0.0000*	

Table 4.3: GARCH-MIDAS model output of different specifications.
The variables in the left column represent the GARCH-MIDAS specification. The GARCH-MIDAS models assume a restricted version so that $\omega_1 = 1$ and $\omega_2 > 1$ which ensures a decaying pattern. The numbers in the second line of each variable represent the corresponding p-values where a significance level of 10% is considered. The estimates μ, α, β are the GARCH parameters. The GARCH-MIDAS models assumed 36 lags and 22 days per month. Changes are used as variables in the GARCH-MIDAS models. CCI is the consumer confidence index, and CPI is the growth rate of consumer price index. IPG denotes the growth rate of the industrial production index, and SPR is the term premium, defined as difference between long-term interest rates and the short-term interest rates. Unemp is the unemployment rate, and the exchange rate index is denoted by FXR. The data for IPG and CPI were taken from FRED database and those for CCI, SPR and Unemp were downloaded from the OECD webpage. The FXR data were available on the Bank of England webpage.

United Kingdom							
	μ	α	β	θ	ω	m	BIC
Rolling RV	0.0004	0.1076	0.8509	0.1486	9.1652	0.0063	-45709.50
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0003*	*0.0000*	
CCI	0.0005	0.1302	0.8500	-0.0152	9.6733	0.0001	-45687.00
	0.0000	*0.0000*	*0.0000*	*0.0048*	*0.0434*	*0.0000*	
CPI	0.0004	0.0935	0.8923	0.0065	2.1510	0.0001	-45696.60
	0.0000	*0.0000*	*0.0000*	*0.1090*	*0.4354*	*0.0000*	
FXR	0.0005	0.0884	0.9019	0.0030	4.3596	0.0001	-36843.40
	0.0000	*0.0000*	*0.0000*	*0.1335*	*0.1934*	*0.0000*	
IPG	0.0004	0.0942	0.8904	-0.0075	1.9000	0.0001	-45699.20
	0.0000	*0.0000*	*0.0000*	*0.0186*	*0.0842*	*0.0000*	
SPR	0.0004	0.0931	0.8926	-0.0147	1.0084	0.0001	-45697.60
	0.0000	*0.0000*	*0.0000*	*0.0599*	*0.0000*	*0.0000*	
Unemp	0.0004	0.0939	0.8914	0.0176	4.8487	0.0001	-45698.60
	0.0000	*0.0000*	*0.0000*	*0.0249*	*0.3212*	*0.0000*	
PC1	*0.0004*	*0.0927*	*0.8935*	*0.0029*	*1.6725*	*0.0001*	-45697.10
	0.0000	*0.0000*	*0.0000*	*0.1743*	*0.2095*	*0.0000*	
United States							
	μ	α	β	θ	ω	m	BIC
Rolling RV	0.0006	0.0936	0.8827	0.1332	2.2985	0.0081	-52783.00
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	
CCI	0.0006	0.0889	0.8957	-0.0469	1.2824	0.0001	-52774.90
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	
CPI	0.0006	0.0871	0.9003	0.0142	3.5939	0.0001	-52767.60
	0.0000	*0.0000*	*0.0000*	*0.0096*	*0.0964*	*0.0000*	
FXR	0.0006	0.0878	0.8994	-0.0012	1.3455	0.0001	-52764.50
	0.0000	*0.0000*	*0.0000*	*0.4123*	*0.3536*	*0.0000*	
IPG	0.0006	0.0889	0.8960	-0.0102	3.9564	0.0001	-52774.30
	0.0000	*0.0000*	*0.0000*	*0.0006*	*0.0013*	*0.0000*	
SPR	0.0006	0.0884	0.8970	0.0125	7.4357	0.0001	-52769.40
	0.0000	*0.0000*	*0.0000*	*0.0132*	*0.0171*	*0.0000*	
Unemp	0.0006	0.0896	0.8942	0.0291	8.4557	0.0001	-52777.50
	0.0000	*0.0000*	*0.0000*	*0.0002*	*0.0118*	*0.0000*	
PC1	0.0006	0.0878	0.8994	-0.0012	1.2373	0.0001	-52764.60
	0.0000	*0.0000*	*0.0000*	*0.4011*	*0.3559*	*0.0000*	

Table 4.4: GARCH-MIDAS model output of different specifications.
The variables in the left column represent the GARCH-MIDAS specification. The GARCH-MIDAS models assume a restricted version so that $\omega_1 = 1$ and $\omega_2 > 1$ which ensures a decaying pattern. The numbers in the second line of each variable represent the corresponding p-values where a significance level of 10% is considered. The estimates μ, α, β are the GARCH parameters. The GARCH-MIDAS models assumed 36 lags and 22 days per month. Changes are used as variables in the GARCH-MIDAS models. CCI is the consumer confidence index, and CPI is the growth rate of consumer price index. IPG denotes the growth rate of the industrial production index, and SPR is the term premium, defined as difference between long-term interest rates and the short-term interest rates. Unemp is the unemployment rate, and the exchange rate index is denoted by FXR. The data for IPG and CPI were taken from FRED database and those for CCI, SPR and Unemp were downloaded from the OECD webpage. The FXR data were available on the Bank of England webpage.

Table 4.3 and Table 4.4 show a relatively rapid decay for the RV specification. Germany has a high decaying pattern with respect to exchange rate, and higher lags have little impact on the long-run volatility. This holds for the unemployment rate in the US, whereas, in the UK, ω has the highest value for consumer confidence. Interestingly, an increase in industrial production leads to higher volatility in the German stock market. Germany is the only country where consumer confidence plays no significant role for volatility, which seems reasonable in the light of the high exports of German companies. That is, the German economy seems to be only marginally affected by domestic consumption and the optimism of German households.

There is even no significant relationship between industrial production and volatility in Canada. In contrast to Germany, higher confidence of Canadian consumers lowers stock market volatility whilst an increase in inflation leads to a lower volatility in the stock market of both countries. Canada has a high decaying pattern with respect to the unemployment rate.

The UK stock market appears to be significantly unrelated to exchange rate changes and to changes in inflation where the latter is only marginally insignificant at the 10% level. The results suggest little impact of higher lags on volatility from CCI.

The parameter estimates of θ support the countercyclical pattern reported in previous papers such as Schwert (1989) or Officer (1973). An increase in industrial production reduces the stock market volatility in the UK and the US.

Unlike the UK stock market volatility, more inflation gives way to higher volatility in the US. The stock market volatility in the US and the UK is not significantly related to changes in the exchange rate in contrast to Germany and Canada. It is interpreted that the insignificant relationship between the exchange rate and the stock market volatility arises from the relatively low proportion of exports of the US GDP and the UK GDP and that the companies in the US and the UK stock market are less dependent on sales abroad (see e.g. Barclays, 2015). In contrast, being one of the largest net exporting countries in the world, Germany is highly dependent on foreign sales and therefore the exchange rate plays a role in the country's economic situation.

All stock markets have in common that RV has the highest parameter estimation for θ, which is significant at the 1% level in all countries. That is, an increase in lagged RV increases the volatility in the current month.

The PC1-GARCH-MIDAS specification returns an insignificant θ for the UK and the US over the period considered for these countries. The long-run component is almost constant during the period, and the GARCH-MIDAS model becomes an asymmetric GARCH(1,1) process with τ as scaling factor and $\tau \approx m$ (see e.g. Sohn, 2009).

To find out to what extent economic variables can explain the variation in expected variance, several papers calculate the variance ratio (VR) statistic of a GARCH-MIDAS specification. The VR is the ratio of the sample variance of the log τ^M component, $\mathrm{var}(\log(\tau_t^M))$, and the sample variance of the log total conditional volatility,

$\mathrm{var}(\log(\tau_t^{RV} g_t^{RV}))$ where M denotes a specific GARCH-MIDAS model with macro variable M. Hence, VR is defined as

$$\mathrm{VR(M)} = \frac{\mathrm{var}(\log(\tau_t^{M}))}{\mathrm{var}(\log(\tau_t^{RV} g_t^{RV}))} \tag{4.11}$$

which follows the definition in Conrad and Loch (2015) who relate the $\mathrm{var}(\log(\tau_t^{M}))$ to the sample variance of the log total conditional variance of the RV model specification for the sake of easier comparison. Conrad and Loch (2015) note that a low $\mathrm{var}(\log(\tau_t^{M}))$ may indicate to smooth movements in the macroeconomic variable and does not necessarily mean that a specific model fits poorly. Only GARCH-MIDAS models that reveal high VRs are potential candidates, which perform better than the simple GARCH model, which is obtained for a constant τ component, i.e. if $\mathrm{var}(\log(\tau_t^{M})) \approx 0$ (Conrad and Loch, 2015).

The VRs of the different GARCH-MIDAS specifications are reported in Table 4.5 for the total observation period and sub-periods.

Germany					
	1991–2015	**-**	**1991–1999**	**2000–2009**	**2010–2015**
Rolling RV	0.4002	-	0.3129	0.4219	0.3324
PC1	0.0323	-	0.0329	0.0351	0.0440
Canada					
	1983–2015	**1983–1991**	**1992–1999**	**2000–2009**	**2010–2015**
Rolling RV	0.5560	0.4859	0.4385	0.6493	0.4245
PC1	0.0188	0.0233	0.0122	0.0155	0.0195
UK					
	1988–2015	**1988–1991**	**1992–1999**	**2000–2009**	**2010–2015**
Rolling RV	0.3378	0.9233	0.2058	0.3486	0.2314
PC1	0.0204	0.0073	0.0458	0.0140	0.0281
US					
	1983–2015	**1983–1991**	**1992–1999**	**2000–2009**	**2010–2015**
Rolling RV	0.1638	0.1559	0.0747	0.1542	0.2320
PC1	0.0029	0.0085	0.0018	0.0012	0.0022

Table 4.5: Variance ratio of the rolling RV and the PC1 GARCH-MIDAS model.
The variance ratio was calculated over the periods shown in the column using the tau and variance from the rolling window RV-GARCH-MIDAS model and the PC1-GARCH-MIDAS. The second column represents the variance ratio over the entire observation period for which all data were available. The observation period for Germany is from May 1991 to February 2015. The observation period for the UK is from February 1988 to February 2015. The observation period for Canada ranges from March 1983 to January 2015 and that for the US ranges from February 1983 to March 2015.

The VR ratios, with respect to the RV model, range from 0.164 for the US to 0.556 for Canada over the total period. The VRs fluctuate over the sub-periods and are highest in the 2000–2009 sub-period except for the US. That is, the GARCH-MIDAS model with rolling RV contributes most to the long-run component during 2000–2009. The VRs show that, with rolling RV, a quite significant proportion of conditional volatility variation can be explained, but there is potential for improving the fraction of conditional volatility. Taking macroeconomic variables in terms of PC1 into account yields even worse VRs and has, therefore, a weak explanatory power. The VR results are consistent with the observation that the long-run component does not follow the spikes in total volatility, which must, therefore, be attributed to the short-run component g. The next section has the objective of exploring the drivers of the volatility components to explain the gap between total volatility and the long-run component and to analyse why the total volatility contribution of economic variables fluctuates considerably over time.

4.6.2 VAR estimation results

The drivers of the short-run volatility component are examined in two steps. The first step is to look at the correlation between the variables in the model before a VAR analysis is employed. A Granger causality test is conducted to test which variables Granger cause movements in the short-run volatility.

4.6.2.1 Summary statistics

The summary statistics are illustrated in Tables 4.6 to 4.9. The raw time series were transformed first before the empirical investigation was conducted.

	Dividend yield	MILLclean	ERP	SENT	Average gRV	Average tauRV
Mean	0.0012	0.0139	-1.2499	0.0654	1.0421	0.0001
Median	-0.0200	-0.0891	-0.5807	-0.3263	0.8319	0.0001
Maximum	0.6700	5.8639	16.3115	5.2548	7.3016	0.0004
Minimum	-0.5800	-5.3564	-22.9106	-2.0905	0.4280	0.0001
Std. Dev.	0.1617	1.6179	6.0731	1.4499	0.7193	0.0001
Skewness	0.5196	0.0986	-0.6421	1.6947	3.8893	1.7236
Kurtosis	5.8443	4.2785	4.0137	5.5087	25.8973	5.5782
Sum	0.330	3.949	-356.228	18.640	296.991	0.041
Sum Sq. Dev.	7.427	743.425	10474.610	596.995	146.955	0.000
Observations	285	285	285	285	285	285

Table 4.6: Summary statistics Germany for the observation period, June 1991 to February 2015.
The short-run and long-run volatility components are estimated using the RV-GARCH-MIDAS specification and are denoted by g and tau, respectively. The values of g and tau used here are averages of daily values of g and tau over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the CDAX. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's, the average first-day return of IPO's and the market turnover. All data were downloaded at a monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to monthly frequency through a cubic spline interpolation.

	Dividend yield	MILLclean	ERP	SENT	Average gRV	Average tauRV
Mean	-0.0021	-0.0255	-3.4039	0.0221	0.9896	0.0001
Median	-0.0100	-0.0825	-2.6244	-0.0298	0.8169	0.0001
Maximum	0.6600	6.2336	15.9162	3.7077	13.2785	0.0009
Minimum	-0.7500	-6.4901	-29.1878	-5.9192	0.4883	0.0000
Std. Dev.	0.1313	1.6674	5.7716	1.2140	0.8082	0.0001
Skewness	0.3679	-0.1686	-0.6586	0.0093	10.1613	4.9503
Kurtosis	9.1531	5.2865	4.4800	4.1900	144.7063	33.1519
Sum	-0.810	-9.739	-1300.294	8.441	378.010	0.033
Sum Sq. Dev.	6.572	1059.278	12691.840	561.510	248.841	0.000
Observations	382	382	382	382	382	382

Table 4.7: Summary statistics Canada for the observation period, April 1983 to January 2015.
The short-run and long-run volatility components are estimated using the RV-GARCH-MIDAS specification and are denoted by g and tau, respectively. The values of g and tau used here are averages of daily values of g and tau over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the S&P/TSX. SENT is the sentiment index estimated, following Baker et al. (2012), using the volatility premium, the number of IPO's and the average first-day return of IPO's. All data were downloaded at a monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to monthly frequency through a cubic spline interpolation.

	Dividend yield	MILLclean	ERP	SENT	Average gRV	Average tauRV
Mean	-0.0027	-0.0089	-4.8243	0.0037	1.0226	0.0001
Median	-0.0150	0.0082	-4.2055	-0.1622	0.8090	0.0001
Maximum	0.7700	5.1850	11.4517	4.3833	7.3102	0.0004
Minimum	-0.7600	-5.6721	-22.9319	-4.5775	0.4543	0.0001
Std. Dev.	0.1831	1.4388	5.7381	1.2030	0.7140	0.0001
Skewness	0.0493	0.0453	-0.4385	0.8505	3.9271	3.1787
Kurtosis	5.9971	4.7622	3.4151	4.7051	26.1889	15.8667
Sum	-0.880	-2.887	-1563.076	1.206	331.329	0.030
Sum Sq. Dev.	10.823	668.661	10634.850	467.473	164.663	0.000
Observations	324	324	324	324	324	324

Table 4.8: Summary statistics UK for the observation period, March 1988 to February 2015.
The short-run and long-run volatility components are estimated using the RV-GARCH-MIDAS specification and are denoted by g and tau, respectively. The values of g and tau used here are averages of daily values of g and tau over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the FTSE All-Share. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's, the average first-day return of IPO's and the market turnover. All data were downloaded at a monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to monthly frequency through a cubic spline interpolation.

	Dividend yield	MILLclean	ERP	SENT	Average gRV	Average tauRV
Mean	-0.0071	-0.0102	-3.1654	-0.0256	1.0364	0.0001
Median	-0.0100	-0.0344	-3.1188	-0.1167	0.6990	0.0001
Maximum	0.8100	6.3584	15.5250	4.2758	18.1460	0.0003
Minimum	-0.5200	-6.2331	-27.4878	-2.8311	0.3233	0.0001
Std. Dev.	0.1213	1.4136	5.1687	1.1019	1.4672	0.0000
Skewness	0.8593	-0.0591	-0.2049	0.5419	7.7436	1.8141
Kurtosis	10.5011	5.1818	4.3018	3.7328	75.5641	6.4814
Sum	-2.750	-3.930	-1218.671	-9.840	399.008	0.045
Sum Sq. Dev.	5.649	767.352	10258.850	466.237	826.682	0.000
Observations	385	385	385	385	385	385

Table 4.9: Summary statistics US for the observation period, March 1983 to March 2015.
The short-run and long-run volatility components are estimated using the RV-GARCH-MIDAS specification and are denoted by g and tau, respectively. The values of g and tau used here are averages of daily values of g and tau over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the S&P500. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's, the average first-day return of IPO's and the market turnover. All data were downloaded at a monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to monthly frequency through a cubic spline interpolation.

Figures 4.2 to 4.5 depict the time series data calculated as described above over the full observation period for Germany, Canada, the UK and the US, respectively.

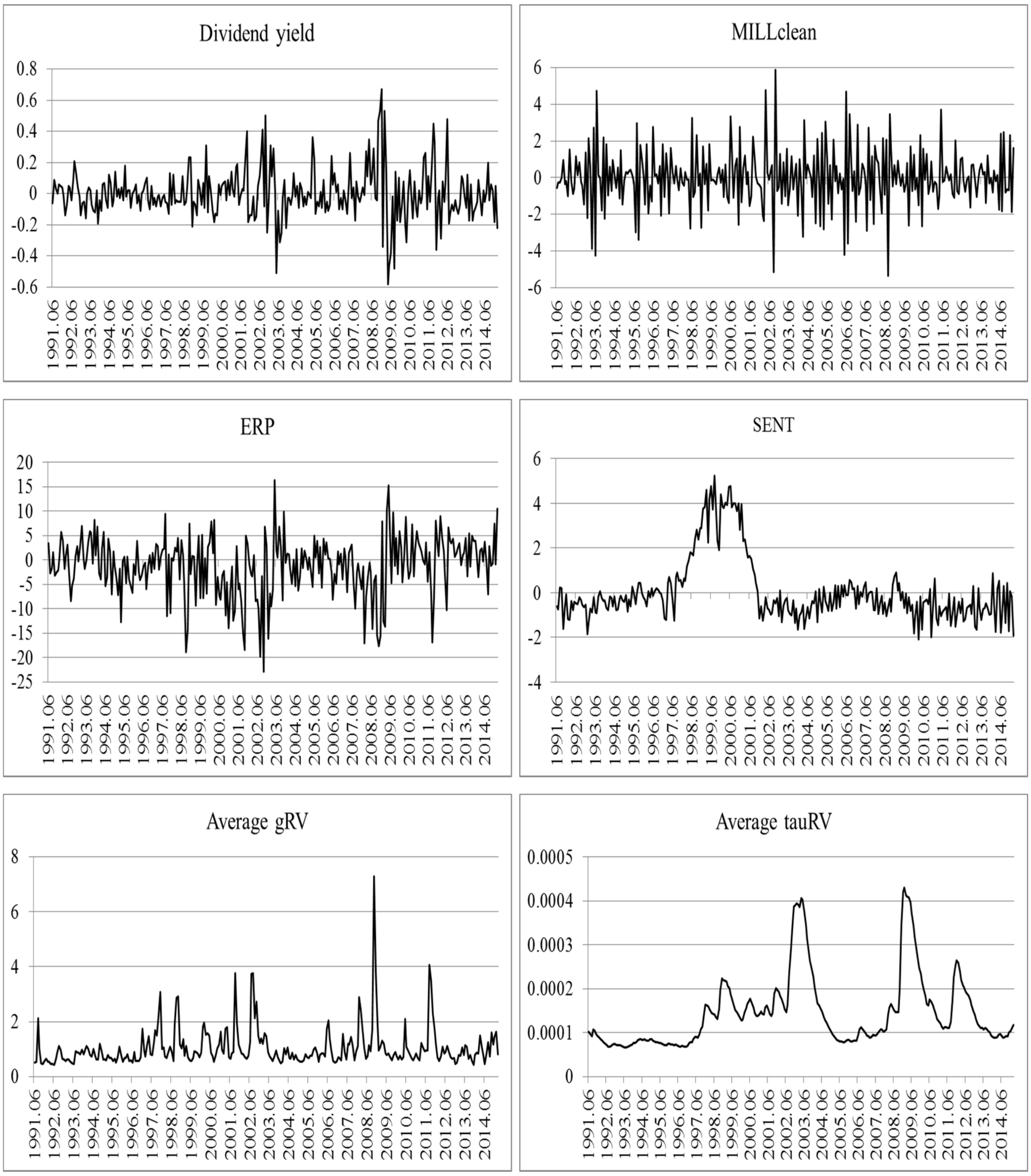

Figure 4.2: Time series plots of variables for Germany.
The short-run and long-run volatility components are denoted by average gRV and average tauRV. The ending RV means that the volatility components are estimated using the RV-GARCH-MIDAS specification. The values of g and tau used here are averages of daily values of g and tau over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the CDAX. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's, the average first-day return of IPO's and the market turnover. All data were downloaded at a monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to monthly frequency through a cubic spline interpolation.

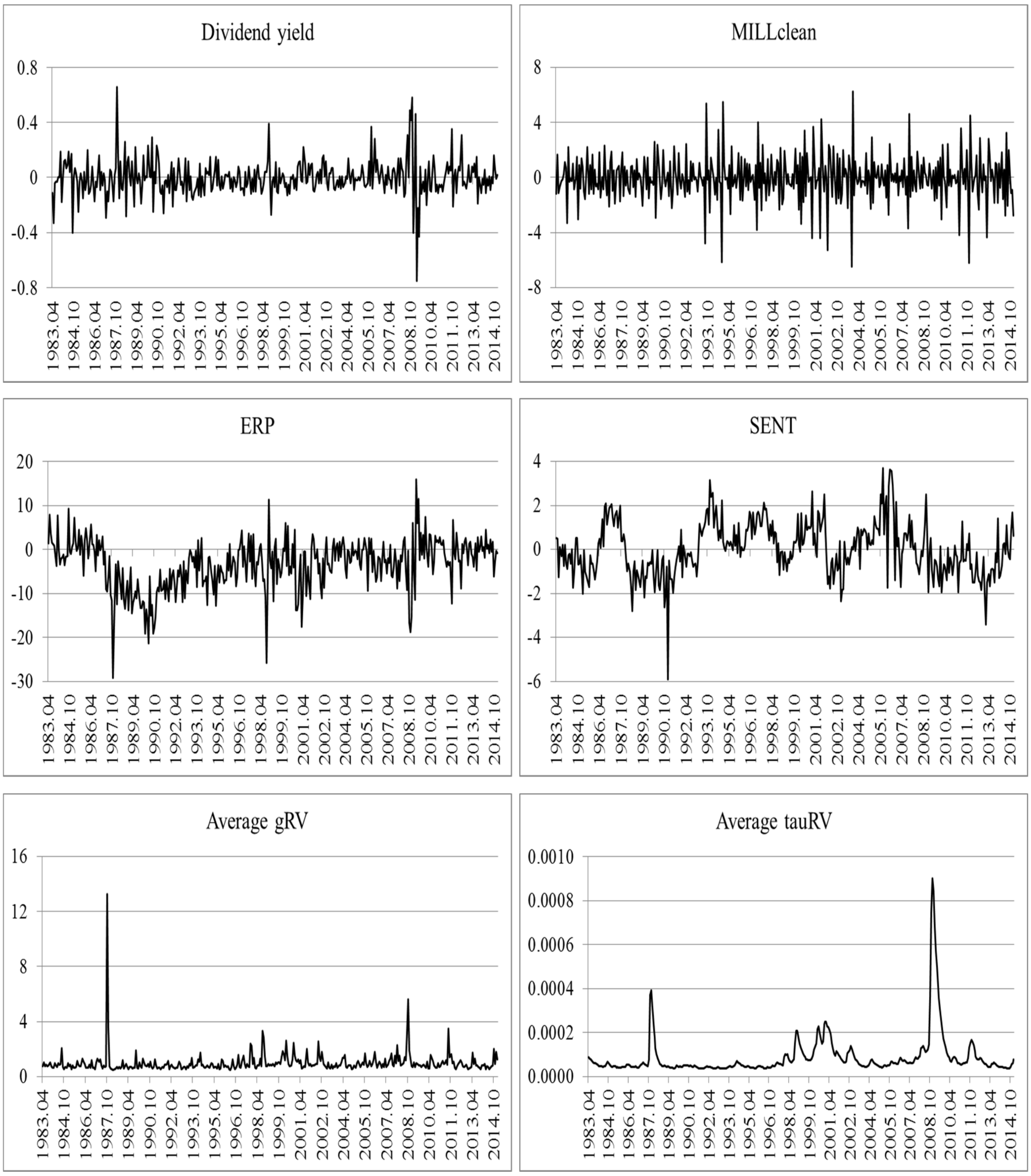

Figure 4.3: Time series plots of variables for Canada.

The short-run and long-run volatility components are denoted by average gRV and average tauRV. The ending RV means that the volatility components are estimated using the RV-GARCH-MIDAS specification. The values of g and tau used here are averages of daily values of g and tau over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the S&P/TSX. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's and the average first-day return of IPO's. All data were downloaded at a monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to monthly frequency through a cubic spline interpolation.

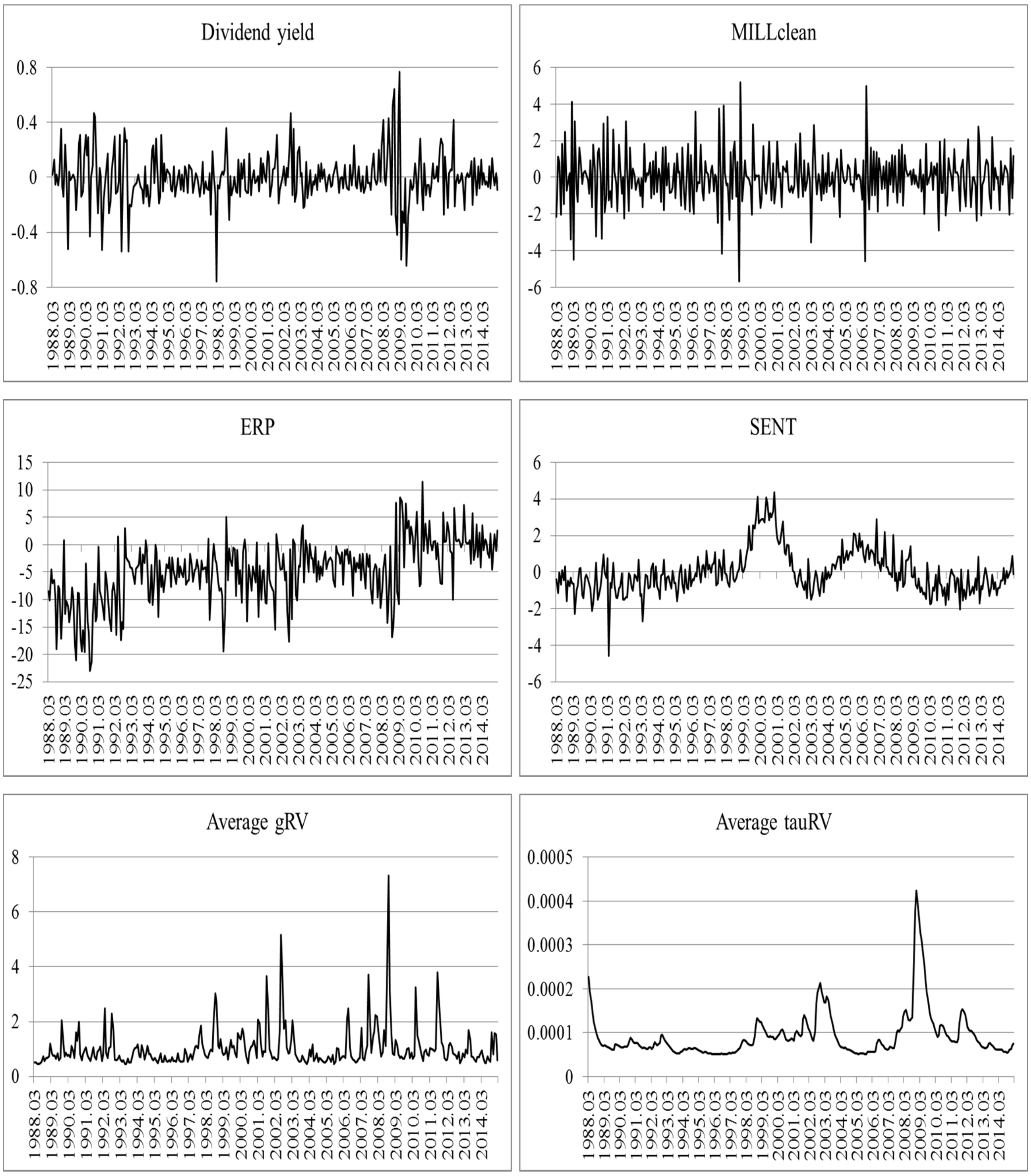

Figure 4.4: Time series plots of variables for the UK.

The short-run and long-run volatility components are denoted by average gRV and average tauRV. The ending RV means that the volatility components are estimated using the RV-GARCH-MIDAS specification. The values of g and tau used here are averages of daily values of g and tau over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the FTSE All-Share. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's, the average first-day return of IPO's and the market turnover. All data were downloaded at a monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to monthly frequency through a cubic spline interpolation.

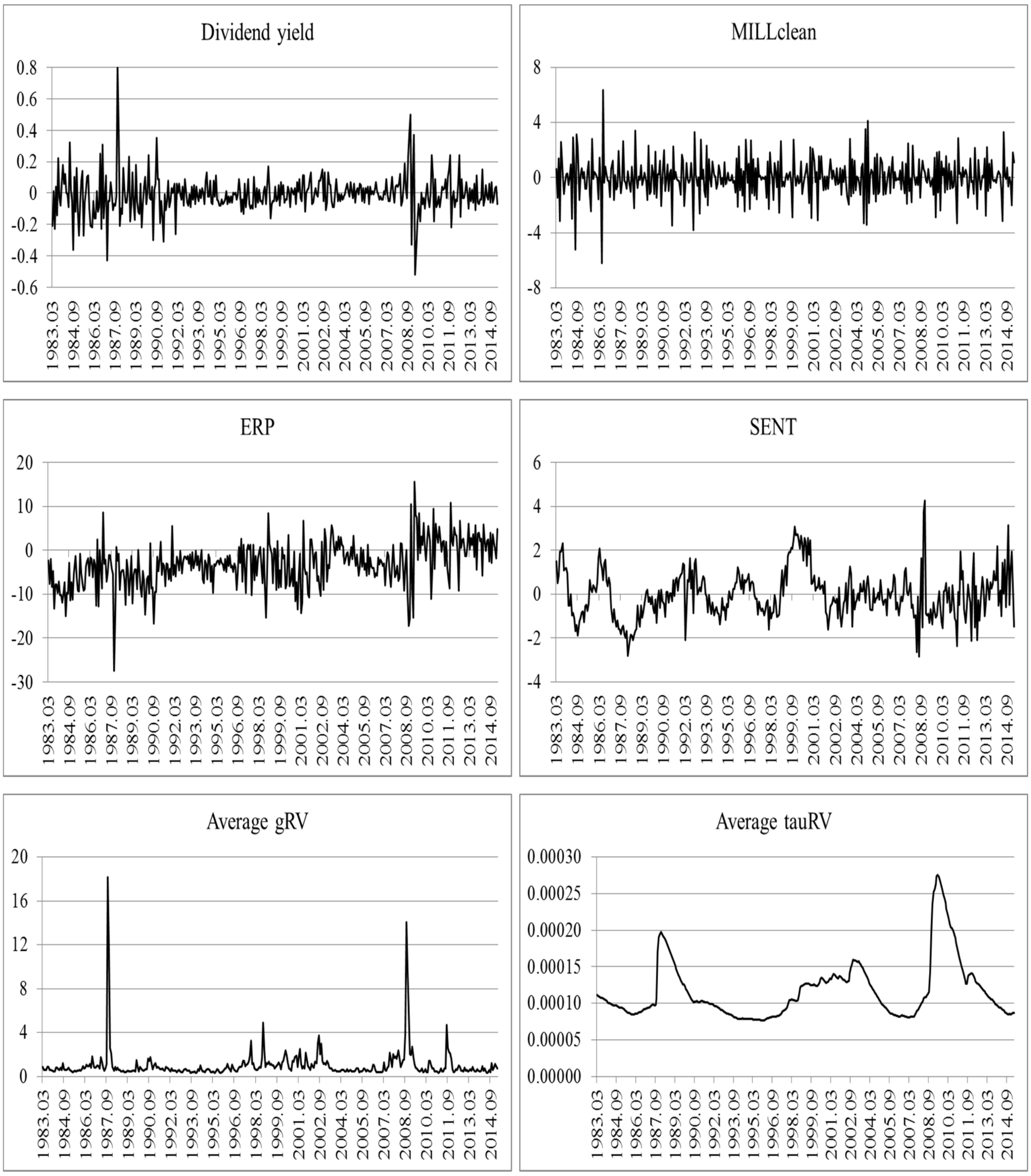

Figure 4.5: Time series plots of variables for the US.
The short-run and long-run volatility components are denoted by average gRV and average tauRV. The ending RV means that the volatility components are estimated using the RV-GARCH-MIDAS specification. The values of g and tau used here are averages of daily values of g and tau over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the S&P500. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's, the average first-day return of IPO's and the market turnover. All data were downloaded at a monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to monthly frequency through a cubic spline interpolation.

Motivated by Liu (2015), MILL enters the subsequent analysis as monthly changes in logarithm, which is referred to as MILLclean. The first differences of the dividend yield (DP) are used to ensure stationary time series according to the Augmented Dickey-

Fuller (henceforth ADF), Phillips-Perron (PP) and the KPSS test.[9] The remaining variables in the VAR were not transformed for the sake of stationarity as these variables were already stationary according to the unit root tests.

Before presenting the Granger-causality test results, it is useful to look at the correlation matrices first. Tables 4.10 to 4.13 demonstrate the ordinary correlation analysis results and display the associated p-values in the second line, which test the hypothesis that the correlation coefficient equals zero.

The results for Germany (Table 4.10) reveal that multicollinearity between the variables is not a big issue. Merely the equity premium is highly negatively correlated with DP at the 1% significance level. The short-run volatility is also higher when DP is higher and is positively correlated with the long-run volatility component, which suggests that the short-run volatility may also be a driver of the long-run component. The relatively strong negative correlation between g and ERP indicates that the investors require a higher ERP when the short-run volatility is lower. There is no significant correlation with sentiment except for ERP, and the long-run volatility is correlated with the short-run volatility. The p-value does not indicate that the long-run volatility is related to illiquidity. Thus, tau is not higher when the market is less liquid.

[9] The results of the unit root tests are not reported here but available upon request.

Correlation *Probability*	Dividend yield	MILLclean	ERP	SENT	Average gRV	Average tauRV
Dividend yield	1.0000					

MILLclean	0.0297	1.0000				
	0.6179	-----				
ERP	-0.8268	-0.0183	1.0000			
	0.0000	*0.7582*	-----			
SENT	0.0780	0.0177	-0.1782	1.0000		
	0.1890	*0.7659*	*0.0025*	-----		
Average gRV	0.4340	0.0853	-0.4902	0.0862	1.0000	
	0.0000	*0.1511*	*0.0000*	*0.1468*	-----	
Average tauRV	-0.0235	-0.0003	-0.0689	0.0540	0.2059	1.0000
	0.6923	*0.9953*	*0.2460*	*0.3635*	*0.0005*	-----

Table 4.10: Correlation matrix for Germany.

The coefficients were calculated using the ordinary Pearson method. The second line displays theprobability. The short-run and long-run volatility components are denoted by average gRV and average tauRV. The ending RV means that the volatility components are estimated using the RV-GARCH-MIDAS specification. The values of g and tau used here are averages of daily values of g and tau over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the CDAX. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's, the average first-day return of IPO's and the market turnover. All data were downloaded at a monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to monthly frequency through a cubic spline interpolation. The observation period ranges from June 1991 to February 2015.

The findings for Canada in Table 4.11 are that g and tau are also positively correlated, and ERP is higher when g is lower. On the contrary, the long-run volatility is higher when DP is higher. For Canada, the results do not suggest a significant correlation of illiquidity with the other variables. The results find that the sentiment is higher when the short-run volatility is higher, which holds for the DP.

Correlation *Probability*	Dividend yield	MILLclean	ERP	SENT	Average gRV	Average tauRV
Dividend yield	1.0000					

MILLclean	0.0066	1.0000				
	0.8970	-----				
ERP	-0.7029	0.0192	1.0000			
	0.0000	*0.7087*	-----			
SENT	0.0149	-0.0184	0.0587	1.0000		
	0.7717	*0.7198*	*0.2522*	-----		
Average gRV	0.2479	0.0701	-0.2120	0.0936	1.0000	
	0.0000	*0.1714*	*0.0000*	*0.0675*	-----	
Average tauRV	0.1291	0.0021	-0.0788	0.0537	0.1282	1.0000
	0.0115	*0.9666*	*0.1244*	*0.2951*	*0.0122*	-----

Table 4.11: Correlation matrix for Canada.
The coefficients were calculated using the ordinary Pearson method. The second line displays the probability. The short-run and long-run volatility components are denoted by average gRV and average tauRV. The ending RV means that the volatility components are estimated using the RV-GARCH-MIDAS specification. The values of g and tau used here are averages of daily values of g and tau over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the S&P/TSX. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's and the average first-day return of IPO's. All data were downloaded at monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to monthly frequency through a cubic spline interpolation. The observation period ranges from April 1983 to January 2015.

In case of the UK, the short-run volatility is significantly correlated with DP, illiquidity and ERP, whereas the long-run volatility is only correlated with the short-run component. The positive correlation between short-run volatility and illiquidity suggests that short-run volatility is higher when the stock market is less liquid. The sentiment is uncorrelated to all other variables in the matrix of Table 4.12.

Correlation *Probability*	Dividend yield	MILLclean	ERP	SENT	Average gRV	Average tauRV
Dividend yield	1.0000					

MILLclean	-0.0257	1.0000				
	0.6450	-----				
ERP	-0.7149	0.0286	1.0000			
	0.0000	*0.6080*	-----			
SENT	-0.0066	0.0696	-0.0122	1.0000		
	0.9058	*0.2115*	*0.8263*	-----		
Average gRV	0.3827	0.1415	-0.3143	0.0689	1.0000	
	0.0000	*0.0107*	*0.0000*	*0.2163*	-----	
Average tauRV	0.0312	-0.0098	0.0810	-0.0225	0.2408	1.0000
	0.5758	*0.8607*	*0.1455*	*0.6868*	*0.0000*	-----

Table 4.12: Correlation matrix for the UK.
The coefficients were calculated using the ordinary Pearson method. The second line displays the probability. The short-run and long-run volatility components are denoted by average gRV and average tauRV. The ending RV means that the volatility components are estimated using the RV-GARCH-MIDAS specification. The values of g and tau used here are averages of daily values of g and tau over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the FTSE All-Share. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's, the average first-day return of IPO's and the market turnover. All data were downloaded at a monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to monthly frequency through a cubic spline interpolation. The observation period ranges from March 1988 to February 2015.

The two volatility components are also positively correlated in the US as displayed in Table 4.13. Also, there is a negative correlation between sentiment and tau so that tau is higher when sentiment is lower while the correlation with g is insignificant. The results suggest that the ERP is negatively correlated with g and positively correlated with tau. In contrast to that of Liu (2015), the results in this study do not reveal that the stock market is more liquid when sentiment is higher, i.e. investors are more bullish regarding the future stock market performance, at least over the period under consideration.

Correlation *Probability*	Dividend yield	MILLclean	ERP	SENT	Average gRV	Average tauRV
Dividend yield	1.0000					

MILLclean	-0.0518	1.0000				
	0.3106	-----				
ERP	-0.7539	0.0514	1.0000			
	0.0000	*0.3142*	-----			
SENT	0.0490	0.0222	-0.0512	1.0000		
	0.3377	*0.6645*	*0.3163*	-----		
Average gRV	0.3389	0.0606	-0.2926	0.0018	1.0000	
	0.0000	*0.2353*	*0.0000*	*0.9721*	-----	
Average tauRV	0.0153	-0.0076	0.1423	-0.1664	0.1577	1.0000
	0.7640	*0.8820*	*0.0052*	*0.0010*	*0.0019*	-----

Table 4.13: Correlation matrix for the US.
The coefficients were calculated using the ordinary Pearson method. The second line displays the probability. The short-run and long-run volatility components are denoted by average gRV and average tauRV. The ending RV means that the volatility components are estimated using the RV-GARCH-MIDAS specification. The values of g and tau used here are averages of daily values of g and tau over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the S&P500. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's, the average first-day return of IPO's and the market turnover. All data were downloaded at monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to a monthly frequency through a cubic spline interpolation. The observation period ranges from March 1983 to March 2015.

4.6.2.2 VAR estimation results for volatility levels

The correlation matrix reveals the relationship between two variables but does not indicate the direction of the relationship. The Granger-causality test reveals the direction of the causality between two variables where the null hypothesis is that variable x does not Granger-cause variable y. The Granger test outcome reports the F-statistics which are Wald statistics of the pairwise test and the corresponding p-value. The test runs in both directions and may reveal a two-way causality between two variables. Hence, in this analysis it is possible that a higher volatility component is caused by some variable and this variable is caused by a volatility component at the same time. The Granger-causality test is conducted on stationary monthly observed variables for all countries under examination (see, e.g. Liu, 2015). Granger causality results are presented and the F-statistic reported along with the corresponding p-values. The Schwarz information criterion determines the appropriate lag order. The interpretation of the results is grouped by countries and each variable is discussed under a certain pair of variables. In so doing, the analysis is focused only on the causation of volatility with other variables so that there are only four pairs of interest.

Table 4.14 shows the Granger-causality test results for Germany with the short-run volatility component. The results indicate that the short-run volatility Granger-causes the DP but the null hypothesis that DP does not Granger-cause short-run volatility cannot be rejected. The same observation holds for the equity premium in the sense that Granger-causality runs from short-run volatility to ERP rather than the other direction. There doesn't seem to be a causation either between g and illiquidity or between g and sentiment in either direction. In all these four pairwise combinations, the p-value is above 10% so that F-statistics are not significant at the 10% level. Hence, the null hypothesis MILL and sentiment do not Granger-cause short-run volatility is accepted, and vice versa.

The Granger causality results are illustrated in Table 4.14 where the F-statistics are shown with the corresponding p-values. The PC1-GARCH-MIDAS model returns similar Granger-causality results for DP and ERP which are both Granger-caused one-way by g. In brief, the results suggest no causation from the variables on g in both GARCH-MIDAS specifications.[10]

[10] The results of the PC1-GARCH-MIDAS specification are reported in Appendix C.2.

Null Hypothesis:	Obs	F-Statistic	Prob.
MILLclean does not Granger-cause Dividend yield	284	0.3222	0.5707
Dividend yield does not Granger-cause MILLclean		3.3008	0.0703
ERP does not Granger-cause Dividend yield	284	0.0366	0.8485
Dividend yield does not Granger-cause ERP		1.0479	0.3069
SENT does not Granger-cause Dividend yield	284	0.0711	0.7899
Dividend yield does not Granger-cause SENT		0.2842	0.5944
Average gRV does not Granger-cause Dividend yield	284	26.7196	0.0000
Dividend yield does not Granger-cause Average gRV		1.2766	0.2595
ERP does not Granger-cause MILLclean	284	6.1279	0.0139
MILLclean does not Granger-cause ERP		0.5334	0.4658
SENT does not Granger-cause MILLclean	284	0.4842	0.4871
MILLclean does not Granger-cause SENT		0.0704	0.7910
Average gRV does not Granger-cause MILLclean	284	0.9983	0.3186
MILLclean does not Granger-cause Average gRV		0.5056	0.4776
SENT does not Granger-cause ERP	284	5.7093	0.0175
ERP does not Granger-cause SENT		0.1590	0.6903
Average gRV does not Granger-cause ERP	284	24.2331	0.0000
ERP does not Granger-cause Average gRV		0.0427	0.8365
Average gRV does not Granger-cause SENT	284	0.6161	0.4332
SENT does not Granger-cause Average gRV		0.0995	0.7527

Table 4.14: Granger-causality results: Germany – incl. the short-run volatility component.
The number of lags in the test regressions was chosen by the Schwarz information criterion. The F-statistics are Wald statistics of the pairwise test. Average gRV denotes the short-run volatility component. The ending RV means that the volatility component is estimated using the RV-GARCH-MIDAS specification with rolling window. The values of g used here are the average of daily values of g over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the CDAX. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's, the average first-day return of IPO's and the market turnover. All data were downloaded at monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to a monthly frequency through a cubic spline interpolation. The observation period ranges from June 1991 to February 2015.

The results using the long-run volatility component, tau, reveal a two-way causation between tau and DP. Interestingly, the equity premium Granger-causes long-run volatility, and there appears to be no causation between tau and illiquidity. Likewise, for the short-run volatility, there is neither causal relationship between long-run volatility and sentiment (Table 4.15). If the tau component is estimated using the PC1, the VAR suggests a causal relationship between tau and sentiment in both the directions, which contrasts the outcome of the RV-GARCH-MIDAS model.

Null Hypothesis:	Obs.	F-Statistic	Prob.
MILLclean does not Granger-cause Dividend yield	283	0.5382	0.5844
Dividend yield does not Granger-cause MILLclean		3.4711	0.0324
ERP does not Granger-cause Dividend yield	283	0.3767	0.6865
Dividend yield does not Granger-cause ERP		1.3506	0.2608
SENT does not Granger-cause Dividend yield	283	0.0742	0.9285
Dividend yield does not Granger-cause SENT		0.2094	0.8112
Average tauRV does not Granger-cause Dividend yield	283	4.3237	0.0142
Dividend yield does not Granger-cause Average tauRV		11.6446	0.0000
ERP does not Granger-cause MILLclean	283	4.8635	0.0084
MILLclean does not Granger-cause ERP		0.3816	0.6831
SENT does not Granger-cause MILLclean	283	0.7508	0.4729
MILLclean does not Granger-cause SENT		0.0319	0.9686
Average tauRV does not Granger-cause MILLclean	283	0.3569	0.7002
MILLclean does not Granger-cause Average tauRV		1.8705	0.1560
SENT does not Granger-cause ERP	283	2.5802	0.0776
ERP does not Granger-cause SENT		0.4310	0.6503
Average tauRV does not Granger-cause ERP	283	0.3042	0.7380
ERP does not Granger-cause Average tauRV		14.3147	0.0000
Average tauRV does not Granger-cause SENT	283	0.8821	0.4151
SENT does not Granger-cause Average tauRV		0.0102	0.9898

Table 4.15: Granger-causality results: Germany – incl. the long-run volatility component.
The number of lags in the test regressions was chosen by the Schwarz information criterion. The F-statistics are Wald statistics of the pairwise test. Average tauRV denotes the long-run volatility component. The ending RV means that the volatility component is estimated using the RV-GARCH-MIDAS specification with rolling window. The values of tau used here are the average of daily values of tau over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the CDAX. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's, the average first-day return of IPO's and the market turnover. All data were downloaded at monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to a monthly frequency through a cubic spline interpolation. The observation period ranges from June 1991 to February 2015.

The Granger-causality test results for Canada are illustrated in Table 4.16. Again, the Granger-causality runs one-way from the short-run component g to the dividend yield DP, which also holds with respect to the equity premium. The results show that the null hypothesis that g does not Granger-cause illiquidity cannot be rejected whereas Granger-causality from sentiment to short-run volatility appears to exist. Alikesentiment, the short-run volatility Granger-causes ERP. The results for PC1 deviate from those with RV in that there is a Granger-causality between g and DP in both directions. There is no Granger-causality from sentiment, but the other way around is true.

Null Hypothesis:	Obs.	F-Statistic	Prob.
MILLclean does not Granger-cause Dividend yield	380	1.0997	0.3341
Dividend yield does not Granger-cause MILLclean		6.9762	0.0011
ERP does not Granger-cause Dividend yield	380	5.7048	0.0036
Dividend yield does not Granger-cause ERP		30.3825	0.0000
SENT does not Granger-cause Dividend yield	380	1.8249	0.1627
Dividend yield does not Granger-cause SENT		1.9520	0.1434
Average gRV does not Granger-cause Dividend yield	380	34.1233	0.0000
Dividend yield does not Granger-cause Average gRV		0.1142	0.8921
ERP does not Granger-cause MILLclean	380	6.9733	0.0011
MILLclean does not Granger-cause ERP		3.6241	0.0276
SENT does not Granger-cause MILLclean	380	0.4108	0.6634
MILLclean does not Granger-cause SENT		0.1951	0.8228
Average gRV does not Granger-cause MILLclean	380	1.7237	0.1798
MILLclean does not Granger-cause Average gRV		1.2064	0.3004
SENT does not Granger-cause ERP	380	1.2561	0.2860
ERP does not Granger-cause SENT		0.4938	0.6107
Average gRV does not Granger-cause ERP	380	23.8060	0.0000
ERP does not Granger-cause Average gRV		0.5047	0.6041
Average gRV does not Granger-cause SENT	380	1.4018	0.2475
SENT does not Granger-cause Average gRV		2.6460	0.0723

Table 4.16: Granger-causality results: Canada – incl. the short-run volatility component.
The number of lags in the test regressions was chosen by the Schwarz information criterion. The F-statistics are Wald statistics of the pairwise test. Average gRV denotes the short-run volatility component. The ending RV means that the volatility component is estimated using the RV-GARCH-MIDAS specification with rolling window. The values of g used here are the averages of daily values of g over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the S&P/TSX. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's and the average first-day return of IPO's. All data were downloaded at monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to a monthly frequency through a cubic spline interpolation. The observation period ranges from April 1983 to January 2015.

The long-run component Granger-causes DP and the other way around that DP appear to Granger-cause tau cannot be accepted at least at the 10% significance level. The null hypothesis that sentiment does not Granger-cause long-run volatility cannot be rejected, whereas the reverse is accepted so that volatility Granger-causes sentiment. Illiquidity does not Granger-cause long-run volatility, nor the reverse is true. The results suggest a one-way causation from tau to equity premium at the 1% significance level (Table 4.17).

If tau is estimated through the PC1-GARCH-MIDAS model, the long-run volatility Granger-causes DP and illiquidity where the causality in the reverse direction must be rejected. The results show a causality from tau to ERP, whereas causality runs from sentiment to long-run volatility, which contrasts the results from the benchmark GARCH-MIDAS specification. For Canada, the causality relationship changes depending on the variable used to estimate tau, and the causation runs from illiquidity and sentiment to tau, respectively.

Null Hypothesis:	Obs.	F-Statistic	Prob.
MILLclean does not Granger-cause Dividend yield	379	0.9980	0.3938
Dividend yield does not Granger-cause MILLclean		5.1917	0.0016
ERP does not Granger-cause Dividend yield	379	5.7245	0.0008
Dividend yield does not Granger-cause ERP		16.5443	0.0000
SENT does not Granger-cause Dividend yield	379	1.2290	0.2989
Dividend yield does not Granger-cause SENT		2.3166	0.0753
Average tauRV does not Granger-cause Dividend yield	379	12.0315	0.0000
Dividend yield does not Granger-cause Average tauRV		1.5041	0.2131
ERP does not Granger-cause MILLclean	379	3.5919	0.0139
MILLclean does not Granger-cause ERP		3.8096	0.0103
SENT does not Granger-cause MILLclean	379	0.6571	0.5789
MILLclean does not Granger-cause SENT		0.0930	0.9639
Average tauRV does not Granger-cause MILLclean	379	0.2632	0.8519
MILLclean does not Granger-cause Average tauRV		0.6737	0.5686
SENT does not Granger-cause ERP	379	0.7088	0.5472
ERP does not Granger-cause SENT		1.9355	0.1234
Average tauRV does not Granger-cause ERP	379	6.6783	0.0002
ERP does not Granger-cause Average tauRV		0.6194	0.6028
Average tauRV does not Granger-cause SENT	379	4.9379	0.0022
SENT does not Granger-cause Average tauRV		0.6687	0.5717

Table 4.17: Granger causality results: Canada – incl. the long-run volatility component.
The number of lags in the test regressions was chosen by the Schwarz information criterion. The F-statistics are Wald statistics of the pairwise test. Average tauRV denotes the long-run volatility component. The ending RV means that the volatility component is estimated using the RV-GARCH-MIDAS specification with rolling window. The values of tau used here are the averages of daily values of tau over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the S&P/TSX. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's and the average first-day return of IPO's. All data were downloaded at monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to a monthly frequency through a cubic spline interpolation. The observation period ranges from April 1983 to January 2015.

The results for the UK illustrated in Table 4.18 reveal a one-way causation from g to DP as well as from g to equity premium, respectively while the reverse is not true. The results do not suggest a causal relationship between g and sentiment but from g to illiquidity. The results from the PC1-GARCH-MIDAS suggest a one-way causation from g to ERP and DP, respectively. Hence, for both GARCH-MIDAS specifications, there is no Granger-causality from variables to g and it can be concluded that Granger-causality comes from g rather than the other direction.

Null Hypothesis:	Obs.	F-Statistic	Prob.
MILLclean does not Granger-cause Dividend yield	322	0.6064	0.5459
Dividend yield does not Granger-cause MILLclean		3.9312	0.0206
ERP does not Granger-cause Dividend yield	322	1.2063	0.3007
Dividend yield does not Granger-cause ERP		40.5264	0.0000
SENT does not Granger-cause Dividend yield	322	0.5176	0.5965
Dividend yield does not Granger-cause SENT		1.2298	0.2937
Average gRV does not Granger-cause Dividend yield	322	17.1112	0.0000
Dividend yield does not Granger-cause Average gRV		1.1777	0.3093
ERP does not Granger-cause MILLclean	322	4.2834	0.0146
MILLclean does not Granger-cause ERP		0.0839	0.9195
SENT does not Granger-cause MILLclean	322	0.3844	0.6811
MILLclean does not Granger-cause SENT		2.5725	0.0779
Average gRV does not Granger-cause MILLclean	322	3.3136	0.0376
MILLclean does not Granger-cause Average gRV		1.7789	0.1705
SENT does not Granger-cause ERP	322	0.0932	0.9111
ERP does not Granger-cause SENT		0.4575	0.6333
Average gRV does not Granger-cause ERP	322	12.4942	0.0000
ERP does not Granger-cause Average gRV		0.7880	0.4557
Average gRV does not Granger-cause SENT	322	0.2559	0.7744
SENT does not Granger-cause Average gRV		1.5664	0.2104

Table 4.18: Granger-causality results: UK – incl. the short-run volatility component.
The number of lags in the test regressions was chosen by the Schwarz information criterion. The F-statistics are Wald statistics of the pairwise test. Average gRV denotes the short-run volatility component. The ending RV means that the volatility component is estimated using the RV-GARCH-MIDAS specification with rolling window. The values of g used here are the averages of daily values of g over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the FTSE All-Share. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's, the average first-day return of IPO's and the market turnover. All data were downloaded at monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to a monthly frequency through a cubic spline interpolation. The observation period ranges from March 1988 to February 2015.

Table 4.19 suggests that tau is Granger-caused by DP but not vice versa. Furthermore, the Granger-causality seems to run in both directions with respect to equity premium as the null hypothesis that tau does not Granger-cause ERP, and the reverse can both be rejected. Between tau and sentiment as well as between tau and illiquidity, there appears to be no causal relationship in either direction as shown in Table 4.19.

Using tau estimated by PC1, the VAR results suggest a Granger-causality relationship in both directions between tau and DP. ERP is the only variable that Granger-causes tau.

Null Hypothesis:	Obs.	F-Statistic	Prob.
MILLclean does not Granger-cause Dividend yield	322	0.6064	0.5459
Dividend yield does not Granger-cause MILLclean		3.9312	0.0206
ERP does not Granger-cause Dividend yield	322	1.2063	0.3007
Dividend yield does not Granger-cause ERP		40.5264	0.0000
SENT does not Granger-cause Dividend yield	322	0.5176	0.5965
Dividend yield does not Granger-cause SENT		1.2298	0.2937
Average tauRV does not Granger-cause Dividend yield	322	0.4210	0.6568
Dividend yield does not Granger-cause Average tauRV		9.3181	0.0001
ERP does not Granger-cause MILLclean	322	4.2834	0.0146
MILLclean does not Granger-cause ERP		0.0839	0.9195
SENT does not Granger-cause MILLclean	322	0.3844	0.6811
MILLclean does not Granger-cause SENT		2.5725	0.0779
Average tauRV does not Granger-cause MILLclean	322	0.6113	0.5433
MILLclean does not Granger-cause Average tauRV		1.0677	0.3450
SENT does not Granger-cause ERP	322	0.0932	0.9111
ERP does not Granger-cause SENT		0.4575	0.6333
Average tauRV does not Granger-cause ERP	322	5.3132	0.0054
ERP does not Granger-cause Average tauRV		7.4348	0.0007
Average tauRV does not Granger-cause SENT	322	1.1560	0.3161
SENT does not Granger-cause Average tauRV		0.1980	0.8205

Table 4.19: Granger-causality results: UK – incl. the long-run volatility component.

The number of lags in the test regressions was chosen by the Schwarz information criterion. The F-statistics are Wald statistics of the pairwise test. Average tauRV denotes the long-run volatility component. The ending RV means that the volatility component is estimated using the RV-GARCH-MIDAS specification with rolling window. The values of tau used here are the averages of daily values of tau over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the FTSE All-Share. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's, the average first-day return of IPO's and the market turnover. All data were downloaded at monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to a monthly frequency through a cubic spline interpolation. The observation period ranges from March 1988 to February 2015.

In case of the US shown in Table 4.20, the short-run volatility Granger-causes all the other variables MILLclean, ERP, DP and sentiment significantly at the 10% level. The causation does not run in the other direction so that it is reasonable to conclude that for the US short-run volatility is not Granger-caused by the variables in the VAR.

If the PC1-GARCH-MIDAS estimated volatility components are included in the VAR, the outcome reveals a two-way causality between g and DP and a Granger-causality from g to illiquidity as well as ERP and sentiment.

Null Hypothesis:	Obs.	F-Statistic	Prob.
MILLclean does not Granger-cause Dividend yield	383	1.0040	0.3674
Dividend yield does not Granger-cause MILLclean		9.4489	0.0001
ERP does not Granger-cause Dividend yield	383	1.0270	0.3591
Dividend yield does not Granger-cause ERP		27.7077	0.0000
SENT does not Granger-cause Dividend yield	383	0.5649	0.5689
Dividend yield does not Granger-cause SENT		2.2997	0.1017
Average gRV does not Granger-cause Dividend yield	383	47.0379	0.0000
Dividend yield does not Granger-cause Average gRV		0.8396	0.4327
ERP does not Granger-cause MILLclean	383	6.8493	0.0012
MILLclean does not Granger-cause ERP		0.2523	0.7772
SENT does not Granger-cause MILLclean	383	0.1282	0.8797
MILLclean does not Granger-cause SENT		0.1438	0.8661
Average gRV does not Granger-cause MILLclean	383	3.6379	0.0272
MILLclean does not Granger-cause Average gRV		0.3125	0.7318
SENT does not Granger-cause ERP	383	0.2338	0.7916
ERP does not Granger-cause SENT		1.4996	0.2245
Average gRV does not Granger-cause ERP	383	19.6327	0.0000
ERP does not Granger-cause Average gRV		0.3554	0.7011
Average gRV does not Granger-cause SENT	383	2.4460	0.0880
SENT does not Granger-cause Average gRV		0.3461	0.7077

Table 4.20: Granger causality results: US – incl. the short-run volatility component.
The number of lags in the test regressions was chosen by the Schwarz information criterion. The F-statistics are Wald statistics of the pairwise test. Average gRV denotes the short-run volatility component. The ending RV means that the volatility component is estimated using the RV-GARCH-MIDAS specification with rolling window. The values of g used here are the averages of daily values of g over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the S&P500. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's, the average first-day return of IPO's and the market turnover. All data were downloaded at monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to a monthly frequency through a cubic spline interpolation. The observation period ranges from March 1983 to March 2015.

In the US, Granger-causality runs from long-run volatility tau to DP but not the other way, a result which also holds for the tau-ERP relationship. In contrast, there is no causality between tau and sentiment. Table 4.21 suggests that illiquidity is not Granger-caused by long-run volatility and vice versa that long-run volatility is not Granger-caused by illiquidity.

The DP Granger-causes tau if PC1 is used to estimate tau, and the results suggest a causality from ERP to the long-run volatility component.

Null Hypothesis:	Obs.	F-Statistic	Prob.
MILLclean does not Granger-cause Dividend yield	383	1.0040	0.3674
Dividend yield does not Granger-cause MILLclean		9.4489	0.0001
ERP does not Granger-cause Dividend yield	383	1.0270	0.3591
Dividend yield does not Granger-cause ERP		27.7077	0.0000
SENT does not Granger-cause Dividend yield	383	0.5649	0.5689
Dividend yield does not Granger-cause SENT		2.2997	0.1017
Average tauRV does not Granger-cause Dividend yield	383	8.5263	0.0002
Dividend yield does not Granger-cause Average tauRV		1.7902	0.1683
ERP does not Granger-cause MILLclean	383	6.8493	0.0012
MILLclean does not Granger-cause ERP		0.2523	0.7772
SENT does not Granger-cause MILLclean	383	0.1282	0.8797
MILLclean does not Granger-cause SENT		0.1438	0.8661
Average tauRV does not Granger-cause MILLclean	383	2.2211	0.1099
MILLclean does not Granger-cause Average tauRV		0.4446	0.6414
SENT does not Granger-cause ERP	383	0.2338	0.7916
ERP does not Granger-cause SENT		1.4996	0.2245
Average tauRV does not Granger-cause ERP	383	4.8021	0.0087
ERP does not Granger-cause Average tauRV		1.9493	0.1438
Average tauRV does not Granger-cause SENT	383	1.3325	0.2650
SENT does not Granger-cause Average tauRV		0.4332	0.6488

Table 4.21: Granger-causality results: US – incl. the long-run volatility component.
The number of lags in the test regressions was chosen by the Schwarz information criterion. The F-statistics are Wald statistics of the pairwise test. Average tauRV denotes the long-run volatility component. The ending RV means that the volatility component is estimated using the RV-GARCH-MIDAS specification with rolling window. The values of tau used here are the averages of daily values of tau over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the S&P500. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's, the average first-day return of IPO's and the market turnover. All data were downloaded at monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to a monthly frequency through a cubic spline interpolation. The observation period ranges from March 1983 to March 2015.

4.7 Conclusion

This chapter compares the realised volatility between four developed countries over a historical period and finds a significant difference between the volatility levels. These findings are the motivation to examine the sources of volatility, and it is reasonable to relate volatility to the macroeconomy as previous papers suggest that macroeconomic data can explain time-varying stock market volatility (Schwert, 1989) and the countercyclical pattern of volatility (Corradi et al., 2013). The GARCH-MIDAS model allows distinguishing between a short-run and a long-run volatility component and link macroeconomic variables to long-run volatility through a filtering process. The outcomes of the GARCH-MIDAS models suggest that indeed the stock market volatility is related to macroeconomic variables and that this relationship differs between the countries in sign and significance. The GARCH-MIDAS results seem plausible and indicate to a different structure of the economy in those countries. However, the variance ratios used to gauge the proportion of expected volatility explained by economic variables point out that their contribution to expected volatility is weak in terms of PC1. The realised volatility itself contributes remarkably to conditional variance explaining over 50% of its variation in Canada over the full sample period and even 64.9% in the 2000's whereas relatively little variation in conditional variance is attributable to RV in the US stock market. The long-run volatility component does not follow the peaks in total market variance, and it is interpreted that the short-run volatility component may capture this fact. The Granger-causality results show that the causation runs mostly from the short-run volatility component to other variables instead of the other direction. This result also holds largely for the long-run component. It is, therefore, reasonable to argue that volatility Granger-causes other variables rather than the other way around.

Overall, the results suggest little effect of macroeconomic variables on conditional volatility compared with the benchmark model. This is consistent with those in Paye (2012), and it is reasonable to argue that RV already contains plenty of information on business conditions. Nevertheless, the findings here need to be qualified in several aspects.

First, the analysis is based on historical data. One could easily include expectations related to macroeconomic conditions in the future and employ a so-called two-sided filter where volatility also depends on future macroeconomic conditions. Second, the countries are considered in isolation using national data in the methodology without considering global or regional specific common factors which may drive national stock markets. Such an analysis was not conducted here and is left for future research.

Chapter 5 Conclusion

Financial systems tend to create financial boom-bust cycles, which can take on such dimensions that they contribute or even cause financial crises and recessions. Turbulences in the financial system and the damage to the provision of credit intermediation and payment services have severe effects on the real economy as it was witnessed in the recent financial crisis, which is one example that demonstrates the significant role of financial stability for modern economies to generate growth and economic welfare. The Global Financial Stability Map (henceforth Map) was introduced to account for the importance of financial stability and the different categories of underlying factors that may reinforce each other. The Map can be altered by adding further categories.

This thesis argued that asset price bubbles are a potential source of risk for financial stability, which materialises when the crisis breaks out. Motivated by the work of Brunnermeier et al. (2017), stock market bubbles were considered as a source of financial instability. There are three issues of interest in this thesis. First, it examines whether longer periods of low volatility influence the formation of bubbles, defined as the difference between actual prices and an average and whether stock market bubbles increase the likelihood of crashes in the stock market. Bubbles are then incorporated to inflate VaR to generate a countercyclical capital buffer against extreme events. The second issue of interest is the contribution of economic sectors to the stability of the financial system and to rank the sectors in accordance with their contribution to systemic risk. In this connection, policy tools that deflate bubbles in asset prices and alleviate economic crises are discussed. Finally, macroeconomic variables are linked directly with volatility to explain the extent to which the conditional stock market volatility can be explained by them. For this purpose, a two volatility component GARCH-MIDAS model is employed and the results are discussed for four developed countries.

The analysis conducted in chapter 2 and chapter 3 is based on the concept of VaR, which is criticised in the literature for not being coherent as VaR lacks the subadditivity property. The non-coherence of VaR led to the introduction of the expected shortfall (ES) as an alternative to VaR. ES is subadditive and accounts for the average size of losses beyond the threshold. However, it takes more computational effort to estimate ES, and backtesting ES is more difficult than VaR. Therefore, VaR was regarded in this work to be more workable than ES. VaR represents the minimum loss which is lost with a probability of α%. The true expected loss, however, rather lies somewhere between the minimum loss and the maximum loss. Keeping this argument in mind, the BubbleVaR approach (BuVaR) makes the expected loss dependent on the price level, which provides information on the business cycle that is not taken into consideration by VaR (Wong, 2013).

Chapter 2 employed a logistic regression to test whether a bubble increases the likelihood of a stock market crash. The logistic regression is run at a monthly frequency and includes a dichotomous dependent variable and several lagged independent variables, including the bubble, realised volatility and macroeconomic state variables over the post-World War II era. The logistic regression returns no significant coefficient for the realised volatility but the bubble. One noteworthy result is that the bubble-crash relationship holds only in the short-run, i.e. around 12 lagged months. Chapter 2 uses the term volatility paradox to describe the phenomenon confirmed by the linear regression that longer periods of low realised volatility significantly affect the formation of stock market bubbles and that bubbles increase the crash risk in stock markets. Hence, volatility, bubbles and crashes in the stock market are significantly related. Bubbles significantly increase the likelihood of stock market crash and the influence of volatility on bubble formation grows larger with the length of the backward-looking period. The results further suggest the advantage of including bubbles to inflate tail risk measures. The inflated VaR measure, BuVaR, covers most of the extreme returns which exceed VaR. Against this background, bubbles should be taken into account in measuring risk, and BuVaR is one step into this direction. However, BuVaR sometimes overestimated the magnitude of negative returns. Therefore, further research should focus on incorporating bubbles into measuring risk to achieve better backtesting results.

As shown in chapter 2, asset prices that evolve explosively due to euphoric investors and econometric methods were used to detect explosive asset price bubbles. In so doing, chapter 2 employed an AR(1) regression to the seasonally adjusted S&P500 price level using a rolling window of 36, 48 and 60 months, and it was shown that AR(1) coefficients above 1.0 well indicate bubble periods. Furthermore, it was argued that AR(1) coefficients provide useful information about the explosive behaviour during bubble periods and their lengths. The results suggest that bubbles tend to deflate over time rather than burst suddenly. Hence, considering the structure of bubbles provides information about the bubble stage that could help improve the predictive power and accuracy of risk measures.

The experience made in the recent financial crisis that bubble bursts in relatively small markets can jeopardise financial stability to such an extent that it hampers the real economy was the motivation of chapter 3, which investigates real economy effects on systemic risk by measuring the marginal contribution of a sector to entire systemic risk. To this end, ΔCoVaR was estimated, which is defined as the difference between CoVaR conditional on an awkwardly situated sector and the CoVaR when a sector is in the normal state. The ΔCoVaR was estimated through quantile regressions using daily data of the dependent and independent variables where the sectors were classified following the 10 industries of the Industry Classification Benchmark (ICB). The ΔCoVaR approach was complemented by a bootstrapped Kolmogorov-Smirnov test to check for statistical significance and statistical dominance. The ΔCoVaRs of the 10 economic sectors of Germany, the UK, and the US, respectively are tested for statistical dominance to rank the sectors according to their contribution to systemic risk. Real economy sectors significantly influence systemic risk, and the influence of sectors differs between the countries and the state of the economy. The results presented in chapter 3 are in line with those of Adrian and Brunnermeier (2016) who find that there is no one-to-one relationship between VaR and ΔCoVaR. This finding was interpreted that sectors have significant externalities on the system, which are not captured by VaR. The pooled OLS regression results support the findings that VaR plays a minor role in explaining ΔCoVaR. The results even suggest that VaR is an insignificant driver of ΔCoVaR with respect to the dominant sectors. As shown in chapter 3, the less dominant sectors in terms of sector dominance are significantly influenced by VaR and their corresponding ΔCoVaR seems to be much more related to their VaR. On the contrary, the most dominant sectors appear to be more dependent on financial conditions and are hence more vulnerable to financial crises than the less dominant sectors. The procyclicality and the evolution of risk over time is the consequence of excessive lending and risk-taking behaviour during booms and the overreaction and deleveraging behaviour during recessions. Countercyclical tools that reduce the risk-taking behaviour and the build-up of asset price bubbles can successfully attenuate financial crises. Macroprudential policy instruments can be applied directly to those sectors where bubbles build up and are more focused than monetary policy tools. The most important macroprudential policy tools of this category are countercyclical capital and liquidity buffers. Hence, the suggested application of an inflator to VaR as demonstrated in chapter 2, which protects stock market participants against events in the fat-tail and reacts early on upward price movements raises the capital buffer in a countercyclical manner and prevents the build-up of bubbles (Brunnermeier and Schnabel (2016), Tumpel-Gugerell, 2011). Nevertheless, as discussed in chapter 3, ex-post policies are also important to maintain the confidence in the financial system and avoid an economic collapse. The recent financial crisis provided the evidence that higher lending and a reduction of interest rates soften the negative impacts on the real economy but are very costly.

Motivated by the broad range of research on volatility in financial markets, chapter 4 compares differences in realised volatility between developed countries over time. The historical volatility of the examined countries depicts a fairly similar pattern, and they have in common that after peaks in volatility, volatility declines to moderate levels and gradually approach to their pre-peak levels. As we saw in chapter 4, the levels of realised volatility are different between the countries and the pairwise t-test employed confirms that this observed difference is statistically significant. Against this background, we saw how conditional volatility could be decomposed in a short-run and a long-run volatility component using the GARCH-MIDAS framework. Chapter 4 further demonstrated how long-run volatility can be directly linked with realised volatility and macroeconomic variables using the GARCH-MIDAS framework. The GARCH-MIDAS model is employed in an international setting, and the results suggest a relationship between macroeconomic variables and stock market volatility, which differs in sign and significance between Germany, Canada, the UK and the US. Hence, it is interpreted that due to the country's economic structure, the stock market volatility depends on the different macroeconomic variables. However, measuring the fraction of expected volatility explained by individual economic variables and in terms of PC1 points out a marginal contribution of economic variables to expected volatility. The comparison of the GARCH-MIDAS model including macroeconomic variables and the realised volatility respectively indicates little effect of macroeconomic variables on conditional volatility, whereas the realised volatility contributes considerably to conditional volatility explaining more than 50% of the conditional volatility in Canada.

The short-run and long-run volatility components are included in two VAR systems separately along with macroeconomic variables as well as firm- and financial market-specific variables. The reported Granger-causality tests reveal the direction of the causality between two variables and indicate that volatility Granger-causes other variables instead of the other direction. As a consequence, it appears reasonable to argue that other variables are Granger-caused by volatility.

This thesis deviates from previous publications such as Brunnermeier (2008) or Jordà et al. (2015), which define bubbles as asset price deviations from their fundamental value, and it defines the bubble as price increase that violates the price trend and cannot be classified as noise. Thus, the bubble is determined as the deviation of the asset price from some long-term average.

However, this definition does not take into account the role of credit making bubbles more dangerous than unleveraged bubbles. Hence, Jordà et al. (2015) propose to distinguish unleveraged bubbles purely driven by irrational exuberance and bubbles driven by a boom in credit referred to as credit boom bubbles (henceforth leveraged bubbles) which can have serious economic consequences (Jordà et al., 2015). Brunnermeier et al. (2017) also consider bubble characteristics and examine how systemic risk is affected by the size and length of asset price bubbles. More sizeable and longer lasting bubble episodes have a higher effect on systemic risk. On the contrary, systemic risk decreases when the bubble declines over a longer period and the degree of previous deflation is higher. The different development of bubbles, therefore, provides useful information regarding the effects of asset price bubbles on systemic risk (Brunnermeier et al., 2017).

The findings of Brunnermeier et al. (2017) call for alternative measures of bubbles, which account for the bubble size and the length of a bubble simultaneously making up a kind of severity index like the one proposed by Contessi and Kerdnunvong (2015) who build on periods of explosive behaviour to construct an index of exuberance. The exuberance index is the sum of the size (defined as the percentage increase of the price index value between the start of the explosive behaviour period and the highest peak within this episode of explosive behaviour) and the duration (defined as the number of quarters the bubble period lasts, i.e. until the CAPE or CAPR levels approach the pre-bubble episode). It measures the severity of the episode of explosive behaviour (Contessi and Kerdnunvong, 2015).

This measure is a backward-looking combination of size and duration. As duration is measured as a number of quarters from the beginning until the end of explosive behaviour, it is dependent on realised data and is, therefore, an ex-post measure that seems not to measure the potential severity of a bubble during an explosive behaviour episode. Chapter 2 shows that AR(1) coefficients can be used as an alternative to time stamp the beginning and the end of bubble episodes. The length of the bubble is determined in this case by the number of AR(1) coefficients. In addition, the AR(1) coefficients indicate the stage of bubble development and indicate deflationary behaviour, which may have some effect on systemic risk in the sense of Brunnermeier et al. (2017). The combination of the components bubble size, length and the value of AR(1) appears to be an interesting starting point for the definition of an extended bubble metric, which conveys useful information for policymakers and investors. The construction of such a measure of bubbles, as well as its combination with the BuVaR approach, is an interesting area of future research.

Furthermore, the findings in chapter 2 were found for the US, and future research should extend the methodology of chapter 2 to several countries, i.e. developed and emerging countries alike, to see possible differences in the results as a consequence of the different levels of economic development, their economy and their financial markets. A comprehensive analysis of a broad range of countries on a global basis, for example, would cope with the Global Financial Stability Map (Map) looking at the global financial stability. That is, the inclusion of a global bubble indicator in the Map would add useful and more comprehensive information about the conditions affecting global financial stability. The discussion in this dissertation demonstrates the meaning of bubbles regarding systemic risk. It also asserts that bubbles in combination with a credit boom are more dangerous for the economy than unleveraged bubbles and combining a bubble indicator with the conditions of the Map is an interesting strand of future research.

Financial market volatility is subject to exogenous shocks from outside the system, i.e. exogenous risk, but Danielsson and Shin (2003) emphasised that most risk is generated endogenously, i.e. within the system, as a consequence of the amplification of exogenous events from fundamentals. If the volatility was unaffected by the actions of market participants, it could simply be modelled through the application of statistical models to past data. However, this assumption of exogenous is appropriate under normal conditions when markets are functioning smoothly. During market turmoil, constraints imposed by risk management systems set in leading to the same reaction of traders and endogenous risk. Thus, there are cases where endogeneity is an important component of price movements (Danielsson and Shin, 2003). Effective risk management requires to differentiate between situations where endogenous risk is important, and it is, therefore, a useful strand of future research to carry out the methodology discussed in the chapters above for different time periods by dividing the entire observation period into sub-periods in dependence of the market conditions. For example, during tranquil periods, the portion of the volatility explained by macroeconomic variables should be higher than in turbulent periods when the feedback effects in the system are much larger and reinforce the initial effect of bad news. Given the apparent difference in the importance of macroeconomic variables with respect to volatility, it would also be an interesting practice to examine whether the magnitude of endogeneity differs depending on the macroeconomic variable, i.e. whether some variables cause individuals to react more intensively than others.

Appendix A: Appendix to Chapter 2

A.1 Probit regression results

12-month lagged value with bubble			**24-month lagged value with bubble**		
	Dependent variable:			*Dependent variable:*	
	(1)	(2)		(1)	(2)
crash.t12	1.845^{***}	1.712^{***}	crash.t24	0.454	0.294
	(0.422)	(0.458)		(0.402)	(0.433)
bubble.t12	0.021^{**}	0.019^{**}	bubble.t24	0.018^{**}	0.018^{*}
	(0.009)	(0.009)		(0.009)	(0.009)
MP.t12		0.082	MP.t24		0.105
		(0.080)			(0.067)
UTS.t12		-0.229^{*}	UTS.t24		-0.103
		(0.127)			(0.117)
UPR.t12		0.023	UPR.t24		0.443
		(0.492)			(0.478)
PPI.t12		0.113	PPI.t24		0.156^{*}
		(0.140)			(0.094)
RV.t12	-0.038	-0.001	RV.t24	0.024	0.023
	(0.057)	(0.062)		(0.053)	(0.056)
Constant	-1.322^{***}	-1.227^{***}	Constant	-1.002^{***}	-1.344^{***}
	(0.332)	(0.390)		(0.319)	(0.425)
Observations	730	730	Observations	730	730
F-stat	7.047^{***}	4.831^{***}	F-stat	1.508	1.659
Chi2	21.144^{***}	33.819^{***}	Chi2	4.525	11.612
Note:		*p<0.1; **p<0.05; ***p<0.01	*Note:*		*p<0.1; **p<0.05; ***p<0.01

Table A.1: Probit regression results for 12-month and 24-month lagged variables.
The monthly bubble was estimated using the average of daily bubbles within the month. The crash represents a stock market crisis indicator, defined as cumulative decrease of at least 25% in real equity prices. Bubble is a price deviation from a benchmark level calculated using a rank filtering process. MP is the log growth rate of industrial production, defined as difference between the log industry production index in month t and month t-1. UTS is the term premium, defined as yield spread between the long-term and the one-year Treasury bonds. UPR is the default premium, defined as yield spread between Moody's Baa and Aaa corporate bonds. PPI is the log growth rate of producer price, defined as difference between the log producer price index in month t and month t-1. RV is the realised volatility, defined as log of the square root of the sum of squared daily stock index returns within a month. The endings 't12' and 't24' to the independent variables refer to 12-month and 24-month lagged observations, respectively. The independent variables were multiplied by 100 before the regression was run. The numbers in brackets are the robust standard errors clustered at the year level. The asterisks *** indicate the 1% significance level; ** indicates the 5% significance level and * indicates the 10% significance level. The observation period is from March 1950 to December 2010.

Marginal effects 12-month lagged values

	Dependent variable:	
	(1)	(2)
crash.t12	0.5935***	0.5395***
	(0.1099)	(0.1267)
bubble.t12	0.0053**	0.0044**
	(0.0022)	(0.0022)
MP.t12		0.0194
		(0.0201)
UTS.t12		-0.0541*
		(0.0286)
UPR.t12		0.0053
		(0.1168)
PPI.t12		0.0268
		(0.0343)
RV.t12	-0.0095	-0.0002
	(0.0137)	(0.0146)
Note:		*p<0.1; **p<0.05; ***p<0.01

Marginal effects 24-month lagged values

	Dependent variable:	
	(1)	(2)
crash.t24	0.1549	0.0959
	(0.1384)	(0.1445)
bubble.t24	0.0058**	0.0057**
	(0.0027)	(0.0028)
MP.t24		0.0329
		(0.0217)
UTS.t24		-0.0324
		(0.0367)
UPR.t24		0.1396
		(0.1506)
PPI.t24		0.0491
		(0.0300)
RV.t24	0.0078	0.0071
	(0.0172)	(0.0177)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A.2: Marginal effects for simple lagged variables probit regression.
The marginal effects are calculated as average partial effects of the variables. The monthly bubble was estimated using the average of daily bubbles within the month. The crash represents a stock market crisis indicator, defined as cumulative decrease of at least 25% in real equity prices. Bubble is a price deviation from a benchmark level calculated using a rank filtering process. MP is the log growth rate of industrial production, defined as difference between the log industry production index in month t and month t-1. UTS is the term premium, defined as yield spread between the long-term and the one-year Treasury bonds. UPR is the default premium, defined as yield spread between Moody's Baa and Aaa corporate bonds. PPI is the log growth rate of producer price, defined as difference between the log producer price index in month t and month t-1. RV is the realised volatility, defined as log of the square root of the sum of squared daily stock index returns within a month. The endings 't12' and 't24' to the independent variables refer to 12-month and 24-month lagged observations, respectively. The independent variables were multiplied by 100 before the regression was run. The numbers in brackets are the robust standard errors clustered at the year level. The asterisks *** indicate the 1% significance level; ** indicates the 5% significance level and * indicates the 10% significance level. The observation period is from March 1950 to December 2010.

Appendix B: Appendix to Chapter 3

B.1 Regression results for the UK

2.5%-quantile sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-0.7428	-0.2341	-0.0508	-0.1305	0.0251	-2.2429	-5.6082	-3.3041	-0.9772	-0.4901
	0.0551	*0.1665*	*0.6338*	*0.7290*	*0.9385*	*0.0003*	*0.0000*	*0.0007*	*0.0091*	*0.0149*
Volatility index	-0.0464	-0.0337	-0.0204	-0.0293	-0.0342	0.0021	0.0189	-0.0410	-0.0436	-0.0749
	0.0001	*0.0000*	*0.0000*	*0.0114*	*0.0006*	*0.9110*	*0.5375*	*0.1695*	*0.0002*	*0.0000*
Liquidity spread variation	-0.0520	-0.0021	-0.0356	-0.0873	-0.1096	0.0049	-0.0935	0.1447	0.0019	0.0097
	0.1436	*0.8910*	*0.0003*	*0.0118*	*0.0003*	*0.9321*	*0.3078*	*0.1049*	*0.9564*	*0.5969*
T-bill spread variation	0.0633	-0.0090	0.0139	-0.0398	-0.0279	0.0825	-0.0237	0.0296	-0.0255	0.0269
	0.1159	*0.6082*	*0.2100*	*0.3096*	*0.4104*	*0.2030*	*0.8195*	*0.7695*	*0.5122*	*0.1973*
Yield spread change	0.0766	-0.0069	0.0083	-0.0081	0.0298	0.0041	0.0157	-0.1154	-0.0652	0.0099
	0.0005	*0.4698*	*0.1674*	*0.7056*	*0.1057*	*0.9066*	*0.7813*	*0.0359*	*0.0021*	*0.3821*
Credit spread change	0.0250	-0.0390	-0.0096	-0.0309	0.0082	0.0292	0.1560	-0.0695	0.0046	0.0729
	0.5335	*0.0267*	*0.3878*	*0.4300*	*0.8083*	*0.6515*	*0.1332*	*0.4911*	*0.9064*	*0.0005*
Return FTSE	0.5602	0.3354	0.3995	0.2748	0.4210	0.6558	1.4852	1.2984	0.2127	0.2302
	0.0000	*0.0000*	*0.0000*	*0.0003*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0049*	*0.0000*
Return real estate	0.0568	0.6644	0.4409	0.2019	0.4741	0.0860	0.8012	-0.0797	0.2675	0.3719
	0.7596	*0.0000*	*0.0000*	*0.2642*	*0.0025*	*0.7735*	*0.0949*	*0.8643*	*0.1362*	*0.0001*

Table B.1: 2.5%-quantile regression results for the UK over the difficult period.

The daily market returns of the sectors are used as dependent variable in the linear quantile regression, which uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The difficult period ranges from 5th January 2000 to 30th April 2003. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

2.5%-quantile ex sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-0.3668	-0.4457	-0.5778	-0.2627	-0.1445	-0.2827	0.3470	0.2631	-0.3584	-0.4265
	0.2053	*0.1746*	*0.0547*	*0.3208*	*0.4222*	*0.2856*	*0.0966*	*0.1556*	*0.3313*	*0.2498*
Volatility index	-0.0151	-0.0135	-0.0082	-0.0267	-0.0183	-0.0230	-0.0487	-0.0401	-0.0231	-0.0216
	0.0893	*0.1802*	*0.3767*	*0.0010*	*0.0010*	*0.0047*	*0.0000*	*0.0000*	*0.0415*	*0.0576*
Liquidity spread variation	-0.0851	-0.0584	-0.0575	-0.0657	-0.0541	-0.0786	-0.0225	-0.0305	-0.0829	-0.0851
	0.0014	*0.0523*	*0.0376*	*0.0069*	*0.0011*	*0.0012*	*0.2381*	*0.0728*	*0.0145*	*0.0124*
T-bill spread variation	-0.0286	0.0074	-0.0458	0.0108	0.0090	-0.0164	0.0306	-0.0250	0.0136	0.0208
	0.3452	*0.8280*	*0.1443*	*0.6944*	*0.6284*	*0.5517*	*0.1553*	*0.1949*	*0.7217*	*0.5892*
Yield spread change	0.0164	0.0290	-0.0132	0.0253	0.0147	0.0236	0.0172	0.0013	0.0028	0.0229
	0.3081	*0.1064*	*0.4402*	*0.0807*	*0.1387*	*0.1060*	*0.1328*	*0.8970*	*0.8890*	*0.2623*
Credit spread change	-0.0359	0.0082	0.0107	-0.0289	-0.0256	-0.0295	-0.0271	0.0063	-0.0593	-0.0476
	0.2322	*0.8110*	*0.7322*	*0.2926*	*0.1721*	*0.2833*	*0.2093*	*0.7429*	*0.1221*	*0.2159*
Return real estate	0.6061	0.4396	-0.0685	0.6168	0.3336	0.6130	0.4307	0.4523	0.6766	0.8079
	0.0000	*0.0095*	*0.6664*	*0.0000*	*0.0002*	*0.0000*	*0.0000*	*0.0000*	*0.0001*	*0.0000*
Return sector i	0.2551	0.4946	1.2003	0.3184	0.4494	0.1288	0.0612	0.2093	0.1056	0.0321
	0.0000	*0.0000*	*0.0000*	*0.0001*	*0.0000*	*0.0023*	*0.0000*	*0.0000*	*0.1419*	*0.5974*

Table B.2: 2.5%-quantile ex sector index regression results for the UK over the difficult period.
The system returns, used as dependent variable in the linear quantile regression, are approximated by the ex sector index returns, which exclude the sector under examination. The regression uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The difficult period ranges from 5th January 2000 to 30th April 2003. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

50%-quantile sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	0.0801	0.1583	0.0994	0.0292	0.0343	-0.1198	-1.3457	-0.3415	0.0903	0.1475
	0.5980	*0.0703*	*0.0741*	*0.7637*	*0.6978*	*0.5781*	*0.0023*	*0.2556*	*0.5455*	*0.3701*
Volatility index	-0.0039	-0.0065	-0.0037	0.0001	-0.0014	0.0010	0.0331	0.0097	-0.0044	-0.0063
	0.4085	*0.0151*	*0.0293*	*0.9821*	*0.6134*	*0.8861*	*0.0144*	*0.2938*	*0.3418*	*0.2129*
Liquidity spread variation	0.0169	-0.0044	-0.0053	0.0015	-0.0004	0.0237	0.0499	-0.0001	0.0181	0.0118
	0.2266	*0.5802*	*0.2958*	*0.8677*	*0.9563*	*0.2307*	*0.2165*	*0.9975*	*0.1861*	*0.4361*
T-bill spread variation	0.0461	-0.0063	0.0092	0.0063	-0.0053	0.0074	-0.0012	0.0252	-0.0145	0.0017
	0.0036	*0.4887*	*0.1121*	*0.5329*	*0.5622*	*0.7413*	*0.9785*	*0.4211*	*0.3510*	*0.9191*
Yield spread change	0.0007	-0.0055	0.0061	0.0019	-0.0031	-0.0104	-0.0301	0.0116	-0.0038	-0.0019
	0.9396	*0.2695*	*0.0523*	*0.7362*	*0.5308*	*0.3948*	*0.2268*	*0.4945*	*0.6509*	*0.8395*
Credit spread change	-0.0246	-0.0430	-0.0177	0.0022	-0.0106	0.0251	-0.0183	-0.0576	0.0301	-0.0065
	0.1197	*0.0000*	*0.0023*	*0.8281*	*0.2487*	*0.2618*	*0.6886*	*0.0656*	*0.0526*	*0.7043*
Return FTSE	0.6331	0.2922	0.3584	0.3037	0.5125	0.7981	1.5096	1.0429	0.4412	0.7143
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return real estate	0.2231	0.4325	0.3827	0.4124	0.3271	0.1203	-0.2878	0.2925	0.0383	0.1609
	0.0023	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.2450*	*0.1733*	*0.0427*	*0.5929*	*0.0418*

Table B.3: 50%-quantile regression results for the UK over the difficult period.

The 50%-quantile represents the median state, and the daily market returns of the sectors are used as dependent variable in the linear quantile regression, which uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The difficult period ranges from 5th January 2000 to 30th April 2003. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

50%-quantile ex sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-0.0084	-0.1329	-0.1480	0.0430	-0.1127	0.0457	0.2360	0.0678	0.0719	-0.0110
	0.9236	*0.1061*	*0.0567*	*0.6750*	*0.0695*	*0.6130*	*0.0018*	*0.4072*	*0.4243*	*0.8940*
Volatility index	0.0000	0.0048	0.0035	-0.0027	0.0029	-0.0017	-0.0076	-0.0019	-0.0026	-0.0003
	0.9997	*0.0552*	*0.1469*	*0.3942*	*0.1256*	*0.5396*	*0.0011*	*0.4442*	*0.3473*	*0.8916*
Liquidity spread variation	-0.0133	-0.0060	0.0054	-0.0119	0.0032	-0.0124	-0.0094	-0.0060	-0.0144	-0.0108
	0.0960	*0.4254*	*0.4491*	*0.2057*	*0.5732*	*0.1353*	*0.1736*	*0.4244*	*0.0812*	*0.1519*
T-bill spread variation	0.0148	0.0153	-0.0010	0.0217	0.0222	0.0243	0.0238	0.0094	0.0206	0.0187
	0.1056	*0.0727*	*0.9054*	*0.0420*	*0.0006*	*0.0097*	*0.0023*	*0.2696*	*0.0276*	*0.0291*
Yield spread change	0.0224	0.0258	-0.0058	0.0264	0.0130	0.0236	0.0246	0.0134	0.0294	0.0179
	0.0000	*0.0000*	*0.1916*	*0.0000*	*0.0002*	*0.0000*	*0.0000*	*0.0033*	*0.0000*	*0.0001*
Credit spread change	-0.0204	0.0088	-0.0142	-0.0301	-0.0045	-0.0273	-0.0286	-0.0186	-0.0284	-0.0291
	0.0243	*0.3085*	*0.0785*	*0.0048*	*0.4826*	*0.0037*	*0.0003*	*0.0292*	*0.0025*	*0.0007*
Return real estate	0.5481	0.2655	0.0836	0.5486	0.2873	0.6847	0.6087	0.5239	0.7181	0.6542
	0.0000	*0.0000*	*0.0419*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return sector i	0.2713	0.6905	1.0355	0.3643	0.5742	0.1827	0.0927	0.1731	0.1459	0.1871
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*

Table B.4: 50%-quantile ex sector index regression results for the UK over the difficult period.
The 50%-quantile represents the median state and the system returns, used as dependent variables in the linear quantile regression, are approximated by the ex sector index returns, which exclude the sector under examination. The regression uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The difficult period ranges from 5th January 2000 to 30th April 2003. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

2.5%-quantile sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-0.9085	-0.3752	-0.0065	-0.3768	-0.9186	-0.6315	-1.7278	-0.3895	-1.5879	-1.1895
	0.2065	*0.0001*	*0.9184*	*0.2124*	*0.0000*	*0.0837*	*0.0029*	*0.5018*	*0.0044*	*0.0001*
Volatility index	-0.0664	-0.0279	-0.0284	-0.0288	0.0054	-0.0423	-0.0075	-0.1007	0.0142	-0.0005
	0.1483	*0.0000*	*0.0000*	*0.1359*	*0.7025*	*0.0695*	*0.8400*	*0.0066*	*0.6890*	*0.9775*
Liquidity spread variation	-0.0124	0.0155	0.0014	-0.0083	0.0110	-0.0382	-0.0315	0.0063	0.0280	-0.0323
	0.8182	*0.0267*	*0.7641*	*0.7145*	*0.5051*	*0.1616*	*0.4672*	*0.8846*	*0.5016*	*0.1459*
T-bill spread variation	0.0276	0.0414	0.0169	-0.0305	0.0184	0.0052	0.0395	0.0007	0.0189	-0.0634
	0.7727	*0.0009*	*0.0443*	*0.4471*	*0.5296*	*0.9145*	*0.6076*	*0.9927*	*0.7987*	*0.1085*
Yield spread change	-0.0285	-0.0075	0.0017	0.0002	-0.0129	0.0343	0.0249	-0.0377	-0.0077	-0.0183
	0.5280	*0.2002*	*0.6633*	*0.9922*	*0.3534*	*0.1350*	*0.4947*	*0.3011*	*0.8266*	*0.3269*
Credit spread change	-0.0130	-0.0463	-0.0106	-0.0369	-0.0062	0.0793	0.0675	-0.0162	0.0536	-0.0213
	0.9104	*0.0021*	*0.2975*	*0.4474*	*0.8610*	*0.1763*	*0.4687*	*0.8618*	*0.5496*	*0.6554*
Return FTSE	1.3873	0.6580	0.4960	0.6972	0.8088	0.8976	1.3760	1.1883	0.5739	1.1427
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0058*	*0.0000*
Return real estate	0.1896	0.2055	0.2862	0.1196	0.1259	-0.2283	-0.1404	0.0007	0.0934	0.0198
	0.3884	*0.0000*	*0.0000*	*0.1956*	*0.0620*	*0.0409*	*0.4282*	*0.9969*	*0.5832*	*0.8277*

Table B.5: 2.5%-quantile regression results for the UK over the calm period.

The daily market returns of the sectors are used as dependent variable in the linear quantile regression, which uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The calm period ranges from 1st May 2003 to 31st July 2007. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

2.5%-quantile ex sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	0.0367	-0.0375	-0.3319	0.1024	0.0253	-0.2437	0.0663	-0.0895	0.0106	-0.3224
	0.8314	*0.6947*	*0.0003*	*0.2878*	*0.8518*	*0.0817*	*0.5696*	*0.4885*	*0.9577*	*0.1786*
Volatility index	-0.0464	-0.0281	-0.0143	-0.0476	-0.0423	-0.0310	-0.0503	-0.0398	-0.0536	-0.0254
	0.0000	*0.0000*	*0.0138*	*0.0000*	*0.0000*	*0.0005*	*0.0000*	*0.0000*	*0.0000*	*0.0972*
Liquidity spread variation	0.0101	-0.0031	-0.0111	0.0081	0.0034	0.0150	0.0061	0.0096	0.0040	0.0160
	0.4349	*0.6615*	*0.1000*	*0.2625*	*0.7373*	*0.1537*	*0.4876*	*0.3210*	*0.7892*	*0.3705*
T-bill spread variation	0.0236	0.0070	0.0309	0.0444	0.0221	0.0062	0.0021	0.0172	0.0027	-0.0011
	0.2983	*0.5793*	*0.0105*	*0.0005*	*0.2200*	*0.7397*	*0.8948*	*0.3164*	*0.9189*	*0.9728*
Yield spread change	0.0045	0.0026	-0.0033	0.0072	0.0117	0.0155	-0.0028	0.0108	0.0244	0.0154
	0.6789	*0.6659*	*0.5657*	*0.2356*	*0.1676*	*0.0773*	*0.6985*	*0.1846*	*0.0511*	*0.3022*
Credit spread change	-0.0036	-0.0124	-0.0029	0.0102	-0.0385	-0.0224	-0.0138	-0.0189	-0.0057	-0.0201
	0.8976	*0.4200*	*0.8413*	*0.5111*	*0.0780*	*0.3206*	*0.4631*	*0.3638*	*0.8602*	*0.6013*
Return real estate	0.3803	0.1841	-0.0513	0.3274	0.3061	0.4530	0.4248	0.4338	0.5015	0.3822
	0.0000	*0.0000*	*0.1554*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return sector i	0.1643	0.5756	1.1054	0.3916	0.5041	0.2447	0.1798	0.1335	0.0380	0.2172
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.4825*	*0.0002*

Table B.6: 2.5%-quantile ex sector index regression results for the UK over the calm period.
The system returns, used as dependent variables in the linear quantile regression, are approximated by the ex sector index returns, which exclude the sector under examination. The regression uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The calm period ranges from 1st May 2003 to 31st July 2007. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

50%-quantile sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	0.2897	0.1202	0.1006	-0.0350	-0.1416	-0.0214	-0.1877	0.2315	0.2114	0.1654
	0.0094	*0.0995*	*0.0006*	*0.6592*	*0.0328*	*0.8339*	*0.1819*	*0.0497*	*0.0391*	*0.0701*
Volatility index	-0.0143	-0.0080	-0.0069	0.0024	0.0094	0.0005	0.0089	-0.0134	-0.0151	-0.0107
	0.0444	*0.0873*	*0.0002*	*0.6384*	*0.0271*	*0.9413*	*0.3208*	*0.0754*	*0.0214*	*0.0667*
Liquidity spread variation	-0.0138	0.0092	0.0028	0.0051	0.0068	-0.0006	-0.0013	-0.0024	-0.0001	0.0041
	0.0969	*0.0907*	*0.1988*	*0.3920*	*0.1701*	*0.9360*	*0.9003*	*0.7881*	*0.9859*	*0.5514*
T-bill spread variation	-0.0323	0.0126	0.0086	0.0098	0.0041	0.0119	0.0169	0.0256	-0.0255	-0.0165
	0.0293	*0.1926*	*0.0285*	*0.3537*	*0.6442*	*0.3813*	*0.3644*	*0.1028*	*0.0605*	*0.1747*
Yield spread change	0.0000	0.0023	0.0010	0.0001	0.0016	0.0006	-0.0003	-0.0006	-0.0163	-0.0090
	0.9987	*0.6206*	*0.6008*	*0.9833*	*0.6976*	*0.9311*	*0.9730*	*0.9359*	*0.0112*	*0.1148*
Credit spread change	0.0024	-0.0063	-0.0068	0.0000	-0.0059	0.0058	-0.0728	0.0198	0.0160	-0.0339
	0.8953	*0.5896*	*0.1490*	*0.9996*	*0.5767*	*0.7257*	*0.0013*	*0.2955*	*0.3316*	*0.0211*
Return FTSE	1.1863	0.5224	0.4401	0.5271	0.6829	0.7595	1.0505	0.8652	0.4828	0.9196
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return real estate	0.1681	0.2385	0.2766	0.2173	0.1607	-0.0580	-0.0553	0.1161	0.1684	0.0024
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0637*	*0.1980*	*0.0013*	*0.0000*	*0.9304*

Table B.7: 50%-quantile regression results for the UK over the calm period.

The 50%-quantile represents the median state, and the daily market returns of the sectors are used as dependent variables in the linear quantile regression, which uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The calm period ranges from 1st May 2003 to 31st July 2007. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

50%-quantile ex sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	0.0480	0.0676	0.0336	0.1758	0.2092	0.2096	0.1956	0.1453	0.0914	0.0674
	0.3399	*0.1155*	*0.5202*	*0.0010*	*0.0000*	*0.0006*	*0.0002*	*0.0076*	*0.1241*	*0.2714*
Volatility index	-0.0034	-0.0045	-0.0020	-0.0114	-0.0136	-0.0129	-0.0126	-0.0097	-0.0056	-0.0042
	0.2895	*0.1004*	*0.5555*	*0.0008*	*0.0000*	*0.0009*	*0.0002*	*0.0051*	*0.1366*	*0.2812*
Liquidity spread variation	0.0034	-0.0026	0.0044	-0.0001	-0.0006	0.0057	0.0031	0.0042	0.0039	0.0024
	0.3696	*0.4242*	*0.2601*	*0.9905*	*0.8730*	*0.2183*	*0.4369*	*0.3057*	*0.3843*	*0.6026*
T-bill spread variation	0.0278	0.0055	0.0022	0.0123	0.0129	0.0245	0.0174	0.0144	0.0280	0.0231
	0.0000	*0.3335*	*0.7475*	*0.0814*	*0.0392*	*0.0025*	*0.0144*	*0.0465*	*0.0004*	*0.0044*
Yield spread change	0.0050	0.0041	-0.0008	0.0078	0.0030	0.0062	0.0042	0.0082	0.0074	0.0081
	0.1132	*0.1236*	*0.8047*	*0.0201*	*0.3142*	*0.1041*	*0.2064*	*0.0169*	*0.0472*	*0.0353*
Credit spread change	-0.0180	-0.0078	-0.0047	-0.0082	-0.0142	-0.0241	-0.0129	-0.0157	-0.0360	0.0007
	0.0262	*0.2592*	*0.5774*	*0.3411*	*0.0612*	*0.0145*	*0.1325*	*0.0732*	*0.0002*	*0.9439*
Return real estate	0.3721	0.2040	-0.0564	0.3021	0.2637	0.4431	0.4324	0.3860	0.4546	0.4136
	0.0000	*0.0000*	*0.0066*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return sector i	0.1716	0.6115	1.0838	0.4418	0.4469	0.1710	0.1491	0.1929	0.1292	0.2258
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*

Table B.8: 50%-quantile ex sector index regression results for the UK over the calm period.
The 50%-quantile represents the median state, and the system returns, used as dependent variables in the linear quantile regression, are approximated by the ex sector index returns, which exclude the sector under examination. The regression uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The calm period ranges from 1st May 2003 to 31st July 2007. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

2.5%-quantile sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-2.0877	-0.2457	-0.3718	-0.9105	-1.5374	0.5653	-0.4432	-0.7236	0.2375	-1.7681
	0.0000	*0.3574*	*0.0002*	*0.0000*	*0.0022*	*0.0808*	*0.1199*	*0.0940*	*0.5734*	*0.0000*
Volatility index	-0.0482	-0.0377	-0.0124	-0.0127	-0.0114	-0.0754	-0.0534	-0.0519	-0.0861	-0.0056
	0.0010	*0.0000*	*0.0002*	*0.0574*	*0.4972*	*0.0000*	*0.0000*	*0.0004*	*0.0000*	*0.5851*
Liquidity spread variation	-0.0099	-0.0010	0.0019	-0.0154	-0.0056	-0.0095	-0.0343	-0.0933	-0.0439	-0.0498
	0.6200	*0.9325*	*0.6769*	*0.0934*	*0.8062*	*0.5247*	*0.0092*	*0.0000*	*0.0241*	*0.0004*
T-bill spread variation	-0.0276	0.0034	0.0403	-0.0319	0.0304	-0.0145	0.0348	0.0671	-0.0726	-0.0106
	0.4598	*0.8828*	*0.0000*	*0.0627*	*0.4798*	*0.6021*	*0.1562*	*0.0716*	*0.0463*	*0.6856*
Yield spread change	0.0106	-0.0041	0.0029	-0.0125	-0.0463	-0.0148	0.0137	0.0645	-0.0109	0.0172
	0.6416	*0.7708*	*0.5780*	*0.2302*	*0.0770*	*0.3830*	*0.3579*	*0.0045*	*0.6236*	*0.2811*
Credit spread change	-0.0516	-0.0124	-0.0106	-0.0059	-0.0200	0.0606	0.0046	0.0295	0.0616	-0.0334
	0.1719	*0.5924*	*0.2244*	*0.7336*	*0.6449*	*0.0316*	*0.8523*	*0.4319*	*0.0940*	*0.2082*
Return FTSE	1.6830	0.5772	0.4496	0.7202	0.5819	0.5378	0.7668	0.7130	0.3993	1.2792
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0002*	*0.0000*
Return real estate	-0.4253	0.0953	0.1950	-0.0214	0.2089	-0.0240	-0.0917	-0.0258	-0.0194	-0.3488
	0.0000	*0.0561*	*0.0000*	*0.5632*	*0.0252*	*0.6906*	*0.0849*	*0.7483*	*0.8056*	*0.0000*

Table B.9: 2.5%-quantile regression results for the UK over the crisis period.

The daily market returns of the sectors are used as dependent variable in the linear quantile regression, which uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The crisis period ranges from 1st August 2007 to 30th October 2009. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

2.5%-quantile ex sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-0.0928	-0.4532	-0.6608	-0.3843	-0.2525	-0.2798	-0.3345	0.0185	-0.2898	-1.2609
	0.6582	*0.0000*	*0.0507*	*0.2331*	*0.1664*	*0.5629*	*0.0472*	*0.9274*	*0.1263*	*0.0000*
Volatility index	-0.0336	-0.0121	-0.0181	-0.0285	-0.0305	-0.0399	-0.0306	-0.0403	-0.0355	0.0048
	0.0000	*0.0000*	*0.1103*	*0.0085*	*0.0000*	*0.0140*	*0.0000*	*0.0000*	*0.0000*	*0.4601*
Liquidity spread variation	-0.0200	-0.0070	-0.0255	-0.0009	-0.0359	-0.0043	-0.0273	0.0050	-0.0363	-0.0116
	0.0393	*0.0375*	*0.1022*	*0.9497*	*0.0000*	*0.8477*	*0.0005*	*0.5939*	*0.0000*	*0.1938*
T-bill spread variation	0.0140	0.0411	0.0136	0.0683	0.0102	0.0950	0.0098	0.0463	0.0441	0.0190
	0.4386	*0.0000*	*0.6401*	*0.0136*	*0.5159*	*0.0220*	*0.5017*	*0.0083*	*0.0073*	*0.2540*
Yield spread change	-0.0104	0.0032	0.0220	0.0218	0.0198	0.0358	0.0066	0.0230	0.0227	0.0042
	0.3392	*0.3921*	*0.2077*	*0.1918*	*0.0359*	*0.1494*	*0.4501*	*0.0283*	*0.0217*	*0.6767*
Credit spread change	-0.0269	-0.0059	-0.0172	-0.0267	-0.0380	-0.0149	-0.0122	0.0030	-0.0184	-0.0439
	0.1410	*0.3568*	*0.5604*	*0.3413*	*0.0171*	*0.7232*	*0.4038*	*0.8647*	*0.2656*	*0.0094*
Return real estate	0.2613	0.1158	-0.0091	0.1865	0.0819	0.2405	0.2103	0.2317	0.2637	0.3128
	0.0000	*0.0000*	*0.9057*	*0.0019*	*0.0207*	*0.0018*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return sector i	0.1906	0.6268	1.0188	0.4329	0.4456	0.3590	0.3592	0.3621	0.3185	0.3081
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0054*	*0.0000*	*0.0000*	*0.0000*	*0.0000*

Table B.10: 2.5%-quantile ex sector index regression results for the UK over the crisis period.
The system returns, used as dependent variables in the linear quantile regression, are approximated by the ex sector index returns, which exclude the sector under examination. The regression uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The crisis period ranges from 1st August 2007 to 30th October 2009. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

50%-quantile sector index returns										
	Basic Materials	Industrials	Financials	Consumer Goods	Consumer Services	Healthcare	Telecomm.	Technology	Utilities	Energy
Intercept	0.2958	0.0050	0.0146	-0.1067	-0.1486	0.1168	-0.1105	0.2187	0.1660	0.3036
	0.2318	*0.9570*	*0.7955*	*0.3822*	*0.1428*	*0.4627*	*0.5023*	*0.2971*	*0.2630*	*0.0600*
Volatility index	-0.0050	-0.0001	-0.0002	0.0022	0.0033	-0.0050	0.0053	-0.0028	-0.0058	-0.0077
	0.5486	*0.9732*	*0.9173*	*0.5925*	*0.3356*	*0.3503*	*0.3330*	*0.6855*	*0.2440*	*0.1552*
Liquidity spread variation	-0.0198	-0.0076	0.0010	-0.0039	-0.0057	0.0051	0.0074	-0.0143	0.0035	0.0024
	0.0829	*0.0779*	*0.7009*	*0.4919*	*0.2204*	*0.4910*	*0.3301*	*0.1391*	*0.6102*	*0.7506*
T-bill spread variation	0.0135	-0.0126	0.0054	-0.0176	-0.0143	-0.0218	0.0054	0.0041	0.0350	0.0077
	0.5254	*0.1169*	*0.2650*	*0.0952*	*0.1024*	*0.1122*	*0.7039*	*0.8218*	*0.0064*	*0.5789*
Yield spread change	0.0194	-0.0092	-0.0064	-0.0071	0.0007	-0.0059	0.0115	-0.0041	0.0262	-0.0021
	0.1351	*0.0590*	*0.0298*	*0.2658*	*0.9030*	*0.4823*	*0.1827*	*0.7064*	*0.0008*	*0.8069*
Credit spread change	-0.0105	-0.0052	-0.0114	-0.0022	-0.0004	-0.0165	-0.0020	-0.0217	0.0203	-0.0057
	0.6246	*0.5195*	*0.0196*	*0.8383*	*0.9684*	*0.2340*	*0.8919*	*0.2355*	*0.1171*	*0.6868*
Return FTSE	1.3863	0.6349	0.4823	0.5193	0.6656	0.5270	0.6128	0.6850	0.5742	1.1337
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return real estate	-0.1187	0.1608	0.1904	0.1192	0.2131	-0.0275	0.0238	0.1079	-0.0392	-0.1631
	0.0103	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.3551*	*0.4384*	*0.0060*	*0.1569*	*0.0000*

Table B.11: 50%-quantile regression results for the UK over the crisis period.

The 50%-quantile represents the median state, and the daily market returns of the sectors are used as dependent variables in the linear quantile regression, which uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The crisis period ranges from 1st August 2007 to 30th October 2009. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

50%-quantile ex sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	0.0062	0.0330	0.3016	0.1384	0.2001	0.0639	0.0209	0.1186	0.0885	0.0203
	0.9317	*0.7059*	*0.0020*	*0.3231*	*0.0056*	*0.5771*	*0.8564*	*0.2015*	*0.3343*	*0.8195*
Volatility index	-0.0003	-0.0005	-0.0091	-0.0028	-0.0054	-0.0003	0.0009	-0.0048	-0.0017	-0.0016
	0.8892	*0.8643*	*0.0056*	*0.5554*	*0.0252*	*0.9468*	*0.8160*	*0.1269*	*0.5775*	*0.5848*
Liquidity spread variation	-0.0010	0.0018	-0.0095	-0.0046	0.0028	-0.0072	-0.0086	0.0060	-0.0050	-0.0003
	0.7739	*0.6562*	*0.0337*	*0.4762*	*0.4061*	*0.1702*	*0.1054*	*0.1627*	*0.2402*	*0.9444*
T-bill spread variation	0.0174	0.0194	-0.0110	0.0251	0.0151	0.0313	0.0135	0.0162	0.0111	0.0157
	0.0052	*0.0096*	*0.1911*	*0.0371*	*0.0149*	*0.0015*	*0.1749*	*0.0437*	*0.1625*	*0.0402*
Yield spread change	0.0083	0.0076	0.0115	0.0133	0.0054	0.0200	0.0089	0.0145	0.0128	0.0045
	0.0276	*0.0913*	*0.0225*	*0.0669*	*0.1502*	*0.0007*	*0.1389*	*0.0026*	*0.0074*	*0.3315*
Credit spread change	-0.0090	-0.0098	0.0109	-0.0093	-0.0028	-0.0039	-0.0146	0.0004	-0.0170	-0.0094
	0.1520	*0.1978*	*0.1999*	*0.4481*	*0.6503*	*0.6935*	*0.1474*	*0.9575*	*0.0343*	*0.2252*
Return real estate	0.3148	0.0971	-0.0559	0.2514	0.1503	0.3424	0.3429	0.2512	0.3645	0.2798
	0.0000	*0.0000*	*0.0122*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return sector i	0.1838	0.6850	1.1945	0.5070	0.4924	0.3589	0.2703	0.3806	0.2593	0.3322
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*

Table B.12: 50%-quantile ex sector index regression results for the UK over the crisis period.

The 50%-quantile represents the median state, and the system returns, used as dependent variables in the linear quantile regression, are approximated by the ex sector index returns, which exclude the sector under examination. The regression uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The crisis period ranges from 1st August 2007 to 30th October 2009. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

2.5%-quantile sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-1.0975	-0.3522	-0.2279	-0.3124	-0.2136	-0.8752	-1.0091	-0.8886	-0.8217	-0.7634
	0.0532	*0.0160*	*0.0252*	*0.0046*	*0.5390*	*0.0004*	*0.0039*	*0.0504*	*0.0001*	*0.0016*
Volatility index	-0.0361	-0.0227	-0.0108	-0.0244	-0.0328	-0.0101	-0.0349	-0.0264	-0.0207	-0.0187
	0.1711	*0.0009*	*0.0231*	*0.0000*	*0.0425*	*0.3794*	*0.0318*	*0.2110*	*0.0369*	*0.0958*
Liquidity spread variation	0.0119	-0.0184	0.0063	0.0108	-0.0256	0.0192	-0.0871	-0.0019	0.0461	0.0408
	0.8531	*0.2641*	*0.5864*	*0.3839*	*0.5153*	*0.4898*	*0.0274*	*0.9704*	*0.0559*	*0.1357*
T-bill spread variation	-0.0728	-0.1170	-0.0063	-0.0602	-0.0374	-0.1921	-0.0337	-0.1984	0.0698	0.0295
	0.6960	*0.0148*	*0.8495*	*0.0962*	*0.7433*	*0.0176*	*0.7687*	*0.1829*	*0.3180*	*0.7102*
Yield spread change	-0.0313	-0.0030	-0.0044	-0.0114	-0.0196	0.0136	-0.0385	0.0174	0.0014	-0.0184
	0.3543	*0.7320*	*0.4653*	*0.0815*	*0.3439*	*0.3520*	*0.0638*	*0.5192*	*0.9118*	*0.2021*
Credit spread change	-0.0230	-0.0167	-0.0037	-0.0015	-0.0324	0.0185	-0.0489	0.0130	0.0153	-0.0103
	0.6493	*0.1987*	*0.6844*	*0.8768*	*0.2962*	*0.3979*	*0.1158*	*0.7478*	*0.4206*	*0.6326*
Return FTSE	1.4093	0.8305	0.4357	0.6166	0.6224	0.6045	1.0262	0.8059	0.5152	1.1952
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return real estate	-0.0930	0.0445	0.1944	0.0458	0.0698	0.0048	-0.3450	0.0430	0.0148	0.0274
	0.5882	*0.3145*	*0.0000*	*0.1698*	*0.5075*	*0.9491*	*0.0011*	*0.7543*	*0.8187*	*0.7079*

Table B.13: 2.5%-quantile regression results for the UK over the recovery period.
The daily market returns of the sectors are used as dependent variable in the linear quantile regression, which uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The recovery period ranges from 1st November 2009 to 31st December 2012. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

2.5%-quantile ex sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	0.2212	-0.2722	-0.2306	-0.2714	-0.6483	-0.6150	-0.2875	0.0067	-0.6450	-0.0543
	0.1573	*0.0001*	*0.2508*	*0.0076*	*0.0000*	*0.0005*	*0.2789*	*0.9576*	*0.0271*	*0.6538*
Volatility index	-0.0471	-0.0128	-0.0267	-0.0213	-0.0018	-0.0114	-0.0323	-0.0387	-0.0154	-0.0280
	0.0000	*0.0001*	*0.0043*	*0.0000*	*0.7142*	*0.1626*	*0.0090*	*0.0000*	*0.2545*	*0.0000*
Liquidity spread variation	0.0173	0.0184	0.0248	0.0261	0.0212	0.0266	0.0688	0.0103	0.0368	0.0230
	0.3290	*0.0215*	*0.2741*	*0.0228*	*0.0708*	*0.1776*	*0.0222*	*0.4681*	*0.2642*	*0.0934*
T-bill spread variation	-0.0193	0.0302	0.0267	0.0650	0.0069	0.0765	0.0942	0.0613	0.0828	0.0192
	0.7063	*0.1922*	*0.6826*	*0.0499*	*0.8388*	*0.1798*	*0.2769*	*0.1362*	*0.3838*	*0.6288*
Yield spread change	0.0011	0.0049	-0.0006	0.0234	0.0256	0.0256	0.0271	0.0056	0.0265	-0.0048
	0.9012	*0.2297*	*0.9562*	*0.0001*	*0.0000*	*0.0104*	*0.0708*	*0.4357*	*0.1100*	*0.4934*
Credit spread change	-0.0224	0.0088	-0.0078	0.0131	0.0057	-0.0124	0.0067	0.0080	-0.0030	-0.0164
	0.1076	*0.1632*	*0.6631*	*0.1482*	*0.5393*	*0.4256*	*0.7773*	*0.4765*	*0.9089*	*0.1300*
Return real estate	0.2535	0.1930	-0.0236	0.1903	0.2965	0.3127	0.3878	0.2473	0.4707	0.2086
	0.0000	*0.0000*	*0.7326*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return sector i	0.1822	0.6505	1.3126	0.6450	0.5064	0.4058	0.1662	0.3936	0.2554	0.3945
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0075*	*0.0000*	*0.0046*	*0.0000*

Table B.14: 2.5%-quantile ex sector index regression results for the UK over the recovery period.
The system returns, used as dependent variables in the linear quantile regression, are approximated by the ex sector index returns, which exclude the sector under examination. The regression uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The recovery period ranges from 1st November 2009 to 31st December 2012. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

50%-quantile sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-0.1462	0.1781	0.1403	0.0763	0.0654	0.0825	-0.0173	0.1798	0.0027	-0.1319
	0.2368	*0.0182*	*0.0002*	*0.2860*	*0.2343*	*0.3919*	*0.8938*	*0.0927*	*0.9802*	*0.1795*
Volatility index	0.0072	-0.0075	-0.0059	-0.0012	-0.0019	-0.0031	0.0031	-0.0064	0.0001	0.0051
	0.2087	*0.0327*	*0.0006*	*0.7135*	*0.4691*	*0.4876*	*0.6038*	*0.1989*	*0.9880*	*0.2676*
Liquidity spread variation	0.0025	-0.0035	-0.0004	-0.0010	-0.0097	-0.0074	-0.0139	-0.0310	-0.0057	-0.0080
	0.8585	*0.6806*	*0.9294*	*0.9058*	*0.1196*	*0.4980*	*0.3420*	*0.0106*	*0.6444*	*0.4711*
T-bill spread variation	0.0361	-0.0087	-0.0230	0.0143	-0.0315	-0.0204	-0.0194	0.0094	0.0175	0.0078
	0.3734	*0.7261*	*0.0589*	*0.5422*	*0.0814*	*0.5200*	*0.6484*	*0.7889*	*0.6265*	*0.8098*
Yield spread change	-0.0038	0.0016	0.0030	-0.0008	0.0037	-0.0108	-0.0014	-0.0056	0.0044	0.0005
	0.6056	*0.7293*	*0.1682*	*0.8573*	*0.2568*	*0.0612*	*0.8526*	*0.3765*	*0.5031*	*0.9281*
Credit spread change	0.0211	-0.0224	-0.0036	0.0030	-0.0065	-0.0062	-0.0050	-0.0252	0.0067	-0.0065
	0.0549	*0.0009*	*0.2725*	*0.6369*	*0.1834*	*0.4689*	*0.6623*	*0.0082*	*0.4893*	*0.4603*
Return FTSE	1.4878	0.7418	0.4744	0.6124	0.7074	0.5739	0.7033	0.6200	0.4983	1.1486
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return real estate	-0.0497	0.1035	0.1399	0.0791	0.0706	0.0504	-0.0245	0.2147	0.0519	-0.0004
	0.1846	*0.0000*	*0.0000*	*0.0003*	*0.0000*	*0.0849*	*0.5313*	*0.0000*	*0.1168*	*0.9894*

Table B.15: 50%-quantile regression results for the UK over the recovery period.

The 50%-quantile represents the median state, and the daily market returns of the sectors are used as dependent variables in the linear quantile regression, which uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The recovery period ranges from 1st November 2009 to 31st December 2012. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

50%-quantile ex sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	0.2506	-0.0148	-0.1056	0.0407	0.0181	0.1554	0.1712	0.0707	0.1803	0.1614
	0.0000	*0.7698*	*0.1693*	*0.5608*	*0.7436*	*0.0769*	*0.0489*	*0.3762*	*0.0665*	*0.0085*
Volatility index	-0.0106	0.0003	0.0060	-0.0021	0.0000	-0.0064	-0.0072	-0.0030	-0.0078	-0.0064
	0.0000	*0.9133*	*0.0926*	*0.5235*	*0.9984*	*0.1167*	*0.0768*	*0.4168*	*0.0893*	*0.0239*
Liquidity spread variation	-0.0092	0.0075	-0.0087	0.0128	0.0030	0.0051	0.0042	0.0160	0.0033	0.0028
	0.0725	*0.1905*	*0.3182*	*0.1056*	*0.6357*	*0.6054*	*0.6716*	*0.0762*	*0.7665*	*0.6839*
T-bill spread variation	-0.0003	0.0105	0.0582	0.0195	0.0196	0.0651	0.0580	0.0141	0.0606	-0.0009
	0.9843	*0.5229*	*0.0199*	*0.3949*	*0.2783*	*0.0233*	*0.0410*	*0.5892*	*0.0586*	*0.9653*
Yield spread change	0.0183	0.0090	0.0105	0.0219	0.0115	0.0296	0.0317	0.0222	0.0303	0.0076
	0.0000	*0.0023*	*0.0192*	*0.0000*	*0.0003*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0341*
Credit spread change	-0.0100	0.0079	0.0043	-0.0071	0.0049	-0.0097	-0.0072	-0.0025	-0.0102	-0.0107
	0.0131	*0.0808*	*0.5281*	*0.2567*	*0.3238*	*0.2166*	*0.3554*	*0.7296*	*0.2451*	*0.0501*
Return real estate	0.2636	0.1647	-0.0359	0.2254	0.2039	0.3068	0.3843	0.3019	0.4092	0.2094
	0.0000	*0.0000*	*0.1756*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return sector i	0.2261	0.6147	1.3825	0.6055	0.6361	0.4459	0.2470	0.3693	0.2477	0.4020
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*

Table B.16: 50%-quantile ex sector index regression results for the UK over the recovery period.
The 50%-quantile represents the median state, and the system returns, used as dependent variables in the linear quantile regression, are approximated by the ex sector index returns, which exclude the sector under examination. The regression uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The recovery period ranges from 1st November 2009 to 31st December 2012. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

B.2 Regression results for Germany

2.5%-quantile sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-1.5892	-1.4513	0.2547	-1.4383	-9.0583	-5.7429	-4.5942	-5.2827	-1.2695	-2.4401
	0.0000	*0.0000*	*0.0129*	*0.0359*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0212*
VDAX NEW	-0.0065	-0.0072	-0.0692	-0.1145	0.1085	0.0064	0.0117	-0.0027	-0.0079	-0.1136
	0.4311	*0.1032*	*0.0000*	*0.0000*	*0.0005*	*0.8475*	*0.4918*	*0.9184*	*0.1168*	*0.0005*
Liquidity spread variation	-0.0052	0.0109	-0.0037	0.0106	0.0261	0.0377	0.0143	0.0180	0.0073	0.0084
	0.3009	*0.0001*	*0.0549*	*0.4073*	*0.1674*	*0.0638*	*0.1655*	*0.2653*	*0.0172*	*0.6726*
T-bill spread variation	0.0138	0.0023	0.0175	0.1487	0.0253	0.0210	-0.0193	0.0208	-0.0066	0.0368
	0.6332	*0.8849*	*0.1151*	*0.0453*	*0.8165*	*0.8581*	*0.7467*	*0.8234*	*0.7085*	*0.7480*
Yield spread change	0.0116	0.0145	0.0091	0.1373	0.0475	0.0259	-0.0258	0.0027	0.0066	0.0257
	0.6636	*0.3084*	*0.3724*	*0.0439*	*0.6356*	*0.8107*	*0.6381*	*0.9751*	*0.6824*	*0.8068*
Credit spread change	-0.0191	-0.0014	0.0247	0.1280	-0.0532	-0.0004	-0.0609	0.0032	0.0288	-0.0622
	0.1874	*0.8539*	*0.0000*	*0.0006*	*0.3306*	*0.9943*	*0.0420*	*0.9447*	*0.0011*	*0.2784*
Return CDAX	0.2357	0.1946	0.2649	0.2134	0.5692	0.7974	1.2218	0.7434	0.1905	0.1198
	0.0000	*0.0000*	*0.0000*	*0.1186*	*0.0047*	*0.0002*	*0.0000*	*0.0000*	*0.0000*	*0.5702*
Return real estate	0.1458	0.5193	-0.1040	-1.1279	0.6818	1.6796	-0.5186	0.5459	0.5306	-0.8210
	0.4914	*0.0000*	*0.1997*	*0.0378*	*0.3931*	*0.0510*	*0.2351*	*0.4227*	*0.0000*	*0.3270*

Table B.17: 2.5%-quantile regression results Germany over the difficult period.
The daily market returns of the sectors are used as dependent variable in the linear quantile regression, which uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The real estate index values for Germany were taken from Bankhaus Ellwanger & Geiger at a weekly frequency and interpolated to a daily frequency before the daily index returns were calculated. The difficult period ranges from 8th November 1999 to 30th April 2003. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

2.5%-quantile ex sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-3.3117	-2.9203	-2.0609	-5.3905	-3.5065	-3.6640	-2.4674	-2.3904	-3.5689	-3.8505
	0.0000	*0.0010*	*0.0256*	*0.0000*	*0.0000*	*0.0000*	*0.0002*	*0.0025*	*0.0000*	*0.0000*
VDAX NEW	0.0033	-0.0040	-0.0561	0.0716	0.0135	0.0126	-0.0215	-0.0120	0.0099	0.0173
	0.8520	*0.8821*	*0.0485*	*0.0000*	*0.2977*	*0.3360*	*0.2957*	*0.6203*	*0.6655*	*0.3982*
Liquidity spread variation	-0.0043	0.0008	0.0096	-0.0107	-0.0035	0.0015	0.0057	-0.0079	-0.0033	-0.0108
	0.6878	*0.9600*	*0.5771*	*0.0415*	*0.6615*	*0.8505*	*0.6516*	*0.5906*	*0.8106*	*0.3868*
T-bill spread variation	0.0149	0.0225	0.1044	0.0454	0.0468	0.0555	0.0026	0.0724	0.0628	0.0586
	0.7992	*0.8076*	*0.2749*	*0.1137*	*0.2804*	*0.2048*	*0.9702*	*0.3746*	*0.4118*	*0.3935*
Yield spread change	0.0337	0.0337	0.1031	0.0527	0.0513	0.0593	0.0151	0.0725	0.0688	0.0705
	0.5293	*0.6891*	*0.2388*	*0.0444*	*0.1941*	*0.1385*	*0.8139*	*0.3297*	*0.3258*	*0.2613*
Credit spread change	-0.0013	0.0401	0.0420	-0.0317	0.0195	0.0034	0.0048	0.0102	0.0139	0.0004
	0.9660	*0.4028*	*0.4015*	*0.0365*	*0.3916*	*0.8838*	*0.8940*	*0.8119*	*0.7303*	*0.9908*
Return real estate	0.8154	0.7014	0.7340	1.3505	1.1031	0.8001	1.0493	0.7289	1.2128	1.0310
	0.0676	*0.3231*	*0.3174*	*0.0000*	*0.0009*	*0.0168*	*0.0457*	*0.2430*	*0.0382*	*0.0496*
Return sector i	0.6630	1.2350	0.5409	0.1006	0.0318	0.0321	0.2109	0.0171	0.1921	0.0285
	0.0005	*0.0003*	*0.0512*	*0.0192*	*0.3022*	*0.2790*	*0.0029*	*0.8267*	*0.5238*	*0.5332*

Table B.18: 2.5%-quantile ex sector index regression results Germany over the difficult period.
The system returns, used as dependent variables in the linear quantile regression, are approximated by the ex sector index returns, which exclude the sector under examination. The regression uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The real estate index values for Germany were taken from Bankhaus Ellwanger & Geiger at a weekly frequency and interpolated to a daily frequency before the daily index returns were calculated. The difficult period ranges from 8th November 1999 to 30th April 2003. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

50%-quantile sector index returns										
	Basic Materials	Industrials	Financials	Consumer Goods	Consumer Services	Healthcare	Telecomm.	Technology	Utilities	Energy
Intercept	0.0559	-0.0667	-0.0016	-0.0115	-0.7235	-0.6282	-0.9694	-1.2666	0.0910	0.0372
	0.4556	*0.3832*	*0.9767*	*0.8723*	*0.0001*	*0.0256*	*0.0000*	*0.0000*	*0.1380*	*0.8779*
VDAX NEW	-0.0031	0.0010	-0.0008	0.0001	0.0109	0.0069	0.0246	0.0252	-0.0031	-0.0088
	0.1775	*0.6815*	*0.6357*	*0.9764*	*0.0498*	*0.4231*	*0.0006*	*0.0017*	*0.1063*	*0.2397*
Liquidity spread variation	-0.0010	0.0018	0.0008	-0.0005	0.0102	0.0093	0.0027	0.0017	0.0003	0.0043
	0.4818	*0.2047*	*0.4421*	*0.6938*	*0.0026*	*0.0792*	*0.5391*	*0.7337*	*0.7700*	*0.3407*
T-bill spread variation	-0.0097	0.0056	-0.0027	0.0088	0.0079	-0.0078	-0.0373	-0.0285	-0.0121	-0.0354
	0.2320	*0.5032*	*0.6516*	*0.2564*	*0.6854*	*0.7991*	*0.1395*	*0.3120*	*0.0684*	*0.1775*
Yield spread change	-0.0114	0.0030	-0.0026	0.0109	-0.0162	0.0007	-0.0329	-0.0181	-0.0079	-0.0298
	0.1273	*0.6936*	*0.6241*	*0.1281*	*0.3664*	*0.9788*	*0.1557*	*0.4831*	*0.1937*	*0.2155*
Credit spread change	-0.0035	0.0036	-0.0020	0.0055	0.0052	0.0098	-0.0064	-0.0238	-0.0034	-0.0117
	0.3855	*0.3839*	*0.4927*	*0.1599*	*0.5914*	*0.5195*	*0.6133*	*0.0914*	*0.3026*	*0.3746*
Return CDAX	0.2209	0.2580	0.3204	0.1135	0.3744	0.7284	1.4175	0.7542	0.0895	0.3315
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return real estate	0.1129	0.2847	0.3053	0.1747	0.1960	0.3172	-0.8226	0.5941	0.0384	0.0829
	0.0574	*0.0000*	*0.0000*	*0.0022*	*0.1690*	*0.1544*	*0.0000*	*0.0040*	*0.4293*	*0.6657*

Table B.19: 50%-quantile regression results Germany over the difficult period.

The 50%-quantile represents the median state, and the daily market returns of the sectors are used as dependent variables in the linear quantile regression, which uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The real estate index values for Germany were taken from Bankhaus Ellwanger & Geiger at a weekly frequency and interpolated to a daily frequency before the daily index returns were calculated. The difficult period ranges from 8th November 1999 to 30th April 2003. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

50%-quantile ex sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-0.2453	-0.2949	-0.3102	-0.3744	-0.1649	-0.2867	-0.1161	-0.0995	-0.1867	-0.3440
	0.0551	*0.0070*	*0.0241*	*0.0052*	*0.1197*	*0.0134*	*0.4677*	*0.3267*	*0.1238*	*0.0020*
VDAX NEW	0.0034	0.0059	0.0051	0.0049	0.0040	0.0042	0.0002	0.0024	0.0009	0.0062
	0.3953	*0.0816*	*0.2271*	*0.2348*	*0.2249*	*0.2431*	*0.9657*	*0.4497*	*0.8026*	*0.0724*
Liquidity spread variation	0.0038	0.0003	0.0036	0.0031	-0.0025	0.0063	0.0041	0.0019	0.0011	0.0017
	0.1112	*0.8856*	*0.1672*	*0.2191*	*0.2075*	*0.0037*	*0.1735*	*0.3123*	*0.6267*	*0.4268*
T-bill spread variation	0.0548	0.0216	0.0256	0.0646	0.0373	0.0302	0.0285	0.0294	0.0599	0.0653
	0.0000	*0.0583*	*0.0721*	*0.0000*	*0.0007*	*0.0116*	*0.0890*	*0.0053*	*0.0000*	*0.0000*
Yield spread change	0.0452	0.0165	0.0196	0.0669	0.0468	0.0233	0.0213	0.0222	0.0504	0.0547
	0.0002	*0.1129*	*0.1322*	*0.0000*	*0.0000*	*0.0331*	*0.1651*	*0.0205*	*0.0000*	*0.0000*
Credit spread change	-0.0002	-0.0065	-0.0033	-0.0053	0.0036	-0.0061	0.0039	0.0051	-0.0059	0.0008
	0.9823	*0.2718*	*0.6580*	*0.4623*	*0.5370*	*0.3290*	*0.6535*	*0.3580*	*0.3694*	*0.8931*
Return real estate	0.4170	0.0219	0.3638	0.4912	0.6213	0.3955	0.5273	0.2295	0.3549	0.3721
	0.0000	*0.8028*	*0.0009*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0044*	*0.0002*	*0.0000*
Return sector i	0.3588	0.8404	0.4548	0.0459	0.1667	0.1109	0.1614	0.1116	0.3002	0.0748
	0.0000	*0.0000*	*0.0000*	*0.0259*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*

Table B.20: 50%-quantile ex sector index regression results Germany over the difficult period.
The 50%-quantile represents the median state, and the system returns, used as dependent variables in the linear quantile regression, are approximated by the ex sector index returns, which exclude the sector under examination. The regression uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The real estate index values for Germany were taken from Bankhaus Ellwanger & Geiger at a weekly frequency and interpolated to a daily frequency before the daily index returns were calculated. The difficult period ranges from 8th November 1999 to 30th April 2003. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

2.5%-quantile sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-0.7560	0.4369	1.7440	-4.8115	-0.9183	0.2351	-1.4871	-0.9638	-0.7627	-2.7122
	0.1320	*0.0002*	*0.0010*	*0.0000*	*0.0001*	*0.1349*	*0.0000*	*0.1193*	*0.1380*	*0.0081*
VDAX NEW	-0.1160	-0.0861	-0.2031	0.0607	-0.0205	-0.0896	-0.0186	-0.1444	-0.0290	-0.0570
	0.0000	*0.0000*	*0.0000*	*0.2308*	*0.0758*	*0.0000*	*0.2103*	*0.0000*	*0.2408*	*0.2464*
Liquidity spread variation	0.0537	0.0068	-0.0156	-0.1013	-0.0254	0.0072	-0.0032	0.0735	-0.0555	-0.0108
	0.0220	*0.2141*	*0.5259*	*0.0396*	*0.0239*	*0.3287*	*0.8227*	*0.0110*	*0.0208*	*0.8218*
T-bill spread variation	0.0919	0.0029	0.0380	-0.1375	0.0335	0.0186	-0.0178	-0.1223	-0.1539	0.0294
	0.3056	*0.8880*	*0.6876*	*0.4656*	*0.4356*	*0.5089*	*0.7463*	*0.2686*	*0.0942*	*0.8723*
Yield spread change	0.0207	0.0251	-0.0065	-0.0430	0.0093	0.0105	0.0064	-0.0157	-0.0616	0.0783
	0.6282	*0.0116*	*0.8843*	*0.6318*	*0.6494*	*0.4329*	*0.8088*	*0.7648*	*0.1590*	*0.3683*
Credit spread change	0.0061	0.0097	0.0087	0.0473	-0.0056	-0.0075	-0.0081	-0.0218	-0.0219	-0.0185
	0.7951	*0.0763*	*0.7259*	*0.3378*	*0.6190*	*0.3110*	*0.5753*	*0.4512*	*0.3636*	*0.6985*
Return S&P 500	0.2254	0.5352	0.3916	0.5257	0.5048	0.6534	0.8550	0.5091	0.3514	0.7823
	0.1033	*0.0000*	*0.0073*	*0.0706*	*0.0000*	*0.0000*	*0.0000*	*0.0029*	*0.0133*	*0.0056*
Return real estate	0.3162	0.2996	0.4879	1.1472	0.3913	0.2590	-0.2275	1.1683	0.1104	0.6178
	0.4044	*0.0007*	*0.2220*	*0.1500*	*0.0316*	*0.0295*	*0.3290*	*0.0126*	*0.7764*	*0.4246*

Table B.21: 2.5%-quantile regression results Germany over the calm period.

The daily market returns of the sectors are used as dependent variable in the linear quantile regression, which uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The real estate index values for Germany were taken from Bankhaus Ellwanger & Geiger at a weekly frequency and interpolated to a daily frequency before the daily index returns were calculated. The calm period ranges from 1st May 2003 to 31st July 2007. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

2.5%-quantile ex sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-1.0061	-1.7027	-1.5974	0.3006	-0.9168	-1.4105	-0.9315	-1.2354	-0.5138	-0.9827
	0.0027	*0.0075*	*0.0007*	*0.0424*	*0.0036*	*0.0383*	*0.2430*	*0.0047*	*0.2357*	*0.1937*
VDAX NEW	-0.0333	-0.0217	-0.0264	-0.0671	-0.0401	-0.0226	-0.0291	-0.0224	-0.0490	-0.0293
	0.0391	*0.4786*	*0.2466*	*0.0000*	*0.0080*	*0.4896*	*0.4487*	*0.2859*	*0.0189*	*0.4206*
Liquidity spread variation	-0.0197	-0.0042	0.0206	-0.0148	0.0043	0.0115	-0.0310	-0.0136	-0.0497	-0.0215
	0.2092	*0.8884*	*0.3510*	*0.0335*	*0.7685*	*0.7169*	*0.4062*	*0.5069*	*0.0143*	*0.5438*
T-bill spread variation	0.0377	-0.0799	0.0216	-0.0500	-0.0160	-0.0250	-0.0307	0.0191	-0.1269	-0.0127
	0.5287	*0.4822*	*0.7979*	*0.0591*	*0.7756*	*0.8371*	*0.8299*	*0.8067*	*0.1018*	*0.9254*
Yield spread change	0.0640	0.0408	0.0423	0.0314	0.0330	0.0428	0.0579	0.0540	0.0363	0.0542
	0.0213	*0.4437*	*0.2810*	*0.0109*	*0.2085*	*0.4506*	*0.3846*	*0.1374*	*0.3125*	*0.3883*
Credit spread change	0.0233	0.0210	0.0252	0.0063	0.0142	0.0187	0.0160	0.0207	0.0168	0.0162
	0.1378	*0.4805*	*0.2549*	*0.3663*	*0.3334*	*0.5574*	*0.6689*	*0.3117*	*0.4075*	*0.6482*
Return real estate	0.6483	0.8747	0.7788	0.3891	0.4944	0.6483	0.6545	0.4557	0.4272	0.6113
	0.0104	*0.0707*	*0.0295*	*0.0005*	*0.0384*	*0.2077*	*0.2754*	*0.1670*	*0.1901*	*0.2821*
Return sector i	0.2339	0.4240	0.2173	0.0792	0.3086	0.1554	0.0126	0.1659	0.2385	0.0114
	0.0015	*0.0448*	*0.0296*	*0.0001*	*0.0003*	*0.3206*	*0.9021*	*0.0056*	*0.0639*	*0.7832*

Table B.22: 2.5%-quantile ex sector index regression results Germany over the calm period.
The system returns, used as dependent variables in the linear quantile regression, are approximated by the ex sector index returns, which exclude the sector under examination. The regression uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg where the credit spread change was calculated based on data from Macrobond. The real estate index values for Germany were taken from Bankhaus Ellwanger & Geiger at a weekly frequency and interpolated to a daily frequency before the daily index returns were calculated. The calm period ranges from 1st May 2003 to 31st July 2007. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

50%-quantile sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	0.0915	-0.0405	0.0480	0.1303	-0.0333	0.1156	-0.1228	-0.1436	0.0497	0.4034
	0.3280	*0.5134*	*0.3885*	*0.0397*	*0.7262*	*0.2374*	*0.2777*	*0.3129*	*0.3099*	*0.0764*
VDAX NEW	-0.0043	0.0014	-0.0039	-0.0027	0.0045	-0.0110	-0.0009	-0.0051	-0.0019	-0.0181
	0.3443	*0.6497*	*0.1500*	*0.3700*	*0.3300*	*0.0192*	*0.8668*	*0.4595*	*0.4214*	*0.0990*
Liquidity spread variation	0.0031	0.0100	0.0042	-0.0103	-0.0011	0.0058	0.0074	0.0097	0.0003	-0.0087
	0.4722	*0.0006*	*0.1087*	*0.0005*	*0.8107*	*0.2039*	*0.1636*	*0.1455*	*0.8867*	*0.4105*
T-bill spread variation	-0.0071	-0.0014	0.0033	-0.0238	-0.0216	0.0079	0.0181	-0.0726	-0.0146	-0.0486
	0.6726	*0.8972*	*0.7428*	*0.0353*	*0.2045*	*0.6524*	*0.3703*	*0.0044*	*0.0955*	*0.2323*
Yield spread change	-0.0153	0.0014	-0.0035	0.0007	0.0014	-0.0024	0.0101	0.0004	-0.0082	0.0055
	0.0546	*0.7914*	*0.4550*	*0.8970*	*0.8585*	*0.7778*	*0.2966*	*0.9716*	*0.0498*	*0.7765*
Credit spread change	-0.0063	-0.0028	-0.0024	0.0025	-0.0042	-0.0087	-0.0018	0.0048	-0.0035	-0.0137
	0.1503	*0.3379*	*0.3649*	*0.3917*	*0.3505*	*0.0583*	*0.7353*	*0.4733*	*0.1266*	*0.1985*
Return S&P 500	0.3645	0.3333	0.4395	0.1919	0.3909	0.5758	0.6434	0.6057	0.1214	0.6202
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return real estate	0.0873	0.1712	0.1429	0.1263	0.2541	0.1572	-0.0687	0.2065	0.0097	0.3250
	0.2169	*0.0003*	*0.0007*	*0.0084*	*0.0004*	*0.0337*	*0.4220*	*0.0551*	*0.7921*	*0.0590*

Table B.23: 50%-quantile regression results Germany over the calm period.

The 50%-quantile represents the median state, and the daily market returns of the sectors are used as dependent variables in the linear quantile regression, which uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The real estate index values for Germany were taken from Bankhaus Ellwanger & Geiger at a weekly frequency and interpolated to a daily frequency before the daily index returns were calculated. The calm period ranges from 1st May 2003 to 31st July 2007. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

50%-quantile ex sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	0.2703	0.2022	0.1103	0.2676	0.2689	0.2084	0.2772	0.3622	0.3170	0.2750
	0.0055	*0.0102*	*0.2038*	*0.0003*	*0.0015*	*0.0142*	*0.0022*	*0.0000*	*0.0007*	*0.0041*
VDAX NEW	-0.0117	-0.0076	-0.0029	-0.0152	-0.0121	-0.0097	-0.0118	-0.0160	-0.0145	-0.0114
	0.0123	*0.0435*	*0.4959*	*0.0000*	*0.0031*	*0.0183*	*0.0067*	*0.0000*	*0.0014*	*0.0135*
Liquidity spread variation	-0.0012	-0.0031	-0.0016	0.0101	-0.0025	-0.0011	-0.0004	-0.0010	-0.0005	-0.0022
	0.7947	*0.4022*	*0.7000*	*0.0036*	*0.5267*	*0.7778*	*0.9203*	*0.7751*	*0.9014*	*0.6244*
T-bill spread variation	-0.0043	-0.0125	0.0007	-0.0097	-0.0075	-0.0066	-0.0021	-0.0034	-0.0064	-0.0120
	0.8051	*0.3736*	*0.9627*	*0.4616*	*0.6211*	*0.6624*	*0.8967*	*0.8030*	*0.7018*	*0.4827*
Yield spread change	0.0184	0.0170	0.0262	0.0196	0.0173	0.0138	0.0146	0.0146	0.0203	0.0205
	0.0222	*0.0097*	*0.0003*	*0.0014*	*0.0142*	*0.0512*	*0.0525*	*0.0217*	*0.0092*	*0.0097*
Credit spread change	0.0052	0.0062	0.0040	0.0011	0.0040	0.0023	0.0021	0.0011	0.0002	0.0042
	0.2577	*0.0926*	*0.3296*	*0.7527*	*0.3107*	*0.5650*	*0.6171*	*0.7533*	*0.9596*	*0.3449*
Return real estate	0.2638	0.2788	0.2336	0.3127	0.2208	0.2200	0.2803	0.2220	0.4262	0.2797
	0.0003	*0.0000*	*0.0004*	*0.0000*	*0.0006*	*0.0006*	*0.0000*	*0.0001*	*0.0000*	*0.0001*
Return sector i	0.0974	0.2799	0.1508	0.0138	0.1806	0.2262	0.1014	0.0542	0.1248	0.0330
	0.0000	*0.0000*	*0.0000*	*0.1711*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*

Table B.24: 50%-quantile ex sector index regression results Germany over the calm period.

The 50%-quantile represents the median state, and the system returns, used as dependent variables in the linear quantile regression, are approximated by the ex sector index returns, which exclude the sector under examination. The regression uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The real estate index values for Germany were taken from Bankhaus Ellwanger & Geiger at a weekly frequency and interpolated to a daily frequency before the daily index returns were calculated. The calm period ranges from 1st May 2003 to 31st July 2007. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

2.5%-quantile sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-0.9072	-0.2863	0.1610	-2.7828	-0.9631	-0.9147	-1.6519	-0.1783	-0.9466	-3.0097
	0.0000	*0.2065*	*0.4992*	*0.0029*	*0.0003*	*0.0494*	*0.0035*	*0.6220*	*0.0694*	*0.0092*
VDAX NEW	-0.0279	-0.0424	-0.0630	-0.1678	-0.0270	-0.0201	-0.0514	-0.0654	-0.0895	-0.0574
	0.0004	*0.0000*	*0.0000*	*0.0000*	*0.0085*	*0.2698*	*0.0199*	*0.0000*	*0.0000*	*0.2027*
Liquidity spread variation	-0.0006	0.0013	-0.0023	0.0164	-0.0028	-0.0017	0.0003	0.0040	0.0026	0.0003
	0.7007	*0.4496*	*0.2162*	*0.0244*	*0.1795*	*0.6421*	*0.9406*	*0.1593*	*0.5165*	*0.9720*
T-bill spread variation	0.0489	0.0374	0.0205	0.2585	0.0087	0.0181	0.0357	-0.0194	0.0192	-0.1255
	0.0136	*0.0968*	*0.3866*	*0.0053*	*0.7369*	*0.6951*	*0.5237*	*0.5889*	*0.7108*	*0.2728*
Yield spread change	0.0222	0.0197	0.0131	0.1581	-0.0302	0.0094	0.0222	-0.0273	0.0027	-0.1165
	0.1833	*0.2985*	*0.5128*	*0.0425*	*0.1678*	*0.8087*	*0.6383*	*0.3673*	*0.9511*	*0.2270*
Credit spread change	0.0194	0.0026	0.0154	-0.0554	-0.0283	-0.0213	-0.0312	-0.0097	-0.0450	0.0065
	0.0343	*0.8067*	*0.1610*	*0.1951*	*0.0186*	*0.3180*	*0.2273*	*0.5613*	*0.0602*	*0.9029*
Return CDAX	0.7409	0.4408	0.7133	-0.3816	0.4242	0.4836	0.6970	0.5249	-0.1166	1.5252
	0.0000	*0.0000*	*0.0000*	*0.0919*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.3575*	*0.0000*
Return real estate	0.1692	0.3938	0.0041	0.4016	0.1688	0.1445	-0.0373	0.4963	-0.2026	0.6605
	0.0494	*0.0001*	*0.9685*	*0.3173*	*0.1356*	*0.4717*	*0.8780*	*0.0016*	*0.3677*	*0.1844*

Table B.25: 2.5%-quantile regression results Germany over the crisis period.
The daily market returns of the sectors are used as dependent variable in the linear quantile regression, which uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The real estate index values for Germany were taken from Bankhaus Ellwanger & Geiger at a weekly frequency and interpolated to a daily frequency before the daily index returns were calculated. The crisis period ranges from 1st August 2007 to 30th October 2009. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

2.5%-quantile ex sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-0.5644	-1.2119	-1.2131	0.1207	-1.2403	-1.7263	-1.4306	-1.0969	-2.1373	-1.2401
	0.1973	*0.1267*	*0.0692*	*0.7922*	*0.0157*	*0.0000*	*0.0000*	*0.0601*	*0.0517*	*0.0076*
VDAX NEW	-0.0550	-0.0659	-0.0684	-0.0645	-0.0461	-0.0174	-0.0263	-0.0475	-0.0320	-0.0435
	0.0014	*0.0339*	*0.0089*	*0.0003*	*0.0215*	*0.0338*	*0.0000*	*0.0373*	*0.4552*	*0.0165*
Liquidity spread variation	-0.0042	-0.0031	0.0041	-0.0035	-0.0034	-0.0060	-0.0059	-0.0038	-0.0053	-0.0021
	0.2204	*0.6216*	*0.4367*	*0.3301*	*0.3936*	*0.0003*	*0.0000*	*0.4099*	*0.5399*	*0.5590*
T-bill spread variation	0.0656	0.1663	0.1260	0.1302	0.1548	0.2009	0.1495	0.1057	0.1703	0.1745
	0.1259	*0.0312*	*0.0450*	*0.0023*	*0.0016*	*0.0000*	*0.0000*	*0.0591*	*0.0944*	*0.0001*
Yield spread change	0.0865	0.2057	0.0894	0.1498	0.1532	0.1735	0.1908	0.1224	0.2332	0.1555
	0.0145	*0.0011*	*0.0830*	*0.0000*	*0.0001*	*0.0000*	*0.0000*	*0.0072*	*0.0046*	*0.0000*
Credit spread change	0.0259	0.0254	-0.0214	0.0276	0.0166	0.0314	0.0280	0.0078	0.0373	0.0255
	0.1977	*0.4867*	*0.4851*	*0.1903*	*0.4822*	*0.0011*	*0.0002*	*0.7712*	*0.4605*	*0.2315*
Return real estate	0.0520	-0.1274	-0.0800	0.2837	-0.1069	-0.2417	-0.1997	-0.2319	0.5167	0.0425
	0.7804	*0.7110*	*0.7730*	*0.1263*	*0.6253*	*0.0090*	*0.0037*	*0.3574*	*0.2438*	*0.8271*
Return sector i	0.4393	-0.0884	0.2264	0.0537	0.0786	0.3017	0.2072	0.1825	0.1531	0.0367
	0.0004	*0.7182*	*0.1002*	*0.2968*	*0.5906*	*0.0000*	*0.0000*	*0.2830*	*0.5058*	*0.4687*

Table B.26: 2.5%-quantile ex sector index regression results Germany over the crisis period.
The system returns, used as dependent variables in the linear quantile regression, are approximated by the ex sector index returns, which exclude the sector under examination. The regression uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The real estate index values for Germany were taken from Bankhaus Ellwanger & Geiger at a weekly frequency and interpolated to a daily frequency before the daily index returns were calculated. The crisis period ranges from 1st August 2007 to 30th October 2009. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

50%-quantile sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-0.1720	-0.0816	0.0594	-0.1342	0.0588	0.2622	-0.1943	-0.0901	0.0839	-0.0837
	0.2103	*0.3188*	*0.5408*	*0.1665*	*0.6260*	*0.0238*	*0.4595*	*0.3208*	*0.4495*	*0.7655*
VDAX NEW	0.0050	0.0008	-0.0025	0.0019	-0.0039	-0.0131	0.0030	0.0039	-0.0075	0.0015
	0.3475	*0.7960*	*0.5103*	*0.6175*	*0.4087*	*0.0040*	*0.7672*	*0.2710*	*0.0844*	*0.8908*
Liquidity spread variation	0.0006	0.0014	0.0001	0.0006	-0.0003	0.0014	0.0009	-0.0004	0.0020	0.0002
	0.5874	*0.0355*	*0.8582*	*0.4653*	*0.7928*	*0.1129*	*0.6532*	*0.6085*	*0.0228*	*0.9140*
T-bill spread variation	0.0155	0.0265	0.0162	0.0020	0.0130	0.0117	-0.0076	0.0254	-0.0077	0.0791
	0.2556	*0.0012*	*0.0930*	*0.8389*	*0.2788*	*0.3088*	*0.7696*	*0.0049*	*0.4844*	*0.0047*
Yield spread change	0.0057	0.0156	0.0158	0.0042	0.0083	0.0067	-0.0127	0.0033	-0.0134	0.0336
	0.6220	*0.0234*	*0.0531*	*0.6081*	*0.4103*	*0.4874*	*0.5646*	*0.6684*	*0.1488*	*0.1526*
Credit spread change	-0.0020	0.0070	0.0059	-0.0022	-0.0013	0.0011	-0.0103	-0.0003	-0.0041	-0.0114
	0.7532	*0.0640*	*0.1868*	*0.6294*	*0.8217*	*0.8386*	*0.3947*	*0.9402*	*0.4173*	*0.3747*
Return CDAX	0.6026	0.4871	0.4341	0.2748	0.3822	0.4486	0.7464	0.4332	0.0711	1.1820
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0086*	*0.0000*
Return real estate	0.0748	0.1392	0.1242	0.0680	0.1827	0.1402	0.1010	0.2062	0.0297	0.2080
	0.2068	*0.0001*	*0.0032*	*0.1046*	*0.0005*	*0.0052*	*0.3733*	*0.0000*	*0.5352*	*0.0864*

Table B.27: 50%-quantile regression results Germany over the crisis period.

The 50%-quantile represents the median state, and the daily market returns of the sectors are used as dependent variables in the linear quantile regression, which uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The real estate index values for Germany were taken from Bankhaus Ellwanger & Geiger at a weekly frequency and interpolated to a daily frequency before the daily index returns were calculated. The crisis period ranges from 1st August 2007 to 30th October 2009. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

50%-quantile ex sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	0.1925	0.0842	0.1163	0.1415	-0.0453	-0.0493	0.0820	0.0519	0.1518	-0.0664
	0.1134	*0.4595*	*0.4581*	*0.1810*	*0.7385*	*0.6376*	*0.5676*	*0.7028*	*0.4059*	*0.6155*
VDAX NEW	-0.0061	-0.0030	-0.0059	-0.0066	-0.0013	-0.0013	-0.0010	-0.0016	-0.0030	-0.0040
	0.2020	*0.5002*	*0.3399*	*0.1117*	*0.8095*	*0.7589*	*0.8595*	*0.7701*	*0.6712*	*0.4380*
Liquidity spread variation	0.0002	0.0010	0.0012	0.0009	0.0014	0.0006	-0.0001	0.0002	0.0007	0.0018
	0.8656	*0.2797*	*0.3239*	*0.2801*	*0.1815*	*0.4349*	*0.9060*	*0.8694*	*0.6219*	*0.0785*
T-bill spread variation	0.0153	0.0248	0.0500	0.0760	0.0505	0.0368	0.0677	0.0310	0.1243	0.0455
	0.1987	*0.0254*	*0.0008*	*0.0000*	*0.0001*	*0.0003*	*0.0000*	*0.0179*	*0.0000*	*0.0004*
Yield spread change	0.0164	0.0289	0.0417	0.0729	0.0433	0.0393	0.0581	0.0371	0.1192	0.0458
	0.0951	*0.0014*	*0.0006*	*0.0000*	*0.0001*	*0.0000*	*0.0000*	*0.0005*	*0.0000*	*0.0000*
Credit spread change	-0.0009	0.0010	-0.0045	-0.0013	-0.0004	-0.0031	0.0047	0.0045	0.0081	0.0020
	0.8691	*0.8548*	*0.5367*	*0.7864*	*0.9498*	*0.5207*	*0.4823*	*0.4752*	*0.3354*	*0.7488*
Return real estate	0.1543	0.1914	0.2453	0.4668	0.2344	0.1535	0.3452	0.2519	0.6602	0.2707
	0.0030	*0.0001*	*0.0002*	*0.0000*	*0.0001*	*0.0010*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return sector i	0.4320	0.4640	0.2793	0.0194	0.4128	0.4966	0.2042	0.4713	-0.0067	0.1284
	0.0000	*0.0000*	*0.0000*	*0.1029*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.8615*	*0.0000*

Table B.28: 50%-quantile ex sector index regression results Germany over the crisis period.

The 50%-quantile represents the median state, and the system returns, used as dependent variables in the linear quantile regression, are approximated by the ex sector index returns, which exclude the sector under examination. The regression uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The real estate index values for Germany were taken from Bankhaus Ellwanger & Geiger at a weekly frequency and interpolated to a daily frequency before the daily index returns were calculated. The crisis period ranges from 1st August 2007 to 30th October 2009. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

2.5%-quantile sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-0.7954	-0.2030	-0.6233	-4.5911	-0.5219	-0.7123	-1.6031	-0.5897	-2.1178	-2.2934
	0.0001	*0.3620*	*0.0002*	*0.0002*	*0.2014*	*0.0050*	*0.0001*	*0.0004*	*0.0018*	*0.0005*
VDAX NEW	-0.0485	-0.0517	-0.0204	0.1203	-0.0347	-0.0437	-0.0581	-0.0340	0.0509	-0.0009
	0.0000	*0.0000*	*0.0166*	*0.0570*	*0.1014*	*0.0009*	*0.0043*	*0.0001*	*0.1467*	*0.9794*
Liquidity spread variation	0.0036	0.0036	0.0004	-0.0516	0.0030	0.0047	0.0122	0.0015	-0.0198	-0.0182
	0.2244	*0.2624*	*0.8686*	*0.0034*	*0.6094*	*0.1947*	*0.0315*	*0.5184*	*0.0418*	*0.0546*
T-bill spread variation	-0.0011	-0.0161	0.0108	0.1492	-0.0161	-0.0638	0.0138	-0.0659	0.0787	0.0398
	0.9525	*0.4138*	*0.4599*	*0.1675*	*0.6561*	*0.0046*	*0.6913*	*0.0000*	*0.1894*	*0.4945*
Yield spread change	-0.0158	0.0012	-0.0005	0.1211	-0.0165	-0.0331	0.0052	-0.0572	0.0460	0.0459
	0.2506	*0.9376*	*0.9656*	*0.1368*	*0.5445*	*0.0509*	*0.8437*	*0.0000*	*0.3087*	*0.2956*
Credit spread change	0.0150	0.0027	-0.0058	0.0569	0.0034	-0.0020	-0.0022	-0.0147	0.0044	-0.0226
	0.0024	*0.6164*	*0.1391*	*0.0518*	*0.7302*	*0.7442*	*0.8155*	*0.0002*	*0.7866*	*0.1524*
Return CDAX	0.6531	0.4677	0.4847	-0.1482	0.5170	0.6529	0.4930	0.6489	0.0960	1.0768
	0.0000	*0.0000*	*0.0000*	*0.6430*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.5884*	*0.0000*
Return real estate	0.4849	0.3667	-0.0129	0.9483	0.4028	0.2590	0.0130	0.3785	-0.0963	-0.3986
	0.0011	*0.0225*	*0.9133*	*0.2806*	*0.1714*	*0.1565*	*0.9633*	*0.0016*	*0.8434*	*0.4004*

Table B.29: 2.5%-quantile regression results Germany over the recovery period.
The daily market returns of the sectors are used as dependent variable in the linear quantile regression, which uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The real estate index values for Germany were taken from Bankhaus Ellwanger & Geiger at a weekly frequency and interpolated to a daily frequency before the daily index returns were calculated. The recovery period ranges from 1st November 2009 to 9th August 2013. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

2.5%-quantile ex sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	-1.5724	-2.2535	-2.1925	-0.0609	-1.8386	-2.0903	-1.4572	-1.7362	-1.5067	-1.5468
	0.0000	*0.0000*	*0.0010*	*0.7618*	*0.0008*	*0.0000*	*0.0109*	*0.0020*	*0.0130*	*0.0012*
VDAX NEW	0.0243	0.0488	0.0447	-0.0649	0.0354	0.0321	0.0381	0.0511	0.0263	0.0349
	0.0350	*0.0447*	*0.1943*	*0.0000*	*0.2119*	*0.1919*	*0.1963*	*0.0774*	*0.4011*	*0.1561*
Liquidity spread variation	-0.0186	-0.0235	-0.0179	0.0046	-0.0183	-0.0153	-0.0223	-0.0235	-0.0212	-0.0211
	0.0000	*0.0005*	*0.0610*	*0.1092*	*0.0204*	*0.0249*	*0.0068*	*0.0036*	*0.0152*	*0.0021*
T-bill spread variation	-0.0027	0.0850	0.0016	0.0240	0.0099	0.0362	0.0369	0.0241	0.0528	0.0328
	0.8835	*0.0269*	*0.9769*	*0.1358*	*0.8240*	*0.3466*	*0.4322*	*0.5978*	*0.2757*	*0.3990*
Yield spread change	0.0037	0.0642	0.0120	0.0289	0.0124	0.0412	0.0202	0.0228	0.0444	0.0217
	0.7874	*0.0199*	*0.7687*	*0.0106*	*0.6984*	*0.1366*	*0.5487*	*0.4916*	*0.1923*	*0.4357*
Credit spread change	0.0131	0.0333	-0.0126	-0.0042	0.0133	0.0168	-0.0126	0.0140	-0.0109	-0.0006
	0.0150	*0.0031*	*0.4268*	*0.3829*	*0.3119*	*0.1407*	*0.3585*	*0.2979*	*0.4519*	*0.9567*
Return real estate	0.5663	0.2301	0.6616	0.6440	0.5108	0.6279	0.8682	0.5915	0.9922	0.9005
	0.0004	*0.4932*	*0.1625*	*0.0000*	*0.1957*	*0.0639*	*0.0318*	*0.1429*	*0.0195*	*0.0073*
Return sector i	0.3000	0.2755	0.2450	0.0364	0.4788	0.1836	0.1156	0.4136	-0.0085	0.0559
	0.0000	*0.0964*	*0.2867*	*0.1111*	*0.0119*	*0.2056*	*0.3622*	*0.0286*	*0.9503*	*0.4001*

Table B.30: 2.5%-quantile ex sector index regression results Germany over the recovery period.
The system returns, used as dependent variables in the linear quantile regression, are approximated by the ex sector index returns, which exclude the sector under examination. The regression uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The real estate index values for Germany were taken from Bankhaus Ellwanger & Geiger at weekly frequency and interpolated to daily frequency before the daily index returns were calculated. The recovery period ranges from 1st November 2009 to 9th August 2013. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

50%-quantile sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	0.0023	0.0519	0.0686	0.1546	0.1373	0.2029	-0.0306	0.0730	-0.0398	0.0588
	0.9778	*0.4719*	*0.2693*	*0.0027*	*0.0318*	*0.0289*	*0.7909*	*0.2998*	*0.6187*	*0.7762*
VDAX NEW	0.0033	-0.0056	-0.0111	-0.0070	-0.0054	-0.0057	-0.0003	-0.0030	-0.0045	-0.0150
	0.4385	*0.1336*	*0.0006*	*0.0083*	*0.1039*	*0.2325*	*0.9602*	*0.4155*	*0.2756*	*0.1620*
Liquidity spread variation	-0.0012	0.0009	0.0019	0.0003	0.0000	-0.0004	0.0008	0.0001	0.0018	0.0014
	0.3297	*0.3766*	*0.0322*	*0.6446*	*0.9734*	*0.7490*	*0.6364*	*0.9459*	*0.1271*	*0.6332*
T-bill spread variation	-0.0057	-0.0025	0.0193	-0.0076	-0.0053	-0.0168	0.0129	-0.0062	-0.0029	0.0171
	0.4340	*0.6964*	*0.0005*	*0.0963*	*0.3540*	*0.0410*	*0.2091*	*0.3210*	*0.6806*	*0.3502*
Yield spread change	0.0021	-0.0073	0.0128	-0.0071	-0.0062	-0.0124	-0.0033	-0.0021	0.0020	0.0131
	0.7030	*0.1317*	*0.0020*	*0.0399*	*0.1443*	*0.0453*	*0.6669*	*0.6532*	*0.7149*	*0.3448*
Credit spread change	0.0055	0.0012	0.0022	0.0002	-0.0010	-0.0009	-0.0055	0.0005	0.0005	-0.0069
	0.0055	*0.4741*	*0.1446*	*0.8520*	*0.5264*	*0.7032*	*0.0468*	*0.7694*	*0.7977*	*0.1624*
Return CDAX	0.6230	0.4266	0.4182	0.2397	0.4321	0.4666	0.5694	0.4360	0.1195	0.7623
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Return real estate	0.0641	0.1314	0.1587	-0.0167	0.1766	0.0542	0.0770	0.1767	-0.0371	-0.0001
	0.2799	*0.0117*	*0.0004*	*0.6530*	*0.0001*	*0.4172*	*0.3549*	*0.0005*	*0.5199*	*0.9995*

Table B.31: 50%-quantile regression results Germany over the recovery period.

The 50%-quantile represents the median state, and the daily market returns of the sectors are used as dependent variables in the linear quantile regression, which uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg, where the credit spread change was calculated based on data from Macrobond. The real estate index values for Germany were taken from Bankhaus Ellwanger & Geiger at a weekly frequency and interpolated to a daily frequency before the daily index returns were calculated. The recovery period ranges from 1st November 2009 to 9th August 2013. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

50%-quantile ex sector index returns										
	Basic Materials	**Industrials**	**Financials**	**Consumer Goods**	**Consumer Services**	**Healthcare**	**Telecomm.**	**Technology**	**Utilities**	**Energy**
Intercept	0.1642	0.1744	0.2338	0.2159	0.1728	0.1468	0.2653	0.0894	0.3649	0.1855
	0.0069	*0.0124*	*0.0006*	*0.0234*	*0.0044*	*0.0478*	*0.0004*	*0.2661*	*0.0001*	*0.0369*
VDAX NEW	-0.0132	-0.0078	-0.0110	-0.0153	-0.0086	-0.0094	-0.0113	-0.0067	-0.0246	-0.0082
	0.0000	*0.0311*	*0.0019*	*0.0019*	*0.0063*	*0.0145*	*0.0032*	*0.1070*	*0.0000*	*0.0739*
Liquidity spread variation	0.0019	0.0001	0.0007	0.0022	0.0003	0.0010	0.0002	0.0008	0.0026	0.0009
	0.0332	*0.9463*	*0.4581*	*0.1053*	*0.7069*	*0.3300*	*0.8630*	*0.5062*	*0.0533*	*0.4708*
T-bill spread variation	0.0166	0.0184	0.0110	0.0502	0.0176	0.0244	0.0256	0.0131	0.0471	0.0280
	0.0010	*0.0013*	*0.0572*	*0.0000*	*0.0004*	*0.0001*	*0.0000*	*0.0457*	*0.0000*	*0.0001*
Yield spread change	0.0115	0.0179	0.0094	0.0490	0.0179	0.0175	0.0259	0.0113	0.0444	0.0300
	0.0018	*0.0000*	*0.0244*	*0.0000*	*0.0000*	*0.0001*	*0.0000*	*0.0172*	*0.0000*	*0.0000*
Credit spread change	-0.0024	-0.0009	-0.0001	0.0022	0.0000	0.0011	0.0008	0.0011	-0.0006	0.0016
	0.1032	*0.6018*	*0.9695*	*0.3461*	*0.9790*	*0.5318*	*0.6646*	*0.5669*	*0.7982*	*0.4568*
Return real estate	0.0703	0.0449	0.0609	0.3858	0.0751	0.1051	0.1470	0.0327	0.1871	0.1364
	0.1036	*0.3671*	*0.2082*	*0.0000*	*0.0850*	*0.0462*	*0.0051*	*0.5728*	*0.0036*	*0.0289*
Return sector i	0.3427	0.4365	0.3692	0.0243	0.4580	0.4217	0.2320	0.4832	0.0608	0.1304
	0.0000	*0.0000*	*0.0000*	*0.0250*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0033*	*0.0000*

Table B.32: 50%-quantile ex sector index regression results Germany over the recovery period.
The 50%-quantile represents the median state, and the system returns, used as dependent variables in the linear quantile regression, are approximated by the ex sector index returns, which exclude the sector under examination. The regression uses the Barrodale and Roberts simplex algorithm as a fitting method. The second line of each variable represents the p-values, and the standard errors are assumed to be iid. The sectors follow the 10 industries of the Industry Classification Benchmark (ICB), and the variables are defined in Table 3.2. The variables are at a daily frequency and were taken from Bloomberg where the credit spread change was calculated based on data from Macrobond. The real estate index values for Germany were taken from Bankhaus Ellwanger & Geiger at a weekly frequency and interpolated to a daily frequency before the daily index returns were calculated. The recovery period ranges from 1st November 2009 to 9th August 2013. After each regression, the insignificant variables at the 10% level were excluded, and the regressions were run again until the regression results only returned significant coefficients. These coefficients were then used to estimate $\widehat{\Delta CoVaR}$.

B.3 Correlation matrix ΔCoVaR

Correlation *Probability*	ΔCoVaR	VaR	Volatility	Size	Leverage	ANFCI
ΔCoVaR	1.0000					

VaR	0.5360	1.0000				
	0.0000	-----				
Volatility	-0.6006	-0.6631	1.0000			
	0.0000	0.0000	-----			
Size	0.2874	0.2112	0.0203	1.0000		
	0.0000	0.0000	0.6378	-----		
Leverage	-0.0422	0.1981	0.0038	0.4234	1.0000	
	0.3277	0.0000	0.9293	0.0000	-----	
ANFCI	-0.3492	-0.1421	0.3889	0.0928	0.0064	1.0000
	0.0000	0.0009	0.0000	0.0310	0.8826	-----

Table B.33: Correlation matrix ΔCoVaR, all sectors.

The coefficients were calculated using the ordinary Pearson method. The second line displays the probability. The correlation matrix was estimated using quarterly variables. VaR is defined as the median of daily 2.5%- $\widehat{\text{VaRs}}$ of sector i within quarter q. Size is defined as sector market value at quarter q. Leverage is the average ratio of the total assets to equity in sector i at quarter q, and volatility of sector i is the realised volatility calculated from daily squared sector within a quarter following Christiansen et al. (2012). The ANFI is defined as financial market stress index as provided by the Federal Reserve Bank of St. Louis at a quarterly frequency. Positive values of ANFCI indicate tighter financial conditions than average, and negative values indicate looser financial conditions than average. Tight financial conditions mean higher risk and lower credit and leverage (see Brave and Kelley (2017) for details). Size and leverage were taken from Bloomberg at a quarterly frequency.

Correlation *Probability*	ΔCoVaR	VaR	Volatility	Size	Leverage	ANFCI
ΔCoVaR	1.0000					

VaR	0.4004	1.0000				
	0.0000	-----				
Volatility	-0.5119	-0.7084	1.0000			
	0.0000	*0.0000*	-----			
Size	0.3485	0.2110	-0.0650	1.0000		
	0.0000	*0.0001*	*0.2431*	-----		
Leverage	-0.2401	0.1788	-0.2353	-0.2722	1.0000	
	0.0000	*0.0012*	*0.0000*	*0.0000*	-----	
ANFCI	-0.3591	-0.0864	0.3240	0.0784	0.0084	1.0000
	0.0000	*0.1206*	*0.0000*	*0.1592*	*0.8799*	-----

Table B.34: Correlation matrix ΔCoVaR, six dominant sectors.
The coefficients were calculated using the ordinary Pearson method. The second line displays the probability. The correlation matrix was estimated using quarterly variables. VaR is defined as the median of daily 2.5%- $\widehat{\text{VaRs}}$ of sector i within quarter q. Size is defined as sector market value at quarter q. Leverage is the average ratio of the total assets to equity in sector i at quarter q, and volatility of sector i is the realised volatility calculated from daily squared sector within a quarter following Christiansen et al. (2012).The ANFI is defined as financial market stress index as provided by the Federal Reserve Bank of St. Louis at a quarterly frequency. Positive values of ANFCI indicate tighter financial conditions than average, and negative values indicate looser financial conditions than average. Tight financial conditions mean higher risk and lower credit and leverage (see Brave and Kelley (2017) for details). Size and leverage were taken from Bloomberg at a quarterly frequency.

Correlation *Probability*	ΔCoVaR	VaR	Volatility	Size	Leverage	ANFCI
ΔCoVaR	1.0000					

VaR	0.7780	1.0000				
	0.0000	-----				
Volatility	-0.7240	-0.6569	1.0000			
	0.0000	*0.0000*	-----			
Size	0.2452	0.2908	0.1112	1.0000		
	0.0003	*0.0000*	*0.1031*	-----		
Leverage	-0.0603	0.0951	0.0852	0.7374	1.0000	
	0.3778	*0.1639*	*0.2125*	*0.0000*	-----	
ANFCI	-0.3406	-0.2623	0.4883	0.1113	0.0091	1.0000
	0.0000	*0.0001*	*0.0000*	*0.1027*	*0.8946*	-----

Table B.35: Correlation matrix ΔCoVaR, four less dominant sectors.
The coefficients were calculated using the ordinary Pearson method. The second line displays the probability. The correlation matrix was estimated using quarterly variables. VaR is defined as the median of daily 2.5%- $\widehat{\text{VaRs}}$ of sector i within quarter q. Size is defined as sector market value at quarter q. Leverage is the average ratio of the total assets to equity in sector i at quarter q, and volatility of sector i is the realised volatility calculated from daily squared sector within a quarter following Christiansen et al. (2012).The ANFI is defined as financial market stress index as provided by the Federal Reserve Bank of St. Louis at a quarterly frequency. Positive values of ANFCI indicate tighter financial conditions than average, and negative values indicate looser financial conditions than average. Tight financial conditions mean higher risk and lower credit and leverage (see Brave and Kelley (2017) for details). Size and leverage were taken from Bloomberg at a quarterly frequency.

Appendix C: Appendix to Chapter 4

C.1 Variables used to construct the sentiment index

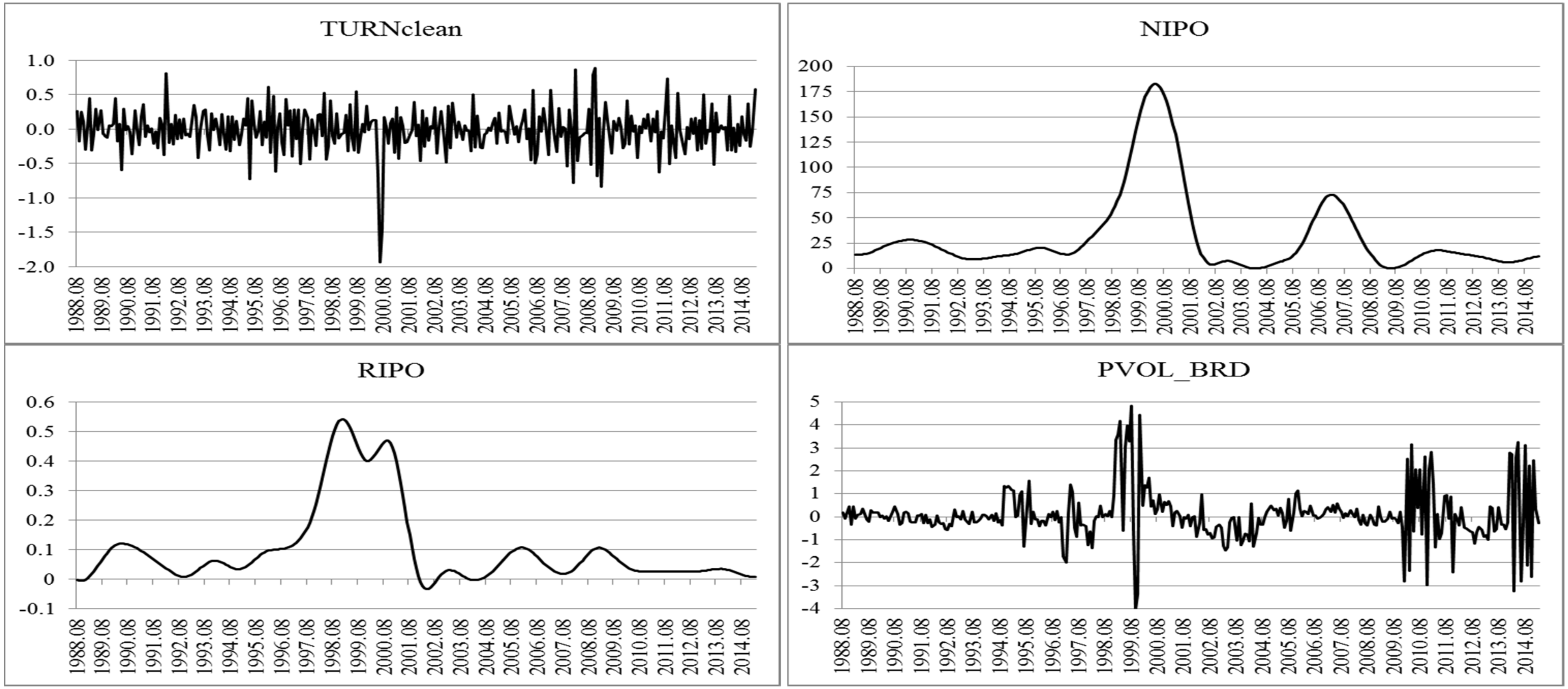

Figure C.1: Variables used to construct the sentiment index for Germany.
TURNclean denotes the first differences of the market turnover (TURN). NIPO is the number of IPOs and RIPO is the average first-day return on IPOs. PVOL denotes the volatility premium. The data required to calculate the variables were downloaded from Datastream at a monthly frequency. NIPO and RIPO were provided by Jay Ritter on an annual basis. The annual IPO data were converted to monthly frequency using a cubic spline interpolation. Unit root tests were employed to test for stationarity.

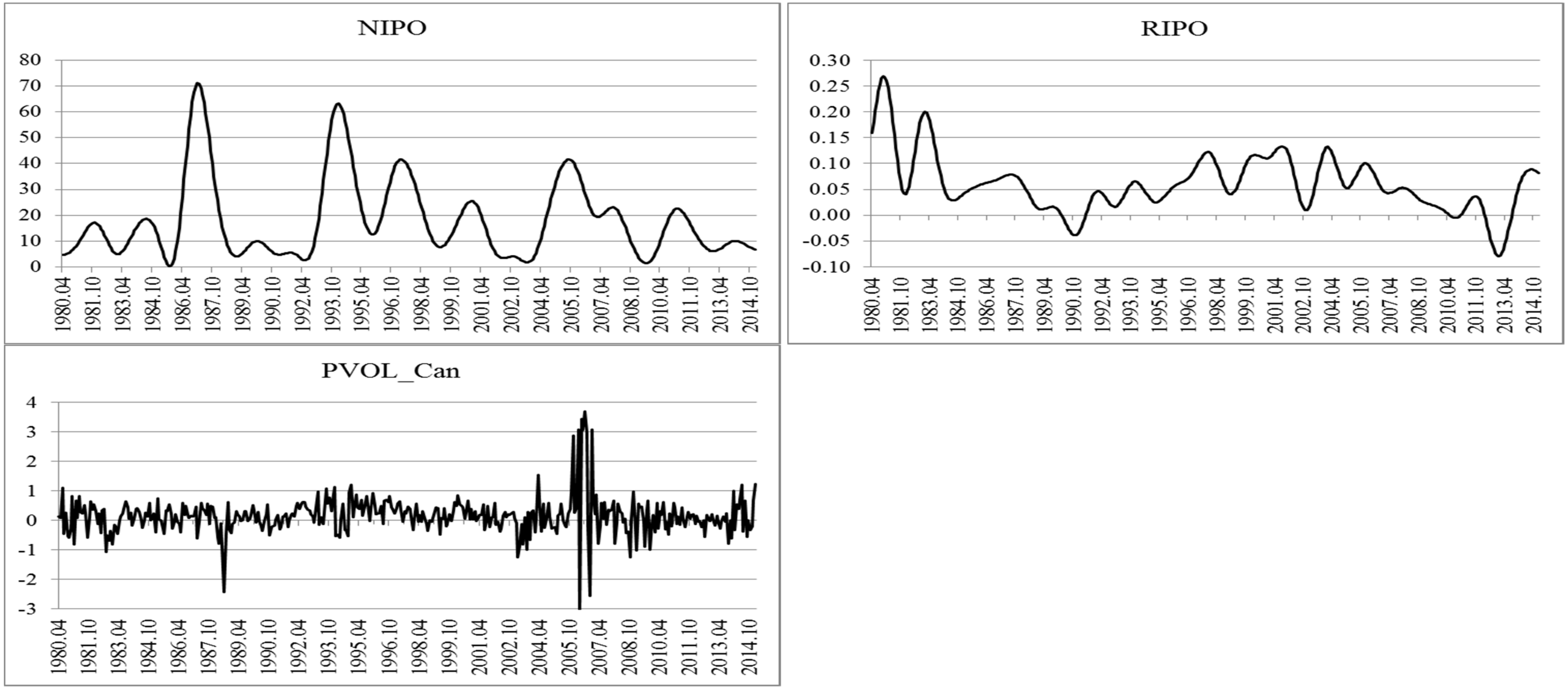

Figure C.2: Variables used to construct the sentiment index for Canada.
The market turnover (TURN) was not included in the sentiment estimation due to the short observation period. NIPO is the number of IPOs and RIPO is the average first-day return on IPOs. PVOL denotes the volatility premium. The data required to calculate the variables were downloaded from Datastream at a monthly frequency. NIPO and RIPO were provided by Jay Ritter on an annual basis. The annual IPO data were converted to monthly frequency using a cubic spline interpolation. Unit root tests were employed to test for stationarity.

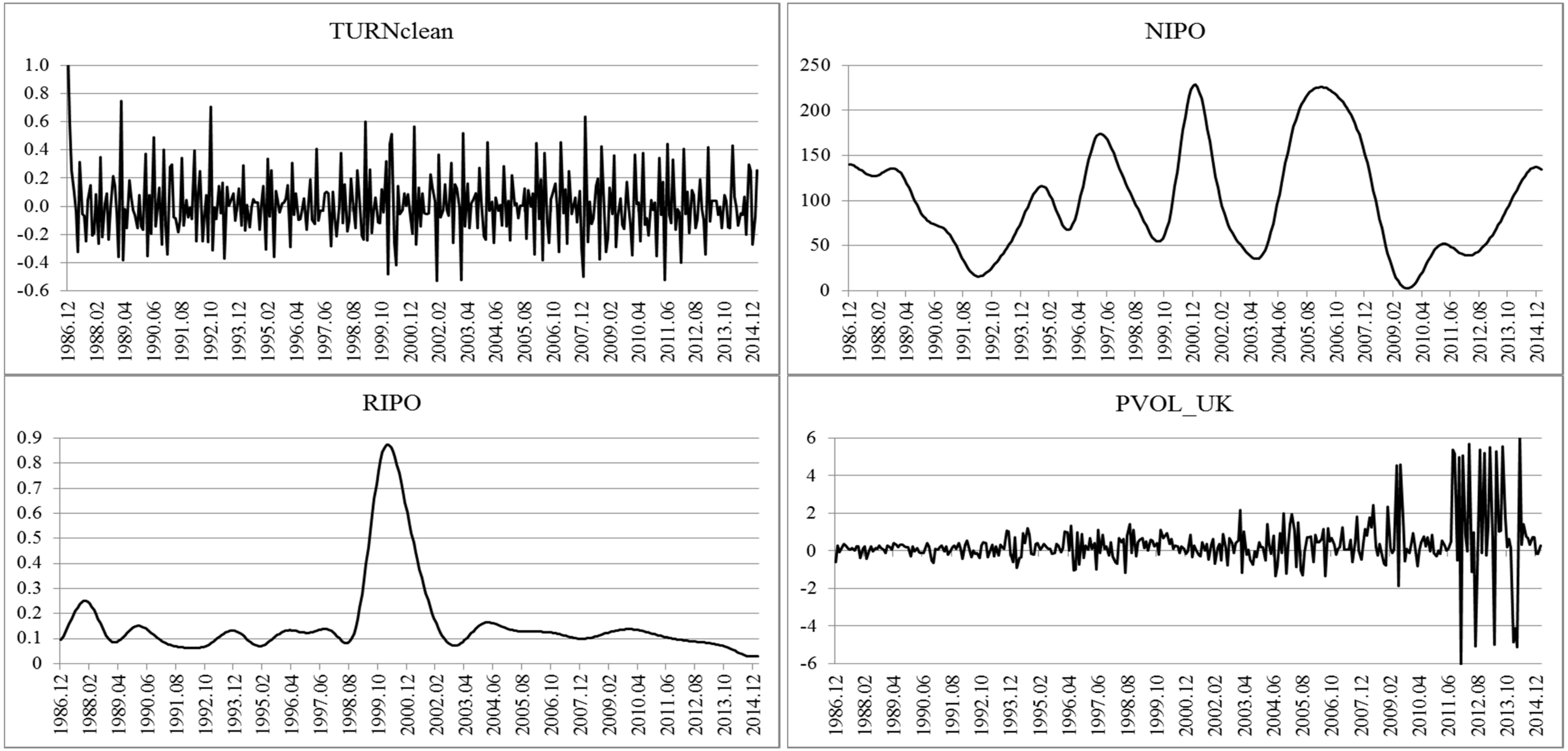

Figure C.3: Variables used to construct the sentiment index for the UK.

TURNclean denotes the first differences of the market turnover (TURN). NIPO is the number of IPOs and RIPO is the average first-day return on IPOs. PVOL denotes the volatility premium. The data required to calculate the variables were downloaded from Datastream at a monthly frequency. NIPO and RIPO were provided by Jay Ritter on an annual basis. The annual IPO data were converted to monthly frequency using a cubic spline interpolation. Unit root tests were employed to test for stationarity.

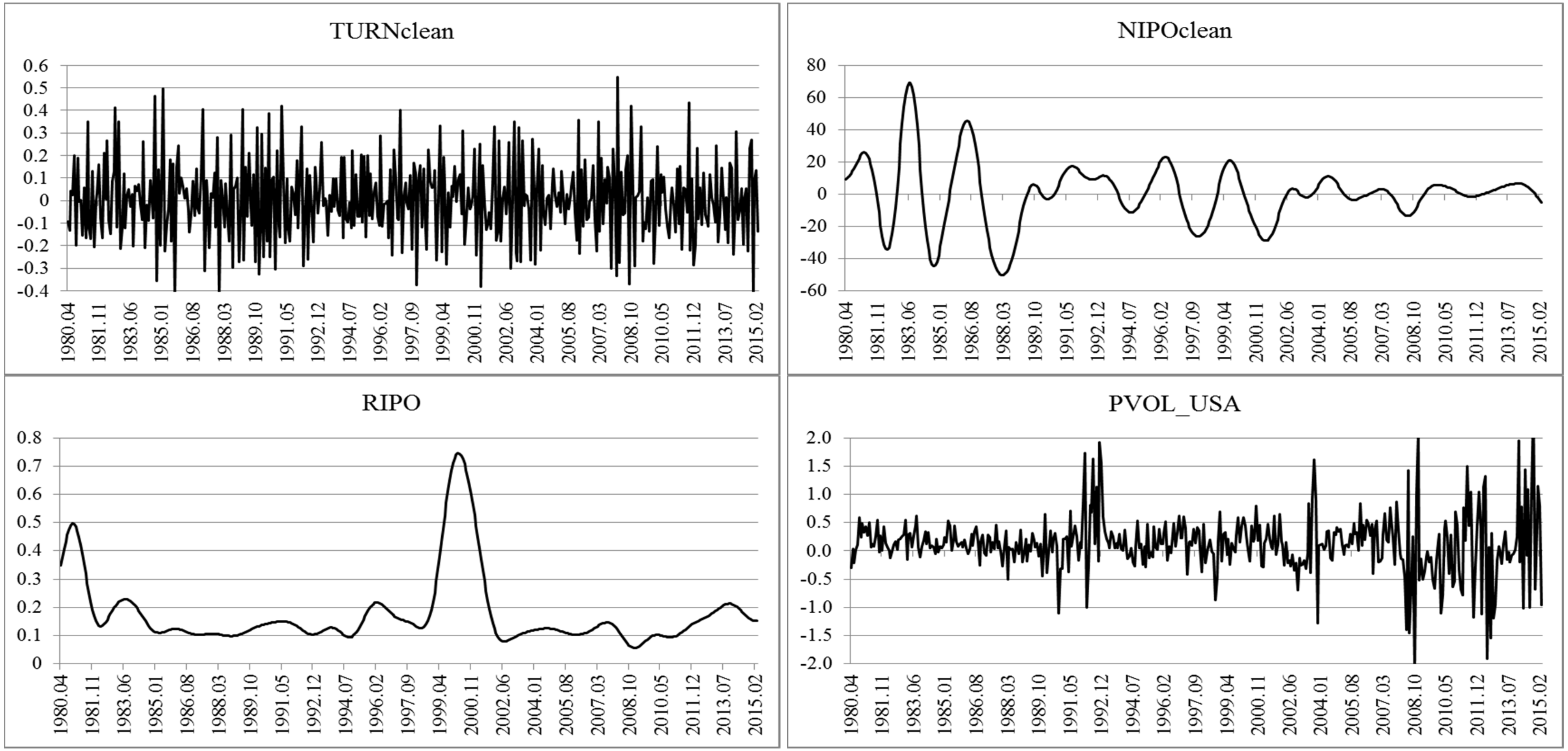

Figure C.4: Variables used to construct the sentiment index for the US.

TURNclean denotes the first differences of the market turnover (TURN). NIPO is the number of IPOs and RIPO is the average first-day return on IPOs. NIPOclean denotes first differences of NIPO which were used. PVOL denotes the volatility premium. The data required to calculate the variables were downloaded from Datastream at a monthly frequency. NIPO and RIPO were provided by Jay Ritter on an annual basis. The annual IPO data were converted to monthly frequency using a cubic spline interpolation. Unit root tests were employed to test for stationarity.

C.2 VAR estimation results PC1-GARCH-MIDAS model

Null Hypothesis:	Obs.	F-Statistic	Prob.
MILLclean does not Granger-cause Dividend yield	284	0.3222	0.5707
Dividend yield does not Granger-cause MILLclean		3.3008	0.0703
ERP does not Granger-cause Dividend yield	284	0.0366	0.8485
Dividend yield does not Granger-cause ERP		1.0479	0.3069
SENT does not Granger-cause Dividend yield	284	0.0711	0.7899
Dividend yield does not Granger-cause SENT		0.2842	0.5944
Average gPC1 does not Granger-cause Dividend yield	284	5.1479	0.024
Dividend yield does not Granger-cause Average gPC1		1.1106	0.2929
ERP does not Granger-cause MILLclean	284	6.1279	0.0139
MILLclean does not Granger-cause ERP		0.5334	0.4658
SENT does not Granger-cause MILLclean	284	0.4842	0.4871
MILLclean does not Granger-cause SENT		0.0704	0.791
Average gPC1 does not Granger-cause MILLclean	284	0.3008	0.5838
MILLclean does not Granger-cause Average gPC1		0.1528	0.6962
SENT does not Granger-cause ERP	284	5.7093	0.0175
ERP does not Granger-cause SENT		0.1590	0.6903
Average gPC1 does not Granger-cause ERP	284	5.9482	0.0154
ERP does not Granger-cause Average gPC1		0.0002	0.9892
Average gPC1 does not Granger-cause SENT	284	0.3104	0.5779
SENT does not Granger-cause Average gPC1		0.0707	0.7905

Table C.1: Granger-causality results: Germany– incl. the short-run volatility component.
The number of lags in the test regressions was chosen by the Schwarz information criterion. The F-statistics are Wald statistics of the pairwise test. Average gPC1 denotes the short-run volatility component. The ending PC1 means that the volatility component is estimated using the PC1-GARCH-MIDAS specification with rolling window. The values of g used here are the average of daily values of g over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the CDAX. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's, the average first-day return of IPO's and the market turnover. All data were downloaded at a monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to a monthly frequency through a cubic spline interpolation. The observation period ranges from June 1991 to February 2015.

Null Hypothesis:	Obs.	F-Statistic	Prob.
MILLclean does not Granger-cause Dividend yield	283	0.5382	0.5844
Dividend yield does not Granger-cause MILLclean		3.4711	0.0324
ERP does not Granger-cause Dividend yield	283	0.3766	0.6865
Dividend yield does not Granger-cause ERP		1.3506	0.2608
SENT does not Granger-cause Dividend yield	283	0.0742	0.9285
Dividend yield does not Granger-cause SENT		0.2093	0.8112
Average tauPC1 does not Granger-cause Dividend yield	283	0.4810	0.6187
Dividend yield does not Granger-cause Average tauPC1		1.2763	0.2807
ERP does not Granger-cause MILLclean	283	4.8635	0.0084
MILLclean does not Granger-cause ERP		0.3816	0.6831
SENT does not Granger-cause MILLclean	283	0.7508	0.4729
MILLclean does not Granger-cause SENT		0.0319	0.9686
Average tauPC1 does not Granger-cause MILLclean	283	0.4076	0.6657
MILLclean does not Granger-cause Average tauPC1		0.3370	0.7142
SENT does not Granger-cause ERP	283	2.5802	0.0776
ERP does not Granger-cause SENT		0.4309	0.6503
Average tauPC1 does not Granger-cause ERP	283	0.6185	0.5395
ERP does not Granger-cause Average tauPC1		1.7819	0.1702
Average tauPC1 does not Granger-cause SENT	283	4.6919	0.0099
SENT does not Granger-cause Average tauPC1		2.5854	0.0772

Table C. 2: Granger-causality results: Germany – incl. the long-run volatility component.

The number of lags in the test regressions was chosen by the Schwarz information criterion. The F-statistics are Wald statistics of the pairwise test. Average tauPC1 denotes the long-run volatility component. The ending PC1 means that the volatility component is estimated using the PC1-GARCH-MIDAS specification with rolling window. The values tau used here are the average of daily values tau over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the CDAX. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's, the average first-day return of IPO's and the market turnover. All data were downloaded at a monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to a monthly frequency through a cubic spline interpolation. The observation period ranges from June 1991 to February 2015.

Null Hypothesis:	Obs.	F-Statistic	Prob.
MILLclean does not Granger-cause Dividend yield	379	0.9980	0.3938
Dividend yield does not Granger-cause MILLclean		5.1917	0.0016
ERP does not Granger-cause Dividend yield	379	5.7245	0.0008
Dividend yield does not Granger-cause ERP		16.5443	0.0000
SENT does not Granger-cause Dividend yield	379	1.2290	0.2989
Dividend yield does not Granger-cause SENT		2.3166	0.0753
Average gPC1 does not Granger-cause Dividend yield	379	17.6181	0.0000
Dividend yield does not Granger-cause Average gPC1		2.5515	0.0554
ERP does not Granger-cause MILLclean	379	3.5919	0.0139
MILLclean does not Granger-cause ERP		3.8096	0.0103
SENT does not Granger-cause MILLclean	379	0.6571	0.5789
MILLclean does not Granger-cause SENT		0.0930	0.9639
Average gPC1 does not Granger-cause MILLclean	379	1.3766	0.2496
MILLclean does not Granger-cause Average gPC1		0.7083	0.5475
SENT does not Granger-cause ERP	379	0.7088	0.5472
ERP does not Granger-cause SENT		1.9355	0.1234
Average gPC1 does not Granger-cause ERP	379	13.2818	0.0000
ERP does not Granger-cause Average gPC1		1.1461	0.3304
Average gPC1 does not Granger-cause SENT	379	4.5061	0.0040
SENT does not Granger-cause Average gPC1		0.4928	0.6875

Table C.3: Granger-causality results: Canada – incl. the short-run volatility component.
The number of lags in the test regressions was chosen by the Schwarz information criterion. The F-statistics are Wald statistics of the pairwise test. Average gPC1 denotes the short-run volatility component. The ending PC1 means that the volatility component is estimated using the PC1-GARCH-MIDAS specification with rolling window. The values of g used here are the averages of daily values of g over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the S&P/TSX. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's and the average first-day return of IPO's. The market turnover is not included due to the short observation period. All data were downloaded at a monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to a monthly frequency through a cubic spline interpolation. The observation period ranges from April 1983 to January 2015.

Null Hypothesis:	Obs.	F-Statistic	Prob.
MILLclean does not Granger-cause Dividend yield	380	1.0997	0.3341
Dividend yield does not Granger-cause MILLclean		6.9762	0.0011
ERP does not Granger-cause Dividend yield	380	5.7048	0.0036
Dividend yield does not Granger-cause ERP		30.3825	0.0000
SENT does not Granger-cause Dividend yield	380	1.8249	0.1627
Dividend yield does not Granger-cause SENT		1.9520	0.1434
Average tauPC1 does not Granger-cause Dividend yield	380	7.5015	0.0006
Dividend yield does not Granger-cause Average tauPC1		0.7542	0.4711
ERP does not Granger-cause MILLclean	380	6.9733	0.0011
MILLclean does not Granger-cause ERP		3.6241	0.0276
SENT does not Granger-cause MILLclean	380	0.4108	0.6634
MILLclean does not Granger-cause SENT		0.1951	0.8228
Average tauPC1 does not Granger-cause MILLclean	380	2.4841	0.0848
MILLclean does not Granger-cause Average tauPC1		0.0648	0.9373
SENT does not Granger-cause ERP	380	1.2561	0.2860
ERP does not Granger-cause SENT		0.4938	0.6107
Average tauPC1 does not Granger-cause ERP	380	3.8114	0.0230
ERP does not Granger-cause Average tauPC1		2.2373	0.1082
Average tauPC1 does not Granger-cause SENT	380	1.4474	0.2365
SENT does not Granger-cause Average tauPC1		2.4814	0.0850

Table C.4: Granger-causality results: Canada – incl. the long-run volatility component.
The number of lags in the test regressions was chosen by the Schwarz information criterion. The F-statistics are Wald statistics of the pairwise test. Average tauPC1 denotes the long-run volatility component. The ending PC1 means that the volatility component is estimated using the PC1-GARCH-MIDAS specification with rolling window. The values of tau used here are the averages of daily values of tau over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the S&P/TSX. The Granger causality test includes first differences of the tauPC1 variable. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's and the average first-day return of IPO's. The market turnover is not included due to the short observation period. All data were downloaded at a monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to a monthly frequency through a cubic spline interpolation. The observation period ranges from April 1983 to January 2015.

Null Hypothesis:	Obs.	F-Statistic	Prob.
MILLclean does not Granger-cause Dividend yield	322	0.6064	0.5459
Dividend yield does not Granger-cause MILLclean		3.9312	0.0206
ERP does not Granger-cause Dividend yield	322	1.2063	0.3007
Dividend yield does not Granger-cause ERP		40.5264	0.0000
SENT does not Granger-cause Dividend yield	322	0.5176	0.5965
Dividend yield does not Granger-cause SENT		1.2298	0.2937
Average gPC1 does not Granger-cause Dividend yield	322	12.3603	0.0000
Dividend yield does not Granger-cause Average gPC1		1.8058	0.1660
ERP does not Granger-cause MILLclean	322	4.2834	0.0146
MILLclean does not Granger-cause ERP		0.0839	0.9195
SENT does not Granger-cause MILLclean	322	0.3844	0.6811
MILLclean does not Granger-cause SENT		2.5725	0.0779
Average gPC1 does not Granger-cause MILLclean	322	1.6543	0.1929
MILLclean does not Granger-cause Average gPC1		0.3828	0.6823
SENT does not Granger-cause ERP	322	0.0932	0.9111
ERP does not Granger-cause SENT		0.4575	0.6333
Average gPC1 does not Granger-cause ERP	322	8.7897	0.0002
ERP does not Granger-cause Average gPC1		1.9914	0.1382
Average gPC1 does not Granger-cause SENT	322	0.1572	0.8546
SENT does not Granger-cause Average gPC1		0.8104	0.4456

Table C.5: Granger-causality results: UK – incl. the short-run volatility component.

The number of lags in the test regressions was chosen by the Schwarz information criterion. The F-statistics are Wald statistics of the pairwise test. Average gPC1 denotes the short-run volatility component. The ending PC1 means that the volatility component is estimated using the PC1-GARCH-MIDAS specification with rolling window. The values of g used here are the averages of daily values of g over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the FTSE All-Share. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's, the average first-day return of IPO's and the market turnover. All data were downloaded at a monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to a monthly frequency through a cubic spline interpolation. The observation period ranges from March 1988 to February 2015.

Null Hypothesis:	Obs.	F-Statistic	Prob.
MILLclean does not Granger-cause Dividend yield	322	0.6064	0.5459
Dividend yield does not Granger-cause MILLclean		3.9312	0.0206
ERP does not Granger-cause Dividend yield	322	1.2063	0.3007
Dividend yield does not Granger-cause ERP		40.5264	0.0000
SENT does not Granger-cause Dividend yield	322	0.5176	0.5965
Dividend yield does not Granger-cause SENT		1.2298	0.2937
Average tauPC1 does not Granger-cause Dividend yield	322	3.7892	0.0236
Dividend yield does not Granger-cause Average tauPC1		11.9969	0.0000
ERP does not Granger-cause MILLclean	322	4.2834	0.0146
MILLclean does not Granger-cause ERP		0.0839	0.9195
SENT does not Granger-cause MILLclean	322	0.3844	0.6811
MILLclean does not Granger-cause SENT		2.5725	0.0779
Average tauPC1 does not Granger-cause MILLclean	322	0.0417	0.9592
MILLclean does not Granger-cause Average tauPC1		0.0364	0.9642
SENT does not Granger-cause ERP	322	0.0932	0.9111
ERP does not Granger-cause SENT		0.4575	0.6333
Average tauPC1 does not Granger-cause ERP	322	2.0779	0.1269
ERP does not Granger-cause Average tauPC1		12.3765	0.0000
Average tauPC1 does not Granger-cause SENT	322	0.4378	0.6459
SENT does not Granger-cause Average tauPC1		1.5176	0.2208

Table C.6: Granger-causality results: UK – incl. the long-run volatility component.

The number of lags in the test regressions was chosen by the Schwarz information criterion. The F-statistics are Wald statistics of the pairwise test. Average tauPC1 denotes the long-run volatility component. The ending PC1 means that the volatility component is estimated using the PC1-GARCH-MIDAS specification with rolling window. The values of tau used here are the averages of daily values of tau over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the FTSE All-Share. The Granger causality test includes first differences of the tauPC1 variable. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's, the average first-day return of IPO's and the market turnover. All data were downloaded at a monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to a monthly frequency through a cubic spline interpolation. The observation period ranges from March 1988 to February 2015.

Null Hypothesis:	Obs.	F-Statistic	Prob.
MILLclean does not Granger-cause Dividend yield	383	1.0040	0.3674
Dividend yield does not Granger-cause MILLclean		9.4489	0.0001
ERP does not Granger-cause Dividend yield	383	1.0270	0.3591
Dividend yield does not Granger-cause ERP		27.7077	0.0000
SENT does not Granger-cause Dividend yield	383	0.5649	0.5689
Dividend yield does not Granger-cause SENT		2.2997	0.1017
Average gPC1 does not Granger-cause Dividend yield	383	37.4833	0.0000
Dividend yield does not Granger-cause Average gPC1		2.3954	0.0925
ERP does not Granger-cause MILLclean	383	6.8493	0.0012
MILLclean does not Granger-cause ERP		0.2523	0.7772
SENT does not Granger-cause MILLclean	383	0.1282	0.8797
MILLclean does not Granger-cause SENT		0.1438	0.8661
Average gPC1 does not Granger-cause MILLclean	383	3.3125	0.0375
MILLclean does not Granger-cause Average gPC1		0.2985	0.7421
SENT does not Granger-cause ERP	383	0.2338	0.7916
ERP does not Granger-cause SENT		1.4996	0.2245
Average gPC1 does not Granger-cause ERP	383	17.9151	0.0000
ERP does not Granger-cause Average gPC1		1.7126	0.1818
Average gPC1 does not Granger-cause SENT	383	5.7061	0.0036
SENT does not Granger-cause Average gPC1		0.2373	0.7889

Table C.7: Granger-causality results: US – incl. the short-run volatility component.

The number of lags in the test regressions was chosen by the Schwarz information criterion. The F-statistics are Wald statistics of the pairwise test. Average gPC1 denotes the short-run volatility component. The ending PC1 means that the volatility component is estimated using the PC1-GARCH-MIDAS specification with rolling window. The values of g used here are the averages of daily values of g over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the S&P500. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's, the average first-day return of IPO's and the market turnover. All data were downloaded at a monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to a monthly frequency through a cubic spline interpolation. The observation period ranges from March 1983 to March 2015.

Null Hypothesis:	Obs.	F-Statistic	Prob.
MILLclean does not Granger-cause Dividend yield	383	1.0040	0.3674
Dividend yield does not Granger-cause MILLclean		9.4489	0.0001
ERP does not Granger-cause Dividend yield	383	1.0270	0.3591
Dividend yield does not Granger-cause ERP		27.7077	0.0000
SENT does not Granger-cause Dividend yield	383	0.5649	0.5689
Dividend yield does not Granger-cause SENT		2.2997	0.1017
Average tauPC1 does not Granger-cause Dividend yield	383	0.7883	0.4554
Dividend yield does not Granger-cause Average tauPC1		2.9439	0.0539
ERP does not Granger-cause MILLclean	383	6.8493	0.0012
MILLclean does not Granger-cause ERP		0.2523	0.7772
SENT does not Granger-cause MILLclean	383	0.1282	0.8797
MILLclean does not Granger-cause SENT		0.1438	0.8661
Average tauPC1 does not Granger-cause MILLclean	383	0.3291	0.7198
MILLclean does not Granger-cause Average tauPC1		0.6461	0.5247
SENT does not Granger-cause ERP	383	0.2338	0.7916
ERP does not Granger-cause SENT		1.4996	0.2245
Average tauPC1 does not Granger-cause ERP	383	0.5217	0.5939
ERP does not Granger-cause Average tauPC1		3.0353	0.0492
Average tauPC1 does not Granger-cause SENT	383	1.0295	0.3582
SENT does not Granger-cause Average tauPC1		0.4713	0.6245

Table C.8: Granger-causality results: US – incl. the long-run volatility component.

The number of lags in the test regressions was chosen by the Schwarz information criterion. The F-statistics are Wald statistics of the pairwise test. Average tauPC1 denotes the long-run volatility component. The ending PC1 means that the volatility component is estimated using the PC1-GARCH-MIDAS specification with rolling window. The values of tau used here are the averages of daily values of tau over one month. MILLclean is the illiquidity measure calculated for the stock market index. MILL is used as logarithmic transformation, and the first differences are calculated to obtain MILLclean. ERP denotes the equity risk premium, calculated as the difference between the stock market index return in month t and the 3-month riskless yield in month t. The dividend yield is the total dividend amount divided by the total market value of all index constituents. First differences of the dividend yield are used. The stock market index is the S&P500. The Granger causality test includes first differences of the tauPC1 variable. SENT is the sentiment index estimated following Baker et al. (2012) using the volatility premium, the number of IPO's, the average first-day return of IPO's and the market turnover. All data were downloaded at a monthly frequency from Datastream. The data on IPO were provided by Jay Ritter on an annual basis and converted to a monthly frequency through a cubic spline interpolation. The observation period ranges from March 1983 to March 2015.

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