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Does Monetary Policy Influence Systemic Risk?

Evidence from the Eurozone Banking Sector.

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ABSTRACT

In this thesis, I explore the link between systemic risk and monetary policy (*Systemic Risk-Taking Channel*) in the Eurozone banking sector. Using a sample from Q1 2004 to Q4 2018 and 14 banks I estimate two systemic risk measures and explore their response to a shock in the Shadow Short Rate (SSR) in a Factor Augmented Vector Autoregressive (FAVAR) model. Furthermore, I develop a theoretical framework for the systemic risk-taking channel that can be used for hypotheses testing in future research. The empirical results are mostly not in line with the previous literature and the predictions of the theory. Evidence suggests that systemic risk only increases for one systemic risk measure as a response to an expansionary monetary policy shock. Furthermore, I find ambiguous evidence for a different response under an unconventional policy regime. In addition, I do not find evidence for a different response of Systemically Important Banks (SIB) compared to Non-SIB and healthy compared to unhealthy banks.

Contents

List of Figures

List of Tables

1. Introduction

What are the effects of a monetary policy shock on the economy? This question is at the heart of much research in economics and finance. As the interest rate affects so many different variables, which are then again interconnected in a large web, i.e. the economy, this type of analysis is difficult and much research needs to be done to fully comprehend the impact monetary policy has. However, in the aftermath of the financial crisis in 2008 and 2009 one particular question has been looming in public and academic debates: Did the low interest rate environment fuel the build-up of the housing bubble in the U.S.? This thesis takes a slightly different approach to answer a similar question: Does monetary policy affect systemic risk? In other words, does this broad policy tool have any unintended consequences on the larger economy in the form of systemic risk? In doing so, I am able to dodge some difficult questions that always follow debates about bubbles, like what is rationale pricing, i.e. when is a bubble a bubble? Or when is it possible to detect a bubble and should the central bank counter the build-up?

Understanding intended and unintended consequences is important to evaluate monetary policy. One of the unintended consequences is the transmission to risk-taking and risk-behaviour: the risk-taking channel (Borio and Zhu, 2008). Research suggest that there is a negative relationship between risk and monetary policy, i.e. easy monetary policy leads to increased risk-taking by banks. However, the risk-taking channel is only able to describe the effect on individual banks' risk. Colletaz et al. (2018) propagate the 'Systemic Risk-Taking Channel', which describes how monetary policy affects systemic risk. Unfortunately, the paper stops short of laying out a theoretical argument why monetary policy should affect systemic risk. While the theoretical nature of Colletaz et al. (2018) is closer to my thesis, my methodology is related to Faia and Karau (2019). The authors apply a variety of different Vector Autoregressive (VAR) type models, e.g. panel VAR, proxy VAR and FAVAR. Both paper conclude that similar to the risk-taking channel, monetary policy easing should increase systemic risk. Alas, to the best of my knowledge, these are the only two paper that explore this link explicitly.

My thesis aims to illuminate the systemic risk-taking channel further. Thus, not only do I provide additional evidence to the scarce literature landscape but I also address several sub-questions that are of interest. In addition, I lay out a theoretical model drawing from Benoit et al. (2017) that aims to provide testable hypotheses for future research. My results are not in line with what Faia and Karau (2019) find. In line with their finding, the systemic risk measure that is solely based on market data (CoVaR) shows the same dynamic as the evidence suggested in Faia and Karau (2019). On the other hand, the second measure is also based on accounting data (SRISK). The response of this measure is close to zero and shows even the opposite sign. Furthermore, I show that an unconventional monetary policy regime is amplifying the effect. For CoVaR the effect is more prolonged, but the response is only slightly amplified. For SRISK, the response vanishes almost completely, i.e. the response is essentially zero. Moreover, I can not find a different effect for SIB and non-SIB banks or for healthy compared to unhealthy banks. The second finding is in line with my hypothesis. Albeit, the first and last two results contradict the hypotheses I formulate. This shows that the research on this topic is far from being conclusive.

Furthermore, I test the robustness of the empirical results. Albeit, slight changes in the identification of the FAVAR model and the sample split change the results greatly. The results from this changed set-up further increase the contradiction with the previous literature. However, setting up the model similar to Faia and Karau (2019) yields robust results for the CoVaR measure. This indicates that the results presented in the literature largely depend on the model set up.

The sample I am using consists of 14 Euro Zone (EZ) banks and the Euro Stoxx Bank index. Why focus on the banking sector in the EZ? First, the banking sector is of great importance for providing the economy with credit. Thus, systemic risk in the banking sector can easily lead to spill-overs to the real economy. Hence, a systemic crisis in the banking sector will have direct consequences for non financial companies. Moreover, the EZ has been underrepresented in the scarce research that exists. Faia and Karau (2019) use a sample of SIB banks and makes no differentiation w.r.t. their nationality. Therefore, their results are potentially problematic, as they use banks that operate in large parts outside the U.S. but she uses monetary impulses from the U.S. Fed. While the evidence presented in Colletaz et al. (2018) focuses on the EZ banking sector, its main objective is to establish the direction of causality rather than the magnitude and the sign of the effect. Also the paper does not provide any structural analysis. Thus, the results should be taken with a grain of salt.

In the second chapter of this thesis I review the literature on systemic risk and the transmission of monetary policy shocks. Subsequently, I develop the theoretical argument for a systemic risk-taking channel and also my hypotheses. Then, I describe the methodology used to estimate the systemic risk measures and the FAVAR model. Chapter five introduces the data used. Afterwards, I present the empirical results and use several robustness checks. The final chapter concludes and discusses the results.

2. Literature Review

As laid out in the previous section, this thesis is concerned with a potential causal link from monetary policy to systemic risk in the EZ banking sector. Therefore, I divide my literature review into two parts. Part one reviews previous academic work on systemic risk. Subsequently I discuss the literature on monetary policy. I focus on the risk-taking channel as I use it in the subsequent chapter. Also I make a difference between the response of banks under conventional and unconventional monetary policy in order to obtain an expectation for my hypothesis.

2.1. Systemic Risk

Throughout this thesis, I use the systemic risk definition by Jorion (2005). He defines systemic risk as risk that arises '[...] when a shock threatens to create multiple simultaneous failures in financial institutions.'. This definition of systemic risk suggests that risk spreads among entities following a trigger event.

Benoit et al. (2017) conduct a thorough review of the systemic-risk literature. They identify three main mechanisms of how bank risk-taking affects systemic risk. First, *systemic risk-taking*, which describes how excessive *systematic* risk-taking by banks advances systemic risk. Excessive here means a level of systematic risk that is above the welfare maximising level. In his speech, Constâncio (2015) argues in a similar way. He specifically mentions excessive leverage and risk-taking by banks as on of the major ways in which banks contribute to the build-up of systemic risk. One main problem of an increased systematic exposure is the correlation of returns. If banks have highly correlated investment positions, their stock returns will be correlated. Hence, they advance systemic risk, by taking on highly correlated investments.

The second mechanism works through *contagion*. If banks become too interconnected, an idiosyncratic shock to one bank will get transmitted through the entire system, threatening to set off a chain reaction. Connections between banks can be direct or indirect. Direct connections would be contractual connections, e.g. Bank A buys a bond from bank B. On the other hand, indirect links include links that arise due to the correlation of investment positions, e.g. fire sales (Adrian and Brunnermeier, 2016). In fact, this was one of the major problems during the financial crisis in 2008/2009.

Furthermore, the *amplification mechanisms* describes why a small shock to either the idiosyncratic or the systematic factor can lead to large losses. This is tightly connected to the other two mechanisms. If a significant number of banks have large systematic risk exposures, small systematic shocks can lead to large losses in the entire industry. Also if banks' portfolios are highly correlated, a small idiosyncratic or systematic shock might get amplified throughout the entire system via indirect connections between banks.

This taxonomy is in line with the literature (see, e.g. Straetmans et al. (2005)). However, Straetmans et al. (2005) tackle the problem from a different angle. While this model describes mechanisms in which banks' behaviour contributes to systemic risk, Straetmans et al. (2005) focus on the trigger event. In their view, risk either spreads across institutions or all firms are affected the same way due to some undiversifiable shock. These two approaches do not contradict another. The mechanisms identified in Benoit et al. (2017) can be thought of as increasing the probability of one of the two triggers of systemic risk in Straetmans et al. (2005)

Large parts of the literature on systemic risk can be sorted into the three mechanisms discussed above: Systemic Risk-Taking, Contagion Mechanisms and Amplification Mechanisms.

Systemic Risk-Taking Mechanism

Systemic risk-taking above the optimal level of risk can arise for a number of different reasons. For example, multiple studies focus on different institutions making correlated investments. Acharya (2009) develops a model with which he explains why banks enter into highly correlated portfolios. This approach was novel as it uses correlations of banks' assets as a measure of systemic risk, as opposed to banks' liability structures. One surprising result is that an increase in competition boosts systemic risk, as it increases correlations in portfolio returns. Furthermore, Acharya (2009) and Acharya and Yorulmazer (2007) analyse the effects of a government bail-out. Their result shows that unconditional government intervention eliminates the incentive to make uncorrelated investments by banks as they will be bailed-out if all of them fail. Thus, they have an incentive to enter into highly correlated portfolios. Moreover, the authors show that banks have a risk-shifting incentive, as their traders bonuses are essentially based on group performance in the industry rather then on their individual performance.

Not only banks' investments but also their risk-exposures can be correlated. One strand of the literature focuses on leverage cycles, i.e. fluctuations of the leverage with the business cycle. Brunnermeier and Sannikov (2014) provide a flexible model and introduce the volatility paradox. They argue that in times of low aggregate risk, banks will tend to increase their equilibrium leverage level and the amplification of shocks will increase. In addition, they show that equilibrium leverage increases with diversification and an increased facilitation of hedging products as banks feel encouraged to keep lower capital buffers for their positions due to risk-sharing.

Another important part of the systemic risk-taking mechanism is that the tail risks have to be 'large enough' (Benoit et al., 2017). If the tail risks are marginal, they might not lead to a systemic crisis, even in an extreme event. Acharya et al. (2010) argue that in the run-up of the financial crisis of 2008/2009, banks build up tail risks using shadow banks. In addition, they show that investors did not punish such excessive systemic risk-taking. In other words, if the tail risk is not substantial enough, the system might be able to absorb systematic and idiosyncratic shocks even if they are severe.

Contagion Mechanism

Contagion mechanisms are usually studied using some form of network analysis. One of the main results is the 'robust-yet-fragile' property of financial networks (Haldane, 2009). The intuition is that an interconnected network is robust for few and small shocks. However, if the shock is large, a less interconnected network would be advantageous. The rationale of this argument is that in case of a small shock, other banks supply the distressed firms with liquidity. On the other hand, if the shock is too large, a stronger interconnectedness leads to a domino effect, where one company after the other fails (Acemoglu et al., 2013).

One interesting point concerning the interconnectedness of banks is voiced by European Central Bank (2016). The authors argue that low interest rates increase the dependency of banks on financial markets and other banks. Assuming a scenario where interest rates stay 'low for long' they show that banks will increase their cross-holdings. Thus, a low interest rate over a prolonged period of time leads to increased interconnectedness between banks.

Amplification Mechanism

Allen and Gale (2004) study liquidity driven amplification mechanisms. The basic idea is that if faced with an adverse shock, banks have to raise capital. Thus, they sell assets. If these banks' actions have a price impact, this might force other banks to also sell their assets as their balance sheets deteriorate. Therefore, a small shock to one institution gets transmitted through the entire network of banks.

Another obvious example for the amplification mechanism are bank runs. Aharony and Swary (1983) and Swary (1986) examine contagion effects in the U.S. banking sector in light of the danger of bank runs. Both papers apply event studies to estimate the effects of contagion risk on capital markets. While Aharony and Swary (1983) analyses the three largest bank failures in the U.S. until 1983, Swary (1986) examines the effect of the crisis of Continental Illinois in 1986. The second paper focuses on banks that are vulnerable to bank runs, due to to a relatively high reliance of funding through deposits. It thereby provides evidence on the extent of systemic interconnectedness of the banking sector.

Systemic Risk in the Eurozone

For this thesis, I am only concerned with systemic risk in the banking sector. Bühler and Prokopczuk (2010) analyse whether systemic risk in the banking sector is high, compared to other sectors. The authors apply a copula model to estimate dependencies between stock returns to estimate the probability of a systemic crisis. Their baseline results suggest that the banking sector experiences a higher degree of systemic risk. However, they go even further and analyse how their measure of systemic risk changes with underlying state variables. The evidence suggests that the banking sector has a comparably high probability of a systemic crisis in times of bear and volatile markets.

Betz et al. (2016) provide an insightful picture of how the network of European Banks evolved over time. Their results show that European Banks became increasingly interlinked between 2006 and the height of the financial crisis. Afterwards, the market fragmented. This trend increased during the EZ sovereign debt crisis of 2012. They also show that this increased fragmentation correlates with an increased correlation between sovereigns and financial institutions' equity returns. While the banking market becomes more fragmented, sovereign bonds become the main transmitter of shocks through the system. Similarly, Acharya and Steffen (2013) analyse systemic risk in the EZ banking sector by applying the Systemic Expected Shortfall measure developed in Acharya et al. (2016). The authors show that sovereign bond positions significantly contribute to systemic risk of individual entities. Their results suggest that investors demand more capital from banks with more exposure to some peripheral sovereign bonds [1]. Further-

[1] The sovereign bonds in question are Greece, Italy, Ireland, Portugal and Spain.

more, they calculate the aggregate capital shortfall is around €600 bln. using accounting data and around €1000 bln. when using market data.

These paper show that studying systemic risk in the Eurozone is of relevance and also highlight why the banking sector is of special interest.

2.2. Monetary Policy

After concluding the review on the systemic risk literature, I now turn to monetary policy. Given the nature of my research question, I focus on transmission channels of monetary policy. In particular I concentrate on the risk-taking channel, as it is the transmission channel that I am building my main argument in the subsequent chapter on. This is also why I discuss the expected magnitude of the mechanisms under conventional and unconventional monetary policy in this chapter.

Conventional and Unconventional Monetary Policy

One of the research question of this thesis is whether monetary policy impulse transmission to systemic risk is different under conventional and unconventional policy. Thus, it is important to define conventional and unconventional policy regimes.

Under a conventional monetary policy regime, the central bank uses the short-term policy rate to influence the inter-bank rates and thus the wider economy. Interest rates are set in response to macroeconomic signals and approximately followed a Taylor-Rule to achieve a low and stable inflation. However, after the financial crisis of 2008/2009 conventional tools proved to be ineffective as the nominal interest rate was close to the Zero Lower Bound (ZLB). Thus, central banks turned to Unconventional Monetary Policy (UCMP) tools (Smaghi, 2009).

Defining an UCMP regime is more difficult. As Joyce et al. (2012) puts it: 'Unconventional monetary policy takes many forms, as it is defined by what it is not rather than what it is.'. In other words, an unconventional monetary policy regime is defined as a regime that is not conventional. The main tool of UCMP are expansions of central banks' balance sheets, which are broadly referred to as Quantitative Easing (QE) and Forward Guidance (FG). The latter tool controls how the central bank communicates its future strategy to the public. However, the problem with pinning down UCMP is the discretion central bankers have with the implementation. As a result, the application of UCMP tools has varied over time and currency area (Joyce et al., 2012).

The ECB operated under a conventional policy regime between its establishment 1999 and the beginning of the financial crisis in late 2007. While the ECB shifted its focus from monetary aggregates to inflation targeting, the central bank's main tools where the money supply and the interest rate. In response to the financial crisis, the ECB eased its monetary policy stance. It lowered the collateral standards for banks, cut interest rates and provided liquidity. Thus, this is the first time, the ECB used UCMP tools to implement monetary policy. However, it was not until 2013 before the ECB fully commited to UCMP and started large scale asset purchase programs (Constâncio, 2018).

Measuring Monetary Policy under UCMP

The problem with measuring monetary policy in times of UCMP is the ZLB. Banks can not impose negative deposit rates on their customers as agents have the option to hold cash, which bears 0% interest rate. Therefore, when nominal interest rates are close to or at the ZLB, nominal interest rates will not display much variation (see Figure 1). In other words, after interest rates are close to zero, the nominal interest rate is not a good measure for monetary policy anymore, as it indicates that there have not been any policy innovations since the policy rate has been close to the ZLB. In 2016, the ECB cut the Repo rate to zero percent.

In the literature two possible variables emerged to circumvent the problem. First, the change of the size of the balance sheet of the central bank was used (Elbourne et al., 2018). As discussed before, the majority of UCMP are QE programs which result in a massive increase of the size of the central bank's balance sheet. Using the change of the central bank balance sheet has two important drawbacks. First, it does not include FG which is an important part of UCMP. On the other hand, the SSR is based on market rates and can thus react to FG shocks. Second, in order to thoroughly investigate causal effects in a structural model, the shocks to the policy measure need to be unpredictable. However, changes to the balance sheet are announced in advance and are thus predictable. If this is not accounted for, the results in a VAR context will be biased (Haldane et al., 2016).

The second variable proposed is the Shadow Short Rate (SSR) (Krippner, 2013). The model is based on the idea that nominal interest rates can not be below zero as agents have to option to chose cash which has an interest rate of zero percent. Krippner's idea was to remove the value of this option from the interest rate. Hence, the result is an estimate of the nominal interest rate in the absence of the option of agents to hold cash. What makes this series so appealing is that it can be used in times of conventional and unconventional monetary policy regimes as it closely tracks the repo rate under a conventional regime (see Figure (1)).

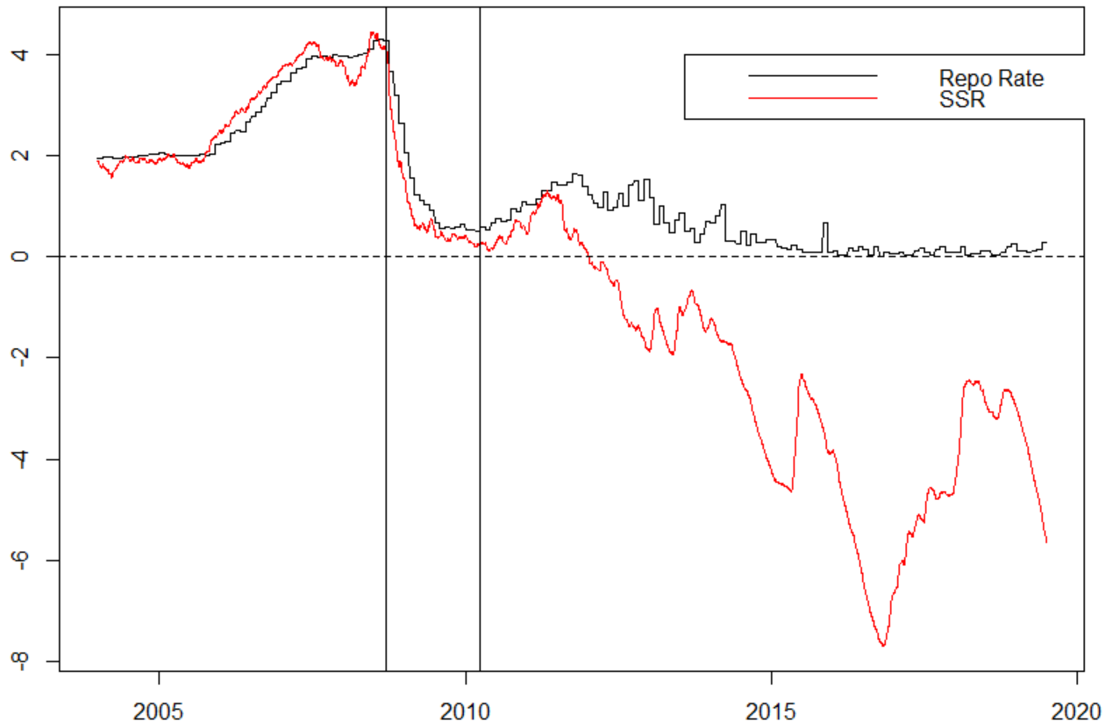

Figure 1: Comparison of the SSR (red line) and the Repo rate (black line). In times of conventional policy, the two measures are similar. In times of unconventional monetary policy, the SSR dips below zero. The horizontal bar marks the zero percent interest rate. Furthermore, the first vertical bar represents the collapse of Lehman Brothers in 2008 and the second the beginning of the Euro Crisis.

After Krippner (2013) introduced the SSR, Wu and Xia (2016) proposed an alternative model to estimate the same series. The difference is that Krippner assumes a two factor and Wu and Xia a three factor model of the term structure. Krippner (2015) and Krippner (2017) voices concern about the sensitivity of the model proposed by Wu and Xia is sensitive to i.a. the sample length. Thus, I opt for the shadow rate estimate procedure in Krippner (2013). The series is available at Factset and does not need to be estimated.

Risk-Taking Chanel

After introducing the difference between the two policy regimes and providing some background on how the ECB operated in the past, I turn to the transmission of monetary policy to the broader economy.

Borio and Zhu (2008) were the first to postulate the *risk-taking channel* of monetary policy. It captures 'the change in the risk-perception and risk-tolerance due to a monetary policy intervention' (Borio and Zhu, 2008, p. 9). The authors argue that the risk-taking channel works through three different sub-channels.

First, the impact on valuations, cash-flows and incomes. This is similar in spirit to the financial accelerator (Bernanke et al., 1996) and balance sheet effects. Figure (2) depicts the concept. A reduction (increase) in the policy rate increases (decreases) the demand for assets which increases (decreases) the prices of these assets. Subsequently, owners of these assets can borrow more (less) money as their financial position improves (deteriorates) and they can pledge more (less) collateral. Thus, the perceived risk would be lower (higher) and banks' risk tolerance would be higher (lower).

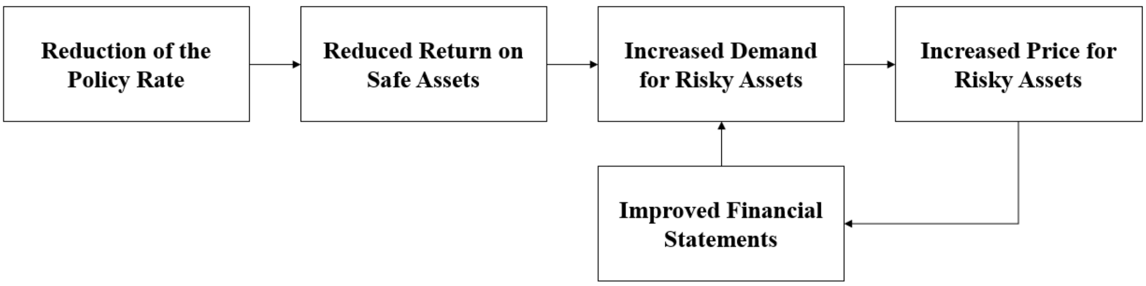

Figure 2: First sub-channel of the risk-taking channel: Influence on cash-flows, valuations and incomes

The effects of this first channel should be stronger under unconventional monetary policy. This becomes clear if one recalls one of the main tools of UCMP: QE. Under QE central banks buy securities in order to boost their prices. Thus, asset prices should increase more under UCMP compared to conventional monetary policy. Therefore, the effect on risk-taking should be positive and stronger under UCMP.

Second, monetary policy has an insurance and transparency effect (Borio and Zhu, 2008). The former stems from a de facto censoring of the risk distribution by the central bank, i.e. the central bank censors downside risk with its behaviour. The latter affects risk perception by decreasing the uncertainty about the future stance of monetary policy.

While Borio and Zhu do not mention this specifically, the central bank has to be credible for this channel to work.

As mentioned above, one of the main tools of UCMP is FG. While the main goal of this tool is to manage inflation expectations, it seems plausible that it also greatly reduces the uncertainty about the future policy path.

Lastly, the search for yield effect transmits policy rates into an increased risk taking by financial institutions. This effect is especially pronounced for institutions that are bound by a promised return rate and when nominal interest rates are close to the ZLB.

Once again, this channel should be stronger when interest rates are low. Under conventional monetary policy, nominal interest rates cannot fall below zero percent. On the other hand, under an unconventional policy regime, interest rates can fall below zero. Thus, the effect should be more pronounced when interest rates are close to or below zero. Negative rates should magnify the effect, i.e. it should be stronger under UCMP.

In addition, to what Borio and Zhu argued, Adrian and Song Shin (2010) introduce the leverage channel. Their basic assumption is that if banks are faced with a shock, they will sell or buy assets rather than raising new capital or distributing dividends. As argued before, a decrease of the policy rate by the central bank will increase asset prices. If leverage is defined as assets plus liabilities divided by assets, leverage ratios will decrease. Thus, banks will seek to restore their initial level of leverage by investing in assets. This feedback loop is similar to that of the financial accelerator discussed before. Also, it is a first indication of how the systemic risk-taking mechanism and monetary policy are connected. I discuss this in more detail in the subsequent chapter.

As this effect is similar to the effect on income, cash-flows and valuations, the outcome under conventional and unconventional policy regimes should be similar to the first sub-channel described at the beginning. Therefore, the effect should be more pronounced under UCMP.

De Nicolo et al. (2010) formulate an important critique and extension of the risk-taking channel. They argue that monetary policy shocks have two simultaneous effects on banks. First, the portfolio effect, which is similar to the three sub-channel discussed above. Hence, the portfolio effect states that banks will increase their risk-taking following an expansionary monetary policy shock. On the other hand, they argue that in the short-run the risk-shifting effect is also relevant. De Nicolo et al. (2010) show that a reduced interest rate leads to a higher intermediation spread, which increases bank profitability. This should boost their equity value, which in turn means that they have more to loose. Therefore, the authors also refer to this as the 'skin in the game' effect. Therefore, I assume that the effect on risk-taking should be more ambiguous than predicted by Borio and Zhu (2008).

Which effect dominates the other depends on bank individual and aggregate sector characteristics. Assuming that banks cannot adjust their capital level in the short-run, the authors conclude that at least in the short-run, the risk-shifting effect depends on the equity value of banks. In the long-run banks capital levels are flexible and banks will increase their leverage and shift towards riskier portfolios. Hence, they predict that in the short-run the effect is ambiguous but in the long-run unambiguously negative.

Empirically, the risk-taking channel has since been confirmed in various studies.
Neuenkirch and Nöckel (2018) analyse the risk-taking channel in the euro area between 2003 and 2016. They use a VAR to show the impact a policy intervention has on the lending standards of banks. Their results confirm the first sub-channel discussed above: An expansionary monetary policy shock lowers the lending standards. Given their sample, they also compare the effects of a decrease in the SSR and the Marginal Refinancing Rate, i.e. the effects under a measure that combines conventional and unconventional monetary policy and one that only measures the former. Surprisingly, their results show that the effect of a conventional monetary policy intervention is larger in magnitude. However, this might be due to the fact that banks take on more risks via other operations than lending. This intuition is confirmed by Brana et al. (2018), who use a threshold regression model to estimate the asymmetric Z-Score and the Distance to Default (DD) as measures of a bank's risk. The asymmetric Z-Score is an accounting data based measure and thus captures more than just a banks lending operations. Their results suggest a stronger response of both the DD and asymmetric Z-Score. Furthermore, their study shows that all their monetary policy indicators (Deposit rate, SSR and the policy rate) influence bank risk-taking significantly under UCMP which is not the case under a conventional monetary policy regime for both risk measures.

Gambacorta (2009) provides further evidence on the existence of the risk-taking channel for a data set of American and EU countries. The authors use a large sample of 600 European and US banks from 1997 to 2009 to predict their probability of default. They control for bank specific balance sheet and broader, country specific macro variables and are able to confirm the risk-taking channel: Low interest rates boost bank risk-taking. Furthermore, they show that a house price growth above its six month average substantially increases the probability of default. This is evidence for the first sub-channel of the risk-taking channel.

Heider et al. (2018) show that the introduction of a negative policy rate in 2014 (deposit facility) results in less lending and more risk-taking by banks with stronger reliance on deposit funding. Banks that rely on other forms of funding are less affected, which the authors explain with the inelasticity of deposit rates, i.e. banks are reluctant to charge their customers negative deposit rates. As lower rates reduce both the return on assets and the funding costs the net worth of a bank that does not transmit negative deposit rates to its customers will decrease in times of negative interest rates. This reduction in net worth will lead to a contraction of lending activity by high-deposit banks. Note that this is closely related to the theoretical argument laid out in De Nicolo et al. (2010). However, the overall lending activity increases as banks with relatively low deposit funding make up for the contraction. High-deposit banks will make riskier loans though.

However, the relation between the risk-taking channel and UCMP seem to vary quite substantially between currency areas and also among markets within currency areas. While Nakashima et al. (2017) are able to show that for Japan, unconventional policy tools do have a significant effect on banks' risk-taking, results from Matthys et al. (2018) for the U.S. point to a different conclusion. They show that risk is priced correctly by banks and the risk-taking is not excessive using a data set for syndicated loans. However, Frame and Steiner (2018) provide evidence for the search for yield behaviour as a result of UCMP in the U.S. but for the Agency Mortgage Real Estate Investment Trusts.

Hattori et al. (2016) add to the literature by examining the effect of unconventional policy on tail risk perception, i.e. the insurance effect discussed above. Using an event study, they find that UCMP has the strongest impact on the option implied probability of a substantial downturn in the immediate future. Following UCMP announcements, this probability decreases. In addition, their results suggest that FG account for the main part of this effect.

It is important to stress that the concepts before only explains banks' individual risk-taking. Literature on expanding similar arguments to systemic risk is largely absent. To the best of my knowledge, Faia and Karau (2019) and Colletaz et al. (2018) are the only paper that analyse the relationship between monetary policy and systemic risk.

Faia and Karau (2019) use a methodology that is very similar to the one I apply in this thesis. They estimate multiple VAR type models, e.g. panel VAR, proxy VAR and FAVAR and use structural analysis to obtain an Impulse Response Function (IRF) for the effect of a monetary policy innovation on systemic risk. As their systemic risk measures they use the Long-Run Marginal Expected Shortfall (LRMES) and $\Delta CoVaR$ and their sample consist of 29 globally SIB banks. Their findings suggest that a reduction of the policy rate increases systemic risk. These findings are robust to different measures of systemic risk, to excluding the 2008 financial crisis from the sample and different empirical models. Also using a FAVAR has the advantage that the structure implied of the economy includes a large set of variables. As a policy measure they use the SSR and the policy rate, both for the U.S.

Faia and Karau (2019) also disentangle the different channels that effect systemic risk and show that systemic risk is not only driven by balance sheet effects but also by macroeconomic spill-overs. The lack of literature however, means that one of the main contributions of this thesis is to provide additional evidence on the subject.

Colletaz et al. (2018) analyse the causality from monetary policy innovations to systemic risk in the EZ. They find that monetary policy causes systemic risk and are able to reject the reverse causality. However, they distinct between the short and the long run: 'a protracted period of easy monetary policy is likely to impact risk tolerance and risk perception, which in turn will have a negative impact on the systemic risk-taking' (Colletaz et al., 2018, P.2). Thus, they apply a short- and long-run measure of causality and find that while the former would reject causality, the latter finds evidence for a causality from monetary policy innovations to systemic risk.

Colletaz et al. (2018) also make a theoretical argument why monetary policy should influence systemic risk. In particular, they identify four mechanisms. First, the three sub-channel of the risk-taking channel in combination with herding behaviour leads to the build-up of systemic risk. I am going to discuss similar thoughts in the next chapter. Second, the authors separately discuss the portfolio allocation effect. I disused this effect in combination with the first sub-channel of the risk-taking channel as I view them as interrelated.

3. Theory

In the previous chapter I reviewed the literature on systemic risk and monetary policy. Now I proceed by laying out the theoretical foundations of the Systemic Risk Taking Channel. In order to make a sound argument, I use a simple model of systemic risk. Subsequently, I develop my hypotheses to the research questions.

3.1. A Stylised Model of Systemic Risk

Benoit et al. (2017) provide an extensive review of the literature on systemic risk. I use their stylised model to describe how banks advance the build-up of systemic risk, as a response to monetary policy shocks.

To set up the model, let x_i be a banks risk exposure, which is divided into a systematic fraction, α_i, and an idiosyncratic component, $1 - \alpha_i$. Furthermore, $y^S = \sum_{i=1}^{N} \alpha_i x_i = \sum_{i=1}^{N} y_i^S$ and $y^I = \sum_{i=1}^{N} (1 - \alpha_i) x_i = \sum_{i=1}^{N} y_i^I$ denote the cumulative systematic and idiosyncratic risk exposure of the banking sector. Both the systematic and the idiosyncratic risk component get compensated by a constant term ρ and a random variable, ϵ, with mean zero and some variance σ^2. Benoit et al. define the *benchmark pay-off* as the return on the i-th firm's equity given, that there is only one firm in the sector. Note that, given the definition of systemic risk above, this implies the absence of systemic risk.

$$\hat{\pi}_i = (\rho^S + \epsilon^S) \times y_i^S + (\rho^i + \epsilon^i) \times y_i^I \tag{1}$$

The first part of this equation should not be surprising, as it simply expresses that systematic risk is priced in financial markets. However, the second part is more of a surprise. Basic finance literature teaches that idiosyncratic risk can be diversified and thus should not be compensated. However, in a connected network, where shocks get amplified and financial distress can spread among banks, it is important to model the idiosyncratic risk component. Hence, for a network of $N \geq 2$ banks the idiosyncratic exposure becomes important. Benoit et al. model the direct links between these institutions using the $N \times N$ matrix $\mathbf{B}$.

$$\mathbf{B} = \begin{bmatrix} b_{1,1} & \dots & b_{1,N} \\ \vdots & \ddots & \vdots \\ b_{N,1} & \dots & b_{N,N} \end{bmatrix}$$

Where $b_{i,j}$ represents the link between the i-th and j-th bank in the system. Subsequently, Benoit et al. define the *realised return* in a system with two or more banks as a function of the vectors of idiosyncratic shocks ($\boldsymbol{\epsilon}^{\boldsymbol{I}}_{(N\times 1)}$), systematic exposures ($\mathbf{Y}^{\mathbf{S}}{}_{(N\times 1)}$) and idiosyncratic exposures ($\mathbf{Y}^{\mathbf{I}}{}_{(N\times 1)}$).

In addition, systematic shocks are again measured by ϵ^S which is a scalar, as the systematic shock is the same for all companies, i.e. it is not specific for each company. Benoit et al. do not explicitly model the realised vector of returns but simply denote its i-th element as a function of the variables described before.

$$\pi_i(\mathbf{Y}^{\mathbf{S}}, \mathbf{Y}^{\mathbf{I}}, \mathbf{B}, \epsilon^S, \boldsymbol{\epsilon}^{\boldsymbol{I}}) \tag{2}$$

Similar to Equation (1), I write the realised return of the i-th company as

$$\pi_i = \underbrace{(\rho^S + \epsilon^S) \times y_i^S}_{\text{Systemic Risk-Taking}} + \underbrace{(\rho^I + \epsilon^I) \times y_i^I}_{\text{Idiosyncratic Risk-Taking}} + \underbrace{b_{i,\cdot} y^I}_{\text{Contagion}} + \underbrace{A}_{\text{Amplification}} \tag{3}$$

$$\pi(\mathbf{Y}^{\mathbf{S}}, \mathbf{Y}^{\mathbf{I}}, \mathbf{B}, \epsilon^S, \boldsymbol{\epsilon}^{\boldsymbol{I}}, A) \tag{4}$$

In this notation, $b_{i,\cdot}$ is the i-th row of the matrix $\mathbf{B}$, which represents the direct links between the i-th bank and the other banks in the system. Note that only idiosyncratic shocks of other banks get transmitted through the row vector $b_{i,\cdot}$ and systematic shocks are still modelled as in (1). Furthermore, Equation (4) is the vector representation of returns, i.e. π is a $N \times 1$ vector of returns of all banks in the system.

In addition to the model presented in Benoit et al. (2017), I added the term A. This term models the amplification effects via e.g. 'fire-sales'. Indirect effects usually leads to an increased correlation in the left tail of the return distribution of firms. Note that I do not specifically model A, as giving A a specific form would not add much value to this highly stylised model.

Note that I add the mechanisms of the systemic risk-taking channel in Equation (3), which I develop in the next chapter.

Benoit et al. (2017) then go on to argue that the defining characteristic of systemic risk is that $\pi_i \neq \hat{\pi}_i$ for some input variables. They conclude that all paper that analyse systemic risk, make some joint statement on the realised returns. To exemplify this, a common measure expresses $Pr(\pi_i < C|\pi < q)$ [2]. Hence, I measures the probability that

[2] This is the CoVaR measure developed by Adrian and Brunnermeier (2016) which I discuss in the

the realised returns of the i-th company are below a threshold C, given that the market is in the q quantile of its return distribution.

3.2. The Systemic Risk-Taking Channel of Monetary Policy

Using the model of systemic risk above, I now continue to first build a theoretical argument how monetary policy influences systemic risk. In the spirit of Borio and Zhu (2008) and Colletaz et al. (2018) I refer to this channel as the *systemic risk-taking channel* of monetary policy. The main idea of the systemic risk-taking channel is that the monetary policy shock gets transmitted through the risk-taking channel and then affects systemic risk. Figure 3 summarises the idea and shows the parts of the stylised model which are affected by the shock. In the subsequent paragraphs, I analyse how an expansionary monetary policy shock gets transmitted through the system.

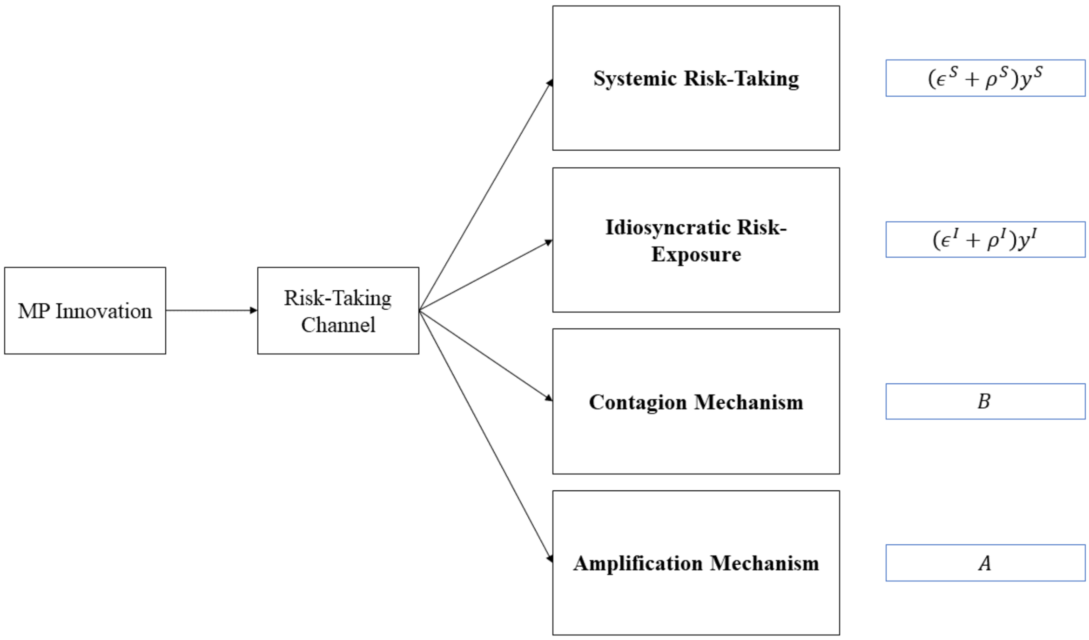

Figure 3: Stylised depiction of the mechanisms within the systemic risk-taking channel.

First, the risk-taking channel predicts an increase in the demand for risky assets. This is due to the four sub-channel of the risk-taking channel discussed before: portfolio effects, search for yield behaviour, insurance effect and procyclical leverage. A policy rate cut will lead to a boost of asset prices. This in turn leads to an improvement of

Methodology section.

the financial statements of both companies and individual agents. As a result, banks will view investments as less risky as the collateral provided will be more valuable. Furthermore, a reduced policy rate will incentivise banks to find return. Finding a higher return means entering into riskier investments. In addition, banks expect the central bank to intervene in times of a downturn. Thus, banks do not expect that the far left tail of the risk distribution will ever be realised. Therefore, banks are willing to engage in risky activities. The final reason why the demand for risky assets increases is the procyclicality of leverage. Given that a policy rate cut increases asset prices, banks leverage will decrease. Hence, to restore it banks have to increase their debt position and enter riskier transactions. In conclusion, all these reasons lead to an increase in the demand for risky assets of banks. In the model, this influences x_i and thereby the idiosyncratic risk-taking and the systematic risk-taking channel. It is difficult to tell, whether banks will increase their systematic or their idiosyncratic risk exposure more, i.e. whether the systemic risk-taking mechanism or the risk-taking channel will prevail and dominate the other. In both cases, the response by banks to an expansionary monetary policy shock is an increase in systemic risk. The risk-taking channel also has an effect on the contagion mechanism.

Faia and Karau (2019) and European Central Bank (2016) argue that a decrease in the policy rate, especially if it is close to the ZLB for a long time increases the reliance of banks on other banks and banks' market orientation. The increased reliance on funding by other banks instead of deposits is due to the inelasticity of deposit rates. Banks are reluctant to charge their customers for their deposits. Thus, policy rate cuts might not be transmitted into similar cuts of the deposit rates. However, the interbank market rates will decrease. As a result, banks will find it cheaper to lend from the interbank market instead of relying on deposits for funding. Moreover, an increased market orientation of banks, can also amplify the contagion effects. Banks that mainly provide services to other banks lose business if other banks slip into a crisis. Note that the increased market orientation of banks can also contribute to an increased amplification mechanism and also an increased systematic risk-taking, i.e. two other main mechanisms of systemic risk. In the model the effects described above have an impact on B. The final argument indicates that it might also have an impact on y^S and A. However, the main point is its influence on B. In addition, the risk-taking channel also transmits into the amplification mechanism. As argued before, the amplification mechanism is more of an overarching mechanism that is influenced by dynamics in the other three channel and in turn also affects these channel. Search for yield behaviour is one of the main drivers of this mechanism. A reduced policy rate diminishes the set of profitable investments. If banks have more or less the same information set, they all identify the same portfolios and proceed with similar strategies. As a result, bank returns will be highly correlated, i.e. the indirect links between banks are strengthened. In the model, the variable affected is A.

Note that all the effects described before lead to an increased difference of the realised returns and the potential returns. Again, this is one of the main characteristics of systemic risk (Benoit et al., 2017). In addition, this is in line with the definition of systemic risk, given above. All the mechanisms make a simultaneous failure of multiple banks more likely or more severe. In addition to my contribution here, Colletaz et al. (2018) also provide some arguments why monetary policy should influence systemic risk. However, the authors fail to convincingly argue why their arguments should increase systemic risk and not just banks' individual risk. Thus, this chapter is novel in that it underpins arguments for the risk-taking channel with a model of systemic risk. This provides a more rigid framework and a clean argument for the systemic risk-taking channel. On the other hand, it is similar to Colletaz et al. (2018) that the (abstract) chain in both structures is: MP innovation → Risk-Taking Channel → Systemic Risk-Taking Channel.

3.3. Hypothesis Development

The main research question this thesis addresses is whether there is a causal link between monetary policy and systemic risk. Within this question, I focus on the Euro area and its banking sector. Given the theoretical considerations above, my expectation is that there is a negative relationship, similar to the risk-taking channel. Hence, I expect a reduction of the policy rate to be associated with an increase in systemic risk.

Furthermore, I address several other sub-questions within this thesis to shed more light on some of the workings of the systemic risk-taking channel. The theory section showed that the systemic risk-taking channel is closely linked to the risk-taking channel. Thus, the discussion of how the risk-taking channel operates differently under conventional and unconventional monetary policy motivates the question whether the relation changes if the policy regime changes. From the discussion above, all arguments point to a stronger relation under UCMP. Also I do not expect the sign to change.

My third and fourth research question is motivated by the critique of the risk-taking channel in De Nicolo et al. (2010). First, is the effect from monetary policy to systemic risk stronger for SIB than for non-SIB? The risk-shifting mechanism should be stronger in the short-run if the moral hazard is greater. It is self evident that banks that are systemically important enjoy implicit government guarantees. Thus, SIBs should have a weaker incentive to act prudently and the risk-shifting mechanism should be less pronounced. Therefore, I predict that SIBs have a greater increase in systemic risk, following an expansionary monetary policy shock. Second, is there a difference for healthy and unhealthy banks? According to De Nicolo et al. (2010), the effect for healthy banks should be weaker in the short-run, as the risk-shifting mechanism is more pronounced. Thus, I predict that healthy banks respond with a smaller increase in systemic risk to an expansionary monetary policy shock.

4. Methodology

4.1. Systemic Risk Measures

The majority of the systemic risk literature can broadly be divided into two categories: VaR-type measures and capital shortfall measures. The former result in some estimate for the VaR level of the financial system, which includes the correlation between the bank and the market. On the other hand, capital shortfall measures try to estimate the expected capital shortfall of the financial system (or an individual bank), conditional on a systemic event. In this thesis, I am going to estimate the two most influential measures: CoVaR (Adrian and Brunnermeier, 2016) and SRISK (Brownlees and Engle, 2016).

CoVaR

Adrian and Brunnermeier (2016) propose CoVaR, which is an estimate of the VaR level of the financial system given that one financial company is in distress. More formally, they write

$$CoVaR_q^{m|i} = P(r_{m,t} < CoVaR_q^{m|C(X_i)}|C(X_i) \tag{5}$$

Where, $C(X_i)$ is a conditioning event, such as company i breaching its VaR q level. In addition, they propose $\Delta CoVaR^i$ as a means to measure a company's contribution to systemic risk. $\Delta CoVaR^i$ measures the change in the CoVaR level of the market given that the i-th institution switches from its median level of returns to its q%-VaR level and can thus be used to rank institutions.

$$\Delta CoVaR_i = CoVaR_q^{m|r_{i,t}=VaR_q^i} - CoVaR_q^{m|r_{i,t}=Median_i} \tag{6}$$

However, both ΔCoVaR and CoVaR are still conditional on one firm. Thus, the estimation procedure yields an estimated series per company included in the sample. Thus, I use the weighted average in each point in time as the aggregated CoVaR to obtain one measure for the aggregated systemic risk in the market.

SRISK

On the other hand, SRISK is a conditional capital shortfall measure, i.e. it's an estimate of the capital shortfall of a company, given that the market is in severe distress. In order to understand this type of measure, the expected shortfall and marginal expected shortfall have to be defined. The expected shortfall is the expected market return, conditional on the market being in distress.

$$ES_{m,t} = E(r_{m,t}|r_{m,t} < C) \tag{7}$$

Where,

- C is some threshold. Note that this is often formulated in terms of the VaR of a company (as done before for CoVaR)

The expected shortfall can be rewritten as

$$ES_{m,t} = \sum_{i=1}^{N} w_{i,t} MES_{i,t} \tag{8}$$

In other words, the Expected Shortfall is the weighted average of the Marginal Expected Shortfalls of each company. More formally, the MES can be written as

$$MES_{i,t+1:t+h} = E_t\left(r_{i,t+1:t+h}|r_{m,t+1:t+h} < C\right) \tag{9}$$

Usually, the MES is computed for h=1, which corresponds to a one day ahead MES. However, it can be computed for longer horizons. If h is larger, the MES is referred to as the Long-Run MES. In essence, the MES and LRMES measure the deterioration of firm equity, given the market is in distress for short and longer horizons, respectively.

Brownlees and Engle (2017) use the concept of the LRMES to define SRISK. The authors define SRISK as

$$SRISK = max[0, W_{i,t}(k \times LVG_{i,t} + (1-k)LRMES_{i,t} - 1)] \tag{10}$$

Where,

- $W_{i,t}$ are the assets of the company.
- k is the prudential asset ratio.
- $LVG_{i,t}$ is the leverage of the firm, defined as (Assets + Liabilities)/Assets.
- $LRMES_{i,t}$ is the MES for $h = 30$.

In order to rank institutions, they compute SRISK% which is the share of the aggregated market SRISK, that can be attributed to the i-th company.

$$\begin{aligned} SRISK_t &= \sum_{i=1}^{N} SRISK_{i,t} \\ SRISK\%_{i,t} &= \frac{SRISK_{i,t}}{SRISK_t} \end{aligned} \tag{11}$$

The main difference between SRISK and CoVaR is that CoVaR solely depends on market data, while SRISK on the other hand also includes accounting data. This has some practical advantages, like availability and consistency of data. Furthermore, it is reasonable to argue that financial markets price in all public information and thus the returns of banks should reflect their balance sheet information. On the other hand, SRISK specifically models accounting data in order to include size and the leverage as main contributors to systemic risk. The question whether CoVaR or SRISK is the superior measure comes down to a more philosophical question: Do market returns reflect all relevant public information and do financial markets price in systemic risk? To circumvent finding a question to these difficult questions, I estimate both measures.

On the other hand, the SRISK suffers because the estimate of the ES and MES are likely to be fairly instable. By definition, the conditioning events are rare, which makes the computation of an expected value difficult.

Both paper (Brownlees and Engle (2016), Adrian and Brunnermeier (2012)) show however that their measures can be used to estimate future downturns in the real economy. This is relevant for systemic risk estimation as one of the key features of systemic risk for some authors are the spill-overs to the real economy. For CoVaR, this is of utmost importance as under some assumptions, the closed form expression can be derived as a scaled version of the market correlation and volatility of a company. Thus, providing evidence that CoVaR has predictive power of real economic downturns in the future after including a volatility measure is vital to the validity of the measure.

In conclusion, both measures have advantages and disadvantages. Thus, I include them both in my analysis.

4.2. Systemic Risk Measures Estimation

GJR-GARCH

In order to estimate SRISK and CoVaR, I use a two step procedure, following Brownlees and Engle (2017) and Adrian and Brunnermeier (2016). First, I estimate univariate GJR-GARCH models for the volatility. Second, I fit a bivariate GARCH-DCC model to estimate the correlation between each company and the market returns.

In order to do so, I first define the return process as

$$r_{i,t} = \epsilon_{i,t} \tag{12}$$

$$\epsilon_{i,t} = \sqrt{h_{i,t}} z_{i,t} \tag{13}$$

Where, $\epsilon_{i,t} \sim F(0, h_{i,t})$ is called a return innovation that has some distribution function F. For a parametric approach, some assumption concerning the F has to be made. I opt for the normal distribution, as Engle (2009) shows that even if this is a misspecification, the parameter estimates are biased yet consistent.

Furthermore, the process for the conditional variance of r_t can be specified in multiple ways. I follow the literature and opt for a GJR-GARCH model. This type of process includes asymmetric effects, which enables me to incorporate different reactions to positive or negative returns in the previous period. This phenomenon is referred to as the Leverage Effect in the literature and is common to find in financial return series (Black, 1976).

$$h_{i,t} = \sigma^2_{i,t} = \omega + \alpha r^2_{i,t} + \beta h_{t-1} + \gamma r^2_{t-1} I^- \tag{14}$$

Where

- $\sigma_{i,t}^2$ denotes the variance of the i-th firm in period t and the market.
- ω is an intercept.
- α and β represent two coefficients for the past squared returns and the past volatility, both with one lag.
- γ incorporates the leverage effect as it interacts with the identification function I^- which takes on only two values: 0 and 1. If the return is below zero it will become 1, else zero. Hence, it allows to directly model the effect of negative returns on the volatility.

Note that Equation (14) is a GARCH(1,1) model, as it includes one lag of both the conditional volatility and squared returns. Of course, the GARCH model can be written in a more general form as a GARCH(p,q) model.
Subsequently, the return series have to be standardized or de-GARCHED. Thus, the means of the return series are subtracted and they are divided by their respective standard deviations.

$$z_{i,t} = \frac{r_{i,t} - \mu_i}{\sigma_{i,t}} \tag{15}$$

As the mean of the series is approximately zero anyway, I do not subtract it. The rationale to de-GARCH the series is to clean them of any GARCH-type volatility effects but leave the correlation dynamics. Thus, the resulting series should not show any signs of clustering or autocorrelation (in the squared series). Furthermore, if the model is correctly specified $z_{i,t} \sim F$, i.e. the standardised returns should approximately follow the distribution chosen for the return innovation.

GARCH-DCC

Afterwards, I use the standardised series $z = (z_{1,t}, \ldots, z_{N,t})'$ to estimate a bivariate GARCH-Dynamic Conditional Correlation (DCC) model in order to estimate correlation matrices. Again, with the specification I follow Brownlees and Engle (2017).

$$\mathrm{Cor}\begin{bmatrix} z_{i,t} \\ z_{m,t} \end{bmatrix} = R_t = \begin{bmatrix} 1 & \rho_{i,t} \\ \rho_{i,t} & 1 \end{bmatrix} = \mathrm{diag}(Q_{i,t}^{-1/2})\ Q_{i,t}\ \mathrm{diag}(Q_{i,t}^{-1/2}) \tag{16}$$

Where,

- $Q_{i,t}$ is the pseudo-correlation matrix of the i-th stock in period t.

- $\rho_{i,t}$ is the correlation between the i-th stock and the market index.

In order to estimate Equation (16), one has to specify the dynamics of Q. Once again, I follow the approach in Brownlees and Engle (2017).

$$Q_{i,t} = \Omega + \alpha_{C,i} \begin{bmatrix} z_{i,t} \\ z_{m,t} \end{bmatrix} \begin{bmatrix} z_{i,t} \\ z_{m,t} \end{bmatrix}' + \beta_{C,i} Q_{i,t-1} \tag{17}$$

To simplify the estimation procedure, it is usually split up into two steps. First, restrict the matrix Ω to be equal to $\bar{R}_i(1 - \alpha_{C,i} - \beta_{C,i})$. Here, $\bar{R}_i = \frac{1}{T}\sum \epsilon_t \epsilon_t'$, i.e. $\bar{R}_i$ is the unconditional correlation matrix of the market and the returns. The second step is to maximize the log-likelihood function [3]. This is known as variance targeting Engle (2009).

The result yields the correlation and variance for each stock and the market. Using normality assumptions for the GARCH models yields another great advantage: Adrian and Brunnermeier (2016) show that CoVaR under the normality assumption, CoVaR has the following closed-form expression:

$$CoVaR_q^{m|C(X_i)} = \Phi^{-1}(q)\sigma_{m,t}\sqrt{1 - \rho_{i,t}^2} + \Phi^{-1}(q)\rho_{i,t}\sigma_{m,t} \tag{18}$$

Where,

- $\Phi(z)$ is the standard normal cummulative distribution function.

- $\rho_{i,t}$ is the correlation between the i-th firm and the market.

- $\sigma_{m,t}$ is the conditional volatility of the market.

In their paper, Brownlees and Engle estimate the LRMES by simulating return paths using the GARCH parameters estimated before. However, there is an approximation, which also follows from the normality assumption for the volatility and correlation processes (Brownlees and F. Engle, 2012).

$$M\hat{E}S_{i,t+1:t+h} = \sqrt{h}\hat{\beta}_{i,t+1}\hat{ES}_{t+1|I_t} \tag{19}$$

[3] I will not go into the details but refer the reader to Engle (2009) for a rigid derivation and explanation.

Where, $\hat{\beta}_{i,t+1} = \hat{\rho}_{i,t+1} \times \frac{\hat{\sigma}_{i,t+1}}{\hat{\sigma}_{i,t+1}}$ and $\hat{ES}_{t+1|I_t}$ can be estimated as the expected value of market returns given that the market is below a certain threshold scaled by the volatility of the market [4].

4.3. Principal Component Analysis

The FAVAR model I estimate, requires the extraction of factors from macroeconomic series. This can be done using Principal Components Analysis (PCA). The general idea of PCA is to reduce the dimensionality of a data set by estimating latent factors that describe the maximum of variation within the data (Lütkepohl, 2014). Thus, by applying principal components, I assume that the underlying economy can be summarised by a set of factors that is smaller than a matrix containing the entire information set. Lütkepohl (2014) writes the factor model as

$$X = \Lambda F + \zeta \tag{20}$$

Where,

- X is a set of M observable economic variables and M is large.
- Λ is a matrix of factor loadings.
- F is a matrix of common factors.
- ζ is a vector of idiosyncratic error terms.

In order to estimate the factor loadings and factors, one has to maximise the variance explained by the common factors or (equivalently) minimise the squared error terms (Lütkepohl, 2014). This estimation can be done in multiple ways, but I focus on Eigenvalue Decomposition (EVD) here. EVD of the variance-covariance matrix of X leads to an estimate of the factor loadings, where the first column refers to the first eigenvector with the largest eigenvalue. These eigenvalues are equivalent to the empirical variance of the factors. Thus, the factors are ordered from the one that explains the largest part of the variance to the smallest. Therefore, dimensionality reduction can be achieved by choosing the first K factors, as they will have the largest marginal contribution to the variance explained by the factors (Lütkepohl, 2014).

[4] $\hat{ES}_{t+1|I_t} = \hat{\sigma}_{m,t} \times \frac{\sum_{i=1}^{t} z_{m,t-i} I[z_{m,t}<c]}{\sum_{i=1}^{t} I[z_{m,t}<c]}$ and $c = log(1+C)/\sqrt{h}\hat{\sigma}_{m,t}$

To choose K several measures have been proposed in the literature. Bai and Ng (2002) propose a measure similar to the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The idea is that including additional factors will increase the amount of variance in the matrix X, but the model will also be less parsimonious. Thus, the model trades off the increase in explained variance to the increase in factors. However, in this thesis, I am simplifying this procedure and manually select the number of factors. While this approach is more or less arbitrary, it greatly simplifies the application of the principal components analysis. On the other hand, Faia and Karau (2019) simply choose the first three factors, and Bernanke et al. (2004) the first five without further explaining why. Therefore, my approach is arbitrary but not extraordinarily compared with the literature.

It is possible to compute the share of the variance explained of X explained by the factors. As said before, the share of the variance explained by each of the principal components will decline with the k. In that sense, one can think of the first K factors as the linear combination that explains the maximum of the variance of X.

However, before estimating the factors, the data needs to be standardised, i.e. the series has to be de-meaned and divided by its standard deviation. Why is standardisation necessary? First, one of the assumptions of performing PCA the way described above, is that the series are mean zero. The easiest way to do this is to de-mean the series. Moreover, X contains series that are on different scales. For example, monetary aggregate levels are denominated in billions of Euros while EURIBOR rates are denoted in percentage points. Thus, the variance of the series are very different. In the data I use, the median variance is 1.695 and the mean is 749.213 before standardising it. Note that after the standardisation, the variance and standard deviation of each series is unity. Without standardising the data, the resulting factors would mostly explain variance from the variables with the largest scale.

$$z_i = \frac{x_i - \mu_i}{\sigma_i} \tag{21}$$

Where,

- x_i is the i-th series in X.
- μ_i is the mean of the i-th series.
- σ_i is the unconditional standard deviation of the i-th series.

4.4. FAVAR

In order to analyse the relationship between the systemic risk measure, as obtained by the estimation routines described above and a policy measure, I apply a FAVAR. The model was first introduced by Stock and Watson (2002) and first applied in the context of monetary policy analysis by Bernanke et al. (2004). Similar to a VAR the FAVAR analyses a vector of time series, henceforth $G_t = (y_{1,t}, \ldots, y_{N,t})'$. However, in addition to the observable time series, the model is augmented by a vector of unobservable factors, obtained by PCA, discussed above, $F_t = (f_{1,t}, \ldots, f_{K,t})'$. Hence, the system can be written as follows.

$$A(L)Y_t = u_t \tag{22}$$

Where,

- $Y_t = (G_t, F_t)$ is a $T \times (N + K)$ matrix of N observable series and K unobservable factors.
- L is the lag operator.
- u_t is a $N + K \times 1$ vector of idiosyncratic error terms which have mean zero and are uncorrelated, i.e. the variance-covariance matrix is diagonal.
- $A(L) = I - A_1L^1 - A_2L^2, ..., A_pL^p$ is the lagged coefficient matrix A.

I refer to the model in Equation (22) as the reduced form FAVAR. In contrast to the factor model presented in Equation (20), the FAVAR assumes a slightly different structure.

$$X_t = \Lambda^f F_t + \Lambda^y G_t + \zeta_t \tag{23}$$

Bernanke et al. (2004) refer to Equation (23) as the 'Observation Equation'. Compared to Equation (20), the observation equation includes the small set of macroeconomic variables of interest, i.e. G_t. Therefore, the assumption is that the unobservable factors *and* the observable macro series together drive the dynamics of the economy, represented by the large information set X_t.

Why would you use a FAVAR rather than a VAR? Bernanke et al. (2004) argue that the model has two key advantages compared to standard VAR models. First, by making use of more time series, the information set the model is based on is likely to reflect the information used by market participants more accurately. If the additional series used in the FAVAR are information used by agents, the estimates from a standard VAR will lead to biased estimates. Second, in a standard VAR the impulse response function can only be observed for the variables included in the model. In a FAVAR model, the set of variables included is much richer, making it possible to observe a larger set of impulse response functions.

Identification

In the end, the question of interest is how a shock in one variable affects the other variables in the system. In order to make that the impulse can clearly be attributed to that variable, i.e. identified, the contemporaneous correlations between the error terms has to be eliminated. In other words, correlation and causation have to be detached. Intuitively, if one does not disentangle correlation from causation, the impulse response functions (probably) represent the response from a mix of policies and not from only monetary policy (Kirchgässner et al., 2007)

The literature contains many different ways in which this disentangling can be achieved. I am going to rely on short-run restrictions or Cholesky decomposition, for three reasons.

First, the implementation of a Cholesky decomposition is straightforward. This also implies, that its theoretical reasoning is sound and understandable. Second, the literature relies heavily on this type of identification scheme (e.g. Faia and Karau (2019), Bernanke et al. (2004) and Wu and Xia (2016)). Third, Colletaz et al. (2018) provide an indication that monetary policy has no short-run effect but a long-run effect on systemic risk. Therefore, an ordering where there is no contemporaneous effect from monetary policy on systemic risk, is in line with their results.

In order to implement this identification scheme, it is necessary to rewrite the VAR model as a moving average infinity process. Note that this can be done only if the system is stable, i.e. all Autoregressive parameters lie within the unit circle (Kirchgässner et al., 2007).

$$\begin{aligned} Y_t &= A^{-1}(L)u_t \\ &= B(L)u_t \end{aligned} \tag{24}$$

Where, $A^{-1}(L) = B(L) = I - \sum_{j=1}^{\infty} B_j L^j$, with I as the identity matrix. The intuition is that the vector of factors and observable time series can be expressed by past shocks of itself. This is referred to as fundamentalness of the system. Knowing Y_t and its past is the same as knowing u_t and its past (Kirchgässner et al., 2007).

In order to implement the identification, the variance-covariance matrix of the reduced for error terms has to be decomposed.

$$\Sigma_{uu} = PP' \tag{25}$$

The idea is to choose P such that $PP' = I$ as then contemporaneous correlations are eliminated and the variances are going to be equal to unity. A Cholesky decomposition achieves just that by decomposing Σ_{uu} into two lower triangular matrices, i.e. P is chosen such that all elements above the diagonal are equal to zero (Kirchgässner et al., 2007).

Using this, the moving average infinity process in Equation (24), can be rewritten by multiplying PP' [5].

$$Y_t = PP'u_t - \sum_{j=1}^{\infty}(B(L)PP'u_{t-j}) \tag{26}$$

Substituting $P'u_t = W_t$ and $B(L)P = \Theta^t$, the system can be rewritten as

$$Y_t = \Theta(L)W_t \tag{27}$$

This results in the structural FAVAR or SFAVAR model. Hence, W_t are referred to as structural shocks, which have a clear eonomic interpretation as $\Sigma_{ww} = P^{-1}\Sigma_{uu}P^{-1} = P^{-1}PP'P^{-1} = I$. Thus, the shocks are contemporaneously uncorrelated. From the equations above it follows that the restrictions put on P are going to restrict the direction of causality in the model. Furthermore, given that P is lower triangular, the ordering of variables will be important and determine the direction of causality (Kirchgässner et al., 2007). To exemplify that, let $Y_t = (CoVaR_t, SSR_t)'$[6]. In this case

$$\Theta^{(0)} = \begin{bmatrix} \theta_{1,1}^{(0)} & \theta_{1,2}^{(0)} \\ \theta_{2,1}^{(0)} & \theta_{2,2}^{(0)} \end{bmatrix}$$

[5]Note that this is possible as $PP' = I$.

[6]Note that the SSR is a measure of monetary policy which will be discussed later in detail.

As P is lower triangular, $\theta_{1,2}^{(0)}$ will be equal to zero in this case. Thus, the contemporaneous effect of a shock of the shadow short rate on the systemic risk measure ($\theta_{1,2}^{(0)}$) will be zero. More generally, the variables ordered below will not have a contemporaneous impact on those ordered above (Kirchgässner et al., 2007).

Cholesky decompositions are popular in Macroeconomics. However, it is crucial to understand its limitations. The main disadvantage of Short-Run restrictions is that it imposes a structure on the economy that is not motivated by the data and very restrictive. A vast literature exists that focuses on exploring ways to ensure that $\Sigma_{ww} = I$ by other means.

Another important point is the lag selection. Note that the model presented in Equation (27) is a structural FAVAR(p) model where p indicates the number of lags included. For the choice of lags standard information criteria can be used such as the AIC or the BIC. Both are suitable, as they punish additional regressors. However, the BIC lays a heavier penalty on an increased number of predictors.

In order to estimate the FAVAR, I use equation-by-equation OLS which can be used if the model is written in its companion form before. The companion form is a way of rewriting a VAR(p) model as a VAR(1) model by stacking the individual equations into a single vector with only one lag (Kirchgässner et al., 2007).

Impulse Response Functions

After estimating the reduced form model and identifying it, it is possible to obtain an IRF. An IRF plots the response the reaction of variable i to a shock in variable j over a time horizon. Thus, it is the first derivative of $Y_{j,t}$ w.r.t. $w_{i,t-p}$.

$$\frac{\partial Y_{j,t}}{\partial w_{i,t-p}} \tag{28}$$

Equation (27) shows that the responses are going to be in the matrices Θ. The impulse is always equivalent to a one standard deviation shock in $u_{i,t}$ (Kirchgässner et al., 2007).

5. Data

My data set consist of three elements. First, daily stock prices from 31.12.2003 to 31.12.2018 of 14 banks which I use to estimate the systemic risk measures [7]. The second data set contains 103 different macro series that can broadly be categorised into six categories: employment, exchange rates, interest rates, money and credit, output and stocks. This differentiation is equivalent to Bernanke et al. (2004). Note that some of the macro series are only available on a quarterly basis. Thus, I choose to use all of them on a quarterly basis. Consistent with the stock data, the series consists of data from Q1:2004 to Q4:2018. The third element of my data, are balance sheet information. I extract the total assets and liabilities from the balance sheets of the 14 banks in order to compute the leverage as *(Assets + Liabilities)/Assets*. This is different then the approach by Brownlees and Engle (2017). However, the data set on Factset is incomplete to a degree where it is not unusable.

Stock Data

The stock data consists of 14 banks where eight are systemically important banks according to the last three annual ranking by the Financial Stability Board, i.e. each of these eight banks has been assessed to be systemically important at least once in the past three years in the FSB ranking. The other banks in the sample are the largest supervised banks from 2018 according to their balance sheet (see European Central Bank (2018)). I download the 15 series (14 banks plus the market index) from Factset. Using the 3776 daily observations I calculate the log returns by taking the log difference of the price series.

$$r_{i,t} = (log(P_{i,t}) - log(P_{i,t-1})) \times 100 \tag{29}$$

Note that this results in a 3775×15 matrix of returns, i.e. one observation is 'lost'. As a market index I use the Euro Stoxx Banks from Factset. Another approach could be to construct a market return as the weighted average of firm returns. This can be beneficial if the market chosen does not reflect the sample of banks' returns.

Figure 4 plots the return distributions for the banks' stock returns and the market. Going into more detail, Table 2 and 3 reveal that the return series are right-skewed, i.e. the mean of the return distribution is larger than the median. Furthermore, I test the series for normality using the Jarque-Bera test. In column 3 of Table 2, I report

[7] For a list of banks, see Table 1 in the Appendix.

the scale of the p-values. For all series I reject the Null of normality on any reasonable significance level [8].

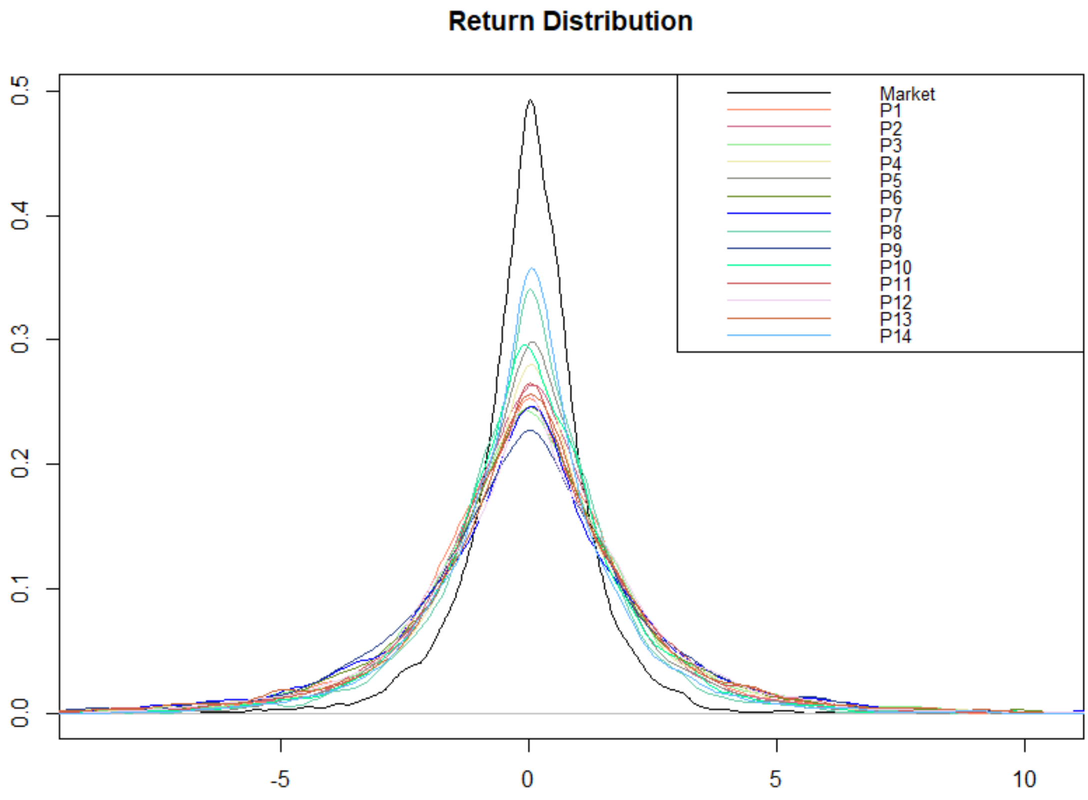

Figure 4: Distribution of Returns.

Furthermore, the volatility as measured by the squared returns appears to be quite persistent and heteroskedastic (see Figure 15 in the Appendix). Thus, the data justifies the use of the GJR-GARCH and GARCH-DCC model to estimate conditional volatilities and correlations.

Balance Sheet Data

As described above, in order to estimate SRISK, I need balance sheet information. Specifically, the measure requires the assets and liabilities of a firm in order to calculate the leverage. Unfortunately the data was not readily available. Thus I hand collected

[8]The p-values are in the area of $1e^{-16}$

them from the banks' quarterly reports. There were some issues, as not all data was available for all points in time. Table **??** in the appendix contains a detailed list of the issues and how I fixed them. Some of these issues where more severe. For example, Societe General only publishes semi-annual data on its website. Therefore, I assume the values in Q1, Q2 and Q3, Q4 to be the same, respectively. All in all however, I do not think that these issues will influence the basic results as most of the missing data only concerns scattered data points.

Macroeconomic Series

Following Bernanke et al. (2004) I use the sub-categories of macro series described before. In particular, I use 30 employment, 5 exchange rate, 20 interest rate, 15 money and credit, 23 output and 10 stock series.

One of the main issues is to make sure all series are stationary before estimating the principal components of the series. Thus, I difference the series to the point where they all are stationary according to the Augmented-Dickey Fuller test. While I have a large cross-section of series, I have very few observations in each time series, the matrix is 59×103. This means that rejecting the Null Hypothesis of the ADF test is going to be difficult. Therefore, I chose a moderate confidence level of $\alpha = 10\%$ as the threshold to rejecting the Null of stationary. It turns out that 81 and 32 variables need to be differenced once and twice, respectively. There is one variable for which the ADF test indicates that it would have to be differenced thrice. This variable corresponds to an index of Employees in the Industry sector (excluding construction) and I can not explain why it behaves this way. Hence, I simply exclude it from my data set. After differencing the series twice, I 'lose' two observations and thus my final matrix of macro series is of dimension 57×102.

Also, as described before, in order to estimate principal components from the data, I standardise the series. Thus, I compute the unconditional variance and mean of each series and first subtract the latter from the series and then divide the de-meaned series by its standard deviation. The resulting standardised series are included in Fiugre 21. In the 'original' 59×103 data set, three values are missing in the subset concerning interest rates and stocks. For simplicity, I take the series average to replace the missing value.

6. Empirical Results

6.1. Systemic Risk Measures

To begin with, I estimate the systemic risk measures. As laid out before, the estimation routine requires the estimation of a univariate GJR-GARCH for each of the bank stock returns and bivariate GARCH-DCC models for the correlation between the stock returns and the market returns. There are some important details concerning the estimation routine. Equivalent to the GJR-GARCH model presented in Equation (14), I choose a GARCH(1,1) process as default. This greatly simplifies the estimation routine as I do not have to find the best model every time. There is also substantial empirical evidence that a GARCH(1,1) is the best and most parsimonious model for most financial time series data (Hansen and Lunde, 2001). I also assume a DCC(1,1) model for simplicity. Furthermore, I assume normality, both for the GJR-GARCH return innovations and for the GARCH-DCC innovations. In addition to these assumptions, I update the sample every quarter, as the systemic risk measures are conditioned on the information set available in the period. Thus, I re-estimate the GJR-GARCH and GARCH-DCC parameters every three months. The first sample consists of all daily observations up to and including 31.12.2005. Note that this process results in daily correlation and volatility estimates. However, to obtain the systemic risk measures on a quarterly basis, I take the last estimate for the correlation and volatility of that quarter to estimate CoVaR and SRISK. Note that usually CoVaR and SRISK are estimated on a monthly basis. However, as I only have quarterly macro series, it makes sense to also estimate the systemic risk measures on a quarterly basis.

The estimated volatility processes are depicted in Figure 16. Comparing these results to the plot of the squared returns in Figure 15, the GJR-GARCH appears to capture the volatility dynamics well. There is a spike in 2008 and in 2012 for most banks, which is not surprising, as the index and the companies are European. More surprisingly, most banks experience an upwards tick in the volatility in 2016 as well. There is one process that sticks out: Banco de Sabadell's (P14) volatility appears to almost have an upward sloping trend. This is unusual, but is also in line with the dynamics of the squared returns for the bank.

More importantly for the estimation of CoVaR, I estimate the volatility of the market index. The market volatility estimate behaves similar to the individual banks' volatilities with three spikes in 2008, 2012 and 2016. However, compared to the banks' volatility, the market volatility appears less persistent. Therefore, the spikes in 2012 and 2016 do not stand out as much as they do in most of the banks' volatilities.

In addition, the correlations of the individual stock returns with the market return have to be estimated. However, the return series used for the GARCH-DCC have to be standardised. The results of this standardisation are plotted in Figure 19. In order to check, whether the methodology worked, I test the standardised residuals for normality. The results are presented in Table 6. Alas, the series do not seem to be normally distributed. However, the excess skewness and kurtosis has been reduced, i.e. the data is more normally distributed than before. Most importantly, the volatility clustering is removed from the data. Now, the remaining series are assumed to be driven solely by their correlation with the market. The results are presented in Figure 17. The correlation of all stocks' returns with the market is positive and for the most part above 0.5. Moreover, the processes appear to be relatively stable over time.

Subsequently, I estimate CoVaR and SRISK. Again, CoVaR can be obtained from the closed form expression presented in Equation (18). From the estimation routine I obtain a CoVaR for each stock. Note that this is the CoVaR of the market, given that this particular stock is in distress. Therefore, I have to set a threshold that determines whether a company is in distress. I opt for the worst 5% of losses, i.e. I choose $q = 5\%$. In order to obtain one systemic risk measure for the entire market, I weight these 14 CoVaR series by their market capitalisation in period t [9].

Interestingly, the estimate for CoVaR shows a spike in 2016 that is similar in magnitude to that in 2008 (see Figure 5). This might be due to a data issue. Exploring the market capitalisation data shows that Nordea Bank makes up the overwhelming majority of the market capitalisation. This seems hardly accurate and is likely due to the sudden drop in the estimated correlation of Nordea (P8, see Figure 17). In this case, the CoVaR measure becomes a more and more scaled up version of the market volatility. Given that the market volatility is quite persistent it makes sense that the CoVaR for Nordea behaves differently in this time. Thus, the result can be explained by the fact that the market value weighted average puts much weight on the CoVaR of Nordea which behaves differntly from most other CoVaR series. Therefore, I repeat the same procedure but this time with equally weighting the banks. The results are presented in Figure 6 and appear more convincing. Again, the plot reveals a major uptick in systemic risk during

[9] The market capitalisation is the number of shares outstanding times the share price adjusted for splits.

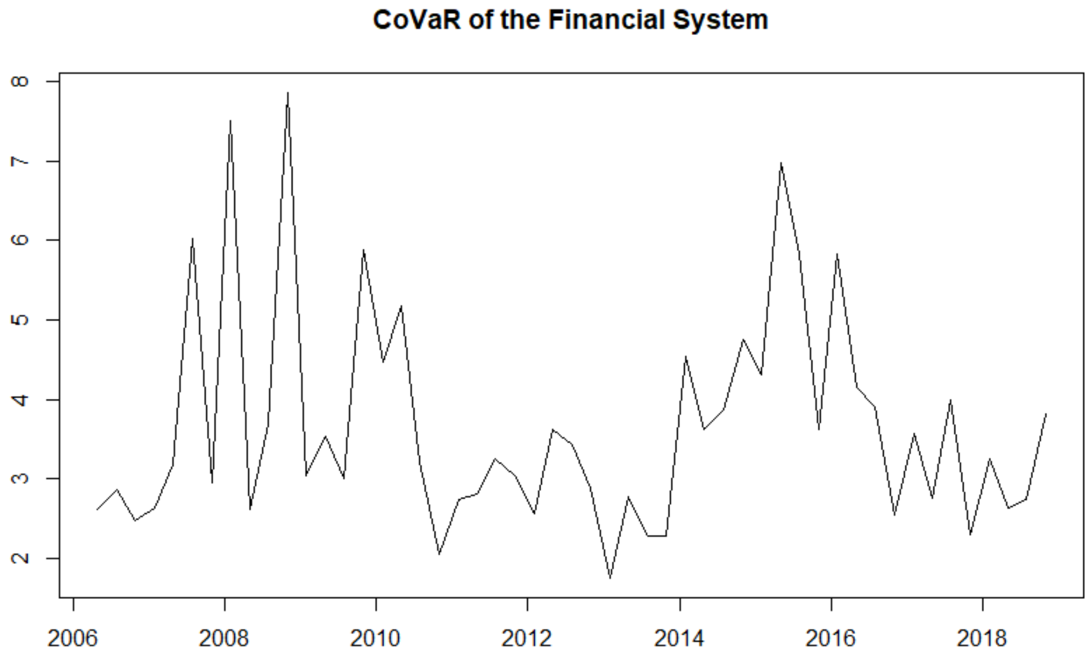

Figure 5: Market capitalisation weighted average of CoVaR.

the 2008/2009 financial crisis. Afterwards the series appears to be less persistent and looks more realistic. Therefore, I am using the series of the equally weighted CoVaR.

Subsequently, I estimate SRISK for each company. Thus, I calculate the Leverage as *(Assets + Liabilities) / Assets*. This is different from Brownlees and Engle (2017) as they use the debt of the firm and the market value of equity. However, the series of debt in Factset has so many and so frequently clustered missing values, that using the series is not useable. In addition, I choose a level of k and c. Following Brownlees and Engle (2017) I choose $k = 8\%$ and $c = 7.5\%$. From Figure 4 it becomes clear that this threshold, c, is far in the left tail of the distribution. Furthermore, I use $h = 66$ to compute the $MES_{i,t+1:t+h}$ of each company for each quarter. Figure 20 depicts the results, which reveal two types of patters in which all 14 banks can broadly be divided. First, a pattern similar to that of CoVaR presented above. An increase around 2008 and 2012 and a small uptick in 2016. Second, a more or less consistent increase since 2008. Summing over all SRISK estimates, yields the aggregate SRISK. Figure 7 reveals that the aggregate capital shortfall increases steadily until 2009. Afterwards, it remains on a similar level until 2013 when it drops, only to increase again in 2014. The magnitude

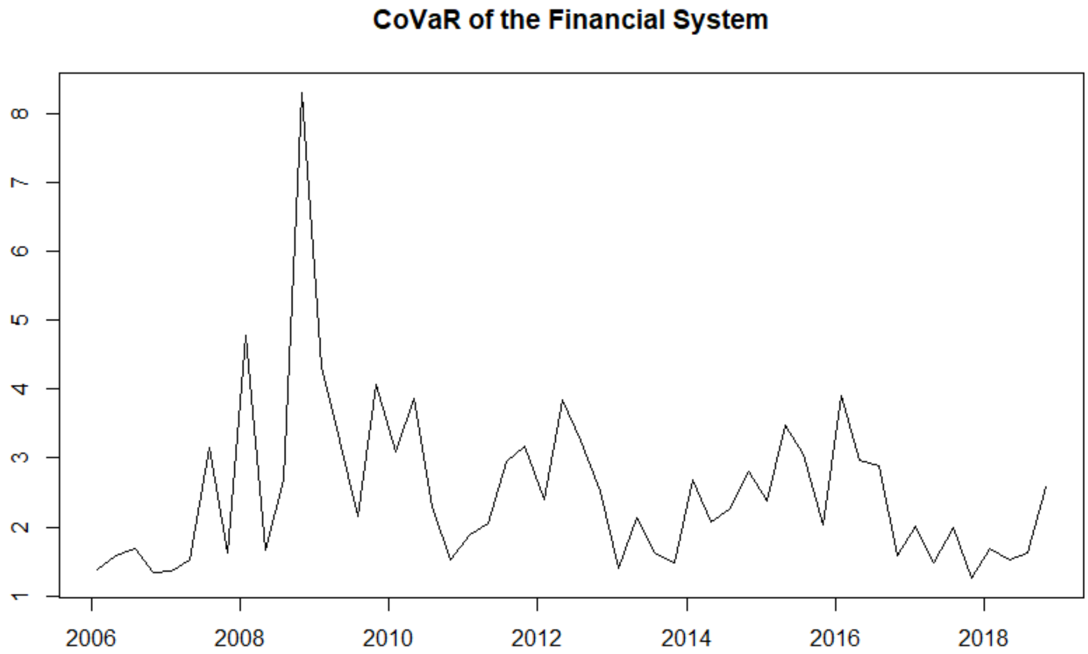

Figure 6: Equally weighted average of CoVaR.

is also in line with the estimates of other authors. As mentioned earlier, Acharya and Steffen (2013) find the capital shortfall in the EZ banking sector to be in between 600 bn. and 1000 bn. Euros. For the FAVAR analysis later, I view the change of the aggregate SRISK as the more interesting variable. The impulse response function than answers the question how does an impulse from the shadow short rate influence the change of the aggregate capital shortfall. Also the series of percentage changes appears to have more variation, which makes it more interesting for an empirical analysis.

6.2. FAVAR

After obtaining the estimates for the systemic risk measures, I can apply the FAVAR methodology. The first step after downloading the macro series is to extract the factors. In order to do this, I make sure these series are stationary and standardised to unit variance and mean zero (see Figure 21). Subsequently, I extract the factors after ordering the factors into fast and slow moving variables. The fast moving factors are the exchange rates, interest rates and stock data. Slow moving variables are employment, money and credit and output. As I said before, I simplify the selection of the number of factors K

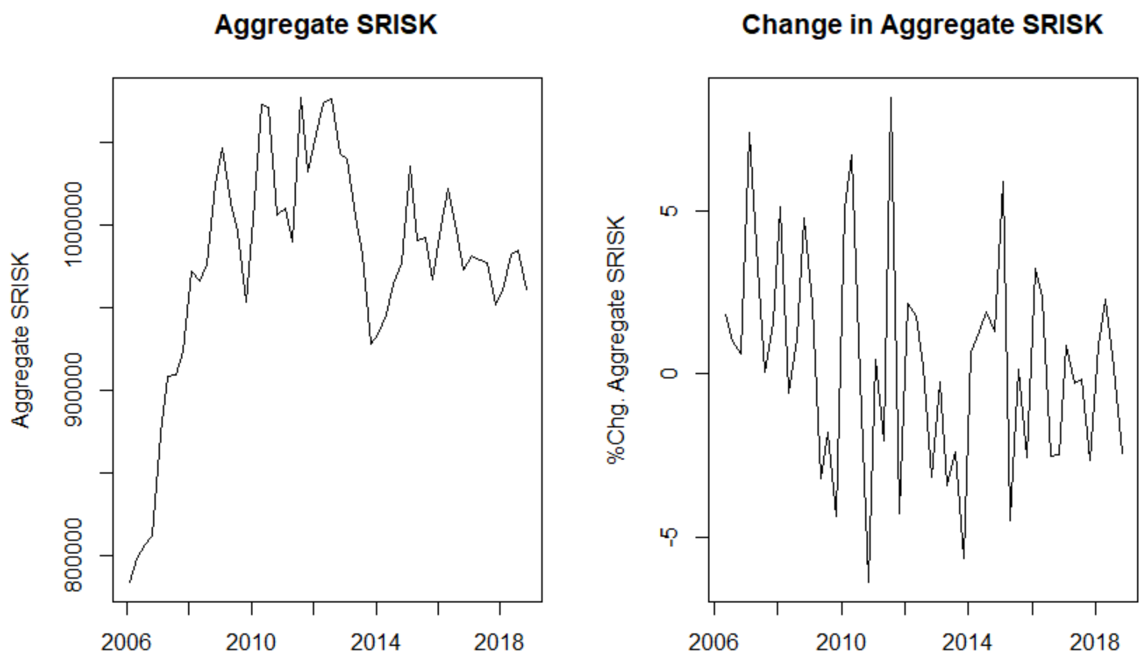

Figure 7: Aggregate SRISK (left panel) computed according to Equation (11). The right panel shows the percentage change of the aggregate SRISK, computed as the log difference of the right hand side series.

by setting $K = 2$. Note that I am using the Cholesky identification for the structural FAVAR. Thus, I need to be able to divide variables into those that the shadow short rate has a short-run impact(fast moving variables) and those on which it does not (slow moving variables).

The result of the PCA is plotted in Figure 8. However, the series do not have any visible differences. Table 5 shows the cumulative variance explained by macroeconomic category for $K = 2$. The lowest cumulative variance explained is 45% for money and credit. On the other hand, the few factors I am including explain the stock and exchange rate data well.

After this, I estimate the reduced form FAVAR using OLS equation-by-equation and use the BIC to select the lag length. The variables are ordered in the following way.

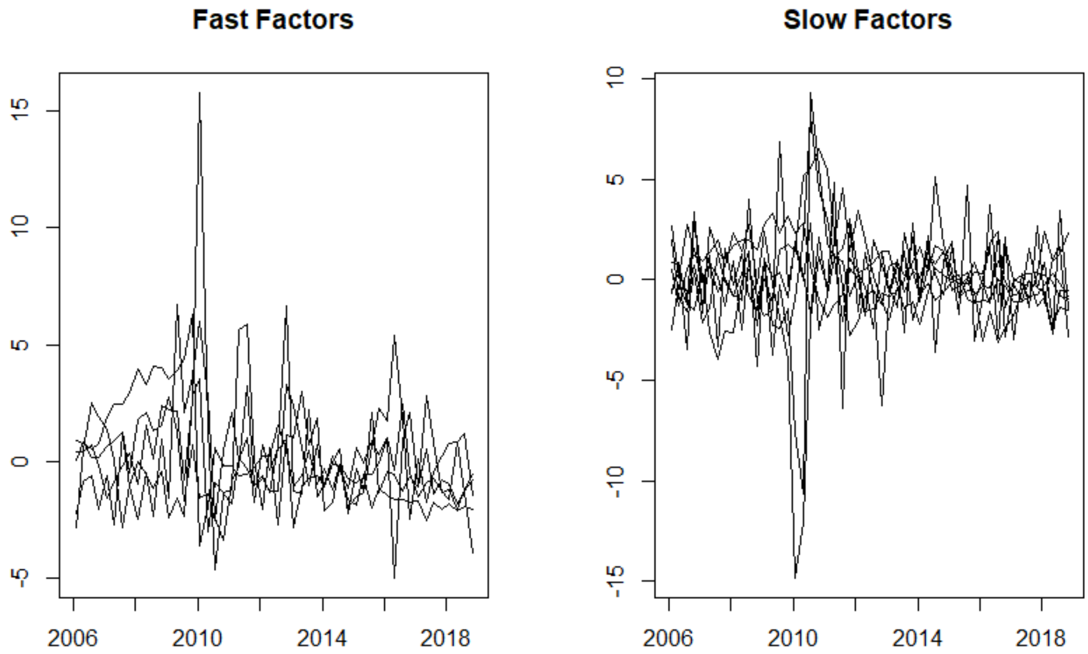

Figure 8: Factors extracted from fast moving variables (left panel) and slow moving variables (right panel)

$$Y_t = \begin{bmatrix} f_t^{\text{slow}} \\ CoVaR_t \ / \ SRISK_t \\ SSR_t \\ f_t^{\text{fast}} \end{bmatrix}$$

Figure 9 presents the IRF of a structural shock in the SSR on the two systemic risk measures employed here. Using the short-run restrictions, the contemporaneous effect is set to zero by default. For CoVaR the results are in line with the theory presented before. A reduction in the policy rate increases systemic risk. However, the effect fades away quickly. On the other hand, the response of the change of SRISK contradicts the theory and previous literature. It shows that an expansionary policy shock decreases systemic risk.

Moreover, the magnitude of the effects is almost negligible. Both axis are scaled in percentage points. The effect of a monetary policy shock on CoVaR is an increase by 0.16 percentage points. For SRISK the response is a 0.04 percentage points decrease

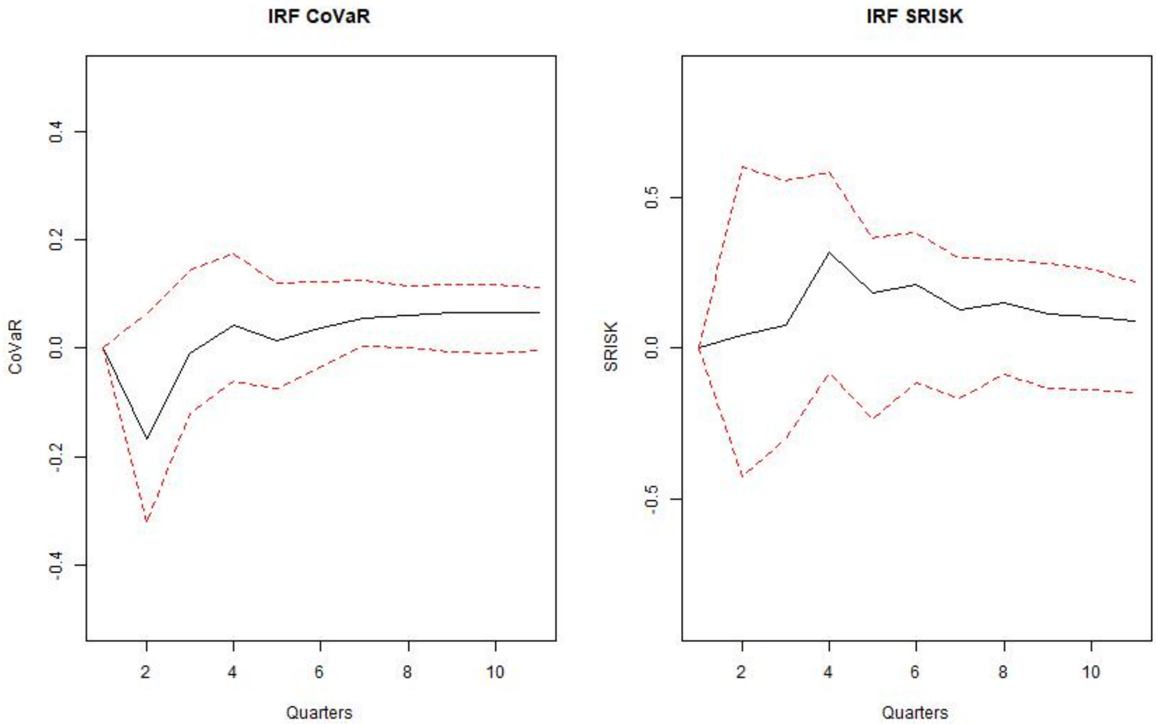

Figure 9: IRF of a shock in the shadow short rate (black solid line) for CoVaR (left panel) and the change in SRISK (right panel). The red dotted lines represent the 95% confidence intervalls.

in the second quarter. Moreover, the effect on CoVaR fades away quickly. After two quarters, the effect is only an increase of 0.01 percentage points.

This result partly contradicts the literature presented before. Faia and Karau (2019) find a more prolonged response for their market data based measure. Also the results in Faia and Karau (2019) point to an unambiguous negative relationship between monetary policy shocks and systemic risk.The theoretical argument laid out before is also not supported by the data and the model.

Another question this thesis seeks to answer is whether the effect confirmed above is whether it is stronger under UCMP compared to conventional monetary policy. Therefore, I compare the period when the ECB started using UCMP tools to the entire period. As a cut-off point, I choose Q3 2008, as this is the time when the ECB started providing liquidity measures, the first UCMP tool they used. Note that it is difficult to compare the period of only CMP and UCMP, as data is scarce and the period, I could use for CMP would only contain eleven data points. Estimates from a model using such a small sample would likely be biased and the problem of overfitting the model arises.

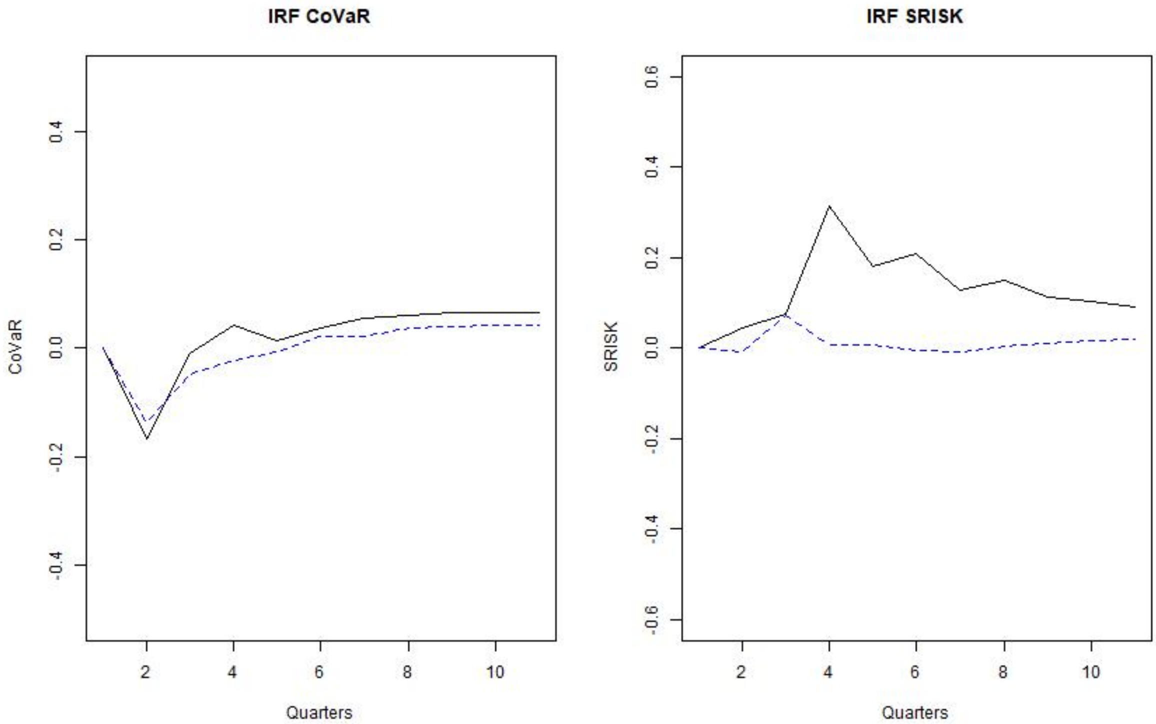

Figure 10: IRF of a shock in the shadow short rate for CoVaR (left panel) and the change in SRISK (right panel). The black solid line is the response from the two systemic risk measures during the entire sample period, and the blue dotted line represents the response only in times of unconventional monetary policy.

Figure 10 suggests that the effect of UCMP measures translated stronger into systemic risk responses. The dotted blue line represents the response of the respective systemic risk variable in times of UCMP while the solid black line is the IRF using the entire sample period. For both measures, the effect under unconventional monetary policy is below that of the entire period. However, for the CoVaR, the response is only marginally below that of the entire sample period. Moreover, the effect appears to be prolonged compared to the entire sample. For the change in SRISK, the response is close to zero. As this is a structural analysis, it is possible to say that the effect of UCMP is stronger than that of CMP. Including times of CMP essentially just reduces the effect and as a result the black line is above the blue line.

A possible explanation for the differences in the response of the two measures could be that SRISK takes into account more dimensions of systemic risk compared to CoVaR. Therefore, this difference might arise due to an adjustment of banks' balance sheets that does not translate into market data and therefore also not into CoVaR.

In addition, I split the sample to investigate whether the responses of SIB and Non-SIB companies differ. Contradictory, to the theory stated above, there is virtually no difference in the response of systemically important banks compared to the rest of the sample (see Figure 11). This could be due to a number of reasons. First, I chose the banks to be the largest unsupervised banks (according to their balance sheet size in 2018). While these banks are certainly of more interest in the context of systemic risk than smaller peers, it might lead to selecting a group of Non-SIB banks that has very similar characteristics than SIBs.

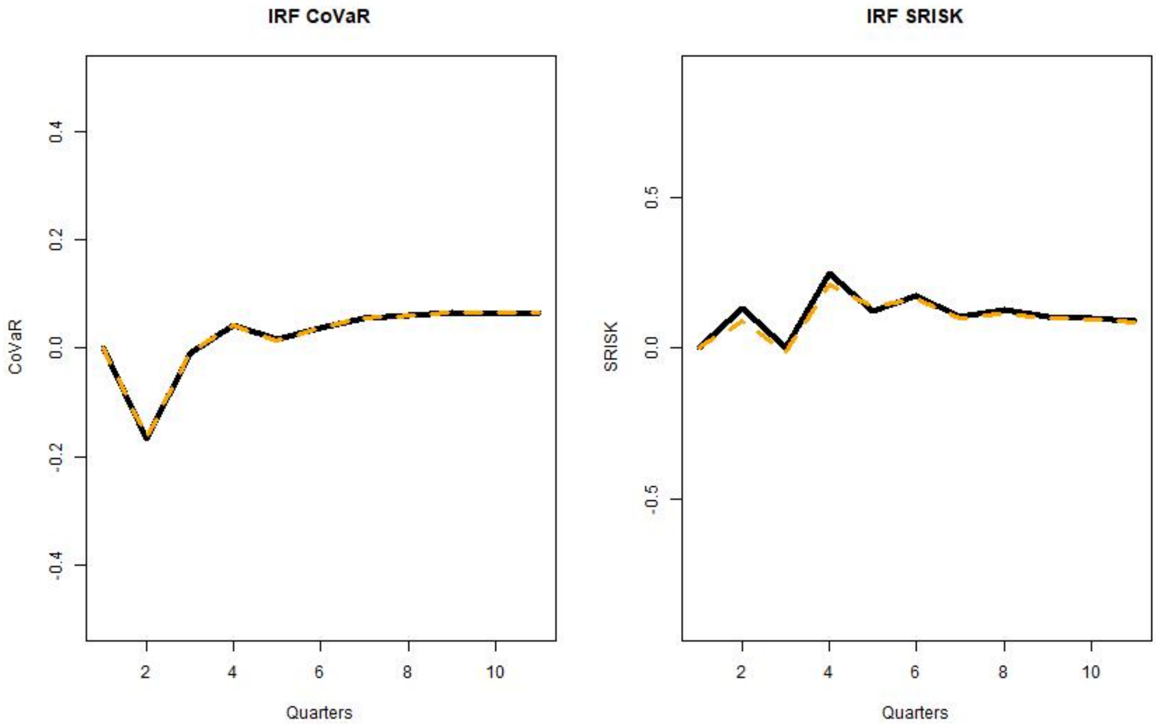

Figure 11: IRF of a shock in the shadow short rate for SIB (black solid line) and Non-SIB (orange dotted line) for CoVaR (left panel) and the change in SRISK (right panel).

Another explanation could be that the theoretical argument made above is simply not supported by the data and SIB and Non-SIB banks do not adjust their systemic behaviour differently as a response to a monetary policy shock.

To answer the question whether the effect is different for healthy and unhealthy banks, I use the five year average Return on Equity (ROE) as a measure of the healthiness of a bank. There are certainly other measures that could be employed here. However, using the ROE has two advantages. First, it is readily available and standardized across companies. Therefore, comparisons using the ROE across companies are straight forward. Second, the ROE is an simple concept that measures the profitability of a company. Thus, taking the five year average of the ROE is a reasonable approximation of a banks profitability. If a bank has not been profitable in the past five years, it is unlikely that it is healthy. I cluster the banks into two groups. Unhealthy banks have a five year average ROE of less than 2%, healthy banks make up the rest of the sample. Therefore, only Commerzbank, Deutsche Bank and Uni Credit are considered unhealthy banks.

Furthermore, De Nicolo et al. (2010) argue that the risk-shifting effect should counter the portfolio effect in the short-run. Therefore, restricting the contemporaneous relationship between systemic risk and the policy measure makes little sense. Hence, I reorder the variables in the following way.

$$Y_t = \begin{bmatrix} f_t^{\text{slow}} \\ SSR_t \\ CoVaR_t \ / \ SRISK_t \\ f_t^{\text{fast}} \end{bmatrix}$$

The results suggest that healthy and unhealthy banks respond similarly to monetary policy shocks compared to healthy banks. Thus, the results here do not confirm the critique voiced by De Nicolo (2010). Figure 12 compares healthy (black solid line) to unhealthy banks (orange dotted line). For CoVaR the differences are not visible and for SRISK, it is only marginal.

7. Robustness Checks

Different Ordering

As I argued before, the identification scheme that I use imposes causality on the data. Therefore, it is interesting to see whether the IRFs are going to show similar effects if I change the ordering of the variables and allow for a contemporaneous effect of monetary policy on systemic risk. That the results here appear not to be very robust towards the ordering of the variables can already be deducted from the different response of the change of SRISK in Figure 12 compared to the other IRFs presented before. Therefore, I am going to estimate the IRFs for the other hypotheses but this time with the following ordering.

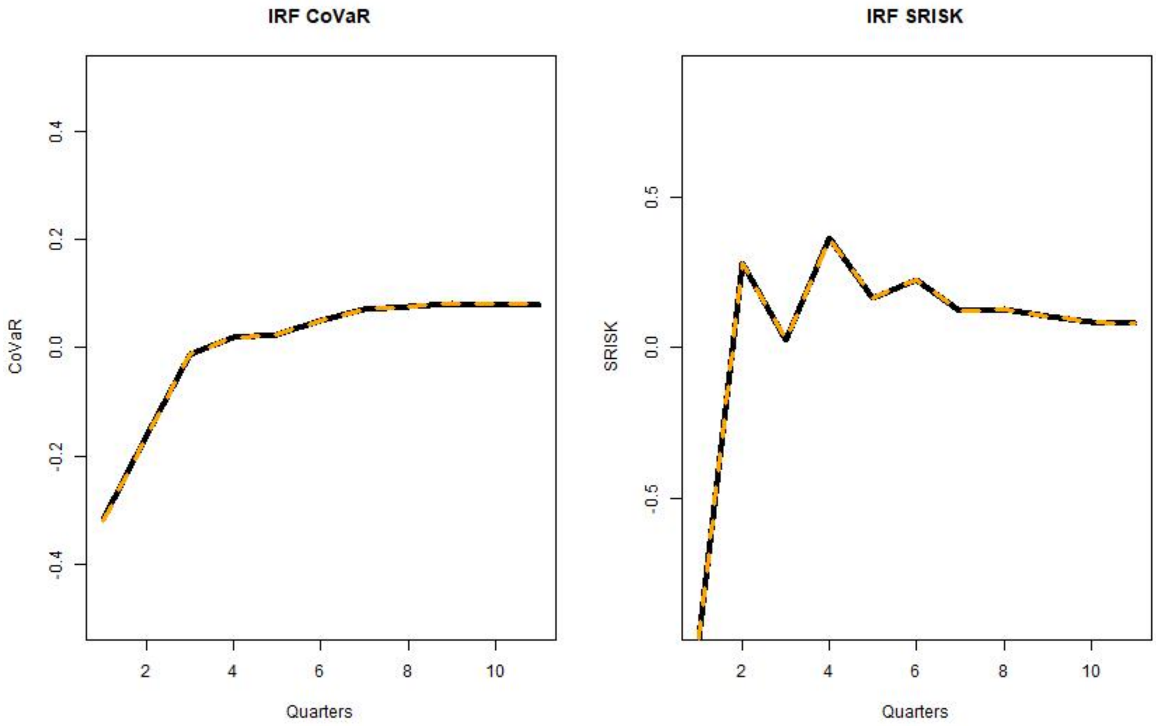

Figure 12: IRF of a shock in the shadow short rate for healthy (black solid line) and unhealthy (orange dotted line) banks for CoVaR (left panel) and the change in SRISK (right panel).

$$Y_t = \begin{bmatrix} f_t^{\text{slow}} \\ SSR_t \\ CoVaR_t \ / \ SRISK_t \\ f_t^{\text{fast}} \end{bmatrix}$$

The results are depicted in Figures 22, 23 , 24 and 25 in the appendix. For both measures of systemic risk, the picture changes dramatically. If the short-run is not restricted, systemic risk in the banking sector increases sharply, following an expansionary monetary policy innovation. Especially for the change in SRISK, this changes the entire interpretation. While the resutls from the baseline model predict that a change in the policy rate has almost no impact on systemic risk, now it seems that the response from the systemic risk measure substantial.

For the other three hypothesis the difference compared to the baseline model is not as striking. However, of course all of them share the sharp increase in systemic risk in $t = 1$. But even with the changed order of variables, the response from the systemic risk measures is stronger under unconventional monetary policy and the responses of SIB and Non-SIB banks and and healthy and unhealthy banks is similar.

Notably, allowing for contemporaneous effects on the systemic risk measure yields results for the first and second hypothesis that are in line with the theory. An expansionary monetary policy shock increases both systemic risk measures (Figure 22). Moreover, the response under unconventional monetary policy is more pronounced and also negative. Therefore, the second hypothesis seems to be robust w.r.t. the ordering.

Different Sample Split

Hence, I continue by further testing the robustness of the results for the second hypothesis. Another way to test the robustness of it is to split the sample differntly. So far, I split the sample at (including) Q3 2008. Now, I split the sample after Q2 2010. Why Q2 2010? The ECB started purchasing government bonds in May 2010 as part of its Securities Markets Program. Therefore, I will regard the asset purchases as the first unconventional policy implemented. Figure 26 compares the response under unconventional monetary policy (blue dotted line) and the entire sample period. The result is strikingly different from the results presented before. Especially, the drop in CoVaR which has been consistent across all other models and specifications disappears. Instead, CoVaR behaves similarly to the change in SRISK and is more or less flat. Therefore, these results sharply contrast what I have found so far and raise serious questions about the results.

Factor Extraction

Another issue that Lütkepohl (2014) brings up regards the FAVAR methodology. He argues that FAVAR models are sensitive to the number of factors included and the background information set. To test this and to produce comparable results, I estimate the FAVAR yet again but extract only five factors from the entire set compared to the 12 I extract before. Note that, I do not extract the factors by category but from the entire set of macro variables at once. Taking the first three and five factors is what Faia and Karau (2019) and Bernanke et al. (2004) do, respectively. The five factors explain around 54% of the variance of the entire set of macroeconomic variables.

Equivalent to the baseline, the variables are ordered such that the SSR has no contemporaneous effect on the systemic risk measure.

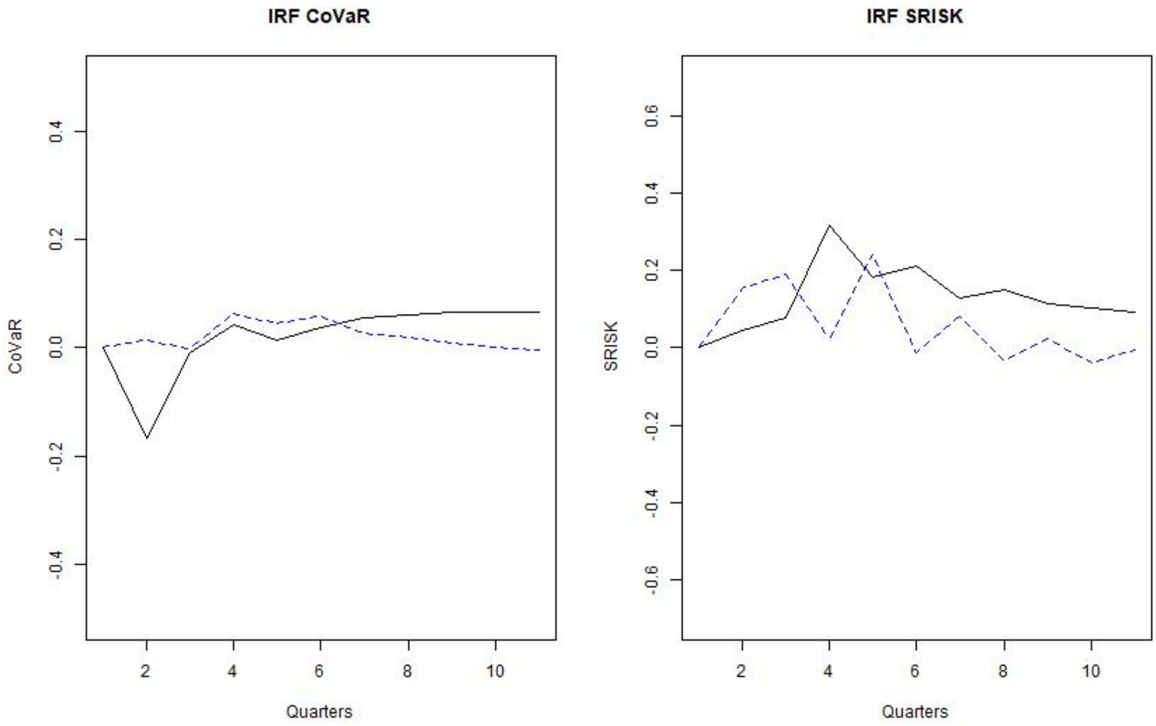

Figure 13: Vis-a-vis comparison of the IRF of CoVaR (left panel) and change in SRISK (right panel) for a shock in the SSR. The blue dotted line is the response under UCMP and the black solid line the response over the entire sample.

$$Y_t = \begin{bmatrix} f_t \\ CoVaR_t \ / \ SRISK_t \end{bmatrix}$$

Figure 14 plots the IRFs. Again the baseline results do not appear to be robust against this change. While CoVaR still decreases, the effect quickly fades away. In addition, SRISK increases following a tightening of the monetary policy stance. This is in conflict with the baseline results as well as the theory laid out in the previous chapters.

8. Conclusion

In this thesis I explored the systemic risk-taking channel using a sample of 14 EZ banks from 2004 to 2018. Furthermore, I combined different paper to introduce a theoretical framework for the systemic risk-taking channel. However, the results presented here are not promising for the systemic risk-taking channel. I did not find a robust relationship between monetary policy impulses and systemic risk. The SRISK measure appeared to

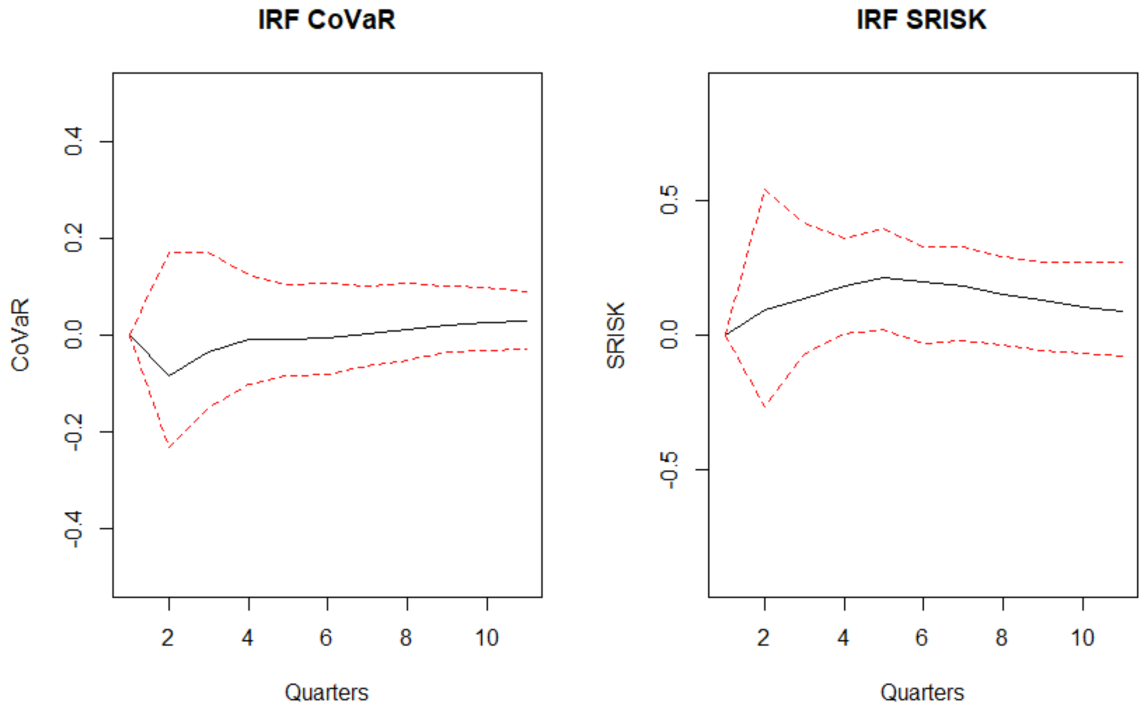

Figure 14: IRF of a shock in the shadow short rate (black solid line) for CoVaR (left panel) and the change in SRISK (right panel). The red dotted lines represent the 95% confidence intervalls. However, only the first five factors are extracted from the entire data set.

either respond with the opposite sign or with almost no change at all. Moreover, the results seem to contradict the first hypothesis even starker if the empirical set up is slightly changed.

On the other hand, the results for the second hypothesis at least for CoVaR support the hypothesis. Also, the results seem to be robust to the ordering of the variables in the FAVAR model. However, splitting the sample period after 2010 instead of 2008 eliminates the effect.

The only hypotheses that are robust are the third and the fourth. Throughout every model set up the responses from SIB compared to Non-SIB and healthy compared to unhealthy banks is virtually the same. However, this contradicts the relationships predicted before.

Extracting the factors similar to other paper, yields more robust results for the CoVaR measure. This indicates, that the model set up is key in the FAVAR analysis.

These findings are in stark contrast to the previous literature on this subject. Therefore, the question remains: Is this because the systemic risk-taking channel does not work the way it is postulated here or is the issue specific to the methodology used here?

One issue is the small sample size. Future research might find a more robust relationship if they use a larger sample of banks. The evidence in Faia and Karau (2019) indicates just that. Another 'natural' data related issue for the EZ is the sample length. For the U.S. the data is available much more consistently for prolonged time frames.

Another point is the identification scheme used here. While Short-Run restrictions have several advantages, their restrictive nature is problematic. Also, FAVARs might be in particular sensitive to this kind of error (Lütkepohl, 2014). Other means of identification might be suited better for the problem, such as sign restrictions.

Furthermore, the VAR used here is a linear VAR. However, the relationship between systemic risk and monetary policy shocks might be non-linear. Therefore, the effect of an easing and tightening might not have the same magnitude. Also more advanced models such as state variable dependent VARs could be employed to explore the relationship further.

A more general critique is the question whether the systemic risk measures are really well suited for this type of analysis. As I argued before, the closed form expression for CoVaR really reduces to a scaled version of the stocks volatility by the correlation with the market. However, the correlation and volatility might be driven by so many things that identification in a structural model is difficult. Another issue is that SRISK does not weigh the liabilities (or the debt in the original paper). It seems intuitive that not all direct links between institutions contribute in the same way to systemic risk. Therefore, a combination of network theory and SRISK might yield more precise estimates. In addition, one important question regarding systemic risk measures is whether they are good at describing systemic risk or the financial crisis of 2008/2009. The problem is that systemic crises in the banking sector are rare and the data from past systemic events is probably not consistent with the data today. Hence, the question has to be asked: Are systemic risk measures too dependent on the financial crisis of 2008? For example, in this application, the CoVaR series did not display any significant variation after 2008/2009. This also explains why the robustness check, where I split the sample after 2010, showed almost no response from systemic risk under UCMP.

In future work, the theoretical framework introduced here could be used for hypothesis testing. One approach could be to include proxies for the individual sub-channels of the systemic risk-taking channel in the VAR and then decompose the forecast error variance in order to explore further which of the variables actually drives the results. This would be of particular interest as for now there is no theoretical foundation for the systemic risk-taking channel. However, in order to establish sound and stable relationships between the variables requires a better understanding of the inner workings of the systemic risk-taking channel.

In conclusion, it is difficult to tell from this thesis, whether the systemic risk-taking channel does not exist in the way that I postulate it or whether the evidence here is the exception. This just goes to show that additional research is needed in this field. An increased understanding is of importance to evaluate monetary policy interventions in the past but also in the future. If there is really a trade-off between financial stability and the inflation targeting by central banks, this needs to be explored and included into policy makers' decision-making frameworks. While this thesis does not provide a conclusive answer to this question, it does lay out a path forward.

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Appendices

A. Abbreviations

EZ	Euro Zone
SIB	Systemically Important Banks
LRMES	Long-Run Marginal Expected Shortfall
ECB	European Central Bank
UCMP	Unconventional Monetary Policy
QE	Quantitative Easing
ZLB	Zero Lower Bound
FG	Forward Guidance
SSR	Shadow Short Rate
MES	Marginal Expected Shortfall
SRISK	Systemic Risk Measure
ES	Expected Shortfall
FAVAR	Factor Augmented Vector Autoregressive
FG	Forward Guidance
VAR	Vector Autoregressive
QE	Quantitative Easing
IRF	Impulse Response Function
EVD	Eigenvalue Decomposition
PCA	Principal Components Analysis
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion

B. Descriptive Statistics

Banks	Generic Name
Euro Stoxx Banks	Market
Deutsche Bank	P1
BNP Paribas SA Class	P2
Credit Agricole	P3
ING Groep	P4
Banco Santander	P5
Societe Generale S A Class	P6
UniCredit S p A	P7
Nordea Bank	P8
Commerzbank	P9
Banco Bilbao Vizcaya Argentaria	P10
Intesa Sanpaolo S p A	P11
Erste Group Bank	P12
KBC Group N V	P13
Banco de Sabadell	P14

Table 1: Generic names for banks which I use throughout the graphs and tables of this Thesis.

	Excess Skewness	Excess Kurtosis	P-Value JB Test
Market	-0.176	6.276	$< 1e^{-10}$
P1	0.147	9.047	$< 1e^{-10}$
P2	0.07	10.958	$< 1e^{-10}$
P3	0.212	7.351	$< 1e^{-10}$
P4	-0.191	17.737	$< 1e^{-10}$
P5	-0.201	10.42	$< 1e^{-10}$
P6	-0.35	10.461	$< 1e^{-10}$
P7	-0.256	7.719	$< 1e^{-10}$
P8	0.326	7.303	$< 1e^{-10}$
P9	-0.172	8.709	$< 1e^{-10}$
P10	0.024	7.578	$< 1e^{-10}$
P11	-0.496	9.044	$< 1e^{-10}$
P12	-0.704	12.254	$< 1e^{-10}$
P13	-0.914	32.851	$< 1e^{-10}$
P14	0.121	8.98	$< 1e^{-10}$

Table 2: Excess kurtosis, excess skewness and p-values of the Jarque-Bera test for normality for the return series. The p-values of the JB test are so small that it is not possible to print all the zeros in this table.

	Min	Max	Mean	Median	Variance	SD
Market	-8.2495	9.9599	0.008	0.034	1.593	1.2621
P1	-17.5359	21.2448	-0.0527	0	6.3552	2.5209
P2	-20.1782	18.9768	-0.0052	0	5.6763	2.3825
P3	-15.0878	23.3615	-0.0159	0	6.6183	2.5726
P4	-32.1362	25.6527	-0.0109	0	8.2057	2.8646
P5	-22.1724	20.8774	-0.0194	0	4.4798	2.1166
P6	-25.5095	21.4255	-0.021	0	7.2306	2.689
P7	-27.1658	19.0067	-0.0648	0	8.2787	2.8773
P8	-13.4139	14.923	0.0152	0	3.7116	1.9266
P9	-27.4583	20.482	-0.0736	0	8.425	2.9026
P10	-17.649	19.9073	-0.0208	0	4.2478	2.061
P11	-26.0594	17.962	-0.0093	0	6.4008	2.53
P12	-32.6216	17.0252	0.0049	0	7.6001	2.7568
P13	-49.5321	40.4843	0.0113	0.0186	10.2707	3.2048
P14	-21.4337	16.7778	-0.0257	0	3.8267	1.9562

Table 3: Descriptive statistics of the return series.

Bank	Issue	Time Frame	Fix
Deutsche Bank	Only quarterly report online	Q1 2004 to Q3 2005	Copy value from quarter for entire year.
BNP Paribas	Only semi-annual reports available	2006 to 2018	Q1 and Q2 and Q3 and Q4 . are the same for every year
ING Group	Only annual reports	2006 to 2013	Copy value from quarter for entire year.
Banco Santander	Liabilities only available from Q1 2008	Q1 2004 to Q1 2008	Liabilities constant between Q1 2004 and Q1 2008.
Societe General	Only semi-annual reports available and no reports available	Entire sample period a nd until Q1 2008	Q1 and Q2 and Q3 and Q4 are the same for every year and until Q1 2008 constant value.
Uni Credit	Missing Value	Q1 2008	Use Q4 2007 value.
Commerzbank	Missing Value	Q4 2018	Use Q3 2018 value.
Intesa Sanpaola	Missing Value	Q4 2011 and Q4 2015	Use respective Q3 value.

Table 4: Data issues and fixes.

C. Tables

Category Macro Series	Cummulative Variance Explained
Employment	55.71
Exchange Rate	99.14
Interest Rate	56.42
Money and Credit	44.90
Output	56.29
Stocks	70.00

Table 5: Cumulative variance explained by factors for each category of macroeconomic variables.

	Excess Skewness	Excess Kurtosis	P-Value JB Test
Market	-0.171	6.293	$< 1e^{-10}$
P1	0.153	9.188	$< 1e^{-10}$
P2	0.069	10.932	$< 1e^{-10}$
P3	0.211	7.336	$< 1e^{-10}$
P4	-0.192	17.727	$< 1e^{-10}$
P5	-0.202	10.438	$< 1e^{-10}$
P6	-0.351	10.421	$< 1e^{-10}$
P7	-0.259	7.740	$< 1e^{-10}$
P8	0.327	7.302	$< 1e^{-10}$
P9	-0.175	8.817	$< 1e^{-10}$
P10	0.032	7.634	$< 1e^{-10}$
P11	-0.499	9.060	$< 1e^{-10}$
P12	-0.705	12.248	$< 1e^{-10}$
P13	-0.913	32.722	$< 1e^{-10}$
P14	0.118	9.035	$< 1e^{-10}$

Table 6: Excess kurtosis, excess skewness and p-values of the Jarque-Bera test for normality for the return series. The p-values of the JB test are so small that it is not possible to print all the zeros in this table.

D. Graphs

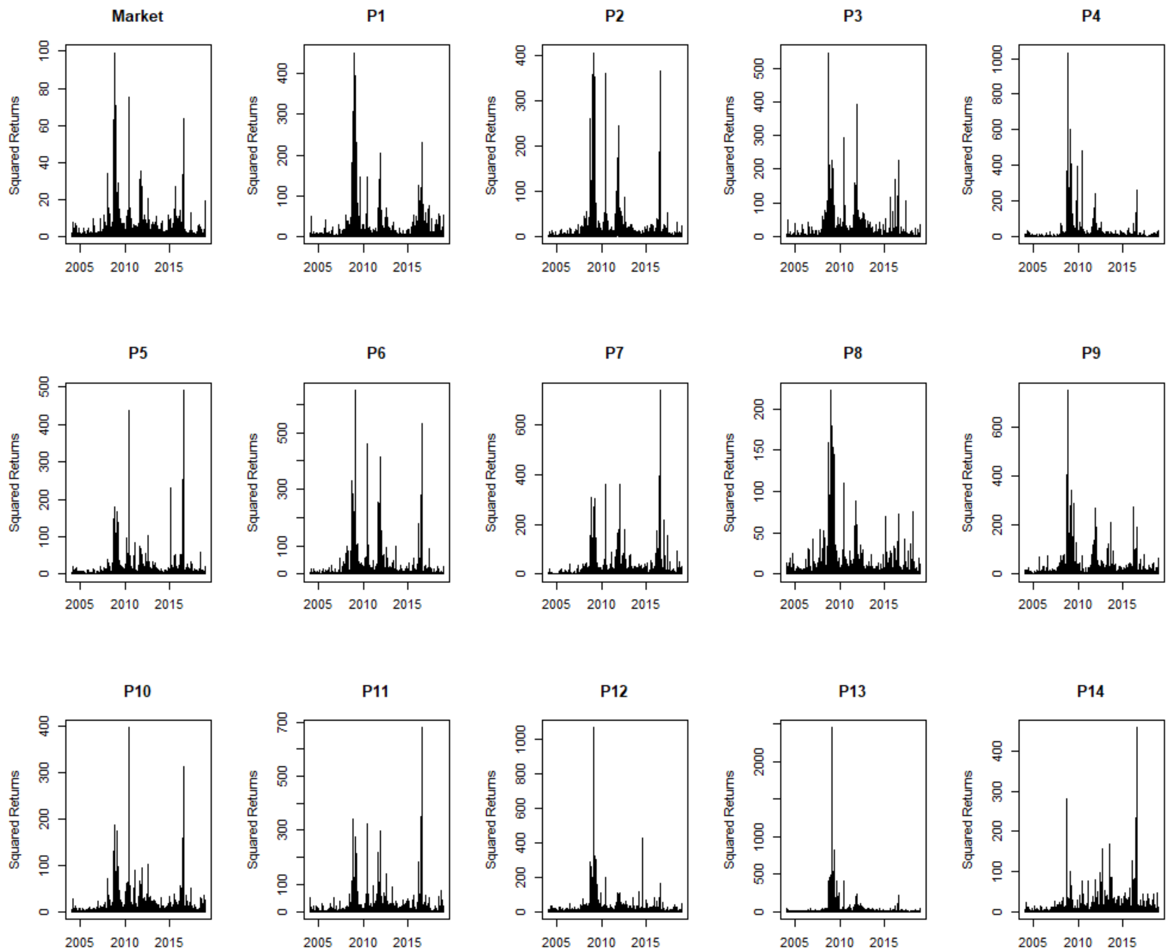

Figure 15: Squared Returns of all companies and the market. Note that all return series are computed by taking the log difference of the prices and then multiplying the result times 100.

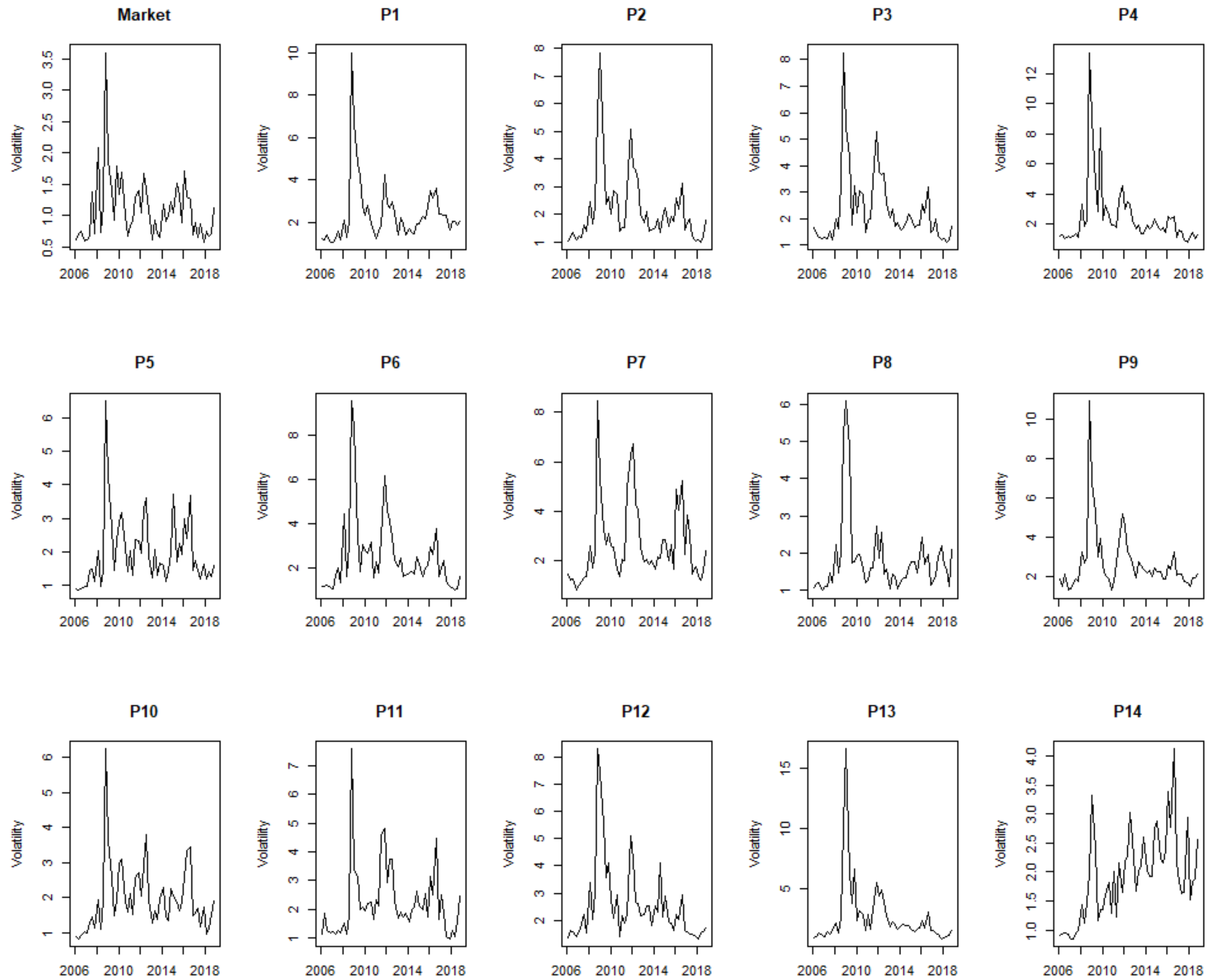

Figure 16: Estimated volatilities from univariate GJR-GARCH models.

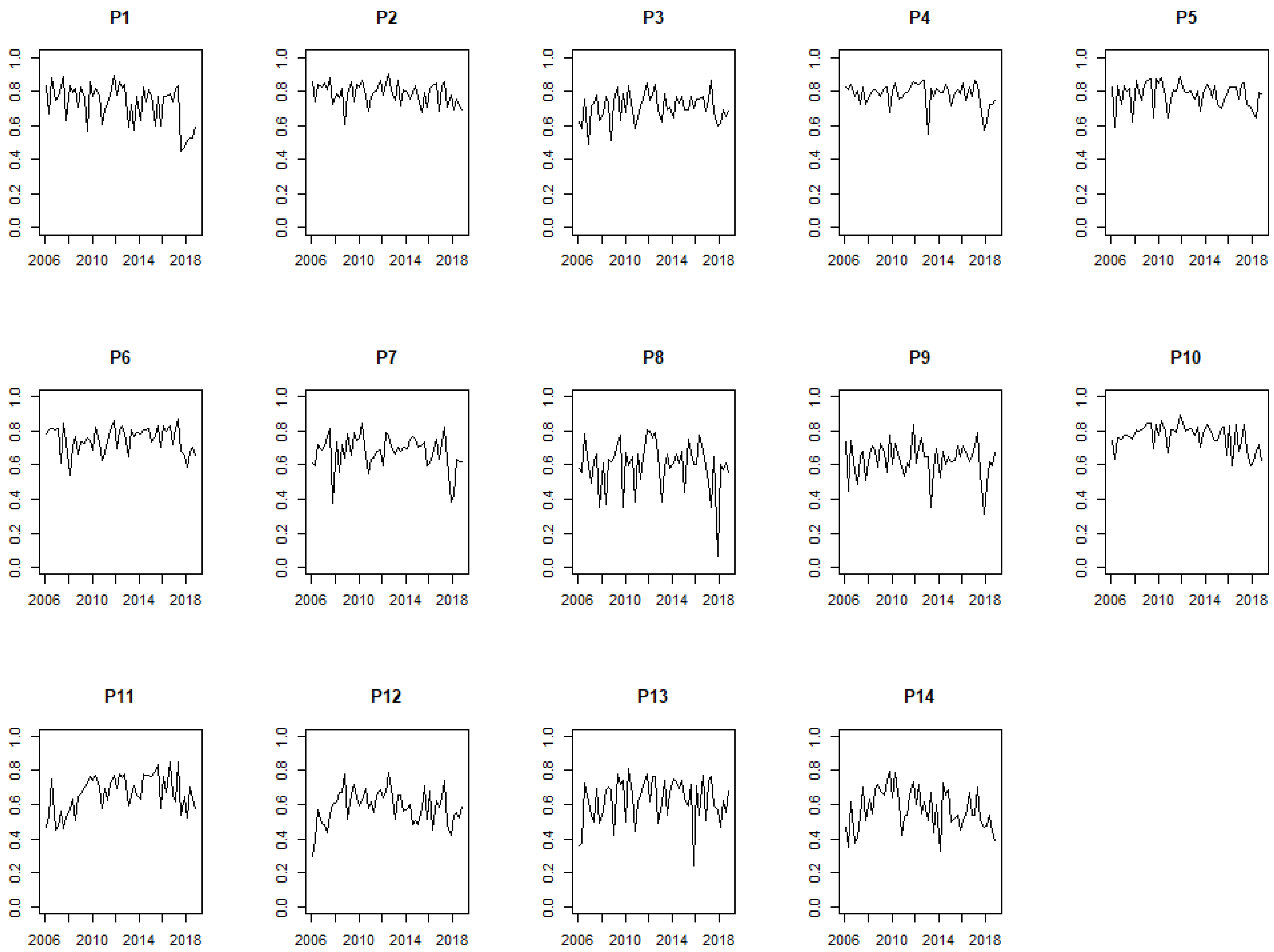

Figure 17: Correlation as estimated by the GARCH-DCC model.

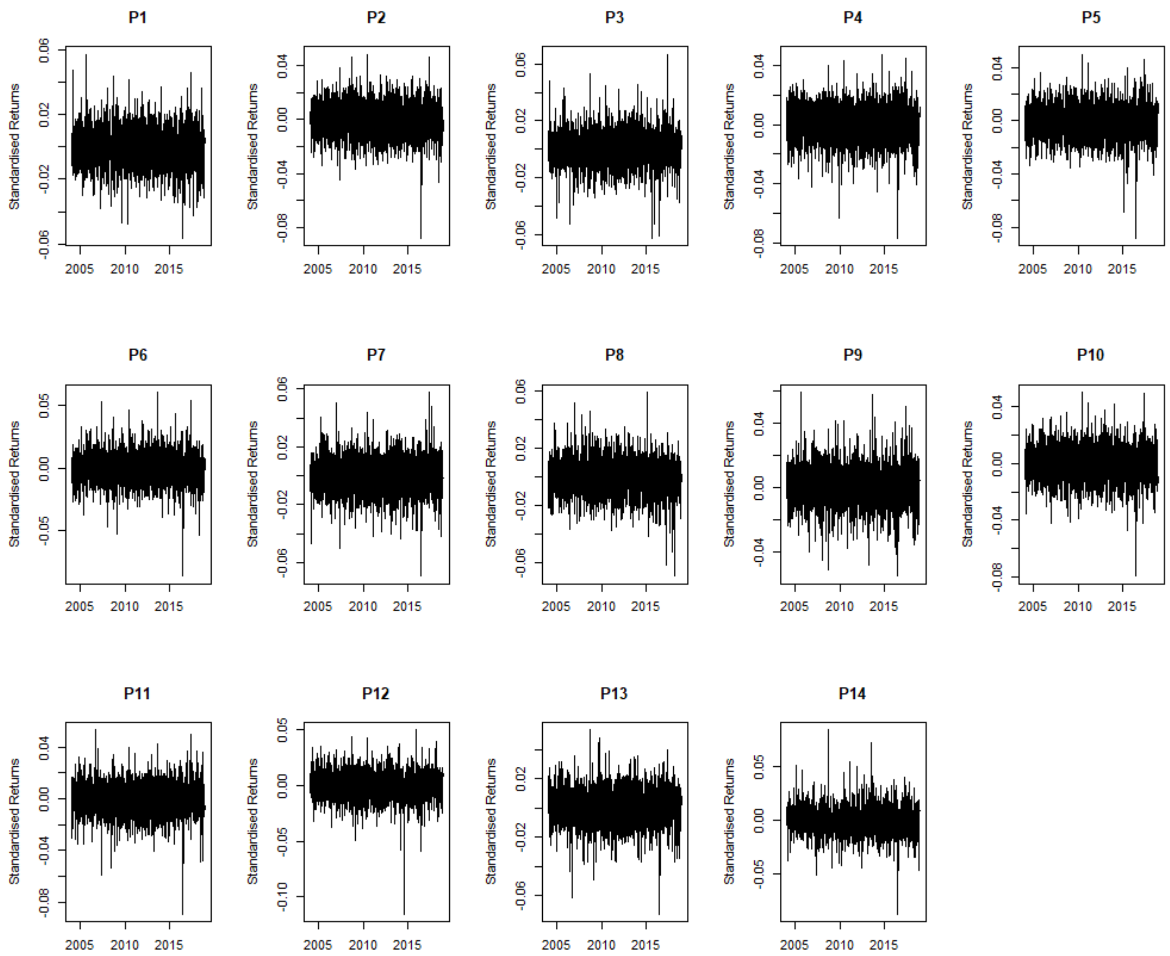

Figure 18: Standardised Returns.

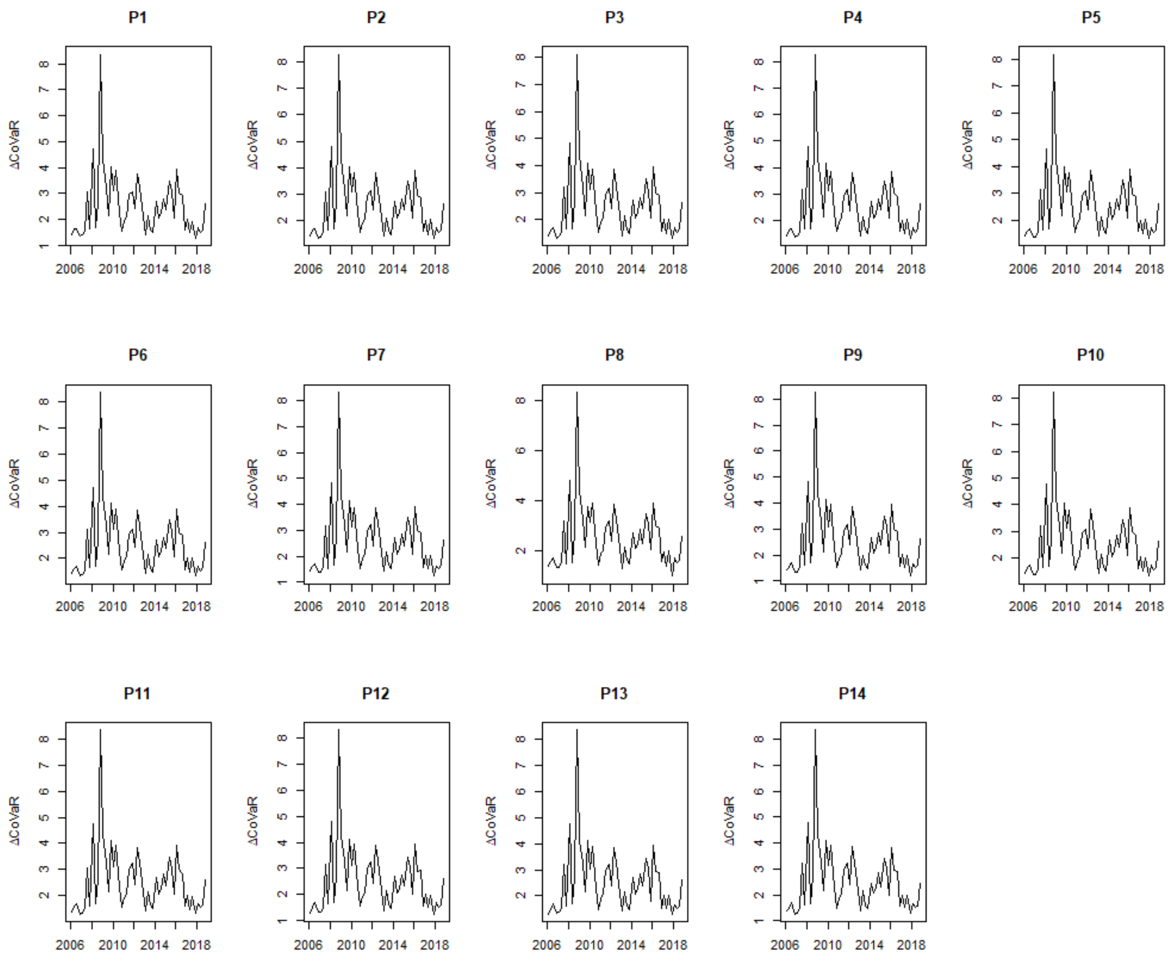

Figure 19: Estimated Delta CoVaR for every stock.

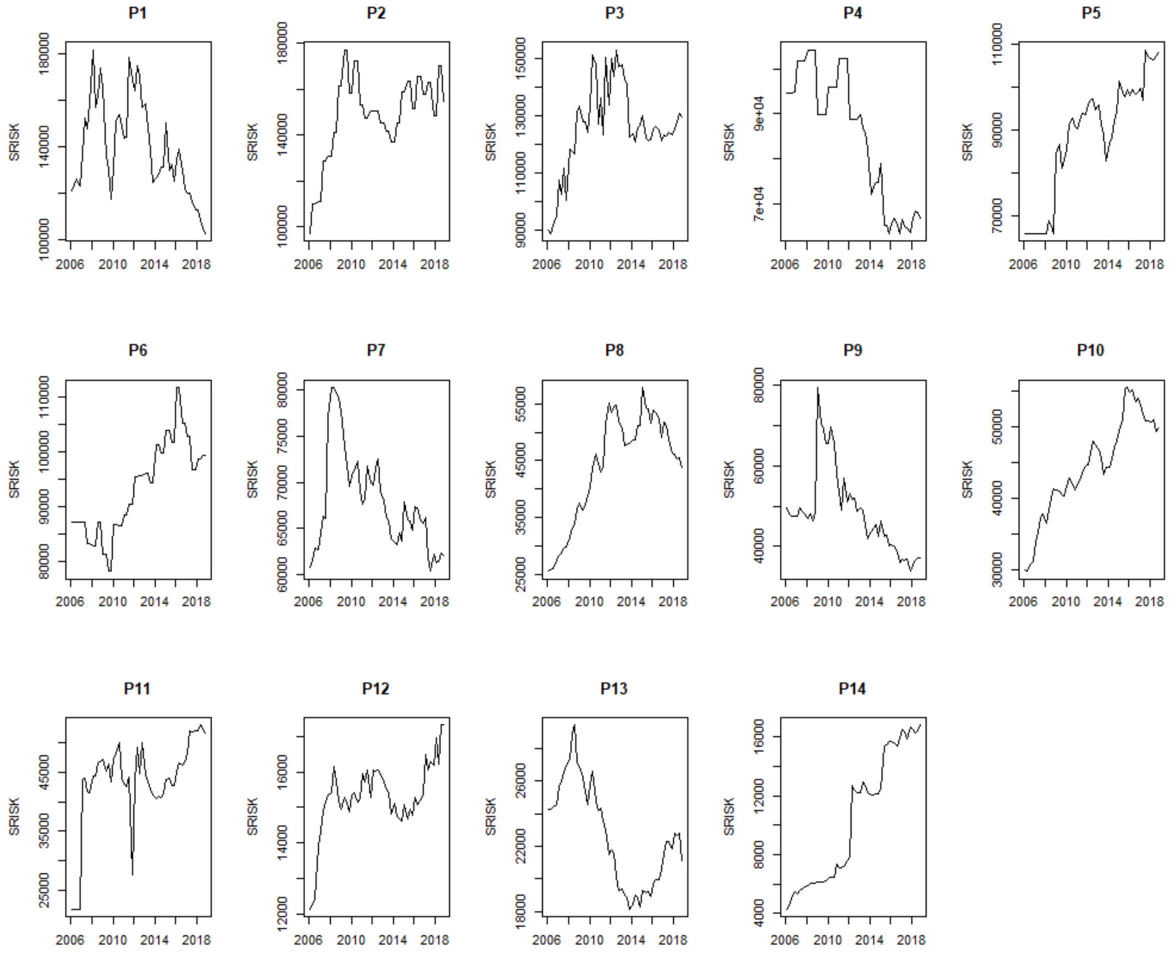

Figure 20: SRISK of all banks in million Euros.

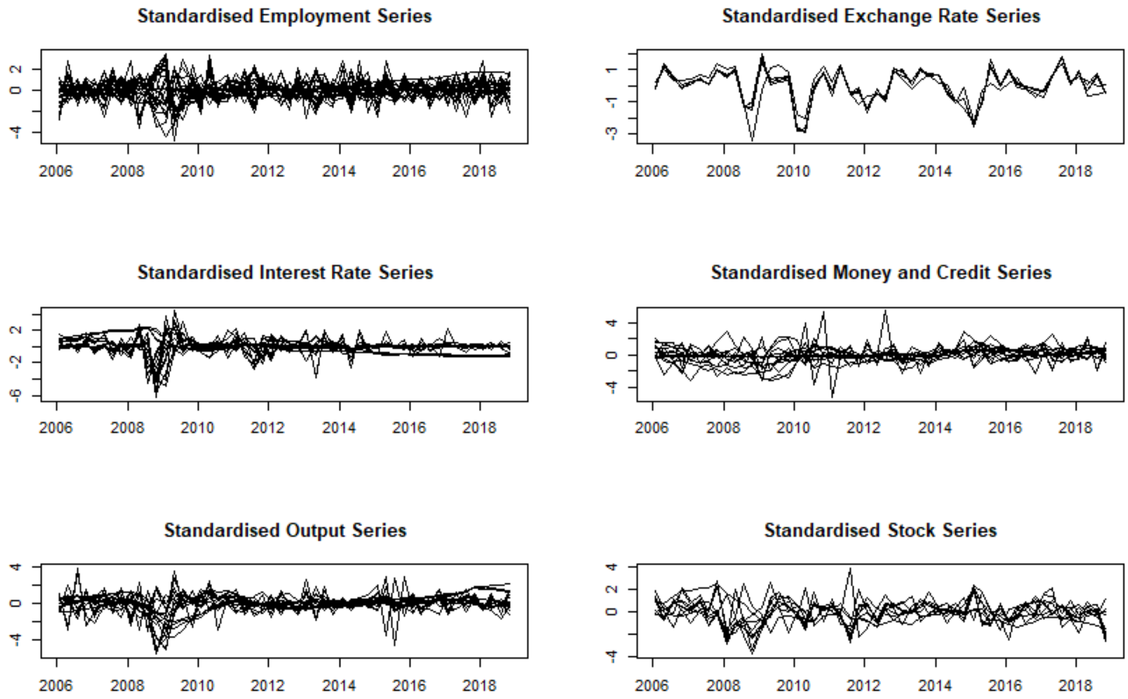

Figure 21: Standardised Macro Series.

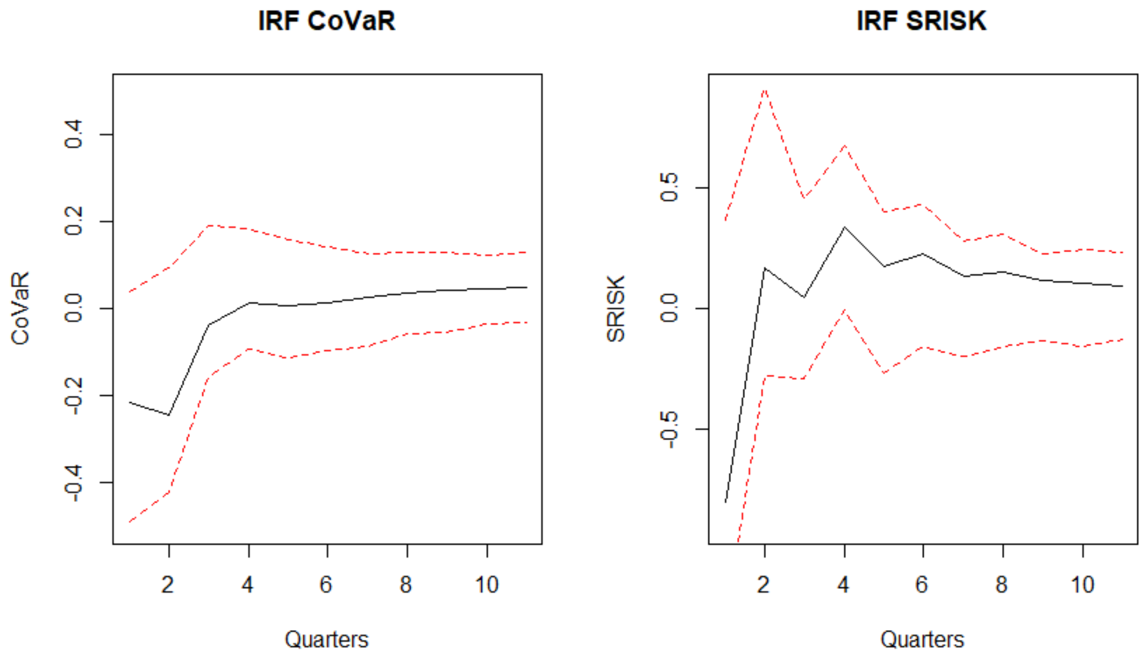

Figure 22: IRF of a shock in the shadow short rate (black solid line) for CoVaR (left panel) and the change in SRISK (right panel). The red dotted lines represent the 95% confidence intervalls.

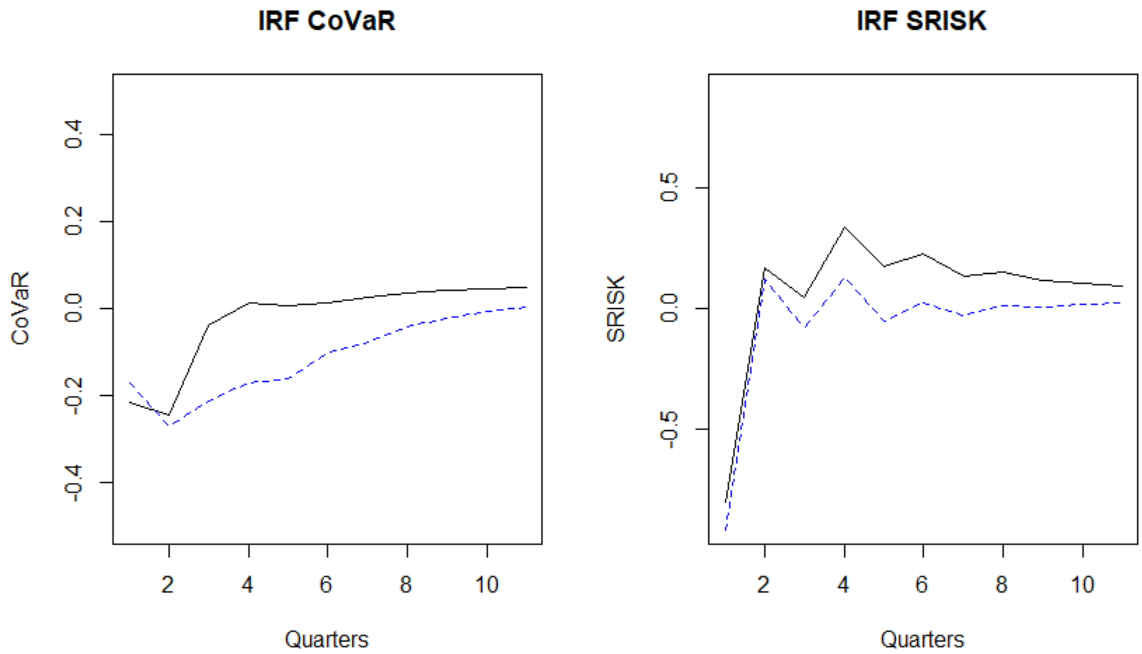

Figure 23: IRF of a shock in the shadow short rate for CoVaR (left panel) and the change in SRISK (right panel). The black solid line is the response from the two systemic risk measures during the entire sample period, and the blue dotted line represents the response only in times of unconventional monetary policy.

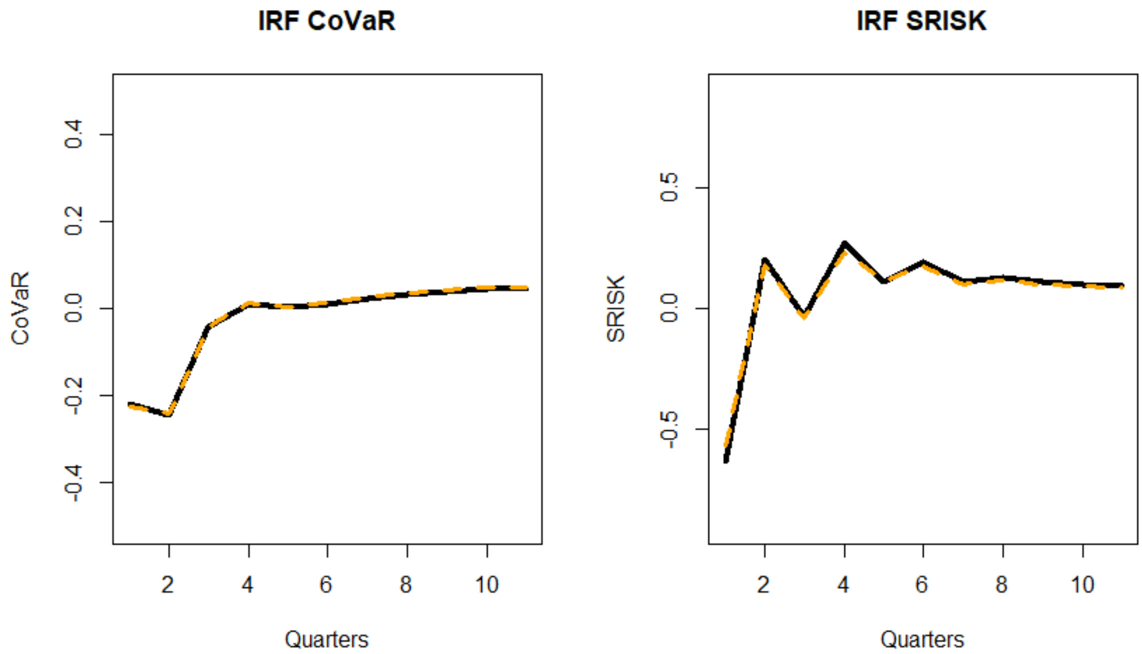

Figure 24: IRF of a shock in the shadow short rate for SIB (black solid line) and Non-SIB (orange dotted line) for CoVaR (left panel) and the change in SRISK (right panel).

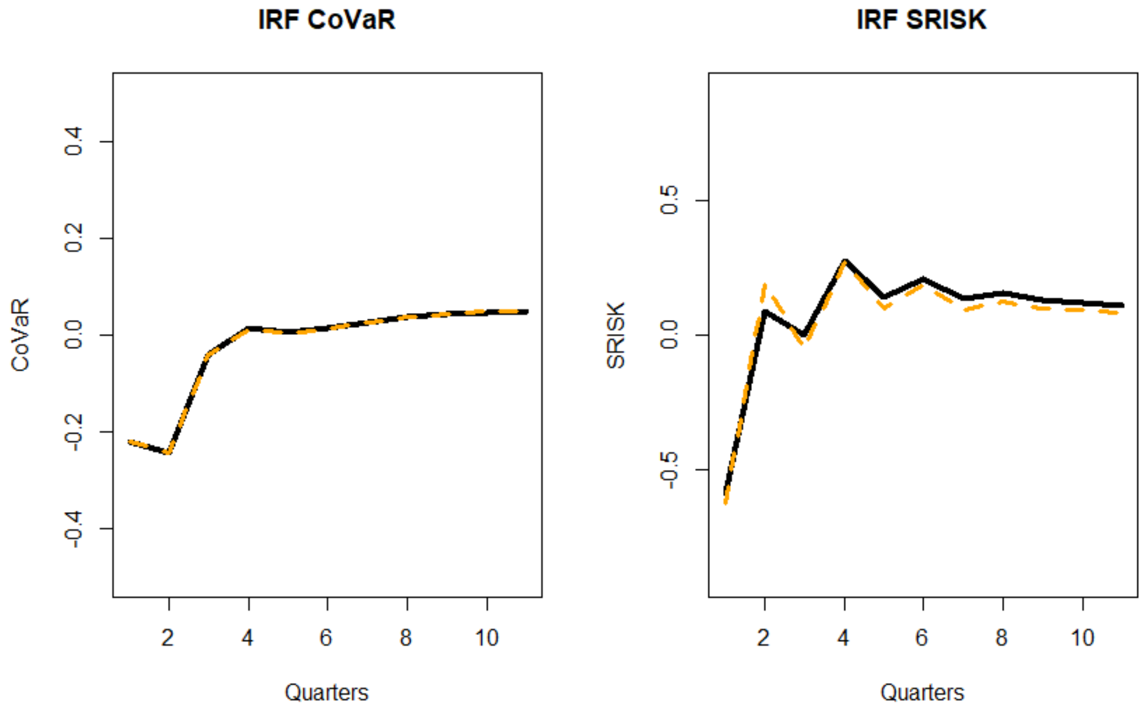

Figure 25: IRF of a shock in the shadow short rate for healthy (black solid line) and unhealthy (orange dotted line) banks for CoVaR (left panel) and the change in SRISK (right panel).

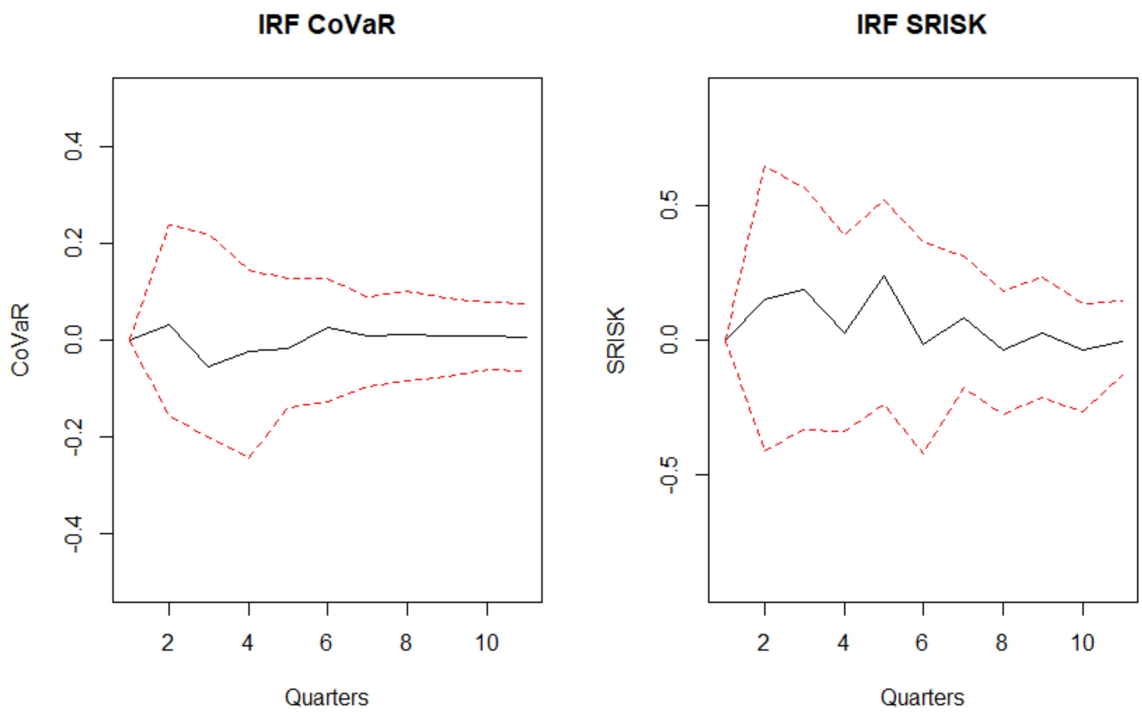

Figure 26: IRF of a shock in the shadow short rate (black solid line) for CoVaR (left panel) and the change in SRISK (right panel). The red dotted lines represent the 95% confidence intervalls. The sample for the UCMP regime starts in Q3 2010.

E. Declaration of Originality

Appendix C: Declaration of Originality MSc Thesis *

By signing this statement, I hereby acknowledge the submitted MSc Thesis titled

Does Monetary Policy Influence Systemic Risk? Evidence from the Eurozone Banking Sector.

to be produced independently by me, without external help.

Wherever I paraphrase or cite literally, a reference to the original source (journal, book, report, internet, etc.) is provided.

By signing this statement, I explicitly declare that I am aware of the fraud sanctions as stated in the Education and Examination Regulations (EERs) of SBE, Maastricht University.

Place: Maastricht

Date: 31.08.2019

First and last name: Melchior Reihlen-Börgers

Study programme: Financial Economics

ID number: i6178410

Signature: Melchior Reihlen-Börgers

* Please complete this page and add it as an appendix to your MSc Thesis on the last page.