Macroeconomic Interdependencies During Financial Crises

Dissertation submitted for the degree of
Doctor of Economics (Dr. rer. pol.)

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at the
Department of Economics
University of Konstanz

Konstanz, 2014

Date of oral examination: 26.05.2014
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To my families

Acknowledgments

This thesis concludes exciting years that I spent in Konstanz, Gerzensee, Cologne, and Washington D.C. On this path I have expanded my horizon steadily. Of course, this would not have been possible without the support and guidance of many people. I would like to take this instance and thank everyone who has contributed in any possible way.[1]

Firstly, I would like to express my deepest gratitude to my supervisor Professor Brüggemann who was always willing to share with me his most valuable resource – his time. He supported me in all aspects of life and spurred my motivation during all times of the PhD. Without his advice and guidance this thesis would not have been possible.

Also I would like to thank other important mentors that have had an important stake in the creation of this thesis. Most importantly, I am very thankful to Professor Pohlmeier, who was my first teacher in econometrics. He contributed strongly to my deep interest in this subject. Further, I would like to thank Professor Franke, Professor Kaas, and Professor Scholl for their discussions and support. Also, I am indebted to Professor Watson and Professor Honoré who always had spare time to discuss my ideas during sessions at the study center in Gerzensee or at conferences around the world.

For the intense months at the Inter-American Development Bank I am grateful to Andrew Powell and Julián Caballero as well as the entire research department. The collaboration during and after the stay has always been an extraordinary pleasure.

Further, I am very thankful to Professor Mosler and Dagmar Weiler from the University of Cologne for providing an inspiring research atmosphere during the last year of this thesis.

[1] The Ph.D. fellowship from the "Stiftung Geld und Währung" (Money and Currency Foundation) is gratefully acknowledged.

I would also like to thank my fellow students in Konstanz or at various other places for ongoing discussions or support. These are Cornelia Abmeier, Fady Barsoum, Christian Matthias Friedrich, Fabian Krüger, Achim Mattes, Anna Müllhäuser, Ulrich Schetter, Sophie Schmitt, Sandra Stankiewicz, Tim Reuter, Peter Rosenkranz, and Jing Zeng. Especially I would like to thank my co-authors Adrian Alter and Fabian Fink for unforgettable moments and great research collaboration. I am sure that this list should be much longer, hence, I am also thankful to all omitted ones.

Further, I would like to recognize my old friends that have (mostly) never attempted to understand what I was doing but by this have supported me in a very special way: Ana-Luísa, Benjamin, Daniel, Dennis, Frederik, Ingo, Julie, and Stephan.

Of course, I am deeply grateful to my families as well. Without my father, Johannes Schüler, and mother, Ruth Schüler, this work would plainly not exist. Similarly, Elisabeth and Josef Schneider - and their entire family - have always been a great guidance to me. Also I am thankful to my grandmother, Else Schüler, and my siblings, Barbara Willkomm and Michael Schüler. Finally, I attribute my last acknowledgement to my daughter, Anna, for the joy she brought to the days that completed this thesis.

Cologne and Konstanz, *Yves Stephan Schüler*

January 2014

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Summary

This thesis has its focus on the analysis of macroeconomic interdependencies during times of financial stress. Not only has the last global financial crisis underscored that the importance of the financial sector has been underestimated by researchers, regulators and policy makers, but also that commonly used statistical methods are not sufficient for an analysis of the risks faced by economies in times of financial turmoil. However, for the formulation of macroprudential regulation both aspects, i.e., the correct assessment of the links of the financial sector to the rest of the economy and their implicit risks are key for the success of these policies. The present work addresses these issues.

More specifically, the first two chapters reflect empirical analyses of contagion mechanisms during times of financial stress. While the first one assesses the systemic component of banking crisis within states, the second chapter points out the important cross border effects of systemic financial crises. Both chapters yield evidence on the systemic risk that a financial crisis poses to advanced and emerging economies. The last chapter presents a novel methodology that, I argue, serves well to overcome the problems with commonly used statistical methods. The proposed methodology enables the researcher to capture nonlinearities present in the data that I relate to the economic cycle. The method represents a flexible tool for the assessment of the dependencies within an economy. It captures the interconnections conditional on the state of each economic sector which the researcher includes in the analysis. This chapter points out the importance of these nonlinearities in the context of the interrelations of financial markets and the real economy. The following paragraphs give an outline of each of the three chapters.

The *first chapter*, which is joint work with Adrian Alter, investigates the interdependence of the default risk of several Eurozone countries (France, Germany, Italy, Ireland, the Netherlands, Portugal, and Spain) and their domestic banks during the

period between June 2007 and May 2010, using daily credit default swaps (CDS). Bank bailout programs changed the composition of both banks' and sovereign balance sheets and, moreover, affected the linkage between the default risk of governments and their local banks. Our main findings suggest that in the period before bank bailouts the contagion disperses from bank credit spreads into the sovereign CDS market. After bailouts, a financial sector shock affects sovereign CDS spreads more strongly in the short run. However, the impact becomes insignificant in the long term. Furthermore, government CDS spreads become an important determinant of banks' CDS series. This so-called two-way feedback mechanism between sovereigns and banks can be seen as evidence for the systemic risk that a banking crisis and the formulation of bailout packages constitutes to the entire economy. States become sensitive to the development of the default risk of financial institutions which questions the state's role of lender of last resort. This, in turn, affects the default risk of banks. At last, the interdependence of government and bank credit risk is heterogeneous across countries, but homogeneous within the same country.

The *second chapter*, which represents a collaboration with Fabian Fink, provides empirical evidence that US financial stress shocks (US-FSSs) are an important driver for economic dynamics and fluctuations in emerging market economies (EMEs). Applying a structural vector autoregression, we analyze the international transmission of US-FSSs to eight EMEs (Brazil, Chile, Korea, Malaysia, Mexico, Philippines, Thailand, South Africa) using monthly data from 1999 to 2012. US-FSSs are identified as unexpected changes in the financial conditions index of the Federal Reserve Bank of Chicago. The index contains systemically relevant financial variables from different US financial sectors. Hence, this study analyzes the effects of a systemic financial crisis in the US in which the overall financial system is affected negatively. Findings indicate that a typical EME experiences similar negative effects as the US economy in response to US-FSSs. Our results emphasize that the transmission through international financial interconnections is dominant, while contagion through trade is inessential. Further, with regard to fluctuations in real economic activity, US-FSSs are as important as all other external factors jointly. In general, US-FSSs represent a crucial driver for volatility in the emerging world; also at business cycle frequencies.

As stated, in the *third chapter* I develop a new methodology that allows to measure the nonlinearities present in the data, or put differently, in the economies. To

this end, I propose to relate conditional quantiles of stationary macroeconomic time series to the different phases of the business cycle. Based on this idea, I introduce a Bayesian quantile structural vector autoregressive framework for the analysis of the effects of uncertainty on the US real economy. For this purpose, I define a novel representation of the multivariate Laplace distribution that allows for the joint treatment of multiple equation regression quantiles. I find significant evidence for asymmetric effects of uncertainty over the US business cycle. The strongest negative effects are revealed during recession periods. During boom phases uncertainty shocks improve the soundness of the economy. Moreover, the phase of the financial sector matters when the real economy is at recession but not if the economy is at boom. When the financial system is in a bad state, an uncertainty shock leads to a deeper recession than in times when the financial system is in a good state. Hence, the results of this chapter suggest that macroprudential regulations are required to focus on the specific state of the economy they would like to address.

Keywords: CDS · Private-To-Public Risk Transfer · Bank Bailout · Generalized Impulse Responses · Financial Stress Shocks · International Transmission · Emerging Markets · SVAR · Uncertainty · Economic Cycles · Quantile SVAR · Multivariate Laplace

Zusammenfassung

Diese Doktorarbeit legt ihren Fokus auf die Analyse von makroökonomischen Zusammenhängen während Zeiten von Finanzstress. Die letzte globale Finanzkrise hat nicht nur unterstrichen, dass die Bedeutung des Finanzsektors von Forschern, Aufsichtsbehörden und Entscheidungsträgern unterschätzt wurde, sondern auch, dass die üblich verwendeten statistischen Methoden nicht ausreichend für eine Analyse der Risiken innerhalb der Ökonomien während Finanzturbulenzen sind. Jedoch beide Aspekte, d.h. die korrekte Einschätzung der Vernetzung des Finanzsektors mit dem Rest der Wirtschaft und ihrer impliziten Risiken, sind für die Formulierung von makroprudentiellen Regulierungen notwendig. Die vorliegende Arbeit behandelt beide Themen.

Die ersten beiden Kapitel sind der empirischen Analyse von Ansteckungsmechanismen während Zeiten von Finanzstress gewidmet. Während das erste Kapitel die systemische Komponente von Bankenkrisen innerhalb von Staaten abschätzt, stellt das zweite Kapitel die wichtigen grenzübergreifenden Effekte von systemischen Finanzkrisen heraus. Somit geben beide Kapitel Hinweise auf die systemischen Risiken, die Finanzkrisen für Schwellenländer und fortgeschrittene Volkswirtschaften aufwirft. Das letzte Kapitel präsentiert eine neuartige Methode, die, so argumentiere ich, die Probleme der üblich verwendeten statistischen Methoden überwindet. Die vorgeschlagene Methode erlaubt dem Forscher die in den Daten vorhandenen Nichtlinearitäten zu erfassen, die ich mit dem ökonomischen Zyklus in Verbindung setze. Die Methode stellt ein flexibles Werkzeug für die Abschätzung der Abhängigkeiten innerhalb einer Ökonomie dar. Sie erfasst Zusammenhänge bedingt auf den Zustand eines jeden ökonomischen Sektors, welchen der Forscher in seiner Analyse modelliert. In einer Anwendung im Kontext von Abhängigkeiten von Finanzmärkten und der Realwirtschaft stelle ich die Wichtigkeit von Nichtlinearitäten heraus. Die folgenden Paragraphen fassen die drei Kapitel der Dissertation kurz zusammen.

Das *erste Kapitel*, das in Zusammenarbeit mit Adrian Alter entstanden ist, untersucht die Interdependenz von Kreditausfallrisiken verschiedener Länder der Eurozone (Deutschland, Frankreich, Italien, Irland, Niederlande, Portugal und Spanien) und ihren heimischen Banken während der Zeit Juni 2007 und Mai 2010 anhand von täglichen Kreditausfallversicherungen (CDS - Credit Default Swaps). Bankenhilfspakete veränderten die Zusammensetzung der Bilanzen von Banken und Staaten und beeinflussten zudem den Link der Kreditausfallrisiken von Staaten und ihren lokalen Banken. Unsere wesentlichen Ergebnisse legen nahe, dass in der Periode vor den Rettungspaketen eine Ansteckung vom Kreditrisikomarkt der Banken zu den Ausfallversicherungen der Staaten vorliegt. Nach den Bailouts beeinflusst ein Schock aus dem Finanzsektor den Staatenkreditspread auf kurze Sicht stärker. Auf Dauer wird dieser Shock jedoch insignifikant. Außerdem sind die CDS-Spreads der Staaten eine wichtige Determinante für Bankspreads in dieser Periode. Dieser sogenannte wechselseitige Feedbackmechanismus zwischen Staaten und Banken kann als Evidenz für das systemische Risiko gesehen werden, das eine Bankenkrise und die Formulierung von Rettungspaketen für eine Volkswirtschaft impliziert. Staaten werden äußerst empfindlich gegenüber Entwicklungen von Ausfallrisiken der Finanzinstitutionen, was wiederum das Ausfallrisiko von Banken beeinflusst, weil es den letztinstanzlichen Kreditgeber in Frage stellt. Schließlich legen unsere Ergebnisse nahe, dass die Interdependenz von Staaten- und Bankenkreditausfallrisiken über Länder hinweg heterogen, innerhalb eines Landes jedoch homogen ist.

Das *zweite Kapitel*, welches eine Zusammenarbeit mit Fabian Fink darstellt, liefert einen empirischen Hinweis darauf, dass US-amerikanische Finanzstressshocks (US-FSSs) ein wichtiger Faktor für ökonomische Dynamiken und Fluktuation in Schwellenländern (EMEs - Emerging Market Economies) sind. Anhand eines strukturellen autoregressiven Modells analysieren wir die internationale Übertragung von US-FSSs auf acht EMEs (Brasilien, Chile, Korea, Malaysia, Mexiko, Philippinen, Thailand, Südafrika) mittels monatlichen Daten von 1999 bis 2012. US-FSSs werden als unerwartete Veränderungen des Finanzkonditionsindex der Federal Reserve Bank of Chicago identifiziert. Der Finanzkonditionsindex enthält systemisch relevante Finanzvariablen aus verschieden Sektoren der US Wirtschaft. Somit analysiert diese Studie die negativen Folgen einer systemischen US Finanzkrise. Die Ergebnisse deuten an, dass ein typisches Schwellenland ähnliche Effekte erleidet, wie die US-Wirtschaft in Antwort auf einen US-FSS. Die Resultate stellen heraus, dass die Übertragung des Schocks durch internationale Finanzverflechtungen dominiert, während eine Ansteckung durch Handel unwesentlich ist. Zudem sind US-FSSs im Hinblick auf Fluktuationen in realwirtschaftlicher Aktivität ebenso wichtig wie alle übrigen externen Faktoren gemeinsam. Generell repräsentieren US-FSSs einen entscheidenden Faktor für die Volatilität der Märkte der Schwellenländer, auch zu Konjunkturzyklusfrequenzen.

Wie bereits erwähnt, entwickle ich im letzten und *dritten Kapitel* der Dissertation eine neue Methodik, die es erlaubt Nichtlinearitäten in den Daten und somit in der Ökonomie zu messen. Hierzu schlage ich vor, bedingte Quantile von stationären makroökonomischen Zeitreihen mit den verschiedenen Phasen des Konjunkturzyklus in Verbindung zu setzen. Aufbauend auf diesem Gedanken formuliere ich ein bayessches strukturelles vektorautoregressives Modell und analysiere die Auswirkungen von Unsicherheit auf die US-amerikanische Realwirtschaft. Zu diesem Zweck definiere ich eine neue Darstellung der multivariaten Laplaceverteilung, die eine gemeinsame Betrachtung von Mehrgleichungsregressionsquantilen erlaubt. Ich finde Hinweise für asymmetrische Effekte von Unsicherheit über den US-amerikanischen Konjunkturzyklus. Die stärksten negativen Effekte werden während Rezessionen festgestellt. Innerhalb von Boomphasen verbessern Unsicherheitsschocks den Zustand der Wirtschaft. Außerdem ist die Phase des Finanzsektors wichtig, wenn sich die Realwirtschaft in einer Rezession befindet. Sie ist nicht entscheidend, wenn sich die Realwirtschaft in einem Boom befindet. Falls das Finanzsystem in einem schlechten Zustand ist, führt ein Unsicherheitsschock zu einer ausgeprägteren Rezession als zu Zeiten, in denen der Finanzsektor in einer guten Phase ist. Die Resultate legen somit nahe, dass makroprudentielle Regulierungen den genauen Zustand der Wirtschaft berücksichtigen müssen.

Chapter 1

Credit Spread Interdependencies of European States and Banks During the Financial Crisis

"The scope and magnitude of the bank rescue packages also meant that significant risks had been transferred onto government balance sheets. This was particularly apparent in the market for CDS referencing sovereigns involved either in large individual bank rescues or in broad-based support packages for the financial sector."

(BIS, 2008, p. 20)

1.1 Introduction

During the recent financial crisis extraordinary measures were taken by central banks and governments to prevent a potential collapse of the financial sector that threatened the entire economy. However, it was widely unknown what the effects would be on the interdependence of the financial and the sovereign sector. Gray (2009, p. 128) argues that "regulators, governments, and central banks have not focused enough on the interconnectedness between financial sector risk exposures and sovereign risk exposures and their potential interactions and spillovers to other sectors in the economy or internationally". The lack of theoretical macroeconomic models that are able to incorporate contagion mechanisms between government and financial sectors have amplified the uncertainty related to the implications of government interventions. Nevertheless, regulators and policy makers need to understand the complex dynamics of risk transmission in order to be able to formulate effective policies and be aware of the risk that may be transferred from the financial sector to the government. This paper proposes a framework for investigating in detail the interdependence of banks' and sovereign credit risk in the Eurozone. Our setup highlights the important changes that have occurred due to the bank bailouts.

As pointed out by Gray et al. (2008), using arguments from contingent claims analysis (CCA)[1], there are several channels linking the banking and sovereign sectors, which are affected by implicit as well as explicit guarantees. A systemic banking crisis can induce a contraction of the entire economy, which will weaken public finances and transfer the distress to the government. This contagion effect is amplified when state guarantees exist for the financial sector. As a feedback effect, risk is further transmitted to holders of sovereign debt. An increase in the cost of sovereign debt will lead to a devaluation of government debt, which will impair the balance sheets of banks holding these assets. Acharya et al. (2011) have recently used the term

[1]This approach is based on Merton's and Black-Scholes' (1973) option pricing work. It can also be employed for measuring sovereign-bank interaction, taking into account the implicit and explicit contingent liability for the financial system.

"two-way feedback" to describe these interdependencies. The authors construct a novel theoretical framework to model the link between bank bailouts and sovereign credit risk. In our paper, we empirically study this feedback effect and show how the linkage between the sovereign and financial sectors was affected during the recent period of turmoil.

The interconnectedness through balance sheets of governments and banks has been described in the context of the financial crisis in other recent empirical studies. For instance, Gerlach et al. (2010) find that, as a consequence of macroeconomic imbalances, especially in peripheral European countries (e.g. Greece, Ireland), a jump in sovereign bond and credit default swap (CDS) spreads may be transmitted from the banking sector. The authors claim that systemic and sovereign risk became more interwoven after governments began to issue guarantees for banks' liabilities. This result is supported by Ejsing and Lemke (2011), who argue that the sensitivity of sovereign CDS spreads to the intensifying financial crisis increased after the bailout of the financial sector. Dieckmann and Plank (2011) also present evidence of a private-to-public risk transfer in the countries where governments stabilized the financial system after the Lehman Brothers' event. Banks' and sovereign CDS became closely linked, with financial institutions holding significant amounts of government debt and states bearing vital contingent liabilities from the financial system. Furthermore, Acharya et al. (2011) provide empirical evidence of the interconnection of financial and sovereign sector credit risk as a result of bailout programs. Our study contributes to the literature in three ways: First, relying on previous studies that emphasize the importance of the domestic financial sector as a determinant of sovereign CDS spreads, we provide detailed empirical evidence of the influence of the domestic financial sector during the financial crisis. Second, in contrast to other studies, we research the credit risk interdependence of banks and governments during the recent turmoil. Using this approach we highlight stark changes that occurred in that interdependence after bank bailouts. Third, we study differences in the private-to-public risk transfer both within countries and across the Eurozone.

In more detail, we study the lead-lag relation between governments' and banks' default risk, with a focus on the effect of the bank bailouts in the midst of the recent financial crisis. First, we investigate whether, prior to the government interventions, an increase in the default risk of banks and states originates mainly from the financial sector. Second, we assess whether public contingent liabilities for the financial sector affected governments' default risk. In tandem, this study examines whether

the default risk of the banking sector is influenced by the sovereign default risk. Finally, we investigate the following two questions: i) Does the perceived degree of a bank's participation in a national rescue scheme influence its dependency on the development of the sovereign spread? ii) Are country-specific bailout characteristics reflected in the impact of government bailout programs?
Methodologically, we consider the relationship between government and banks' CDS spreads, as they provide a proxy for default risk.[2] We conduct this analysis by applying the theory of cointegration, Granger-causality, and impulse responses to daily CDS series, which are able to capture changes in the dynamic relation between government and bank credit risk. We consider sovereign CDS from seven EU member states (France, Germany, Italy, Ireland, the Netherlands, Portugal, and Spain) together with a selection of bank CDS from these states. We divide the analyzed period, i.e. June 2007 until May 2010, into the time before and after bank bailout programs were implemented.
Our main findings suggest that in the period *preceding* government intervention, the contagion from bank credit spreads disperses into the sovereign CDS market. This finding can be interpreted as evidence of the systemic feature of the recent financial crisis. The default risk spills over from the financial system to the entire economy and calls into question the government's capacity to repay its liabilities. *After* government interventions, due to changes in the composition of both banks' and sovereign balance sheets, we find that the government CDS spreads have increased importance in the price discovery mechanism of the banks' CDS series. Furthermore, a financial sector shock affects the sovereign CDS spreads more strongly in the short run. However, the impact becomes insignificant in the long term. Based on a bank's dependency on future government aid, we are able to capture differences and similarities in the outcomes of bank bailouts within the same country. Finally, our cross-country analysis reveals noticeable differences in the outcomes of state interventions.
From a policy perspective, our results imply an elevated financing cost for countries with contingent liabilities from the financial sector and a higher volatility in sovereign yield spreads. In assessing the total cost of bank bailouts, governments need to include increased interest payments due to augmented spreads. Furthermore, the banking system is sensitive to the economic health of the host country and the

[2]The objective of this paper is not to investigate the accuracy of this proxy. Our research design takes this link as given, even though there might have been distortions in this proxy during the recent turmoil.

credibility of the support measures.

The paper is organized as follows. In section 2 we discuss studies related to our research. Section 3 presents our hypotheses, the data, our sub-sample selection procedure, and the methodology. In Section 4 we present our results and Section 5 concludes.

1.2 Related Literature

Our study contributes to, at least, two strands of literature: On the one hand, it is linked to the literature that investigates the determinants of bond and CDS spreads and their returns, especially in the midst of financial crisis. On the other, it is related to the analysis of the effects of bank bailouts on the credit risk of governments and banks.

Tied to the first strand and relying on a structural model, Schweikhard and Tsesmelidakis (2009) conclude that credit and equity markets were decoupled during the financial turmoil. They find support for the "too-big-to-fail" hypothesis, as some companies' debt holders benefited from government interventions, and a shift of wealth took place from taxpayers to creditors after the bailout programs. During the crisis, some other factors might have influenced CDS prices (e.g. counterparty or liquidity risk). Collin-Dufresne et al. (2001) find that changes in credit spreads are mostly driven by a systematic factor; however, they are not able to identify it. Berndt and Obreja (2010) study determinants of European corporate CDS returns and identify the common factor, which explains around 50% of the variation, as the super-senior tranche of the iTraxx Europe index, referred to as *"the economic catastrophe risk"*. Similar to our study, Dieckmann and Plank (2011) find evidence of a private-to-public risk transfer for countries whose governments have intervened in the financial system. By employing panel regressions, the authors analyze the determinants of changes in sovereign CDS spreads, and find that both domestic and international financial systems play an important role in explaining the dynamics of CDS spreads. They also argue that countries in the European Monetary Union (EMU) are more sensitive to the health of the financial system than non-EMU countries. Fontana and Scheicher (2010) identify the main determinants of bond and CDS spreads. They include in their set of explanatory factors proxies for market liquidity and global risk appetite, and these are found to be significant. Furthermore, they employ a lead-lag analysis for bond and CDS markets and find that for France, Germany, the Netherlands, Austria, and Belgium the cash market dominates, while for Greece, Italy, Ireland, Spain, and Portugal the CDS market is more important in terms of price discovery. Hull et al. (2004) and Norden and Weber (2004) analyze the impact of unique events on CDS markets, such as credit rating announcements. Both studies find that markets anticipate both news and reviews of downgrades, and that credit rating announcements contain important information and have a significant effect, especially on the CDS market.

Furthermore, there are studies that solely investigate the sovereign bond market. Using a GARCH-in-mean model, Dötz and Fischer (2010) analyze the EMU sovereign bond spreads during the financial crisis and find that the implied probability of default reached unprecedented values and the increased expected loss component made some sovereign bonds lose their status as a “safe haven” investment. Gerlach et al. (2010) analyze the determinants of Eurozone sovereign bond spreads. They show that the size of the banking sector has an important explanatory value for changes in bond spreads, suggesting that markets perceive countries with a large stake in this sector at higher risk of stepping up and rescuing the banks. Employing a dynamic panel, Attinasi et al. (2009) highlight the main factors that explain the widened sovereign bond spreads in some Eurozone countries for the period that covers the core part of the financial crisis in Europe.

Within the second strand of literature, Ejsing and Lemke (2011) investigate the co-movement of CDS spreads of Eurozone countries and banks with a common risk factor, i.e. the iTraxx CDS index of non-financial corporations. The authors find that the government bailout and guarantee programs for the financial sector induced a drop in the credit spreads for banks but a jump in governments’ CDS spreads. Furthermore, the sovereign CDS series became more sensitive to the common risk factor, while the banks’ CDS spreads became less so. Besides providing a model for the interrelation of bank and government credit risk, Acharya et al. (2011) outline the same mechanism empirically, showing a widening of the sovereign and a narrowing of the bank CDS spreads. Focusing on the financial crisis, Demirgüç-Kunt and Huizinga (2010) find that bank CDS spreads are significantly affected by the deterioration of public finance conditions. A high sovereign debt burden impairs the ability to provide support to the financial sector and too-big-to-fail banks might thus become too-big-to-be-saved.

1.3 Hypotheses, Data, and Econometric Methodology

1.3.1 Hypotheses

In this subsection we develop the hypotheses to be tested in our study. Firstly we describe the main transmission channels that emerge when either a (systemic) banking crisis develops or sovereign distress appears. Based on Acharya et al. (2011), Gray (2009) and IMF (2010), we present both directions of the contagion mechanism. If a financial institution faces funding and/or liquidity issues, this can trigger a sharp rise in its default risk and may have specific contagion effects: *(I)* the bank cannot pay its obligations to another financial counterparty which in turn can set off funding/liquidity difficulties for the latter and increases its perceived default risk; *(II)* the state might intervene in order to prevent bank bankruptcies. This private-to-public risk transfer augments the probability of default for the state and lowers the default risk of the financial institution. If *(I)* occurs, difficulties within the entire financial system (e.g. systemic banking crisis) might arise and translate into a contraction of the economy, which would also weaken public finances (e.g. a decrease in the present value of taxes) and, again, the sovereign default risk would increase.

In the case of a country's distress, in the first wave, the contagion to other entities can be triggered via three direct channels (Chapter 1, IMF (2010)): *(i)* from the affected state to other countries that are highly interconnected through bilateral trade or share similar problems (e.g. public deficit, funding needs, etc.); *(ii)* from the distressed country to domestic banks as the market value of government bonds held by these banks decreases, and government support loses credibility; *(iii)* from the impaired state to foreign banks that hold government (or bank) bonds (or other assets) from the affected country.

Before the recent government interventions, we argue that financial sector issues had a systemic component, leading to contagion mechanism *(I)*. Thus, the rising default risk of banks had an indirect effect on governments' credit risk. Additionally, state interventions in response to financial sector problems were possibly expected by market participants. Thus, the perceived sovereign default risk increased but was considered of limited importance in terms of having any visible impact on banks' default risk.

Hypothesis 1. *Prior to state interventions, changes in the default risk of banks affect the default risk of European governments, but not vice-versa.*

After government interventions, states not only bear an asset exposure to the banking sector but their balance sheets contain contingent liabilities (e.g. government guarantees) as well. Thus, the sensitivity of government default risk to the banking sector risk is expected to increase. Furthermore, through the *credibility* of government contingent liabilities, changes in government default risk have a direct impact on the perceived risk of financial institutions.

Hypothesis 2 (a)**.** *In the period after a government intervention, changes in the default risk of banks affect the sovereign default risk more strongly than before.*

Hypothesis 2 (b)**.** *After bailout programs have been implemented, an increase/decrease in sovereign default risk causes a change in the default risk of the domestic banks in the same direction.*

Some banks received direct capital injections from their governments. If the capital injections were sufficient, we would expect the dependency on future bailouts to be the same as for the rest of the financial sector. On the other hand, in case of a partial recapitalization or any other insufficient intervention, the bank in question should be highly sensitive to the health and credibility of the host government. The following hypothesis links the sensitivity of banks' default risk to the probability of future government support.

Hypothesis 3. *The bank's sensitivity to the sovereign default risk increases with the bank's reliance on future government aid.*

Our last hypothesis compares the outcomes of bailout programs in different countries. The magnitude of different support measures provided by each country was heterogeneous among the analyzed Eurozone countries. This was induced by, at least, three factors: *(i)* the economic health of the country, *(ii)* the size of its financial sector relative to the total economy and *(iii)* the exposure of the banking sector to the systemic crisis.

Hypothesis 4. *Heterogeneity of bailout programs across European countries translates into asymmetric interdependence between sovereign and banks' default risk.*

The model introduced by Acharya et al. (2011) describes in detail this feedback mechanism, i.e. how financial sector and sovereign default risk are linked. The authors present a three-period model, in which a financial and corporate sector jointly produce aggregate output. There exists a potential underinvestment problem. Bank bailouts are used to help resolve this problem in the financial sector. The framework predicts that bank bailouts increase sovereign credit risk. The latter affects the financial sector as the value of guarantees and bond holdings decreases. This linkage implies a post-bailout increase in the co-movement of government and financial sector default risk.

1.3.2 Bailout Specific Characteristics

In order to compare the selected countries, we relate our analysis to the specific bailout schemes provided in each country. Hence, we look at the magnitude of the different support measures utilized by each country, while additionally considering the particular aid offered to each bank. Following Stolz and Wedow (2010), we categorize the general set of measures, emphasizing the differences and similarities across countries. Even though there are differences in the number and types of institutions involved in banking crisis management, there is less variation across the countries in terms of the types of support measures that were applied. The financial aid programs can be classified into four broad categories: capital injections, guarantees for bank liabilities, asset support programs, and deposit insurance (see Table 1.3.1).

Table 1.3.1: Government Support Measures for Financial Institutions (October 2008 - May 2010)

Country	Capital Injection		Liability Guarantees		Asset Support		Total Commitment	Deposit Insurance
	Within Schemes	Outside Schemes	Guaranteed issuance of bonds	Other guarantees, loans	Within Schemes	Outside Schemes	as % of 2008 GDP	in EUR
France	8.3 (21)	3	134.2 (320)	0	- (-)	-	18%	70,000
Germany	29.4 (40)	24.8	110.8 (400)	75	17 (40)	39.3	25%	Unlimited
Ireland	12.3 (10)	7	72.5 (485)	0	8 (90)	-	319%	Unlimited
Italy	4.1 (12)	-	- (-)	0	- (50)	-	4%	103,291
Netherlands	10.2 (20)	16.8	54.2 (200)	50	- (-)	21.4	52%	100,000
Portugal	- (4)	-	5.4 (16)	0	- (-)	-	12%	100,000
Spain	11 (99)	1.3	56.4 (100)	9	19.3 (50)	2.5	24%	100,000

Notes: All amounts are in billions of EUR, except for the last two columns. Figures in brackets denote total committed funds and figures outside brackets are the utilized amounts up to May 2010. "Within schemes" refers to a collective bailout program that can be accessed by any bank that fulfills the requirements for that particular aid scheme. "Outside schemes" refers to individually tailored aid measures (ad hoc schemes). *Source*: Stolz and Wedow (2010)

Based on the ratio of total commitment to GDP, the selected countries can be ranked (from high to low): Ireland, the Netherlands, Germany, Spain, France, Portugal, and Italy. Furthermore, the set of countries can be clustered into three groups: Ireland (high commitment - above 75% of GDP); the Netherlands, Germany, Spain, and France (medium commitment - 20% - 75% of GDP); Portugal and Italy (low commitment - below 20% of GDP).

1.3.3 Data and Sub-Sample Selection

We use daily CDS spreads collected from Datastream[3] for seven European countries together with two banks from each country, a total of 21 institutions: **France (FR)**, BNP Paribas (BNP), Société Générale (SG), **Germany (DE)**, Commerzbank (COM), Deutsche Bank (DB), **Italy (IT)**, Intesa Sanpaolo (ISP), Unicredito (UCR), **Ireland (IR)**, Allied Irish Banks (AIB), Bank of Ireland (BOI), **the Netherlands (NL)**, ABN Amro Bank (ABN), ING Group (ING), **Portugal (PT)**, Banco Comercial Portugês (BCP), Banco Espírito Santo (BES), and **Spain (SP)**, Banco Santander (BS), Banco Bilbao Vizcaya Argentaria (BBVA). The selection of bank and sovereign CDS series was restricted by data availability. In order to maintain a homogeneous framework, i.e. the same number of banks from each country, while achieving the longest time frame possible, we were able to use only two bank CDS series for each country. All of the selected banks are important financial institutions, most (8 out of 14) belonging to the iTraxx Europe index. In terms of CDS spreads, we decided to use contracts on senior unsecured debt with 5 years maturity, as they are the most liquid ones.

Briefly, a CDS is a bilateral agreement that transfers the credit risk of a reference entity, which can be a corporation, a sovereign, an index, or a basket of assets that bears credit risk, from the "protection buyer" to the "protection seller". The former party pays a periodic fee to the latter party (the credit-risk taker), and in return is compensated with a payoff in the case of default (or a similar credit event) of the underlying entity.[4] The CDS spread represents the insurance premium and is paid quarterly until either the contract ends or a credit event (e.g. default) occurs. CDS markets are commonly used as a proxy for credit risk.

Our sample covers the time span from 1 June 2007 to 31 May 2010 and includes 772 observations of daily data for each of the selected series.[5] Prior to performing the econometric analysis, we log-transform the CDS levels, as suggested by Forte and Pena (2009). Further justification for this step is provided by the relatively low

[3] We downloaded CDS data from Datastream, which is provided by Credit Market Analysis (CMA).

[4] In the case of cash settlement only, the difference between the par value of the bond (notional amount of the loan) and its recovery value when the credit event occurs is paid in cash by the protection seller. In the case of physical settlement, the par value is paid in exchange for the physical underlying bond.

[5] In the case of Ireland, the sample starts on 4 October 2007 because of inconsistencies with the data obtained from Datastream.

sovereign CDS spreads early in the sample period compared to later on.

Our aim is to analyze the linkages between bank and sovereign CDS series in a two sub-period setup: *(i)* before and *(ii)* during and after bank aid schemes were implemented. In order to capture other structural breaks, we follow BIS (2009) and divide the entire time span into six stages.[6] We group the first two stages (i.e. Stage 1+2) to form the sub-period before government interventions took place and the last three stages (i.e. Stage 4+5+6) to constitute the sub-period during and after the implementation of bank aid schemes. When issues concerning structural breaks appear in our stability analysis (see Section 1.3.4 and 1.A), we analyze stages in combinations (i.e. Stage 4+5, Stage 5+6) or individually.

Stage 3 is excluded from our analysis. It is regarded as a period of structural market adjustments, in which the dependencies between the analyzed CDS series shift. BIS (2009) defines the third stage as lasting from mid-September until late October 2008. Thus, it commences with the bankruptcy of Lehman Brothers, which can be seen as the peak event of the financial crisis. After a period of financial market turmoil, the first coordinated policy measures stabilize investor's confidence at the end of the third stage.[7] Because of the accumulation of structural breaks during this stage, and due to the fact that it lasts for only 30 trading days, econometric analysis does not yield meaningful results. The following outlines the remaining five stages included in our analysis.

The first stage runs from June 2007 to mid-March 2008 and contains 203 observations. This period is characterized by financial stress, triggered by fears of losses due to US subprime mortgage loans and spillovers to European banks (e.g. IKB Deutsche Industriebank, BNP Paribas). The second stage begins in March 2008 with the liquidity shortage of Bear Stearns. This time span consists of 126 observations and ends in mid-September 2008 with the collapse of Lehman Brothers. The fourth stage is defined as lasting from late October 2008 to mid-March 2009 and contains 98 observations. This period is marked by concerns about a deepening of the global recession. By issuing guidelines[8] for European states, the European Commission gives the green light for bank bailout programs. Stage 5 starts in mid-March 2009, when the first signs of recovery appear. Announcements by central

[6]BIS (2009) covers only our first five stages, from 1 June 2007 to 15 March 2009, when Stage 5 starts. For the time span that was not included in the latter study, we define a sixth stage. The last stage is selected to start based on developments in the sovereign CDS market at the end of 2009.

[7]UK authorities intervened in financial markets and major central banks tried to control the situation with coordinated actions.

[8]IP/08/1495

banks concerning balance sheet expansions, and the range and the amount of assets to be purchased, lead to significant relief among the financial markets. The fifth stage ends on 30 November 2009, right before the inception of the sovereign debt crisis in Europe. This stage includes 143 observations. Stage 6, the last one in our sample, begins in December 2009 and ends on 31 May 2010. It consists of 172 observations. This period is marked by concerns about European sovereign debt. For instance, fears arose that Greece's debt crisis would spread to Portugal, Spain, Italy, and Ireland.[9] On 9 May 2010, European governments set up a rescue fund for aiding Eurozone countries in trouble.

1.3.4 Econometric Methodology

In order to analyze the dynamics of the short- and long-run interdependencies between the selected CDS series, this study employs a bivariate vector error correction (VEC)[10] and bivariate vector autoregressive (VAR) framework. Besides interpreting the cointegration relations, we additionally conduct tests on Granger-causality and consider impulse responses in order to describe the entire dynamics between the CDS spreads.

We conduct our analysis by considering two main sub-periods: before and during/after the government bailouts. Results from the Granger-causality and impulse response analyses are reported for these two periods. Only the study of the long-run relations, i.e. using the VEC framework, makes use of further sub-samples, as required.[11] Impulse responses are obtained using the VEC framework, if available for the two main periods. If the tests do not clearly indicate that there is a long-run relation, we obtain the impulse responses from a VAR with the variables modeled in log-levels. Thus we do not cancel out the dynamic interactions in the levels, as opposed to modeling the variables in first differences, and leave the dynamics of the series unrestricted, i.e. we follow an "agnostic" approach. The Granger-causality tests used in this paper are Wald tests on lag-augmented VARs, as proposed by Dolado and Lütkepohl (1996). This test is chosen as it guarantees the validity of the

[9] On 6 May 2010, Moody's emphasized a possible contagion for banks. This coincided with a major US stock market crash and both events led to a plunge of stock markets around the world. When we exclude events related to the intensifying Greek debt crisis, i.e. when we end our sample period on 5 May, our econometric analysis yields the same conclusion.

[10] During tranquil times we believe that the CDS series of the financial and government sectors are stationary. However, during times of market turmoil we argue that both are impacted by the same stochastic trend, because they are linked by the channels described in Subsection 1.3.1.

[11] See 1.A for further information.

asymptotic distribution of the test statistic even when there is uncertainty about the cointegration properties and stationarity of the variables.
For a global view on the interrelations of the series we employ *generalized impulse responses* (GIR), as proposed by Pesaran and Shin (1998). Routinely, the analysis of impulse responses is carried out via the application of the Cholesky decomposition. However, to do so the researcher has to specify some causal ordering of the variables. In our case, a theory defining such ordering is hard to justify, especially in the context of daily data. As a result, we decided to use GIR because no ordering is necessary and contemporaneous relations are allowed for. One can regard GIR as the effects of a shock in the structural error of the variable that is ordered first in the system of orthogonalized impulse responses. To model the uncertainty around our point estimates of impulse responses, we apply the recursive-design wild bootstrap, as described in Gonçalves and Kilian (2004). This bootstrap technique delivers valid confidence bands in the case of conditional heteroskedasticity. We simulate the 95% confidence intervals using 2000 replications. In our bivariate setup, i.e. with a sovereign CDS spread (in short 'Sov') and a selected domestic bank CDS spread (in short 'Bk'), the GIR function can be written as follows:

$$\begin{pmatrix}\psi^{Sov}_{Sov}(n)\\ \psi^{Bk}_{Sov}(n)\end{pmatrix} = \sigma^{-1/2}_{(Sov,Sov)}\Phi_n\Sigma_u\begin{pmatrix}1\\0\end{pmatrix}, \qquad \begin{pmatrix}\psi^{Sov}_{Bk}(n)\\ \psi^{Bk}_{Bk}(n)\end{pmatrix} = \sigma^{-1/2}_{(Bk,Bk)}\Phi_n\Sigma_u\begin{pmatrix}0\\1\end{pmatrix}, \tag{1.1}$$

where $\sigma_{(j,k)}$ is the variance related to the error of variable j,k ($j,k \in \{Sov, Bk\}$) and n denotes the period after the impulse occurred. Φ_n represents the matrix of vector moving average coefficients at lag n, which can be calculated in a recursive way from the VAR coefficient matrices. It is worth emphasizing that, as we deal with possibly cointegrated VAR models, the effects of shocks may not die out asymptotically (Lütkepohl, 2007, pp. 18-23, 263). For example, $\psi^{Sov}_{Bk}(n)$ denotes the response of the sovereign log CDS to a shock in Bk, n periods ago. The interpretation of the impulse responses follows the usual reading for semi-elasticities. For instance, taking into account that $\Phi_0 = I_K$, an impulse in variable j in period 0 means a unit increase in the structural error that leads to an increase in the respective CDS series by $\sigma^{1/2}_{(j,j)}$%. In order to facilitate a comparison of the results across banks and countries, we standardize each series of impulse responses, i.e. the responses caused by the same shock are divided by the standard deviation of the impulse variable; in the example above, our responses would be divided by $\sigma^{1/2}_{(j,j)}$. This means that the

initial response of the j-th variable to its own shock is equal to 1 or 100% of the initial shock of size of one standard deviation. Responses can, thus, be interpreted as percentages of the initial shock in the impulse variable.
In the following, the VEC and VAR model setups are discussed. A VEC model (VECM) with $p-1$ lags can be written as follows:[12]

$$\begin{pmatrix} \Delta cds_{Sov,t} \\ \Delta cds_{Bk,t} \end{pmatrix} = \begin{pmatrix} \alpha_{Sov} \\ \alpha_{Bk} \end{pmatrix} (\beta_{Sov} cds_{Sov,t-1} + \beta_{Bk} cds_{Bk,t-1} + \beta_0) + \sum_{i=1}^{p-1} \begin{bmatrix} \gamma_{SovSov,i} & \gamma_{SovBk,i} \\ \gamma_{BkSov,i} & \gamma_{BkBk,i} \end{bmatrix} \begin{pmatrix} \Delta cds_{Sov,t-i} \\ \Delta cds_{Bk,t-i} \end{pmatrix} + u_t, \quad (1.2)$$

where $cds_{j,t}$ with $j \in \{Sov, Bk\}$ refers to log $\text{CDS}_{j,t}$, i.e. the logarithmized CDS series of the country or bank. $\Delta cds_{j,t}$ denotes the difference between $cds_{j,t}$ and $cds_{j,t-1}$. β_0 is a (restricted) constant, and u_t is assumed to be $wn(0, \Sigma_u)$[13]. The γ-coefficients portray the short-run dynamics. In contrast, the β-coefficients describe the long-run relationship between banks and sovereign log-CDS spreads. β_{Sov} is normalized (i.e. $\beta_{Sov} = 1$) and only β_{Bk} is estimated. The loading coefficients, α, measure *the speed of adjustment* with which a particular CDS adjusts to the long-run relationship.[14]
The bivariate VAR setup with p-lags can be written as follows:

$$\begin{pmatrix} cds_{Sov,t} \\ cds_{Bk,t} \end{pmatrix} = \nu + \sum_{i=1}^{p} \begin{bmatrix} \alpha_{SovSov,i} & \alpha_{SovBk,i} \\ \alpha_{BkSov,i} & \alpha_{BkBk,i} \end{bmatrix} \begin{pmatrix} cds_{Sov,t-i} \\ cds_{Bk,t-i} \end{pmatrix} + u_t, \quad (1.3)$$

where ν is a vector of intercepts and the α's refer to the respective VAR coefficients.[15]

1.4 Results

This section presents the results for long-run and short-run relationships and, in addition, considers the GIR. First, the cross-country analysis is presented and then

[12] We use the notion of $p-1$ lags, to reinforce of the fact that a VECM($p-1$) has a VAR(p) representation.

[13] wn stands for "white noise" and refers to a discrete time stochastic process of serially uncorrelated random variables with the abovementioned first two moments.

[14] For further details on the interpretation of the long-run relations in a VEC framework, please see 1.A.

[15] The Granger-causality test (e.g. the bank does not Granger-cause the government CDS series if and only if the hypothesis $H_0 : \alpha_{SovBk,i} = 0$ for $i = 0, \ldots, p$ cannot be rejected) in this paper is carried out on a VAR with $p+1$ lags.

we report specific results for three of the countries. Table 1.4.1 shows the results of the Granger-causality tests for all countries, Table 1.4.2 outlines the results from our cointegration analysis and Table 1.4.3 summarizes the GIR for all countries.

Table 1.4.1: Results of Granger-Causality Tests for all Countries.

Country	Period	Independent	Dependent	p-value	Independent	Dependent	p-value
France	Before	BNP	FR	0.948	SG	FR	0.662
		FR	BNP	**0.014**	FR	SG	**0.059**
	After	BNP	FR	**0.089**	SG	FR	**0.096**
		FR	BNP	**0.000**	FR	SG	**0.002**
Germany	Before	COM	DE	**0.005**	DB	DE	0.152
		DE	COM	0.711	DE	DB	0.772
	After	COM	DE	**0.008**	DB	DE	**0.003**
		DE	COM	**0.009**	DE	DB	**0.004**
Ireland	Before	AIB	IR	0.499	BOI	IR	**0.002**
		IR	AIB	0.333	IR	BOI	0.451
	After	AIB	IR	0.174	BOI	IR	0.216
		IR	AIB	**0.000**	IR	BOI	**0.000**
Italy	Before	ISP	IT	**0.000**	UCR	IT	**0.002**
		IT	ISP	0.156	IT	UCR	0.536
	After	ISP	IT	0.392	UCR	IT	0.348
		IT	ISP	**0.008**	IT	UCR	**0.002**
Netherlands	Before	ABN	NL	**0.062**	ING	NL	**0.012**
		NL	ABN	0.705	NL	ING	0.160
	After	ABN	NL	**0.003**	ING	NL	**0.040**
		NL	ABN	**0.059**	NL	ING	**0.033**
Portugal	Before	BCP	PT	**0.001**	BES	PT	**0.000**
		PT	BCP	0.909	PT	BES	0.846
	After	BCP	PT	0.871	BES	PT	0.871
		PT	BCP	**0.000**	PT	BES	**0.000**
Spain	Before	BBVA	SP	**0.001**	BS	SP	**0.000**
		SP	BBVA	**0.024**	SP	BS	**0.009**
	After	BBVA	SP	**0.023**	BS	SP	**0.020**
		SP	BBVA	**0.000**	SP	BS	**0.000**

Notes: This table presents the Granger-causality tests for the entire period before government interventions and for the entire period during and afterwards. "Before" stands for *Stage 1+2* and "After" denotes *Stage 4+5+6*. We report the p-values of the tests. The significant results are emphasized in bold. The results show whether the independent variable Granger-causes the dependent variable.

1.4.1 Cross-Country Analysis

The results of the impulse response analysis underline the change in the interdependence of European sovereign CDS spreads and bank CDS spreads over the sample period. As we analyze the levels of the CDS spreads, our responses in the long run (after 22 days) report whether a long-term change in the respective CDS series occurs due to a shock in either the sovereign or the financial sector. Table 1.4.4 shows the percentage of long-run responses that are reported to be significantly/insignificantly different from zero after 22 days.

Comparing the periods before and after government interventions, one can observe the pronounced effects of the risk transfer mechanism. The ratio of significant bank responses to a sovereign shock increases from 14.29% before to 100% after the interventions. In contrast, the percentage of significant country responses to a banking sector shock decreases from 100% before to 21.43% after. The banks for which we do still see significant responses after the bailouts are the Portuguese banks and one of the Italian banks (Intesa Sanpaolo). In the period before the bailouts, there is a

Table 1.4.2: Results of Cointegration Analysis for all Countries.

Country	Period	Sov - Bk_1	α_{Sov}	α_{Bk}	β_{Sov}	β_{Bk}	Constant
France	Stage 1 + 2	FR - BNP	-0.085	0.024	1.000	-1.059	2.031
			[-3.273]	**[2.050]**	-	**[-6.997]**	**[3.693]**
		FR - SG	-0.124	0.022	1.000	-0.892	1.584
			[-3.991]	**[1.864]**	-	**[-8.934]**	**[4.136]**
	Stage 4 + 5 + 6	FR - BNP	0.018	0.018	1.000	-2.795	8.237
			[3.582]	**[3.154]**	-	**[-5.636]**	**[3.889]**
		FR - SG	0.017	0.015	1.000	-3.821	13.769
			[3.712]	**[3.136]**	-	**[-5.614]**	**[4.425]**
Germany	Stage 1 + 2	DE - COM	-0.108	-0.009	1.000	-0.719	1.235
			[-3.943]	[-0.583]	-	**[-5.775]**	**[2.458]**
		DE - DB	-0.122	0.009	1.000	-0.930	2.087
			[-4.046]	[0.561]	-	**[-7.866]**	**[4.428]**
	Stage 5	DE - COM	-0.045	0.004	1.000	-1.007	1.330
			[-2.211]	[0.233]	-	**[-1.913]**	[0.541]
	Stages 4 + 5 + 6	DE - DB	0.015	0.011	1.000	-3.432	12.382
			[3.442]	**[3.068]**	-	**[-5.082]**	**[3.944]**
Ireland	Stage 2	IR - AIB	-0.278	0.008	1.000	-0.567	-0.520
			[-3.826]	[0.171]	-	**[-5.432]**	[-1.032]
		IR - BOI	-0.475	-0.043	1.000	-0.581	-0.349
			[-5.170]	[-0.655]	-	**[-10.122]**	[-1.212]
	Stage 4 + 5 + 6	IR - AIB	0.014	0.060	1.000	-0.724	-1.116
			[1.012]	**[4.582]**	-	**[-6.905]**	**[-1.903]**
		IR - BOI	-0.002	0.096	1.000	-0.694	-1.292
			[-0.086]	**[5.414]**	-	**[-10.794]**	**[-3.584]**
Italy	Stage 1 + 2	IT- ISP	-0.012	0.020	1.000	-1.404	2.003
			[-2.282]	**[2.078]**	-	**[-6.927]**	**[2.706]**
		IT - UCR	-0.010	0.014	1.000	-1.502	2.647
			[-2.110]	**[1.767]**	-	**[-5.845]**	**[2.658]**
	Stage 5	IT - UCR	0.021	0.097	1.000	-1.280	1.462
			[0.761]	**[3.318]**	-	**[-9.331]**	**[2.247]**
	Stage 4 + 5 + 6	IT - ISP	0.003	0.066	1.000	-0.864	-0.922
			[0.162]	**[3.167]**	-	**[-9.881]**	**[-2.393]**
Netherlands	Stage 1 + 2	NL - ABN	-0.097	0.002	1.000	-0.829	1.416
			[-3.865]	[0.146]	-	**[-8.708]**	**[3.734]**
		NL - ING	-0.152	-0.009	1.000	-0.741	1.013
			[-4.763]	[-0.410]		**[-13.565]**	**[4.787]**
	Stage 6	NL - ABN	-0.017	0.038	1.000	-1.596	4.158
			[-0.944]	**[2.929]**	-	**[-5.938]**	**[3.243]**
	Stage 4 + 5	NL - ING	0.007	0.042	1.000	-1.572	3.125
			[0.427]	**[3.353]**	-	**[-7.475]**	**[3.220]**
Portugal	Stage 2	PT - BCP	-0.031	0.128	1.000	-0.986	0.715
			[-1.030]	**[2.313]**	-	**[-8.592]**	[1.443]
		PT - BES	-0.151	0.072	1.000	-0.789	0.101
			[-2.916]	[0.682]	-	**[-15.128]**	[0.420]
	Stage 4 + 5 + 6	PT - BCP	0.021	0.037	1.000	-0.793	-0.701
			[1.808]	**[3.687]**		**[-4.811]**	[-0.892]
		PT - BES	-	-	-	-	-
Spain	Stage 1 + 2	SP - BBVA	-0.019	0.023	1.000	-1.631	3.658
			[-1.693]	**[2.975]**	-	**[-7.714]**	**[4.404]**
		SP - BS	-0.022	0.023	1.000	-1.619	3.632
			[-1.931]	**[2.871]**	-	**[-7.873]**	**[4.488]**
	Stage 4 + 5 + 6	SP - BBVA	0.032	0.061	1.000	-0.985	-0.009
			[1.927]	**[3.756]**	-	**[-5.796]**	[-0.012]
		SP - BS	0.043	0.072	1.000	-1.106	0.527
			[2.555]	**[4.258]**	-	**[-7.215]**	[0.743]

Notes: This table presents the cointegration relationships that passed the stability test. Sub-periods are only included if the longer period did not pass the stability test (see Section 1.3.4). Coefficients are labeled in reference to equation (1.2). β-coefficients describe the long-run relationship between banks' and sovereign log-CDS spreads. The loading coefficients α measure *the speed of adjustment* with which a particular CDS adjusts to the long-run relationship. When α_{Sov} is significant and has the opposite sign to β_{Sov} it means that the sovereign adjusts back to the long-run equilibrium defined by $\beta' y_t = 0$, whenever $\beta' y_t \neq 0$. Whenever one of the α-coefficients is not significant, it means that the respective variable can be argued to provide the stochastic trend that determines the long-run relation and it is not adjusting at all to the long-run equilibrium. Whenever an α-coefficient is significant but with the same sign as the respective β parameter, the variable moves the entire equilibrium (see 1.A). t-statistics are reported in square brackets.

Table 1.4.3: Generalized Impulse Responses

	Imp.	Resp.	Before Gvt. Interventions[1] Days 0	1	5	22	Rem.	During/After Gvt. Interventions[2] Days 0	1	5	22	Rem.
FR	FR	FR	1.000	0.657	0.579	0.328		1.000	1.203	1.186	0.923	
		BNP	0.046^n	0.120	0.150	0.228		0.565	0.755	0.731	0.483	
	BNP	BNP	1.000	1.006	0.942	0.835		1.000	1.052	0.891	0.290^n	
		FR	0.230^n	0.204^n	0.418	0.764		0.452	0.584	0.416	-0.227^n	
	FR	FR	1.000	0.638	0.495	0.217		1.000	1.201	1.114	0.790	
		SG	0.030^n	0.080^n	0.125^n	0.192^n		0.499	0.691	0.642	0.348	
	SG	SG	1.000	1.121	1.083	1.004		1.000	1.041	0.843	0.206^n	
		FR	0.202^n	0.246^n	0.502	0.840		0.520	0.626	0.383	-0.389^n	
DE	DE	DE	1.000	0.780	0.474	0.157		1.000	1.132	1.072	0.587	*VAR*
		COM	0.088	0.125	0.101^n	0.040^n		0.425	0.592	0.627	0.550	*VAR*
	COM	COM	1.000	1.091	1.088	1.171		1.000	1.060	1.004	0.580	*VAR*
		DE	0.285^n	0.356	0.285^n	0.675		0.435	0.608	0.441	-0.254^n	*VAR*
	DE	DE	1.000	0.778	0.461	0.201^n		1.000	1.140	1.129	0.889	
		DB	0.071	0.103	0.125^n	0.146^n		0.433	0.615	0.611	0.412	
	DB	DB	1.000	1.092	1.117	1.094		1.000	1.156	1.034	0.428^n	
		DE	0.267^n	0.453	0.450	0.898		0.569	0.766	0.603	-0.127^n	
IR	IR	IR	1.000	0.539	0.526	0.397	*VAR*	1.000	1.266	1.123	1.270	
		AIB	0.122^n	0.184^n	0.181^n	0.195^n	*VAR*	0.251	0.512	0.769	1.276	
	AIB	AIB	1.000	1.168	1.172	0.755	*VAR*	1.000	0.953	1.063	0.676	
		IR	0.266^n	0.263^n	0.331	0.524	*VAR*	0.291	0.385	0.221^n	0.282^n	
	IR	IR	1.000	0.529	0.500	0.397	*VAR*	1.000	1.268	1.116	1.250	
		BOI	0.115^n	0.194	0.211^n	0.222^n	*VAR*	0.212	0.508	0.677	1.410	
	BOI	BOI	1.000	1.088	1.142	0.803	*VAR*	1.000	0.831	0.807	0.459^n	
		IR	0.216^n	0.400	0.365	0.431	*VAR*	0.220	0.222^n	0.134^n	0.259^n	
IT	IT	IT	1.000	1.031	0.981	0.966		1.000	1.275	1.378	1.379	
		ISP	0.498	0.350^n	0.519^n	0.619^n		0.760	1.021	1.226	1.477	
	ISP	ISP	1.000	1.074	1.122	0.729		1.000	1.179	1.156	0.960	
		IT	0.152	0.316	0.359	0.482		0.570	0.708	0.751	0.752	
	IT	IT	1.000	1.043	0.923	0.921		1.000	1.259	1.262	0.851	*VAR*
		UCR	0.537	0.471^n	0.542^n	0.573^n		0.696	0.892	0.936	0.746	*VAR*
	UCR	UCR	1.000	1.064	1.125	0.785		1.000	1.083	0.992	0.539	*VAR*
		IT	0.197	0.332	0.352	0.475		0.598	0.712	0.632	0.205^n	*VAR*
NL	NL	NL	1.000	0.658	0.469	0.204^n		1.000	1.143	1.095	0.744	*VAR*
		ABN	0.047^n	0.093^n	0.094^n	0.073^n		0.347	0.468	0.473	0.364	*VAR*
	ABN	ABN	1.000	1.003	1.132	1.173		1.000	1.111	1.084	0.836	*VAR*
		NL	0.104	0.095	0.328	0.730		0.408	0.594	0.506	0.016^n	*VAR*
	NL	NL	1.000	0.680	0.434	0.160^n		1.000	1.152	1.165	1.012	*VAR*
		ING	0.109^n	0.171	0.184^n	0.136^n		0.438	0.585	0.623	0.587	*VAR*
	ING	ING	1.000	0.962	1.075	1.135		1.000	1.123	1.011	0.539	*VAR*
		NL	0.233^n	0.135^n	0.400	0.759		0.606	0.785	0.723	0.368^n	*VAR*
PT	PT	PT	1.000	0.982	0.949	0.806	*VAR*	1.000	1.264	0.990	1.170	
		BCP	0.342	0.387	0.406	0.424	*VAR*	0.535	0.785	0.809	1.056	
	BCP	BCP	1.000	1.104	1.022	0.713	*VAR*	1.000	1.151	1.105	1.002	
		PT	0.227	0.358	0.396	0.450	*VAR*	0.724	0.897	0.675	0.653	
	PT	PT	1.000	0.980	0.941	0.791	*VAR*	1.000	1.259	1.306	1.079	*VAR*
		BES	0.295	0.325	0.353	0.402^n	*VAR*	0.542	0.804	0.941	1.000	*VAR*
	BES	BES	1.000	1.141	1.066	0.750	*VAR*	1.000	1.250	1.298	1.098	*VAR*
		PT	0.207	0.371	0.421	0.483	*VAR*	0.794	0.975	0.954	0.599^n	*VAR*
SP	SP	SP	1.000	0.554	0.527	0.482		1.000	1.202	0.953	1.012	
		BBVA	0.061^n	0.128^n	-0.067^n	0.172^n		0.648	0.874	0.682	0.806	
	BBVA	BBVA	1.000	1.083	1.018	0.595		1.000	1.172	0.804	0.586	
		SP	0.133^n	0.175^n	0.605	0.511		0.651	0.812	0.537	0.398	
	SP	SP	1.000	0.559	0.552	0.486		1.000	1.188	0.897	0.950	
		BS	0.069^n	0.146^n	-0.053^n	0.168^n		0.663	0.893	0.628	0.739	
	BS	BS	1.000	1.085	0.999	0.573		1.000	1.155	0.690	0.405	
		SP	0.142^n	0.172^n	0.648	0.511		0.652	0.808	0.418	0.226^n	
Avg.	SOV	SOV	1.000	0.743	0.629	0.465		1.000	1.210	1.127	0.994	
		BK	0.174	0.206	0.205	0.256		0.501	0.714	0.741	0.804	
	BK	BK	1.000	1.077	1.079	0.865		1.000	1.094	0.985	0.615	
		SOV	0.205	0.277	0.419	0.609		0.535	0.677	0.528	0.197	

Notes: "Res." abbreviates Response, "Imp." Impulse, and "Rem." Remark. Each impulse variable has an effect on itself and the second variable of the bivariate system. A unit shock in the structural error leads to a one standard deviation (in %) increase in the level of the impulse variable. This effect is normalized to 1. The GIR of the second response variable represents the percentage change in the level, given the normalized impulse. ^{n} denotes insignificant effects, by considering bootstrapped 95% confidence intervals with 2000 replications. [1] denotes Stage 1+2 and [2] denotes Stage 4+5+6. We report contemporaneous responses (Days = 0) and effects after 1 day, 5 days (after one week), and 22 days (after one month). *VAR* means that we use a VAR in levels to obtain the GIR. This is done when tests and/or cointegration relation checks do not indicate an equilibrium relation for the whole of Stage 1+2 or Stage 4+5+6. In the "Avg." section, we provide the mean impulse responses to a shock in sovereign CDS spreads (SOV) and to a shock in bank CDS spreads (BK).

Table 1.4.4: Percentage of Significant/Insignificant Responses in the Long Run (after 22 days)

	Bank → Country		Country → Bank	
	Before	During/After	Before	During/After
Significant	100%	21.43%	14.29%	100%
Insignificant	0%	78.57%	85.71%	0%

Notes: Significant/Insignificant refers to evaluating a 95% confidence interval estimated using a recursive-design wild bootstrap with 2000 replications. The left side of the table concerns the country responses to a banking sector CDS shock. The right side refers to banks' responses to a sovereign CDS shock. "Before" concerns the period preceding banking sector bailouts and "During/After" the period during and after government interventions.

stark contrast between the result that all banks are found to impact their respective sovereign CDS series and only a very small fraction of countries affect bank CDS spreads. We argue that the roots of this finding are in the systemic component of the crisis, which originated from financial institutions and spilled over onto the sovereign CDS market. In the period after the bailouts, the picture changes completely: the effects of sovereign shocks on bank CDS spreads become permanent, while banking sector shocks are less important than before. As emphasized in other recent papers, these findings reflect the private-to-public risk transfer.

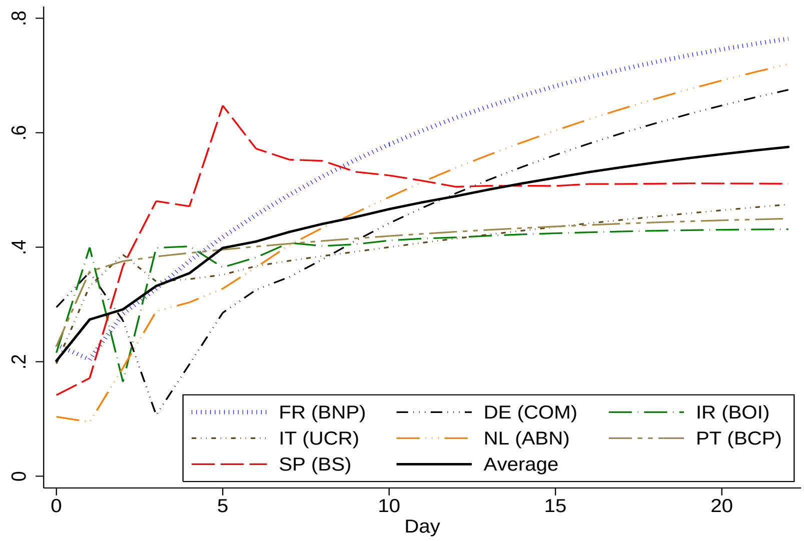
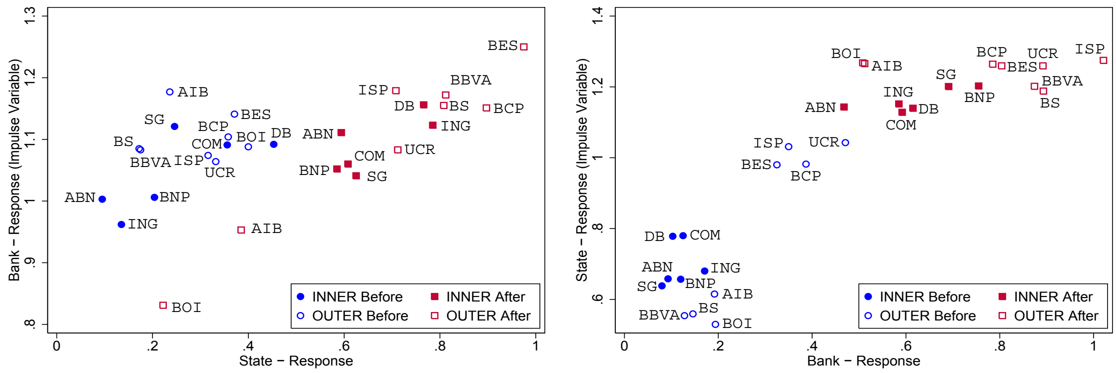


Figure 1.4.1: Effects of a Banking Sector Shock on Government Spreads: Before Government Interventions
Notes: Sources of the banking shock are written in parentheses. Shocks to bank spreads within the same country have very similar impacts on the sovereign spread in the period before government interventions. Only one of the two bank responses per country are depicted as the results are similar. The "Average" line represents the mean of the sovereign responses to shocks in the seven bank CDS spreads.

Figure 1.4.1 depicts the state responses to banking sector shocks. Considering the long-run effects (after 22 days) depicted in this graph, which are all estimated to be significant, the countries can be separated into two groups: INNER composed of FR,

DE and NL (with responses above the “Average” line) and OUTER composed of IR, IT, SP and PT (with responses below the “Average” line). The results for the INNER group can be argued by a weak interest (i.e. low liquidity of the CDS contracts) in insuring against a country default in the period before Lehman Brothers’ collapse. This could have led first to market inefficiency and then to a strong adjustment effect as the volume increased. Furthermore, the size of the INNER banks’ exposures to the subprime-linked securities was considered much bigger than that of the OUTER banks. On the other hand, in this period, the OUTER countries were already at levels (of sovereign CDS spreads) closely linked to their domestic banks’ CDS spreads, i.e. public imbalances and high debt burdens were priced in for the latter group, thus these spreads adjusted less after the bailouts.
Concentrating on the point estimates of the responses at day 1, i.e. Figure 1.4.2 (a) and (b), two important results can be emphasized. Firstly, one can see how the bank bailouts affected the risk transfer mechanism and secondly that the same INNER and OUTER groups can be distinguished in the short run as well. In terms of the change in the risk transfer mechanism, Figure 1.4.2 (a) reveals that the sovereign CDS series are more sensitive to banking sector shocks than before the bailouts, while the sensitivity of the banks to their own shocks remain of a similar magnitude. Only the responses of the Irish banks AIB and BOI to state shocks seem to stay at approximately the same level as before the bailouts, while their impacts on themselves decrease. Thus, the risk transfer from banks to governments seems to be most evident in Ireland. In the case of a country shock (Figure 1.4.2 (b)), we find an increase in sensitivity in both dimensions. Countries as well as banks suffer more from a government shock after the bailouts. In terms of the second point that can be made about the short run, in the period during/after bank bailouts, the responses one day after each shock, almost all of which are significantly different from zero, can be clustered into the INNER and OUTER groups, as before.
As noted above, the importance of a sovereign shock augments dramatically in the post-intervention era. Figure 1.4.3 depicts the entire impulse response series of the selected banks to a shock in the government sector. Sorting banks by the effects they experience in the long run, which are shown to be significant in all cases, we obtain the following ranking (from lowest effect to highest): Société Générale (SG), ABN Amro Bank (ABN), Deutsche Bank (DB), BNP Paribas (BNP), Commerzbank (COM), ING Group (ING), Banco Santander (BS), Unicredito (UCR), Banco Bilbao Vizcaya Argentaria (BBVA), Banco Comercial Português (BCP), Banco Espírito



(a) Bank Shock

(b) Country Shock

Figure 1.4.2: Responses on Day 1 after the Shock

Notes: Responses of both variables of the bivariate systems are plotted (i.e. bank response (y-axis) vs. country response (x-axis) and country response (y-axis) vs. bank response (x-axis)). For example, ∘ ABN is located at (1,.1), indicating that a shock (on day 0, before government interventions) in the CDS series of ABN, leading to a 1% increase in the ABN spread, affects the Dutch CDS spread by 0.1% on day 1.

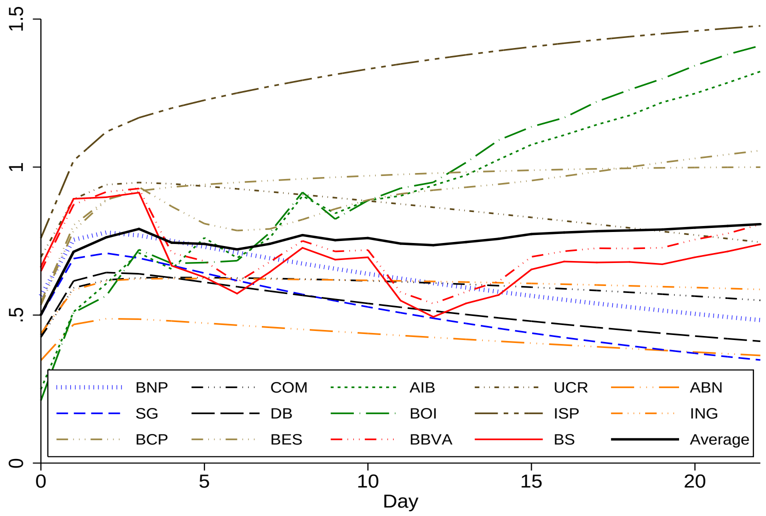


Figure 1.4.3: Effects of a Sovereign Shock on Bank Spreads: After Government Interventions.

Notes: The "Average" line represents the mean of the bank responses to shocks in the seven sovereign CDS spreads.

Santo (BES), Allied Irish Banks (AIB), Bank of Ireland (BOI), Intesa Sanpaolo (ISP). The long-run responses of the banks from the same country are generally clustered. The only exception are the Italian banks, with ISP being more sensitive to sovereign shocks than UCR (148% compared to 75%). While SG is affected by only 35% of the initial shock, the strongest three impacts range from 128% to 148%. ISP and the Irish banks respond most strongly to sovereign shocks. They are followed by the Portuguese and then the Spanish banks, with the Italian UCR coming between BBVA and BS. At the bottom of the ranking are the Dutch, German and French banks.

1.4.2 Specific Country Analysis

In this subsection, we present the results for three of the countries: Germany, Ireland and Italy. These were selected for their differing total commitment to the financial sector (offered in their bailouts) relative to their 2008 GDP. Ireland is the country with the highest commitment and Italy that with the lowest, while Germany can be argued to lie in the middle of these two.

1.4.2.1 Germany

In the case of Germany, we analyze, using a bivariate setup, the German (DE) sovereign CDS spread in relation to the CDS spreads of Commerzbank (COM) and Deutsche Bank (DB), respectively. The results for the tests of Granger-causality are depicted in Table 1.4.1, the cointegration relations in Table 1.4.2, and the impulse responses in Table 1.4.3.[16]

Cointegration and Granger-Causality Analysis

For the entire period before the government interventions (i.e. Stage 1+2), we find evidence of a stable long-run equilibrium relationship between the German CDS spread and both bank CDS series. The hypothesis that both estimated β-coefficients for the banks are equal to -1 cannot be rejected using a standard t-test. The error correction equation, e.g. for the relation with DB, can be written as follows:

$$cds_{DE,t} = \underset{(0.118)}{0.930} \times cds_{DB,t} - \underset{(0.471)}{2.087} - ec_t,$$ [17]

where ec_t refers to the value of the long-run relation at time t and standard errors are provided in parentheses. As the variables are measured in logs, the β-coefficients may be interpreted as elasticities, yielding a bank-sovereign CDS equation. This relation implies, neglecting the rest of the estimated dynamics in the model, that a 1% increase in the CDS spread of DB leads to a 1% increase in the CDS spread of DE. For COM the same interpretation applies.

The α-coefficients in the relations of DB and COM with DE suggest that the bank spreads do not adjust to any deviations from the long-run equilibrium, while the

[16] Test results and the graph of the German sovereign CDS together with the German banks' CDS time series are presented in 1.B.2.

[17] The cointegration graph is provided in Figure 1.B.8.

German CDS spread adjusts at a rate of $\hat{\alpha}_{DE} = -0.122$ and $\hat{\alpha}_{DE} = -0.108$ to changes in the DB and COM spreads respectively. A formal test confirms this result as $cds_{DB,t}$ and $cds_{COM,t}$ are found to be weakly exogenous, which leads to the argument that DB and COM provide the stochastic trend in the cointegration relations. Tests for Granger-causality indicate that only COM Granger-causes DE at the 1% significance level in the period before state interventions took place.
After the bank aid schemes are in place, the long-run relations change. Firstly, we do not find a stable long-run relation for DE-COM for the entire post-intervention period, but only in Stage 5. We find equal values for the β-coefficients as in the pre-intervention results, implying the same elasticities as mentioned above. However, the constant changes from 1.24 (before) to insignificant (after), yielding the interpretation that the gap between the two CDS series vanishes. In contrast, we find a cointegration relation for DE and DB for the entire post-intervention period. The relation between COM and DE in Stage 5 yields the conclusion that COM is weakly exogenous and DE adjusts at a rate of $\hat{\alpha}_{DE} = -0.045$, which is close to the α-value from the period before the interventions took place. In the second cointegration relation, which considers all three stages after the bailouts together, we find that the equilibrium for DE moves in the direction of its development (as DE's α- and β-coefficients are both positive). Furthermore, Granger-causality tests for the period during and after state interventions indicate that all variables Granger-cause each other at the 1% level.

Impulse Response Analysis

The results of the impulse response analysis are depicted in Figure 1.4.4. The analysis of the period before government interventions refers to the VECM setup; only in the period after interventions do we use a VAR framework to examine the relationship between DE and COM. In all graphs, the three solid lines represent the impulse responses before the interventions, with the light ones indicating the 95% bootstrapped confidence interval. The bold dotted line describes the responses during and after the rescue schemes had been implemented and the light dotted lines the bootstrapped confidence bands. Firstly, we observe that the pattern in the left panel strongly resembles the pattern in the right panel. In the upper-right corner of each panel, the effects of a shock in the bank CDS spread on the German CDS are plotted. Before the interventions (solid line), a banking sector shock permanently affects the government CDS series, while in the period afterwards (dotted) there is

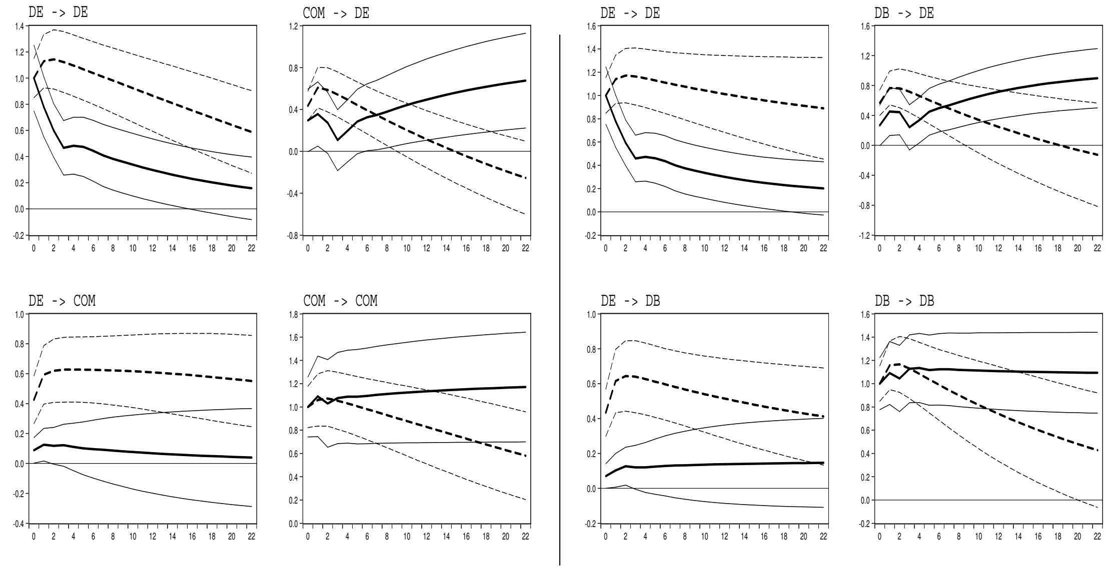


Figure 1.4.4: Generalized Impulse Responses for Germany: (Solid) Before, (Dotted) During & After Government Interventions

Notes: Solid lines: responses before government interventions (bold) and the 95% bootstrapped confidence interval (thin). Dotted lines: responses during and after government interventions (bold) and the 95% bootstrapped confidence interval (thin). X-axis: number of days (after the shock). Y-axis: impact relative to a one standard deviation shock in the impulse variable. ***[Left Panel]*** Upper-Left: DE (impulse variable) - DE (response variable). Lower-Left: DE (impulse var.) - COM (response var.). Upper-Right: COM (impulse var.) - DE (response var.). Lower-Right: COM (impulse var.) - COM (response var.). ***[Right Panel]*** Upper-Left: DE (impulse var.) - DE (response var.). Lower-Left: DE (impulse var.) - DB (response var.). Upper-Right: DB (impulse var.) - DE (response var.). Lower-Right: DB (impulse var.) - DB (response var.).

only a temporary effect.

In the case of a government shock spilling over onto the banking sector, we notice that DB (right panel) and COM (left panel) are only affected in the very short-run ($t \leq 3$) before the interventions. In the period after the bank bailouts, we find that both series react permanently to a shock stemming from the sovereign.

Additionally, the graphs show that the effects of a banking sector shock on itself are stronger in the pre-interventions period, as they are estimated to have a permanent effect. The responses after the state interventions suggest a decrease in the impact of the latter for both banks. The shocks from the government CDS spread on itself have a stronger impact in both bivariate setups (i.e. in the analyses based on each of the two banks) after the interventions.

Discussion

From October 2008 until the end of May 2010, Germany provided total support to the local financial sector of EUR 619.1bn, or 25% of total 2008 GDP. From a total committed amount of EUR 64.8bn for capital injections, EUR 54.5bn were demanded by German banks up to the end of May 2010. Germany pledged EUR

475bn in the form of liability guarantees, of which local banks utilized EUR 185.8bn up to the end of our time frame.

SoFFin[18] granted COM an individual guarantee for issuing EUR 15bn of debt securities.[19] Furthermore, SoFFin provided EUR 8.2bn in the form of a silent equity holding ("silent participation") and COM's recapitalization by the government amounted to EUR 10bn.[20] On the other hand, DB, the biggest German bank, resisted state capital injections. Given the complete recapitalization of COM we would expect a lower reliance on government guarantees, but we find no significant differences in the dynamics of the two bank CDS series in relation to the German sovereign CDS spread. Furthermore, our results suggest that investors anticipated the direct support for COM, as the Granger-causality tests support the idea that the CDS spreads of COM contain important information for determining the German spreads. A shock to the sovereign spread has a permanent effect on the CDS spread of COM. Thus, before the interventions, we have evidence that the dynamics of the two series differ, suggesting that the link between the CDS series of COM and DE is more sensitive than the link between DB and DE.

COM is known to have had severe difficulties during the last crisis, which led SoFFin to provide extra support to this bank. The results of our empirical analysis underline that the dynamics of the two banks do not substantially differ in the post-intervention period. Assuming that this similarity is a consequence of the extra support provided, we conclude that the German rescue schemes were successful in transferring the default risk. Thus, the extra funding for COM was necessary in order to induce a credible perception that the tail risk of the latter had been absorbed by the state. We find that shocks to both banks have a weaker effect on their own spreads after the bailout schemes had been implemented. However, the result is stronger for DB. The cost of this positive aspect is a higher sensitivity of both banks to developments in the government CDS spreads. Notably, the German spread is not influenced in the long term by banking sector shocks after the bailout measures have been provided.

Altogether, the results highlight that the contagion emerged from the banking sector and spilled over onto German sovereign CDS spreads in the period before the rescue schemes had been implemented. Thus, we find evidence in favor of H1. The depen-

[18] The German Special Fund for Financial Market Stabilization (SoFFin) is in charge of managing the German financial support programs.

[19] https://www.commerzbank.de/en/hauptnavigation/aktionaere/service/archive/ir-nachrichten_1/2008_5/ir_nachrichten_detail_08_2203.html

[20] These capital injections were announced to the public on 3 November 2009.

dence in the other direction is weaker or only exists in the very short run. Afterwards, developments in the perceived default risk of all series are strongly interwoven, as suggested by the cointegration analysis and the results of the Granger-causality tests. Furthermore, the impulse responses highlight a stronger interdependency between all series, while an unexpected change in the bank CDS series has only a temporary effect on the sovereign CDS spread (H2a, H2b). Moreover, we find no strong differences in the dynamics of COM and DB in relation to changes in the German CDS spreads (H3). Our results suggest that the extra support for COM credibly transferred the default risk on to the government's balance sheet.

1.4.2.2 Ireland

Within the set of analyzed countries, the results for Ireland reveal most clearly the impact of government interventions. As the dynamics for both setups, i.e. Ireland (IR) - Allied Irish Banks (AIB) and Ireland (IR) - Bank of Ireland (BOI), resemble each other strongly we report only one of them. Tests of Granger-causality are depicted in Table 1.4.1, cointegration relations in Table 1.4.2, and impulse responses in Table 1.4.3.[21]

Cointegration and Granger-Causality Analysis

The cointegration analysis uncovers a long-run relation in Stage 2, in which $\hat{\beta}_{AIB} = -0.567$. Interpreting the cointegration coefficients for the period before the interventions, a 1% increase in bank CDS spreads translates into an approximate 0.57% gain in the Irish spread. The gap (the constant from the cointegration equation) between the two CDS series is insignificant.

Furthermore, in the period before government interventions there is evidence that the stochastic trend originates from the banking sector and affects the sovereign CDS series. The estimated α-coefficient for AIB is not significantly different from zero and the hypothesis of weak exogeneity for the banking sector series cannot be rejected. Thus, we conclude that the series of AIB influences IR in the long run. In the short run, Granger-causality is not significant in either direction.

During and after the interventions the dynamics change and emphasize a different role of the Irish CDS spread, which we argue occurs because of the government interventions. The error correction equation can be written as

[21] Preliminary test results and the graph of the respective time series are presented in 1.B.3.

$$cds_{IR,t} = \underset{(0.105)}{0.724} \times cds_{AIB,t} + \underset{(0.587)}{1.116} - ec_t.$$[22]

Comparing elasticities, we now find an increase in $\hat{\beta}_{AIB}$ to 0.724, implying that a 1% increase in the Irish spread augments the bank spread by 1.38%.[23] The gap between the two series is enlarged and is significantly different from zero.
The estimated α-coefficients suggest that during and after the interventions the Irish spread provides the stochastic trend, as the weak exogeneity of this series cannot be rejected. Only the bank CDS spread adjusts to deviations from the long-run equilibrium, at a rate of $\hat{\alpha}_{AIB} = 0.06$. The prominent role of the Irish CDS series is also emphasized in the short-run dynamics, where we find that the CDS spread of IR Granger-causes the CDS spread of AIB but not vice versa during this period.

Impulse Response Analysis

The GIR depicted in Figure 1.4.5 underline the shift in the dependence between the two CDS series. Firstly, the graph in the upper right corner indicates that a shock from the banking sector permanently influences the government CDS spread before the interventions but only does so temporarily ($t \leq 2$) afterwards. The opposite pattern is found for a government sector shock. In the pre-intervention period, the graph in the lower left corner highlights that the latter shock does not significantly influence the CDS spread of AIB, while there is a permanent impact in the period during and after implementation of the rescue schemes. Moreover, the remaining two graphs (upper left and lower right corners) suggest that there has been a change in the sensitivities to shocks from the same sector. A banking shock has a permanent effect on itself before the interventions but a much lower one afterwards. For the Irish spread, the GIR results show an opposing development. Whilst both deviations are permanent, that after interventions is far stronger.

Discussion

Not surprisingly, the study of the Irish risk transfer mechanism depicts the clearest change in dynamics, as Ireland is, by far, the country that made the greatest total commitment to the financial sector relative to its GDP. Remarkably, this amounted to 319% of 2008 GDP, or in monetary terms, EUR 592bn. Up to the end of May 2010, EUR 99.8bn were required in total by the Irish banks. This amount includes EUR 19.3bn that were used as capital injections (Table 1.3.1). Both banks in our

[22] The cointegration graph is provided in Figure 1.B.9.

[23] This number is obtained by normalizing the coefficients by the estimated β-coefficient of AIB.

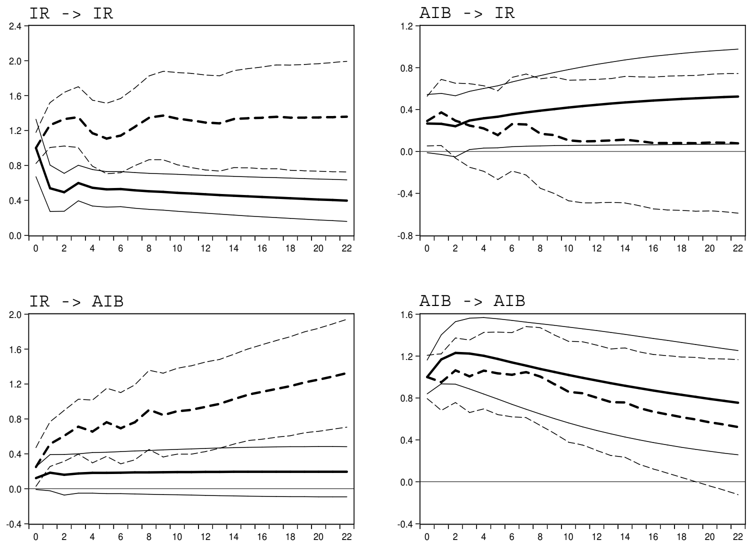


Figure 1.4.5: Generalized Impulse Responses for Ireland: (Solid) Before, (Dotted) During & After Government Interventions

Notes: Upper-Left: IR (impulse variable) - IR (response variable). Lower-Left: IR (impulse var.) - AIB (response var.). Upper-Right: AIB (impulse var.) - IR (response var.). Lower-Right: AIB (impulse var.) - AIB (response var.). Solid lines: responses before government interventions (bold) and the 95% bootstrapped confidence interval (thin). Dotted lines: responses after government interventions (bold) and the 95% bootstrapped confidence interval (thin). X-axis: number of days (after the shock). Y-axis: impact relative to a one standard deviation shock in the impulse variable. Generalized impulse responses for BOI behave similarly to those for AIB.

study were recapitalized by the Irish government on 21 December 2008 and approved by the European Commission on 26 March 2009 (BOI) and 12 May 2009 (AIB).[24] Under this scheme, AIB and BOI were each provided with EUR 3.5bn. The similar public aid structures for the two banks lead to homogeneous findings, which supports our H3.

The impact of a banking sector shock on itself decreases substantially after the measures have been provided. Furthermore, there is a significant impact on the government spreads but only in the short run. The flip side of the coin is the strong influence of government sector shocks on the banks after the rescue schemes had been put in place, which amplified the serious issues in the Irish financial sector as sovereign debt problems emerged.

Combining the results from the two analyses, we find strong evidence in favor of H1, H2a, and H2b. Pre-bailout, the data show that the channel through which risk is spread into the market originates from the banking sector rather than the government. After the government interventions, the risk transfer mechanism puts more weight on the developments of the government CDS spread. As the government

[24] IP/09/744 and IP/09/483.

takes over the tail risk from the banks, the development of the Irish CDS series begins to play an increasingly important role. Only in the very short run do changes in banks' CDS spreads influence the government series during and after the state intervention. The effects of banking sector shocks on itself have weakened post-bailout, similar to the German case.

1.4.2.3 Italy

The main cointegration relations between Italy and the selected domestic banks (Intesa Sanpaolo (ISP) and Unicredito (UCR)) are presented in Table 1.4.2. Table 1.4.1 presents the findings from the Granger-causality tests and Table 1.4.3 the GIR.[25]

Cointegration and Granger-Causality Analysis
In the period before government support was provided to the Italian banking industry (i.e. Stage 1+2), we find that the banks' and sovereign CDS series are tied together in a long-run equilibrium. Interpreting the β-coefficients, neglecting the remaining dynamics of the system, we argue that in the long-run a 1% increase in ISP's (UCR's) CDS spread leads to a 1.4% (1.5%) increase in the CDS series of Italy. The gaps (i.e. the constants in the cointegration relations) between the two CDS series are estimated to be significantly different from zero in both setups. The speed of adjustment, reflected by the estimated α-coefficients, is faster for the banks' CDS spreads, i.e. $|\hat{\alpha}_{IT}| = 0.012 < 0.020 = |\hat{\alpha}_{ISP}|$ and $|\hat{\alpha}_{IT}| = 0.010 < 0.014 = |\hat{\alpha}_{UCR}|$. Regarding the short-run dynamics, the results reveal that Italy is Granger-caused by the developments in ISP's and UCR's CDS spreads in Stage 1+2, consistent with our assumption that the information from the financial sector was systemically important then.

During and after the implementation of the Italian bank bailout program the dynamics between the sovereign and banks' CDS spreads change. Firstly, UCR is found to be in a stable long-run equilibrium with the Italian government CDS series only during Stage 5. In this setup, the estimated β-coefficients imply that a 1% increase in the government spread induces an upward adjustment of UCR's CDS of 0.78%. The error correction mechanism of IT-ISP for the entire post-intervention period is

$$cds_{IT,t} = \underset{(0.087)}{0.864} \times cds_{ISP,t} + \underset{(0.385)}{0.922} - ec_t.^{26}$$

[25]Preliminary test results and the graph of the respective time series are presented in 1.B.4.
[26]The cointegration graph is provided in Figure 1.B.10.

A marginal change in the Italian CDS series by 1% leads to an adjustment in cds_{ISP} by 1.16%. The elasticities of the two banks cannot be compared as they refer to different stages in our sample period. The constant is significantly different from zero in both setups.
In the period after government interventions, the loading coefficients indicate that Italy provides the stochastic trend, as the CDS series of the latter is tested to be weakly exogenous. This result implies that, although the Italian CDS spread does not adjust to deviations from the long-run equilibrium, the banks' CDS spreads react to these changes. In contrast to the results for the pre-intervention period, after government interventions the Italian CDS spreads Granger-cause both bank CDS spreads but not vice versa.

Impulse Response Analysis

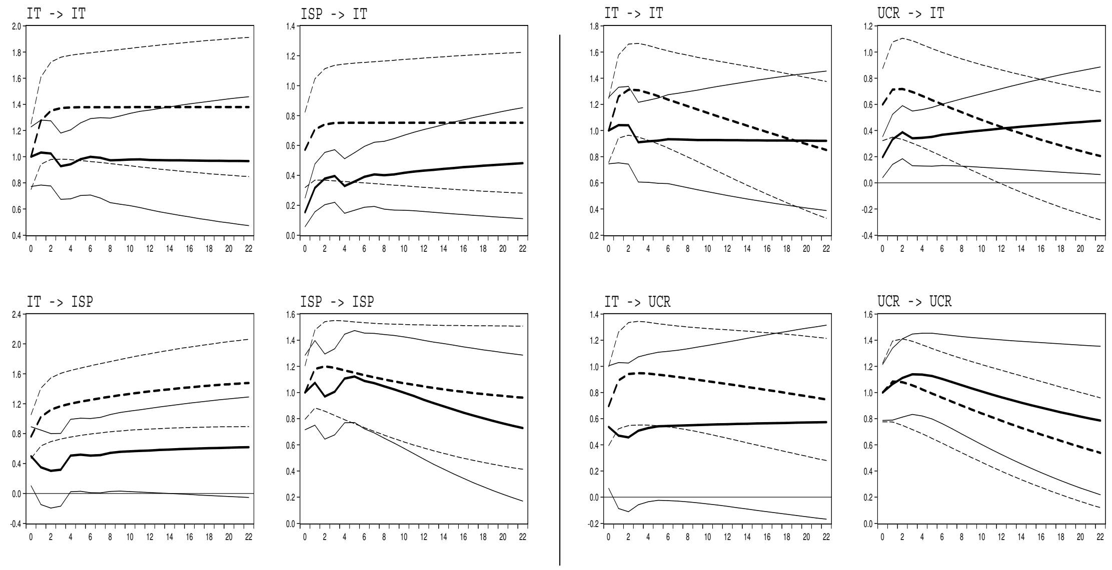


Figure 1.4.6: Generalized Impulse Responses for Italy: (Solid) Before, (Dotted) During & After Government Interventions
Notes: ***[Left Panel]*** Upper-Left: IT (impulse variable) - IT (response variable). Lower-Left: IT (impulse var.) - ISP (response var.). Upper-Right: ISP (impulse var.) - IT (response var.). Lower-Right: ISP (impulse var.) - ISP (response var.). ***[Right Panel]*** Upper-Left: IT (impulse var.) - IT (response var.). Lower-Left: IT (impulse var.) - UCR (response var.). Upper-Right: UCR (impulse var.) - IT (response var.). Lower-Right: UCR (impulse var.) - UCR (response var.). Solid lines: responses before government interventions (bold) and the 95% bootstrapped confidence interval (thin). Dotted lines: responses after government interventions (bold) and the 95% bootstrapped confidence interval (thin). X-axis: number of days (after the shock). Y-axis: impact relative to a one standard deviation shock in the impulse variable.

The graph in the upper right corner of each panel of Figure 1.4.6 depicts the effect of a banking shock on the sovereign CDS series. The solid line emphasizes that, pre-intervention, risk permanently spread to the government CDS series. After the interventions, a shock originating from ISP (left panel) is found to lead to a permanent shift in the government CDS spread, while a shock from UCR (right panel) shifts the Italian CDS series by a greater amount but only temporarily ($t \leq 12$). These findings support our H2a and H3. In contrast, in the period before interventions (solid lines), the effects of a shock in the government sector (the lower-left graph in each panel) are significant in the short run for both banks. During/after the interventions (dotted lines), the impact is stronger and permanent, in line with our H2b. The pattern of bank shocks on their own series is very similar in the two periods (the lower-right corner in each panel). A government shock has a stronger effect on itself in the period after interventions, in both setups.

Discussion

Italy has one of the highest debt burdens of all the European Union countries.[27] This fact led the Italian government to pledge a total of EUR 62bn in its bailout package, representing slightly more than 4% of 2008 GDP. This ratio is the lowest among all the countries analyzed in this paper. Actual capital injections accounted for EUR 4.1bn out of a committed amount of EUR 12bn. Italy also promised to support its domestic banks with an asset purchase scheme worth EUR 50bn, which had not been utilized by the end of our time frame. Compared with the other countries analyzed, the Italian government offered no liability guarantees in its support measures for financial institutions. Notably, this instrument was highly utilized elsewhere in our sample of countries. On 20 March 2009, ISP started a procedure to obtain EUR 4bn in public aid for recapitalization.[28] On the other hand, UCR, which is the biggest Italian bank, did not request any capital from Italy. The increased possibility of government aid being given to ISP in the future is reflected in our GIR analysis: the CDS series of ISP became more sensitive to unexpected changes in the Italian spread than the CDS series of UCR. This result and the cointegration relation between IT and ISP (in Stage 4+5+6) provide evidence in support of our third hypothesis (H3). Since ISP did not make use of any public support, the tail risk of the bank was not completely transferred to the Italian government. A shock to the bank has an even stronger effect on the bank itself post-bailout. The increased impact on the government CDS of a shock to the bank underpins the idea that investors believe

[27] Italy's public debt was estimated to be around 105% of GDP in 2008.

[28] `http://www.group.intesasanpaolo.com/scriptIsir0/si09/contentData/view/content-ref?id=CNT-04-000000003F8D4`
According to this document, on 29 September 2009 ISP decided that it would no longer participate in the Italian aid program for the banking sector, the so-called "Tremonti Bonds" program, but would issue debt to private investors.

that any difficulties faced by ISP will feed back to the government sector. In the case of UCR, we detect a similar pattern to that seen in other countries: the effect of a banking sector shock on the banking sector decreases slightly.
Before Lehman Brothers' default, the systemic banking crisis spilled over into the sovereign market, which is supported by the Granger-causality analysis results, and by the permanent effect of a banking sector shock shown by the GIR analysis. However, movements in IT's CDS spread have an effect on the bank spreads as well, which partly contradicts our H1. After the state interventions, this relation becomes more pronounced, with IT now Granger-causing both banks, providing the stochastic trend in the cointegration relations, and government shocks causing strong deviations in the banks' CDS series. Nonetheless, the banks still influence the government CDS series, albeit only temporarily in UCR's case. Bailout schemes seem not to limit the effects of banking sector shocks on itself, as the intensity of those effects is almost the same as in the period before government interventions. Thus, Italy's banks still maintain the tail risk that was transferred to the government's balance sheet in other countries. This can be related to the small commitment the Italian government made to the financial sector relative to other countries' governments. The lack of liability guarantees as part of the bailout mechanism, and the low usage of the bailout funds offered, might have further contributed to the differences in the outcome for Italy. Moreover, the credibility of the support package is in question, as Italy had a high debt burden even before the financial crisis. This is also reflected in the cost of insuring the Italian government bonds and the impact of Italian CDS spread changes on the creditworthiness of Italian banks. Lastly, as was found in other countries, the sovereign spreads are more sensitive to sovereign shocks after the bank support schemes have been put in place.

1.5 Conclusions

The recent financial crisis led governments to design aid programs for their financial institutions. The magnitude and dimensions of these programs were unique in European history. A series of bank failures would have threatened the whole economy since the financial system incorporates a systemic component. Hence, governments, along with central banks, took crucial steps to attempt to rescue the financial system. By arguing that the government bailout programs marked an important event for investors, we derive hypotheses about how the relations between the government and financial sectors would be expected to change as a result. First, we hypothesize that the increase in default risk prior to the interventions originated mainly from the financial sector. After the bailout programs had been set up by the European governments, we argue that the sensitivity of the sovereign default risk to financial sector shocks would have increased due to the private-to-public risk transfer. Moreover, the default risk of the banking sector is asserted to be strongly influenced by the government sector. Market stakeholders' expectations about a bank's future participation in the rescue schemes should affect its CDS sensitivity to changes in sovereign credit risk. Finally, we argue that country-specific bailout characteristics are important determinants of the changes in these linkages.

As stated in our first hypothesis, before the government interventions, sovereign credit risk is strongly affected by movements in bank CDS spreads, while changes in the sovereign CDS spreads have a weak impact on both the bank and sovereign CDS markets. Our findings support this in the case of FR, DE, IR, NL and SP but not in the case of IT and PT. Portugal's and Italy's default risk seem to have played an important role in the development of their local banks' default risk even before the Lehman Brothers event.

For the second set of hypotheses (H2a, H2b), we can conclude homogeneously that, during and after the government interventions, changes in the sovereign CDS spreads contribute permanently to the financial sector CDS spreads. On the other hand, changes in banks' default risk are found to affect the sovereign CDS spreads only transitorily. Relative to the period before the bailouts, changes in banks' default risk have a stronger impact in the short run (i.e. on days 0 and 1) in all countries, while for most countries the influence becomes insignificant in the long run (i.e. after 22 days); exceptions are IT, SP and PT.

Countries offering similar state aid to both analyzed banks (i.e. FR, IR, SP, and PT) show an equal bank CDS sensitivity to the changes in sovereign credit risk. Banks in Germany (DB and COM) and Italy (ISP and UCR) were differently involved in the rescue schemes, but we only find heterogeneous linkages between the Italian banks' and the sovereign CDS spreads. Our results suggest that the extra aid provided to COM has been successful in absorbing the default risk, while the high probability of future government aid being needed by ISP strongly links the default risk of the latter to the development of the Italian CDS spread and amplifies its sensitivity to shocks in both the banking and the sovereign sector. Furthermore, in the case of Ireland, our results indicate that the bailout schemes led to the desired result, in the sense that the default risk has clearly been transferred from the financial sector to the government.

Lastly, the cross-country analysis reveals heterogeneity in the impact of the bank support programs. On the one hand, the effects of a sovereign shock on banks from the same country are closely linked; on the other hand, the effects of a sovereign shock on banks across countries can be clustered in to two groups: INNER (FR, DE, NL) and OUTER (IR, IT, PT, SP).

With regards to policy implications, it is vital to note that the effectiveness of bank bailouts strongly depends on the economic health of the host country and, thus, the credibility of the rescue scheme. To weaken this link, regulators should provide incentives for banks to hold diversified government bond portfolios, in line with portfolio management theory. Sovereign bonds are often zero risk-weighted under Basel regulations, which sets the wrong incentive. It would be optimal if the diversified portfolio of sovereign bonds was not highly correlated with the government guarantees. Concerning international cooperation, BIS (2011) suggests that banks with branches or subsidiaries in several countries should be closely monitored by their domestic regulators, and closer cooperation between the countries concerned should benefit euro-wide financial stability. In addition, our study highlights, in line with previous research, elevated financing costs for countries with contingent liabilities in the financial sector and a higher volatility in sovereign yield spreads. Thus, in assessing the total cost of bank bailouts, governments need to include higher interest payments due to augmented spreads. Moreover, our results indicate that, even before the bank bailouts, there was an increased financing cost for governments, implying that investors anticipated future bailouts. Regulators could internalize this negative externality by setting up a systemic capital surcharge or by levying a tax, as suggested in Acharya et al. (2011).

With respect to future research, by applying the same methodology in the analysis of credit risk interdependence between European states, researchers could shed light on the dynamics of the public-to-public risk transfer mechanism in the Eurozone. Drawing a comparison between the private-to-public and public-to-public transfer mechanisms, policy makers could gain important insights into how INNER sovereign CDSs are affected by the risk transfer from the OUTER group.

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Appendix 1.A Further Issues on Methodology

1.A.1 VEC-Analysis - Selection of Sub-Stages

The selection of sub-stages for the study of the long-run relations is carried out using the following steps: if the tests (see below) do not provide evidence of cointegration relations for a certain stage, we consider its sub-periods. Also, if the stability of a cointegration space is rejected we consider a finer grid for the time periods. To investigate this, we consider recursively estimated eigenvalues as proposed by Hansen and Johansen (1999). Cointegration results are only reported for the stages that pass the stability test using the 1% critical value as a decision boundary. If there is no evidence of a (stable) cointegration relation on the finer grid either, we report none for the entire stage (i.e. before or during/after government interventions).

1.A.2 Pre-Analysis of the Data, Model Specification, and Estimation

First, we apply the standard unit root (stationarity) testing procedures, i.e. the Augmented-Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests, to the respective time series in each sub-sample.[29] All of the latter include an intercept because we disregard the possibility of a zero mean or trend stationary process. The latter process is not considered as it is economically unreasonable to assume that CDS series rise perpetually. We do not analyze systems of CDS series in a VECM if there is evidence that one or both series are stationary as in this case they cannot share a joint stochastic trend. For detecting a common stochastic trend, this study considers, both the Engle-Granger ADF test and Johansen's trace and maximum eigenvalue tests. The latter tests focus only on the setup with a restricted constant. As argued before, any deterministic trend in the variables or cointegration relation would be economically unjustified. When a common stochastic trend is detected by one of the previous tests and stability of the cointegration space is not rejected, we model the series in a VECM framework. If not, we proceed as described above. In finalizing our exact specifications of the models, we determine the optimal lag order p by, first, minimizing one of the common information criteria[30] and, second, taking care of the remaining serial correlation in the residuals.[31] The VECM is estimated by Johansen's maximum likelihood

[29] Results are available upon request from the authors.
[30] Aikaike information criterion, Hannan Quinn criterion, Schwarz criterion, and final prediction error
[31] When applicable, we also look at the plots of the cointegration relations in order to check whether these can be argued to be stable. The plot is expected to a show a time series that fluctuates nicely around some mean.

procedure and the VAR model via ordinary least squares.

1.A.3 Interpretation of Long-Run Relations in a VECM

The loading coefficients, α, measure *the speed of adjustment* with which a particular CDS adjusts to the long-run relationship. The adjustment forces start acting whenever the long-run relation (defined by $\beta' y_{t-1} = 0$, where $y_{t-1} = (cds_{Sov,t-1}, cds_{Bk,t-1})'$) is out of equilibrium, i.e. if $\beta' y_{t-1} \neq 0$. If α_{Sov} is significant and has the opposite sign to β_{Sov} (i.e. in our setup $\alpha_{Sov} < 0$) it means that the "sovereign" is driven by the error correction mechanism or, put differently, that it adjusts back to the long-run equilibrium defined by $\beta' y_{t-1} = 0$, whenever $\beta' y_{t-1} \neq 0$. Equivalently, when α_{Bk} is significant and has the opposite sign to β_{Bk}, it shows the speed of adjustment of the "bank" to the equilibrium. When both α-coefficients are significant and have the opposite signs to their respective β-coefficients, the variables are said to be in a real cointegration relationship; both series are taking part in the error correction mechanism. Whenever one of the α-coefficients is not significant, it means that the respective variable can be argued to provide the stochastic trend that determines the long-run relation. This can be formally tested using a likelihood ratio test through a zero restriction on this parameter. If the restriction cannot be rejected, the variable of the respective α-coefficient is called *weakly exogenous*. Furthermore, it is not adjusting at all if the variables are not in long-run equilibrium, i.e. when $\beta' y_{t-1} \neq 0$. Whenever an α-coefficient is significant but with the same sign as the respective β-parameter, the variable is said not to be part of the error correction mechanism as the forces in the model do not attract both series back to the equilibrium. Series in this setup can only define a long-run relation if the variable that is in a formal error correction relation adjusts faster to the new equilibrium than the other variable. One can think of this phenomenon as the variable that is not part of the error correction mechanism moving the entire equilibrium (i.e. when the variable increases in value, a long-run equilibrium will be established with both series at a higher value). In the literature, the term overshooting is used to describe this occurrence.[32]

[32] For a discussion of a model with overshooting, please refer to Hansen and Johansen (1998).

Appendix 1.B Specific Country Analysis

1.B.1 France

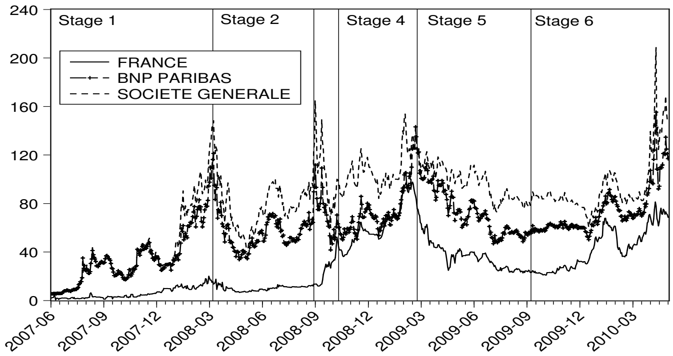

Figure 1.B.1: France: CDS Level Series

Table 1.B.1: France: Bivariate Cointegration Tests

Period	Variables	Lags	Trace Statistic		Max Eigenvalue		Engle-Granger Test
			$r = 0$	$r = 1$	$r = 0$	$r = 1$	
Stage 1	FR - BNP	0	**0.021**	0.212	**0.031**	0.212	-2.406
	FR - SG	0	**0.006**	0.119	**0.012**	0.119	**-4.446**
Stage 2	FR - BNP	*					
	FR - SG	1	**0.038**	0.332	**0.040**	0.332	**-5.701**
Stage 1 + 2	FR - BNP	1	**0.017**	0.109	**0.045**	0.109	**-3.102**
	FR - SG	1	**0.005**	0.147	**0.010**	0.147	**-4.455**
Stage 4	FR - BNP	6	*0.119*	0.130	0.296	0.130	-1.507
	FR - SG	5	0.764	0.779	0.706	0.779	-1.663
Stage 5	FR - BNP	2	0.321	0.290	0.477	0.290	-2.260
	FR - SG	8	**0.062**	0.124	0.158	0.124	**-3.101**
Stage 6	FR - BNP	1	0.611	0.583	0.631	0.583	-2.033
	FR - SG	1	0.507	0.504	0.554	0.504	-1.573
Stage 4 + 5	FR - BNP	1	0.282	0.735	0.192	0.735	-1.163
	FR - SG	1	0.295	0.944	0.142	0.944	-2.458
Stage 5 + 6	FR - BNP	1	0.211	0.447	0.216	0.447	-2.535
	FR - SG	1	**0.105**	0.297	0.138	0.297	-2.053
Stage 4 + 5 + 6	FR - BNP	1	**0.057**	0.313	**0.067**	0.313	-2.230
	FR - SG	1	**0.072**	0.514	**0.054**	0.514	-2.250

Notes: Trace and Max Eigenvalue are the Johansen test statistics (with a restricted constant). p-values are reported. The respective null hypothesis is denoted by $r = \{0, 1\}$, where e.g. $r = 1$ denotes one cointegration relation. * signifies that at least one of the series is stationary. For the Engle-Granger test the ADF test statistic is reported; critical values at 5% and 10% are -3.37 and -3.07 respectively.

1.B.2 Germany

Table 1.B.2: Germany: Bivariate Cointegration Tests

Period	Variables	Lags	Trace Statistic		Max Eigenvalue		Engle-Granger Test
			$r = 0$	$r = 1$	$r = 0$	$r = 1$	
Stage 1	DE - COM	0	**0.044**	0.171	**0.086**	0.171	**-3.696**
	DE - DB	3	0.113	0.177	0.226	0.177	**-4.024**
Stage 2	DE - COM	*					
	DE - DB	*					
Stage 1 + 2	DE - COM	3	**0.014**	**0.062**	**0.057**	**0.062**	**-4.441**
	DE - DB	3	**0.005**	**0.048**	**0.027**	**0.048**	**-5.273**
Stage 4	DE - COM	1	0.413	0.663	0.350	0.663	-1.012
	DE - DB	1	**0.064**	0.331	**0.071**	0.331	-1.596
Stage 5	DE - COM	1	0.164	0.496	0.146	0.496	-2.983
	DE - DB	7	**0.0471**	0.117	0.124	0.117	-1.778
Stage 6	DE - COM	1	0.688	0.529	0.763	0.529	-1.368
	DE - DB	1	0.724	0.682	0.711	0.682	-0.900
Stage 4 + 5	DE - COM	1	**0.0421**	0.2814	**0.052**	0.2814	-1.485
	DE - DB	*					
Stage 5 + 6	DE - COM	*					
	DE - DB	*					
Stage 4 + 5 +6	DE - COM	1	**0.0063**	0.1166	**0.0145**	0.1166	-1.774
	DE - DB	1	**0.0692**	0.2769	**0.0919**	0.2769	-2.088

Notes: Trace and Max Eigenvalue are the Johansen test statistics (with a restricted constant). p-values are reported. The respective null hypothesis is denoted by $r = \{0, 1\}$, where e.g. $r = 1$ denotes one cointegration relation. * signifies that at least one of the series is stationary. For the Engle-Granger test the ADF test statistic is reported; critical values at 5% and 10% are -3.37 and -3.07 respectively.

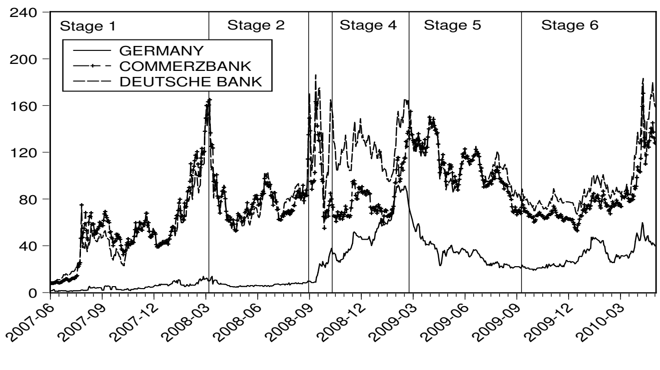

Figure 1.B.2: Germany: CDS Level Series

1.B.3 Ireland

Table 1.B.3: Ireland: Bivariate Cointegration Tests

Period	Variables	Lags	Trace Statistic		Max Eigenvalue		Engle-Granger Test
			$r = 0$	$r = 1$	$r = 0$	$r = 1$	
Stage 1	IR - AIB	2	0.429	0.620	0.389	0.620	-1.361
	IR - BOI	2	0.390	0.601	0.354	0.601	-1.325
Stage 2	IR - AIB	1	0.232	0.999	**0.080**	0.999	-2.577
	IR - BOI	1	**0.010**	0.997	**0.002**	0.997	**-3.376**
Stage 1 + 2	IR - AIB	2	0.323	0.354	0.421	0.354	-2.099
	IR - BOI	2	0.436	0.306	0.628	0.306	-2.155
Stage 4	IR - AIB	0	**0.016**	0.233	**0.021**	0.233	-1.806
	IR - BOI	1	0.260	0.330	0.349	0.330	-1.981
Stage 5	IR - AIB	1	0.227	0.183	0.445	0.183	-1.630
	IR - BOI	1	0.269	0.151	0.579	0.151	-2.149
Stage 6	IR - AIB	4	**0.049**	0.679	**0.024**	0.679	-1.918
	IR - BOI	4	0.177	0.786	**0.098**	0.786	-2.900
Stage 4 + 5	IR - AIB	1	**0.005**	0.129	**0.011**	0.129	-1.948
	IR - BOI	1	**0.027**	0.393	**0.023**	0.393	-1.892
Stage 5 + 6	IR - AIB	9	**0.003**	0.122	**0.005**	0.122	-3.080
	IR - BOI	9	**0.001**	0.117	**0.002**	0.117	-3.202
Stage 4 + 5 + 6	IR - AIB	9	**0.001**	0.057	**0.006**	0.057	-2.446
	IR - BOI	9	**0.000**	0.164	**0.000**	0.164	-3.055

Notes: Trace and Max Eigenvalue are the Johansen test statistics (with a restricted constant). p-values are reported. The respective null hypothesis is denoted by $r = \{0, 1\}$, where e.g. $r = 1$ denotes one cointegration relation. * signifies that at least one of the series is stationary. For the Engle-Granger test the ADF test statistic is reported; critical values at 5% and 10% are -3.37 and -3.07 respectively.

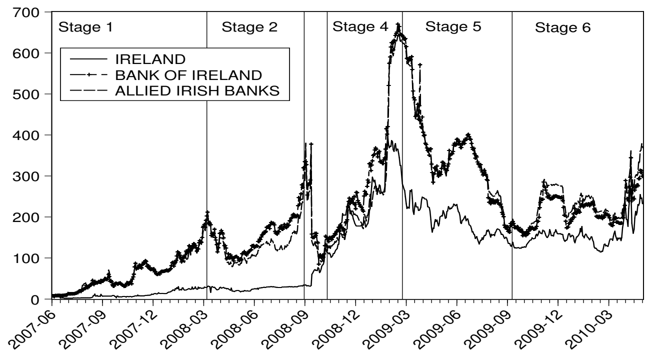

Figure 1.B.3: Ireland: CDS Level Series

1.B.4 Italy

Table 1.B.4: Italy: Bivariate Cointegration Tests

Period	Variables	Lags	Trace Statistic		Max Eigenvalue		Engle-Granger Test
			$r = 0$	$r = 1$	$r = 0$	$r = 1$	
Stage 1	IT - ISP	3	0.107	0.130	0.267	0.130	-1.948
	IT - UCR	3	0.140	0.180	0.278	0.180	-1.538
Stage 2	IT - ISP	1	**0.089**	0.919	**0.032**	0.919	-2.574
	IT - UCR	1	0.195	0.936	**0.083**	0.936	-1.797
Stage 1 + 2	IT - ISP	4	**0.052**	0.131	0.125	0.131	-2.313
	IT - UCR	3	**0.083**	0.108	0.236	0.108	-1.883
Stage 4	IT - ISP	1	0.761	0.561	0.829	0.561	-1.931
	IT - UCR	1	0.946	0.898	0.910	0.898	-1.696
Stage 5	IT - ISP	2	**0.091**	0.125	**0.231**	0.125	-2.334
	IT - UCR	2	**0.044**	0.143	**0.098**	0.143	-2.140
Stage 6	IT - ISP	4	0.248	0.389	0.293	0.389	**-3.125**
	IT - UCR	1	0.821	0.530	0.908	0.530	-1.762
Stage 4 + 5	IT - ISP	3	0.158	0.803	**0.082**	0.803	-2.181
	IT - UCR	1	0.590	0.584	0.605	0.584	-1.554
Stage 5 + 6	IT - ISP	4	**0.042**	0.768	**0.017**	0.768	-2.846
	IT - UCR	*					
Stage 4 + 5 + 6	IT - ISP	1	**0.059**	0.514	**0.042**	0.514	**-3.450**
	IT - UCR	1	0.284	0.256	0.453	0.256	-1.893

Notes: Trace and Max Eigenvalue are the Johansen test statistics (with a restricted constant). p-values are reported. The respective null hypothesis is denoted by $r = \{0, 1\}$, where e.g. $r = 1$ denotes one cointegration relation. * signifies that at least one of the series is stationary. For the Engle-Granger test the ADF test statistic is reported; critical values at 5% and 10% are -3.37 and -3.07 respectively.

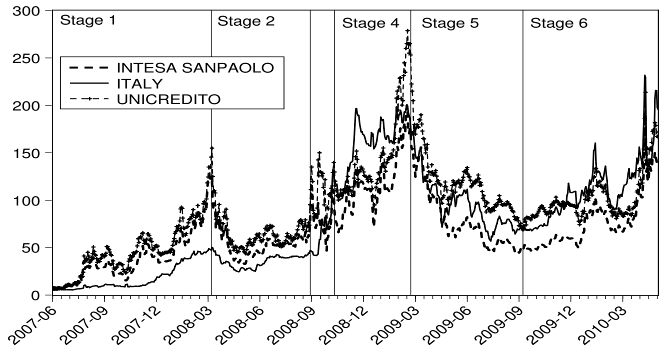

Figure 1.B.4: Italy: CDS Level Series

1.B.5 The Netherlands

Table 1.B.5: The Netherlands: Bivariate Cointegration Tests

Period	Variables	Lags	Trace Statistic		Max Eigenvalue		Engle-Granger Test
			$r = 0$	$r = 1$	$r = 0$	$r = 1$	
Stage 1	NL - ABN	0	**0.029**	**0.099**	**0.085**	**0.099**	**-3.646**
	NL- ING	0	**0.007**	0.155	**0.014**	0.155	**-4.389**
Stage 2	NL - ABN	*					
	NL- ING	*					
Stage 1 + 2	NL - ABN	2	**0.005**	**0.059**	**0.021**	**0.059**	**-3.422**
	NL- ING	2	**0.002**	**0.145**	**0.004**	**0.145**	**-3.918**
Stage 4	NL - ABN	5	0.151	0.474	0.139	0.474	-2.419
	NL- ING	0	0.932	0.761	0.940	0.761	-1.385
Stage 5	NL - ABN	1	0.106	0.085	0.349	0.085	-2.801
	NL- ING	1	**0.095**	0.119	0.252	0.119	-2.662
Stage 6	NL - ABN	6	**0.082**	0.617	**0.051**	0.617	**-3.350**
	NL- ING	7	0.862	0.862	0.794	0.862	**-3.053**
Stage 4 + 5	NL - ABN	1	0.132	0.536	*0.104*	0.536	-1.622
	NL- ING	8	0.220	0.890	*0.107*	0.890	-2.243
Stage 5 + 6	NL - ABN	*					
	NL- ING	*					
Stage 4 + 5 + 6	NL - ABN	1	0.624	0.848	0.487	0.848	-1.422
	NL- ING	1	0.522	0.750	0.427	0.750	-2.372

Notes: Trace and Max Eigenvalue are the Johansen test statistics (with a restricted constant). p-values are reported. The respective null hypothesis is denoted by $r = \{0, 1\}$, where e.g. $r = 1$ denotes one cointegration relation. * signifies that at least one of the series is stationary. For the Engle-Granger test the ADF test statistic is reported; critical values at 5% and 10% are -3.37 and -3.07 respectively.

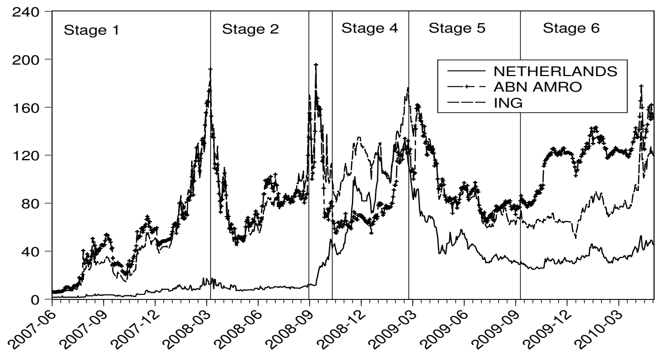

Figure 1.B.5: The Netherlands: CDS Level Series

1.B.6 Portugal

Table 1.B.6: Portugal: Bivariate Cointegration Tests

Period	Variables	Lags	Trace Statistic		Max Eigenvalue		Engle-Granger Test
			$r = 0$	$r = 1$	$r = 0$	$r = 1$	
Stage 1	PT - BCP	1	0.272	0.420	0.307	0.420	-1.997
	PT - BES	3	0.280	0.464	0.293	0.464	-1.986
Stage 2	PT - BCP	1	*0.103*	0.599	**0.069**	0.599	**-3.570**
	PT - BES	2	**0.028**	0.688	**0.013**	0.688	**-3.374**
Stage 1 + 2	PT - BCP	0	**0.038**	0.078	0.135	0.078	-2.647
	PT - BES	0	**0.038**	0.093	*0.119*	0.093	-2.349
Stage 4	PT - BCP	6	0.291	0.717	0.206	0.717	-0.711
	PT - BES	6	0.257	0.874	0.135	0.874	-1.036
Stage 5	PT - BCP	1	0.302	0.182	0.584	0.182	-2.256
	PT - BES	*					
Stage 6	PT - BCP	1	**0.057**	0.596	**0.034**	0.596	-1.573
	PT - BES	1	0.188	0.546	0.157	0.546	-1.711
Stage 4 + 5	PT - BCP	1	0.344	0.411	0.408	0.411	-2.074
	PT - BES	1	0.318	0.643	0.258	0.643	-0.837
Stage 5 + 6	PT - BCP	1	**0.054**	0.652	**0.029**	0.652	-1.458
	PT - BES	1	0.349	0.659	0.283	0.659	-1.724
Stage 4 + 5 + 6	PT - BCP	1	**0.049**	0.472	**0.037**	0.472	-2.104
	PT - BES	1	0.378	0.571	0.355	0.571	-1.769

Notes: Trace and Max Eigenvalue are the Johansen test statistics (with a restricted constant). p-values are reported. The respective null hypothesis is denoted by $r = \{0, 1\}$, where e.g. $r = 1$ denotes one cointegration relation. * signifies that at least one of the series is stationary. For the Engle-Granger test the ADF test statistic is reported; critical values at 5% and 10% are -3.37 and -3.07 respectively.

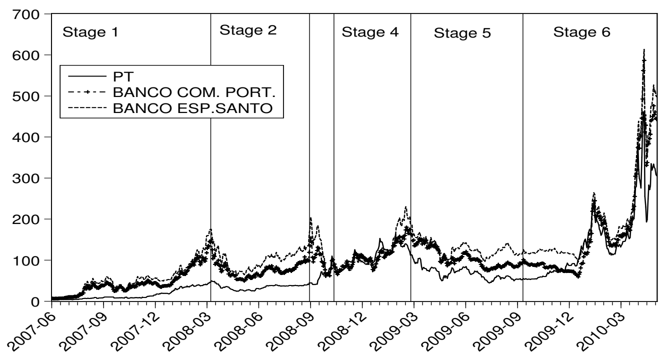

Figure 1.B.6: Portugal: CDS Level Series

1.B.7 Spain

Table 1.B.7: Spain: Bivariate Cointegration Tests

Period	Variables	Lags	Trace Statistic		Max Eigenvalue		Engle-Granger Test
			$r=0$	$r=1$	$r=0$	$r=1$	
Stage 1	SP - BBVA	1	0.130	0.148	0.296	0.148	-2.712
	SP - BS	1	**0.086**	0.146	0.196	0.146	-2.860
Stage 2	SP - BBVA	1	**0.017**	0.468	**0.011**	0.468	**-6.240**
	SP - BS	2	**0.020**	0.578	**0.011**	0.578	**-6.905**
Stage 1 + 2	SP - BBVA	1	0.013	0.102	**0.036**	0.102	**-3.851**
	SP - BS	1	**0.006**	0.090	**0.018**	0.090	**-3.420**
Stage 4	SP - BBVA	1	0.503	0.569	0.506	0.569	-1.395
	SP - BS	2	**0.026**	0.136	**0.058**	0.136	-2.000
Stage 5	SP - BBVA	1	0.507	0.407	0.628	0.407	-1.828
	SP - BS	1	0.545	0.441	0.651	0.441	-2.348
Stage 6	SP - BBVA	4	0.778	0.535	0.862	0.535	-2.008
	SP - BS	4	0.740	0.561	0.804	0.561	-2.108
Stage 4 + 5	SP - BBVA	1	0.300	0.416	0.345	0.416	-1.589
	SP - BS	2	**0.080**	0.243	0.121	0.243	-1.987
Stage 5 + 6	SP - BBVA	1	0.606	0.563	0.640	0.563	-2.088
	SP - BS	4	0.487	0.927	0.299	0.927	-2.012
Stage 4 + 5 + 6	SP - BBVA	11	**0.078**	0.459	**0.065**	0.459	-2.427
	SP - BS	1	**0.066**	0.184	0.124	0.184	-2.619

Notes: Trace and Max Eigenvalue are the Johansen test statistics (with a restricted constant). p-values are reported. The respective null hypothesis is denoted by $r = \{0, 1\}$, where e.g. $r = 1$ denotes one cointegration relation. * signifies that at least one of the series is stationary. For the Engle-Granger test the ADF test statistic is reported; critical values at 5% and 10% are -3.37 and -3.07 respectively.

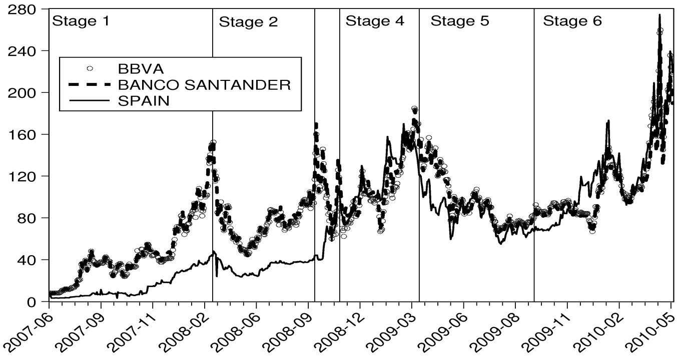

Figure 1.B.7: Spain: CDS Level Series

1.B.8 Cointegration Graphs

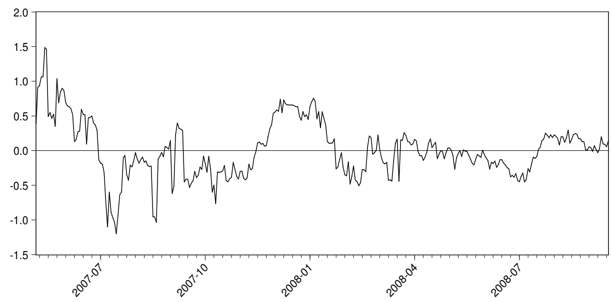

Figure 1.B.8: Cointegration Graph of Germany and Commerzbank (Before Government Interventions)

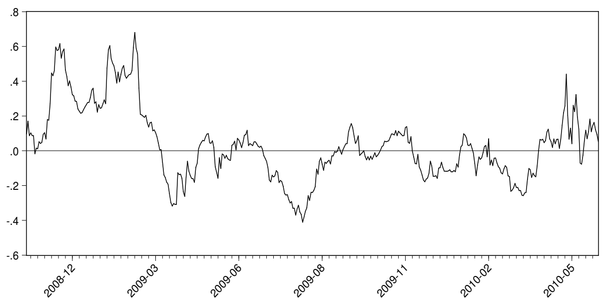

Figure 1.B.9: Cointegration Graph of Ireland and Allied Irish Banks (During and After Government Interventions)

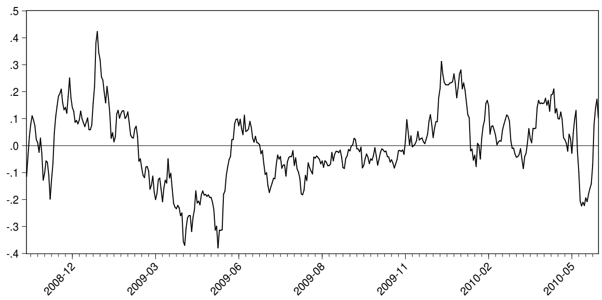

Figure 1.B.10: Cointegration Graph of Italy and Intesa Sanpaolo (During and After Government Interventions)

Chapter 2

The Transmission of US Financial Stress: Evidence for Emerging Market Economies

"... the [global financial] crisis has been a bitter reminder that, for all their benefits, deeper trade and financial linkages can serve as a mechanism for magnifying shocks and intensifying their effects on the real side of a nation's economy."

(Kose and Prasad, 2010, p.4)

2.1 Introduction

Emerging market economies (EMEs) share, in contrast to the advanced world, two distinct properties: first, EMEs are characterized by a high degree of fluctuations in economic fundamentals and second, EMEs are strongly vulnerable to external shocks. For instance, volatility of GDP has been about 50% higher than the respective figure for advanced economies from 1960 to 2008 (Kose and Prasad, 2010). External factors may actually explain parts of this high variability, i.e., international financial market transactions such as foreign capital flows have proven to be important determinants of booms and busts in EMEs (Calvo et al., 1993; Calvo, 1998). As the last global financial crisis has remarkably shown, the financial shock that originated in the US spread *rapidly* and *intensively* to the emerging world. Deeper trade relations and international financial linkages may have contributed to the extent of the contagion. Figure 2.1.1 shows growth rates of output for a group of emerging market countries and the US from the first quarter of 2006 to the fourth quarter of 2009. The synchronized performance of both time series underlines how quickly the US financial shock spread to the group of EMEs. However not only this event, but also past episodes of financial stress have highlighted that financial conditions in the US play an important role for the macroeconomic dynamics in emerging market economies. Thus, the analysis of *financial vulnerability* is key to guide future research and policies.

In this study we address the relevance of US financial stress for emerging market economies. In particular, we provide empirical evidence for the following three questions: 1) How does US financial stress affect the dynamics of macro-variables in EMEs? 2) Are international *trade* or *financial* linkages more important for the transmission? 3) How important is US financial stress for explaining the high volatility in the emerging world?

We examine the role of US financial stress for EMEs by employing a structural vector autoregression (VAR), which is estimated via Bayesian techniques. Our data set contains monthly data from 1999 to mid 2012 for eight EMEs (Brazil, Chile, Korea, Malaysia, Mexico, Philippines, South Africa, Thailand) and we conduct the study on a bilateral basis with the US and one emerging market country at a time. US financial stress shocks are identified as unexpected changes in the National Financial

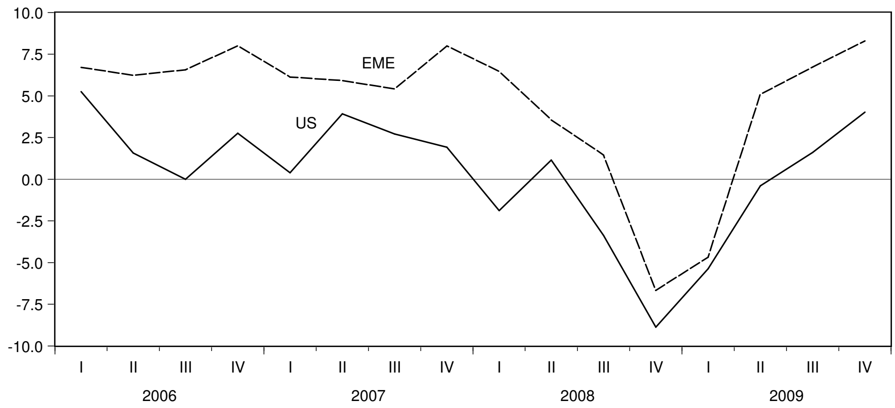

Figure 2.1.1: Growth in GDP in Emerging Market Economies and the United States, 2006-2009

Notes: This figure shows the annualized quarter over quarter real GDP growth rate, which is constructed as a weighted by GDP at purchasing power parity average. The EME series is based on 20 emerging market countries: Argentina, Brazil, Chile, Colombia, Estonia, Hungary, India, Indonesia, Korea, Latvia, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Thailand, Turkey, and Venezuela. All countries, except for Korea, are classified as EMEs according to the IMF. Data are obtained from the IMF.

Conditions Index (NFCI). This financial conditions index is published by the Federal Reserve Bank of Chicago and contains systemically relevant financial variables from different US financial sectors. The NFCI comprises important information of risk, liquidity, and leverage in the money markets, debt and equity markets, and the banking system. The advantage of a financial conditions index is clearly the fact that it captures *overall* financial conditions in the US financial sector. This feature is particularly beneficial since the US financial system is highly interconnected and thus tighter financial linkages in the US lead to shocks that affect *general* financial conditions rather one specific sector as the last financial crisis has remarkably shown. Shocks in the US financial sector are then interpreted as financial stress shocks, i.e., a worsening of financial conditions in US financial markets.

Several findings emerge from our analysis: first, EMEs experience similar negative effects as the US economy in response to US financial stress shocks. After one year, the decline in real economic activity for most of the EMEs is even slightly more pronounced than the decrease in the US. Second, the transmission of US financial stress shocks occur through international financial linkages. An adverse shock to the US financial system dries up capital flows from the US to the EME. The decline in cross-border lending results in tighter financing conditions for EMEs. Capital inflow reversals generate a pressure on the currency of EMEs such that the exchange rate depreciates. Reduced international liquidity, thus tighter financing conditions, finally affect the EMEs real economy negatively. On the other hand, we do not find an important role for the transmission through the trade channel. Third, US financial stress that changes US financing conditions plays an important role in explaining fluctuations in EME macro-variables. On average, up to 21% of the variation in EME real GDP is due to US financial stress. Moreover, US financial stress shocks are as important as all other external shocks jointly in explaining the volatility in EMEs. In the short-run, i.e., at business cycle frequencies, our results indicate that US financial stress shocks account for a substantial fraction of cyclical variation in EME macro-variables. On average, up to 17% of the cyclical variation in real economic activity is due to the US financial stress shock.

This paper contributes to the empirical macroeconomic literature that focuses on the international transmission of shocks to EMEs: Canova (2005) analyzes the transmission of US real demand, real supply, and monetary policy shocks to Latin American countries. His results show that US monetary policy shocks affect the group of countries considered, while real demand and supply shocks generate insignificant responses. Mackowiak (2007) focuses on countries from different geographic regions (Asia and Latin America). Additionally to Canova (2005) he reports the proportions of the variation explained by monetary policy shocks and concludes that those are less important relative to other external shocks. However, both authors find that external shocks are important in explaining fluctuations in EMEs. We contribute to this strand of literature in three aspects. First, we focus on the international transmission of financial stress from the US to EMEs. Our framework enables us to isolate US financial stress from US monetary policy, which we exploit to compare their relative importance. Second, in contrast to previous studies we empirically assess which channels (trade and/or financial) are relevant for cross-country spillovers. Third, our analysis gives detailed information on how much of the volatility in the emerging world is due to US financial stress, monetary, and all external shocks jointly. To our knowledge, this study is also the first empirical analysis that measures the contribution of US financial stress, US monetary, and all external shocks to the *cyclical* variation, i.e., at business cycle frequencies, of EMEs' macro-variables. With regard to the financial disruption of 2007, it represents a necessity to shed light on the macroeconomic consequences for the emerging world of deeper financial linkages.

Furthermore, our paper relates to the recent empirical macro-finance literature that considers the impact of financial shocks on the real economy, e.g., Lown and Morgan (2006), Gilchrist et al. (2009), Helbling et al. (2011), Kalemli-Ozcan et al. (2012), and Hristov et al. (2012). Hubrich and Tetlow (2012) employ, similar to the present study, an index of financial stress to analyze the transmission to the US real sector. While their study focuses on the macro-finance link in a closed economy setup, our paper contributes to this literature in deepening the understanding on how financial stress in the US affects the dynamics and the volatility in the emerging world. Finally, this paper is related to recently emerging VAR studies employing indices of overall

conditions, see, e.g., Baker et al. (2013) for the impact of overall economic policy uncertainty shocks on the macroeconomy.
The remainder of the paper is structured as follows. In Section 2.2 we present the empirical model, the econometric approach, and the data set. Section 2.3 discusses how US financial stress shocks affect emerging market economies considering impulse responses and variance decompositions. Finally, Section 2.4 concludes.

2.2 The Empirical Model

2.2.1 A Structural Vector Autoregression

Let y_t $(n \times 1)$ be a vector of random variables at time t, C a vector of constants, $\mathcal{A}$ and $\mathcal{A}_l$ coefficient matrices of size $n \times n$, and ε_t $(n \times 1)$ be the exogenous structural shocks at time t. n denotes the number of variables included in the model, T the sample size, and p the lag length. We consider the following structural VAR model:

$$y_t'\mathcal{A} = C + \sum_{l=1}^{p} y_{t-l}'\mathcal{A}_l + \varepsilon_t', \quad \forall \quad 1 \leq t \leq T. \tag{2.1}$$

The initial conditions $y_0, \ldots, y_{1-p}$ are fixed. Using this notation columns refer to equations, e.g., column i, where $i = 1, \ldots, n$, of matrix $\mathcal{A}$ ($\mathcal{A}_l$) refers to equation i. Further, the structural innovations are assumed to be normally distributed with

$$E(\varepsilon_t | y_1, \ldots, y_{t-1}) = 0 \quad \text{and} \quad E(\varepsilon_t \varepsilon_t' | y_1, \ldots, y_{t-1}) = \mathbf{I}_n, \tag{2.2}$$

where $\mathbf{I}_n$ denotes the identity matrix of dimension n. To study the international transmission of US shocks we use a two-country setup, i.e., our analysis is conducted on a bilateral basis with the US and one EME at a time. We assume that the emerging market country behaves like a small open economy, i.e., the EME variables do not enter the equations of the US variables. The assumption of a small open economy is introduced to model (2.1) in the following way (see Cushman and Zha (1997)): let $y_{1,t}$ $(n_1 \times 1)$ reflect the variables pertaining to the US sector and $y_{2,t}$ $(n_2 \times 1)$ the time series belonging to the respective EME. Thus, $n = n_1 + n_2$ are the total number of variables considered in the VAR. This structural model with block exogeneity restrictions can be written as

$$y_t'\mathcal{A} = C + \sum_{l=1}^{p} \begin{bmatrix} y_{1,t-l}' & y_{2,t-l}' \end{bmatrix} \begin{bmatrix} \mathcal{A}_{11,l} & \mathcal{A}_{12,l} \\ 0 & \mathcal{A}_{22,l} \end{bmatrix} + \varepsilon_t'. \tag{2.3}$$

The compact form of model (2.3) is given by

$$y_t'\mathcal{A} = x_t'\mathcal{F} + \varepsilon_t', \tag{2.4}$$

where

$$x_t' = \begin{bmatrix} y_{t-1}' & \dots & y_{t-p}' & 1 \end{bmatrix} \quad \text{and} \quad \mathcal{F}' = \begin{bmatrix} \mathcal{A}_1' & \dots & \mathcal{A}_p' & C' \end{bmatrix}.$$

The dimension of $\mathcal{F}$ is $n \times k$, where $k = np + 1$. The parameters of the structural model are $(\mathcal{A}, \mathcal{F})$.

2.2.2 Bayesian Inference

The structural VAR model with identifying restrictions on $\mathcal{A}$ and zero restrictions on $\mathcal{F}$ is estimated with Bayesian techniques. To obtain small-sample inferences of $(\mathcal{A}, \mathcal{F})$ we follow the method proposed by Waggoner and Zha (2003) and simulate the joint posterior distribution of the structural parameters given the data. Gibbs sampling requires to draw first $\mathcal{A}$ from its marginal posterior distribution and given each draw of $\mathcal{A}$ we simulate draws of $\mathcal{F}$ from its conditional posterior distribution. We consider 25,000 replications where 5,000 are discarded as burn-in draws.[1] Further, we introduce Bayesian prior information according to Sims and Zha (1998). This informative prior extends the commonly known *random-walk prior* (Litterman, 1986) to structural vector autoregressions. Thus, the prior expresses the beliefs that in the reduced form model each variable in the system follows a random-walk. Besides this, a lag-decay prior is imposed on the conditional prior covariance matrix of $\mathcal{F}$ that effectively dampens the effects of long lags. Therefore this informative prior decreases the risk of over-fitting of richly parameterized structural VAR models. In addition, we follow Sims and Zha (1998) and introduce dummy observations as a component of the prior that favor unit roots and cointegration. Literally speaking, we simply add artificial observations to the data matrix considered in our estimation. Without dummy observations as a part of the prior an unreasonable large share of variation is attributed to the deterministic component.[2] Thus, the described Bayesian approach with prior information is particularly suitable for this class of model because our structural VAR model is of high dimension and the degrees of freedom are low.

[1] We monitor and ensure convergence through trace plots.

[2] The hyperparameters of this prior are set to standard values previously used in Bayesian structural VAR analysis (see, e.g., Sims and Zha (1998), Robertson and Tallman (2001), Sims and Zha (2006b)). In the notation of Sims and Zha (1998), we employ $\lambda_0 = 0.6$, $\lambda_1 = 0.1$, $\lambda_2 = 1.0$, $\lambda_3 = 1.2$, $\lambda_4 = 0.1$, $\mu_5 = 5.0$, and $\mu_6 = 5.0$.

2.2.3 Data Set

The time frame of our analysis covers the period from 1999M1 until 2012M6. We consider this specific period for two reasons: first, for this period macro-variables are available at the monthly frequency for all emerging market countries in our sample. Second, this period coincides with a rapid increase in financial linkages between the emerging and advanced world (Kose and Prasad, 2010). As we employ monthly data we specify the lag length of our model in (2.3) to be $p = 12$.

We study eight countries from different geographic regions (Latin America, Asia, and Africa) that are classified as emerging markets economies: Brazil (BR), Chile (CL), Korea (KR), Malaysia (MY), Mexico (MX), Philippines (PH), Thailand (TH), and South Africa (ZA).[3] For each EME we consider six different variables that measure real economic activity, trade relations with the US, foreign capital flows from the US, interest rates, international competitiveness, and inflation. The time series applied for this purpose are real GDP (q), bilateral exports over imports (x), bilateral net accumulation of foreign stocks (b), the prime lending rate (i), the real effective exchange rate (s), and the consumer price index (π).

We model the US economy by including five variables. These measure real economic activity, world prices, inflation, interest rates, and financial stress in the US financial system. For real economic activity real GDP (q^*) is used; for world prices we consider the IMF index of world commodity prices (p^*); for inflation the consumer price index (π^*) is employed, and for interest rates we include the effective federal funds rate (i^*). Moreover, US financial stress (f^*) is captured by the National Financial Conditions Index of the Federal Reserve Bank of Chicago. The time series for real GDP series are interpolated from quarterly to monthly frequency using the method described by Bernanke et al. (1997). All variables are employed in levels. Further, all time series are log-transformed, except for the interest rates, the trade ratio, and the financial conditions index. The data for the US and the emerging market countries are obtained from Datastream and seasonally adjusted when necessary. The exact sources, transformations, and descriptions are depicted in Appendix 2.A.

Provided that the measure of US financial stress is the key variable of this analysis, the following presents it in more detail. The Federal Reserve Bank of Chicago constructs a measure of US financial conditions to monitor the stability of the whole US financial system with a focus on traditional and newly developed financial markets and their interconnections. The NFCI is regularly updated and constructed as a weighted average of a series of financial indicators.[4] The weights are determined

[3] All countries, but Korea, are classified as EMEs by the IMF. Korea is listed as an EME by, e.g., MSCI. However, its status is debated as some indexes already include Korea in the group of advanced countries.

[4] The NFCI time series commences in 1973.

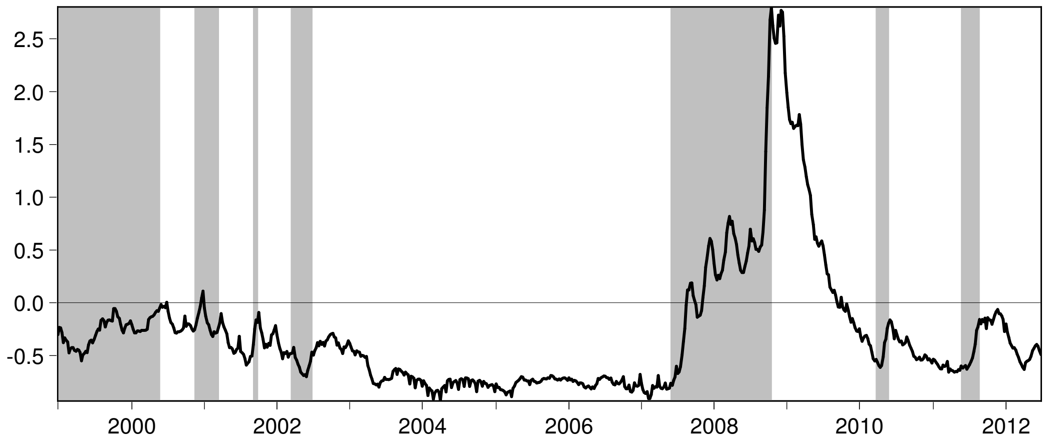

Figure 2.2.1: National Financial Conditions Index

Notes: Shaded areas mark times of deteriorating US financial conditions. Details are provided in the text.

by principal component analysis, however allowing for a variation in the frequency and availability of the time series. It summarizes 100 systemically relevant financial variables from money markets, debt and equity markets as well as from the banking system. Table 2.A.2 in Appendix 2.A provides an overview of the financial sectors covered. In the money markets greatest weights are attached to US commercial paper spreads indicating a risk of default, US interest rate swap spreads reflecting investors perceptions of credit risk, and the TED spreads which serve as an indicator of credit risk as well. Furthermore, the debt and equity markets are mostly driven by corporate bond spreads and the VIX, a volatility measure of the US stock market. Survey-based indicators of credit conditions for consumers and businesses are the key variables in the banking system. In sum, the NFCI measures overall financial conditions. It does not contain variables that function as indicators of US monetary policy.

Figure 2.2.1 displays the NFCI from 1999M1 to 2012M6. In general an increase in its value marks a deterioration of US financial conditions. More specifically, it reflects a rise in, for instance, the US commercial paper spreads, the US interest rate swap spreads, or the VIX. Further, it represents a decrease, e.g., in the credit conditions for consumers. The zero line corresponds to a situation where the US financial system operates at the historical average state of financial conditions. Positive values indicate episodes where the US financial system experiences tighter financial conditions compared to its historical average. As the NFCI is updated on a regular basis the historical average is allowed to adjust to new developments. The graph shows clearly that the NFCI is able to match historical episodes of stress in US financial markets (shaded grey areas). At the beginning of our period one can relate the steady increase of the index to the events related to the dot-com bubble. Between

the end of 2000 and 2001, we see the effects of the Argentine Crisis. Succeeding, there is a spike that can be related to the terrorist attacks (“9/11”). Also the post “9/11” stock market crash in mid 2002 is visible, which happened as a second wave of turmoil in response to the attacks starting from March 2002. It coincides with the bankruptcy of Enron that raises concerns about the correctness of companies' accounts. In the following, conditions were rather smooth until the outbreak of the financial crisis. Two events are captured clearly by the NFCI: mid 2007, where fears on losses on US subprime mortgages loans led to system wide financial stress and the peak of the financial crisis, which occurred with the bankruptcy of Lehman Brothers mid 2008. Further, the NFCI portrays signs of the sovereign debt crisis at the beginning of 2010. The deterioration of financial conditions mid 2011 can be related to the US debt crisis in which the US congress disagreed about raising the debt ceiling that led to system wide financial stress.
In line with the above discussion, Brave and Butters (2012) show via the receiver operator characteristics (ROC) methodology that the NFCI identifies with 95% accuracy historical episodes of financial turmoil contemporaneously and 80% at a lead of up to one year. Next to major financial crises, the study also considers episodes of financial stress that had less magnitude on the US financial markets.

2.2.4 Identification and Structural Interpretation

The identification strategy employed is non-recursive and we impose overidentifying restrictions on $\mathcal{A}_{11}$, i.e., the US block of $\mathcal{A}$. The identification approach follows the structural VAR literature on monetary policy shocks, e.g., Leeper and Zha (2003), Sims and Zha (2006a), and Sims and Zha (2006b), adjusted for the fact that we consider US financial conditions in our model. Hence, the approach in this paper serves the purpose to identify a US financial stress and a monetary policy shock. The contemporaneous restrictions are set as follows:

$$\mathcal{A}_{11} = \begin{array}{c} \\ q^* \\ \pi^* \\ i^* \\ f^* \\ p^* \end{array} \begin{array}{c} \begin{array}{ccccc} \text{PS} & \text{PS} & \text{MP} & \text{FS} & \text{Inf} \end{array} \\ \begin{pmatrix} a_{11,11} & a_{11,12} & 0 & a_{11,14} & a_{11,15} \\ 0 & a_{11,22} & 0 & a_{11,24} & a_{11,25} \\ 0 & 0 & a_{11,33} & a_{11,34} & a_{11,35} \\ 0 & 0 & 0 & a_{11,44} & a_{11,45} \\ 0 & 0 & 0 & 0 & a_{11,55} \end{pmatrix} \end{array}. \tag{2.5}$$

To the left of matrix $\mathcal{A}_{11}$ in (2.5) the respective variables are depicted. Above this matrix, we provide the names of the sectors, in which shocks arise.

Production Sector (PS): This identification scheme assumes that the production sector (q^*, π^*) does not react contemporaneously to changes in the rest of the system. This assumptions reflects the belief that production and prices do not respond to shocks from outside the sector. The relation of the variables belonging to the production sector is not distinctly modeled and we assume for simplicity an upper triangular structure.
Monetary Policy (MP): The federal funds rate (i^*) is assumed to be the instrument of the US monetary authority. It is assumed that within the month the monetary authority does not observe the variables of the production sector q^* and π^*, which are typically available only at a lower frequency (e.g., quarterly). For this reason the production sector variables do not enter the information set of the monetary authority. Moreover, we impose the restriction that the monetary authority does not immediately react to stress in the US financial system. This assumption is motivated by the fact that during the recent financial crisis the Federal Reserve responded to the financial shock with a delay of at least 2 months.[5]
Financial Sector (FS): The third sector corresponds to the US financial system and is represented by the financial conditions index. Since the financial conditions index contains fast-moving variables the production sector as well as changes in the monetary policy are allowed to affect the US financial system contemporaneously.
Information (Inf): The fourth sector is called "Inf", depicting that it responds quickly to new information. The identified shock has no clear economic meaning as the behavior within this sector is not specified. Nonetheless, it relates to other disturbances that are not explained by the production sector, monetary policy, or financial stress.
The identification of the EME block is recursive (upper triangular). The ordering of the variables in this block is arbitrary as it does not affect our analysis of the US financial stress or monetary policy shock.
The identification scheme discussed leads to a SVAR model that is globally identified. This result is obtained by applying the rank conditions for global identification of identified structural models established in Rubio-Ramírez et al. (2010). Further, to investigate whether our identification strategy is meaningful, we plot in Appendix 2.B Figure 2.B.1 our identified shock series of financial stress. We conclude that the identification approach followed in this paper recovers innovations that are structurally meaningful. Major shocks can sensibly be related to past difficulties that arose within the US financial sector. It should be noted that the identified financial innovations series represent shocks that do not depend on general economic conditions. Thus, we recover structural residuals that do not present the effects of, e.g., recessions or booms. Further, the inclusion of the price index of world commodities

[5]For the timeline of policy responses to the Global Financial Crisis we refer to `www.newyorkfed.org/research/global_economy/policyresponses.html` (Accessed January 22,2013).

assures that our financial shock does not relate to any adverse events associated with world prices. This is an important aspect when analyzing countries that are heavily dependent on commodity markets.

2.3 The Transmission of US Financial Stress

2.3.1 The Dynamics of US Financial Stress Shocks

This section examines the dynamics of the US and a typical emerging market country in response to a financial stress shock to the US financial system. The impulse response functions are presented with posterior 68% probability bands as proposed by Sims and Zha (1999). The point estimate corresponds to the median. The maximum of the time horizon is set to 36 months. Due to the multitude of emerging market countries in our sample the analysis faces the problem to sieve and expose the most important findings in a condensed manner. Due to the homogeneity of our results across countries, we aggregate the findings over all EMEs by using a variance weighting scheme. That is, the median response of a particular point in time for each country is weighted by the inverse of its variance relative to the sum of the inverse of the variances of the median responses for all countries. Hence, this weighting scheme down-weights the noisiest response. For completeness, Appendix 2.C depicts the plots of the impulse responses for each emerging market country with posterior 68% probability bands separately.

The first part of Figure 2.3.1 portrays how the US economy reacts to a financial stress shock of about one standard deviation.[6] The positive deviation of US financial conditions (f^*) indicates that actual and expected financing conditions for households and businesses deteriorate, uncertainty in equity markets rise, and spreads in money and debt markets increase. This general worsening in US financial conditions leads to a sharp decline in US real economic activity (q^*) in the following months. After one year, i.e., the response at month twelve, real GDP declines by about 0.31%. US inflation (π^*) and world commodity prices (p^*) fall in response, whereas the drop in world commodity prices is contemporaneously. A financial stress shock leads to a US deflation of about 0.17% and world commodity prices fall by 2.24% after one year. Furthermore, the monetary authority reacts to a US financial stress shock by decreasing the federal funds rate. After one year the rate is lowered by approximately 0.10 basis points. Thus, the responses for the US are significant, have the expected sign, and make intuitively sense: In reply to a worsening of US financing conditions

[6] To interpret the effects of a financial stress shock correctly it is important to note that the recent financial crisis led in our analysis to a worsening of financial conditions by more than eight standard deviations in mid 2007.

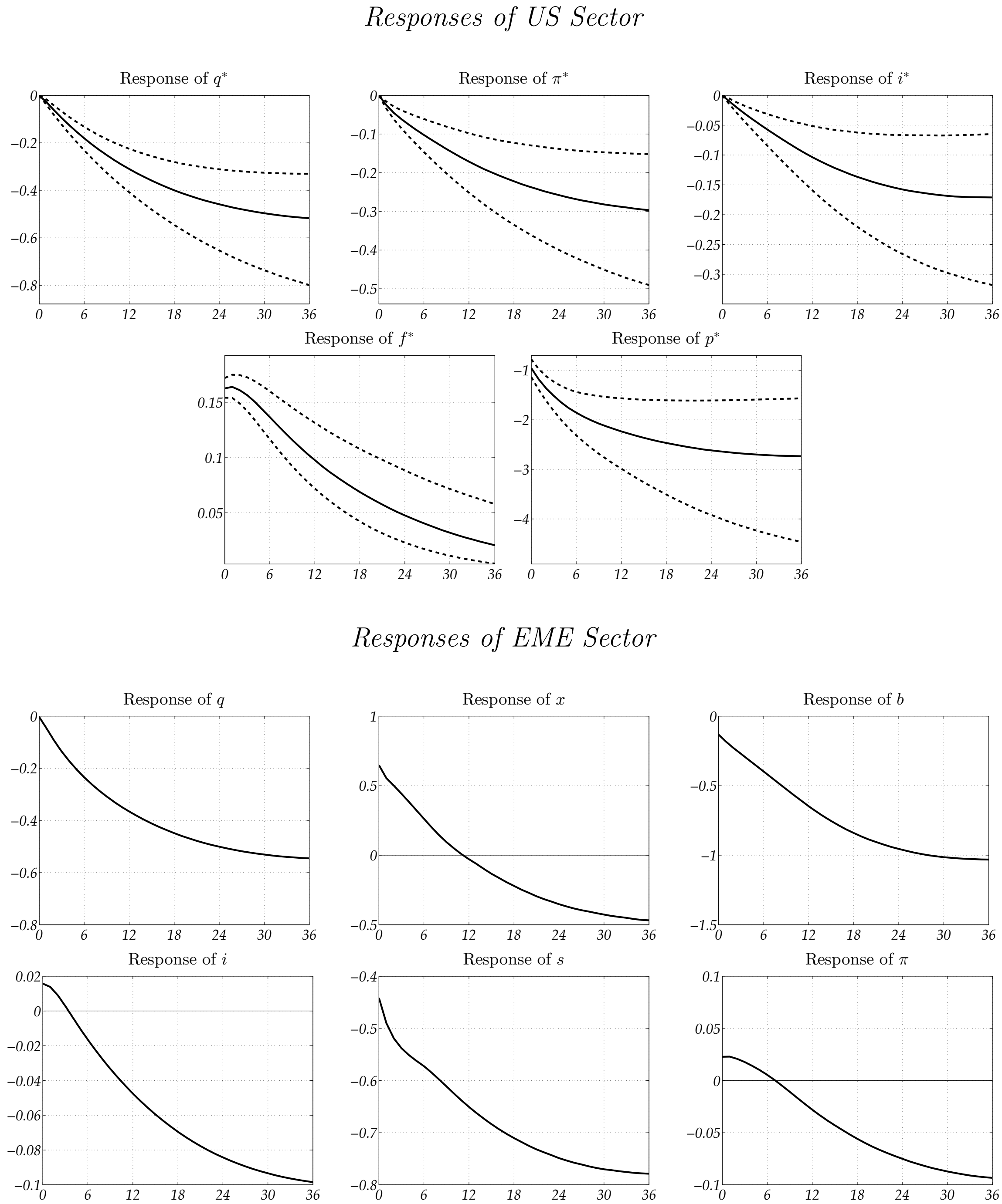

Figure 2.3.1: Response Functions of the US and a Typical EME to a US Financial Stress Shock

Notes: The impulse responses are all in percentage deviations (y-axis) except for the responses of interest rates (i, i^*) and trade relations (x) that are deviations in basis points. The x-axis represents months after the shock. The US response functions are presented with posterior 68% probability bands (dashed lines). The EME response functions are volatility weighted averages across all countries. f^* denotes the measure of US financial conditions; q^* (q) log of real GDP; π^* (π) log of consumer price index; i^* (i) interest rate; p^* log of world price index; x exports over imports; b log of net accumulated foreign stocks; s log of real effective exchange rate.

aggregate demand for goods and services as well as investments fall due to financially constrained households and firms. The slowdown in demand forces the price level

in the US down. However, the decline in aggregate demand and investment both have adverse effects on real economic activity. In order to absorb the contagion of the negative real effects of the financial stress shock the monetary authority reacts by an expansionary monetary policy to stimulate the recovery of the US economy.
The second part of Figure 2.3.1 displays the transmission dynamics of US financial stress to a typical emerging market country. Several findings emerge: the economy of a typical emerging market country is affected by the US financial stress shock as strongly as the US economy itself. We find a sharp negative response in real economic activity and the economy continues to slow down for the following months. After one year our estimate reports a decline of about 0.41% on average. The median decline in real GDP at month twelve is larger than in the US for all EMEs in our sample, except for the Philippines. Mexico and Thailand are affected most strongly and experience a reduction of 0.56% and 0.63%, respectively. The adverse effect on real economic activity is significant for all countries.
The transmission of US financial stress shocks can mainly occur through international trade linkages or financial markets: first, our measure of trade relations (x) increases contemporaneously by 0.65 basis points (b.p.), which means that a typical EME exports more relative to its imports in response to a financial stress shock. After one year these dynamics reverse. However, the country by country analysis reveals that this effect is only significant for Mexico (0.72 b.p.), and Philippines (1.18 b.p). Second, a typical emerging market country experiences noticeable foreign capital outflows (b). Regarding the timing we find that the drop in foreign capital flows is contemporaneously with a magnitude of about 0.13%. After one year we observe a decline of about 0.64%. The country by country analysis points out that the negative response of foreign capital flows is significant for all countries, except for Chile, where we find an inflow of foreign capital. Thus, for almost all EMEs our results indicate that the dynamics of trade are not significant. On the other hand, we find strong negative effects on foreign capital flows in response to financial stress in the US financial system. Hence, these findings clearly highlight the propagation of financial stress shocks through international financial markets.
The monetary authority in a typical EME responds first with an increase in its interest rate (i) of about 0.02 basis points. After six months it reacts to the ongoing in the economy with an expansionary monetary policy. The exceptions are Mexico and Philippines, which respond with a contemporaneously increase in its interest rate but they do not follow an expansionary monetary policy path afterwards. Further, in a typical EME the currency depreciates instantaneously in response to a US financial stress shock. The contemporaneously drop in the exchange rate (s) is of about 0.44%. We find evidence for an exchange rate depreciation in response to a

US financial stress shock for all countries, except for the cases of Chile and Malaysia, where responses are not significant. The reaction of inflation (π) is ambiguous across countries. For most of the countries the response of inflation is not significant.
The dynamics of the EME variables are in line with theoretical considerations. A typical emerging market country depends heavily on foreign capital inflows which render the economy highly vulnerable to external shocks (Calvo, 1998). Conclusively, financial stress in the US financial system may lead to a sudden stop of foreign capital inflows in a typical emerging market country. Foreign capital inflow reversals generate a downward pressure on the currency leading to a depreciation of the real exchange rate. The monetary authority defends the pressure on the currency by increasing the interest rate and to avoid further foreign capital outflows. Furthermore, US credit market conditions tighten such that a typical emerging market country becomes financially constrained. Tight domestic credit conditions limit the space of financial resources and lead to a slowdown in real economic activity.

2.3.2 The Importance of US Financial Stress Shocks

This section discusses the importance of financial stress shocks in explaining the high volatility in emerging markets' macroeconomic variables. Besides this, we relate our findings to the role of monetary policy shocks and emphasize on the joint importance of external shocks. Table 2.3.1 summarizes the results of our forecast error variance decomposition exercise for all EMEs. For comparative purposes Table 2.3.1 displays the fraction of the variance in US real economic activity, the federal funds rate, and US inflation explained by US financial stress shocks. We report the average forecast error variance decompositions over two sets of horizons: from month 1 until 24 and month 25 up to 48. To summarize the most important results it suffices to focus on the horizon from month 25 to 48. This is done subsequently.
Three important results emerge from this analysis: first, US financial stress accounts for a sizeable portion of fluctuations in EME real economic activity (q), foreign capital flows (b), interest rates (i), and exchange rates (s). On average, US financial stress accounts for 21% in the variation of real economic activity, 17% in the variation of foreign capital flows, 18% in the variation of interest rates, and 22% in the variation of the exchange rate. Moreover, the results for real economic activity become more striking if we relate the variation explained by the financial stress shock to the variation explained by the *remaining* external shocks for each country. This figure underscores the importance of financial stress shock for the volatility in real economic activity, as the fraction of the variance of the latter variable explained by the US financial stress shock is of the same size as the fraction of the variance accounted for by the remaining external shocks. Relating these findings to the esti-

Table 2.3.1: Forecast Error Variance Decomposition Analysis

			BR	CL	KR	MX	MY	PH	TH	ZA	Av.	US
q	*Financial Stress*	*1-24*	10	5	10	11	9	7	9	11	9	17
		25-48	20	14	18	27	23	19	18	30	21	41
	Monetary Policy	*1-24*	4	2	2	3	2	2	2	3	2	2
		25-48	6	3	4	6	4	3	3	5	4	5
	All External Shocks	*1-24*	43	15	26	27	29	38	20	24	28	100
		25-48	52	27	35	45	43	52	31	47	42	100
x	*Financial Stress*	*1-24*	3	3	3	3	3	4	2	3	3	-
		25-48	9	8	7	7	8	8	7	8	8	-
	Monetary Policy	*1-24*	2	3	2	2	2	2	2	2	2	-
		25-48	4	5	4	4	3	3	4	4	4	-
	All External Shocks	*1-24*	11	10	9	10	8	13	9	9	10	-
		25-48	20	18	16	16	16	20	17	17	18	-
b	*Financial Stress*	*1-24*	3	7	9	3	14	7	9	5	7	-
		25-48	8	13	12	8	29	20	24	18	17	-
	Monetary Policy	*1-24*	2	2	2	2	2	2	5	4	2	-
		25-48	4	4	4	4	4	6	8	7	5	-
	All External Shocks	*1-24*	25	14	20	14	24	13	19	13	18	-
		25-48	35	22	27	25	42	32	36	30	31	-
i	*Financial Stress*	*1-24*	2	8	9	6	9	3	11	6	7	6
		25-48	6	15	21	8	28	7	33	23	18	18
	Monetary Policy	*1-24*	6	4	8	4	10	2	7	2	5	91
		25-48	8	4	17	7	17	3	12	6	9	77
	All External Shocks	*1-24*	13	18	29	15	24	10	31	12	19	100
		25-48	20	28	47	21	52	17	56	34	34	100
s	*Financial Stress*	*1-24*	18	2	41	31	4	3	20	13	17	-
		25-48	20	7	48	37	9	9	33	13	22	-
	Monetary Policy	*1-24*	4	3	12	3	2	2	2	9	5	-
		25-48	5	5	12	7	4	5	4	8	6	-
	All External Shocks	*1-24*	29	12	60	47	13	11	44	28	31	-
		25-48	34	19	67	56	22	21	54	28	38	-
π	*Financial Stress*	*1-24*	3	7	2	4	4	2	6	3	4	9
		25-48	8	13	6	8	13	7	17	7	10	25
	Monetary Policy	*1-24*	5	3	5	2	1	2	1	2	3	1
		25-48	10	4	9	4	3	4	3	5	5	4
	All External Shocks	*1-24*	22	48	32	13	35	28	44	27	31	100
		25-48	36	58	45	24	49	41	54	38	43	100

Notes: "All External Shocks" denotes the fraction of the variance of a given variable explained by all external shocks jointly. "*1-24*" and "*25-48*" depict the average value of the forecast error variance decomposition (in percent) between the forecast horizon 1 to 24 and 25 to 48, respectively. The last column "US" only contains the results for the variables included in the US block. q denotes log of real GDP; x exports over imports; b net accumulated foreign stocks; i interest rate; s real effective exchange rate; π log of consumer price index.

mates for the US economy the result of large spill-over effects is emphasized. In the case of real GDP of a typical EME, the variation explained by US financial stress (21%) is more than a half of the variation in US real economy (41%); for interest rates we find extensive spill-overs to EMEs since US financial stress shocks explain of about the same portion (18%) in both variables (i, i^*).
Second, US monetary policy shocks are not important for emerging market economies relative to US financial stress and other external shocks. For a typical emerging market country, US monetary policy accounts on average for about 4-6% in the variation in real economic activity, trade, foreign capital flows, exchange rate, and inflation. 9% in the variation are explained in the case of interest rates.[7]
Third, our findings indicate that external shocks are in general an important source for fluctuations in emerging market economies. For instance, all external shocks jointly account for 42% in the variation of real economic activity, 18% of the variation in trade, 31% in the variation of foreign capital flows, 34% in the variation of interest rates, 38% in the variation of exchange rates, and 43% in the variation of inflation.[8]

2.3.3 The Contribution of US Financial Stress Shocks to Cyclical Fluctuations

This section discusses the contribution of US financial stress shocks to the *cyclical* variation of economic time series in the emerging world. Moreover, we relate our findings to the contribution of monetary policy shocks and external shocks jointly to the variation at business cycle frequencies. Table 2.3.2 summarizes the decomposition of variance that can be related to business cycles frequencies (24 to 96 months). We apply the method by Altig et al. (2011) and use spectral decompositions to obtain the median fraction of variance in the business cycle frequencies accounted for by the US financial stress shock, the monetary policy shock, and all external shocks jointly.
Looking at the findings, we emphasize in what follows three results: first, for a typical emerging market country US financial conditions are important in the short-run relative to other external and internal shocks. US financial stress shocks account for 17% of the cyclical variation in real economic activity (q), 13% of the cyclical variation in foreign capital flows (b), 17% of the cyclical variation in interest rates

[7]Compared to, e.g., Uhlig (2005), our number related to the variance in US output explained by a US monetary policy shock is slightly smaller. We attribute this to the fact that our time horizon differs. This includes the argument that the federal funds rate is close to the zero lower bound at the end of our sample, which possibly mitigated the responsiveness to monetary policy.
[8]The strong differences in the results for the variation explained in exchange rates can be related to the exchange rate regime followed by the respective country. EMEs that pursue a managed floating regime or crawling peg show higher sensitivity, while countries with fixed pegs and bands less.

Table 2.3.2: Decomposition of Variance: Business Cycle Frequencies

		BR	CL	KR	MX	MY	PH	TH	ZA	Av.	US
q	*Financial Stress*	15	11	14	21	19	16	13	26	17	36
	Monetary Policy	5	3	3	7	5	3	3	5	4	6
	All External Shocks	53	27	33	44	44	52	27	47	41	100
x	*Financial Stress*	5	4	5	5	4	5	4	4	5	-
	Monetary Policy	3	3	3	3	2	2	2	2	3	-
	All External Shocks	17	14	15	15	13	18	15	13	15	-
b	*Financial Stress*	5	11	11	6	24	13	18	15	13	-
	Monetary Policy	4	3	3	3	3	5	11	5	5	-
	All External Shocks	34	22	28	25	38	26	37	28	30	-
i	*Financial Stress*	4	24	22	10	26	5	27	21	17	13
	Monetary Policy	9	7	15	6	19	3	11	6	9	81
	All External Shocks	23	41	53	25	53	15	55	36	38	100
s	*Financial Stress*	17	5	42	31	5	5	24	13	18	-
	Monetary Policy	4	4	15	4	4	4	3	11	6	-
	All External Shocks	32	19	68	51	21	18	49	33	37	-
π	*Financial Stress*	6	18	4	6	10	4	12	6	8	17
	Monetary Policy	6	6	5	3	2	2	3	4	4	4
	All External Shocks	33	66	42	24	49	39	55	38	43	100

Notes: Numbers are the median fraction of variance in the business cycle frequencies, 24 to 96 months, accounted for by the financial stress shock, monetary policy shock, and all external shocks jointly. Av. indicates the average across EME. The last column "US" only contains the results for the variables included in the US block. q denotes log of real GDP; x exports over imports; b net accumulated foreign stocks; i interest rate; s real effective exchange rate; π log of consumer price index.

(i), and 18% in the cyclical variation of exchange rates (s). For the cyclical variation in trade (x) and inflation (π) we find that US financial shocks play only a minor role, i.e., 5% and 8%, respectively. Comparing the estimates for the US with a typical emerging market economy the results indicate that the spill-overs from the US to the emerging world are remarkable. For real economic activity we find on average for an EME that 17% of the cyclical variation is explained by US financial stress, whereas for the US the fraction of the cyclical variance is about 36%. For interest rates the results are more striking because the estimates indicate that the cyclical variation explained by the US financial stress shock is larger than in the US (17% vs. 13%). Besides this, our results reveal that a US financial stress shock contributes more to the cyclical fluctuations than other external shocks, except for the cyclical variation in trade and inflation.

Second, US monetary policy shocks are not important for the cyclical variation in EME macro-variables. The largest contribution of monetary policy shocks to the

cyclical variation in EME variables is found for interest rates (9% on average).
Third, our estimates indicate that external shocks contribute significantly to the cyclical variation in EMEs. External shocks jointly account for 41% of the cyclical variation in real economic activity, 30% of the cyclical variation in foreign capital flows, 38% of the cyclical variation in interest rates, 37% of the cyclical variation in exchange rates, and 43% of the cyclical variation in inflation. Among these, the US financial stress shock reflects the most important driver of the external factors for the cyclical variation in EMEs.

2.3.4 Robustness of the Empirical Results

In order to assess the sensitivity of the empirical findings, we conduct several robustness checks addressing our measure of financial stress. Rather than using the aggregate measure of financial stress (NFCI), we re-estimate our VAR replacing the NFCI with three different sub-indexes one at a time that form a sub-set of the latter metrics. That is, the Federal Reserve Bank of Chicago constructs three sub-indexes of the NFCI (risk, credit, and leverage). Each sub-index contains a subset of financial variables used in the NFCI. The risk sub-index captures financial uncertainty and funding risk in the US financial sector; the credit sub-index measures credit conditions of businesses and households; and the leverage sub-index is composed of measures for debt and equity markets.
The main results are supported by this exercise. Nonetheless, some differences emerge: for the risk and credit sub-index results are qualitatively similar but weaker than in our benchmark case using the NFCI. Moreover, we find partially insignificant results for the leverage sub-index. The sub-index that reaches closest to the original results of our paper is the risk sub-index. This stresses our interpretation of our financial sector shock as financial stress.

2.4 Concluding Remarks

This paper evaluates the role of US financial stress for the economic dynamics and fluctuations of emerging market economies. We provide for a large set of emerging market countries empirical evidence on the vulnerability to US financial stress shocks.
Our findings suggest that these shocks have been important in driving the dynamics and fluctuations in EMEs. US financial stress shocks affect EMEs as strongly as the US economy. We find evidence that cross-country spill-overs occur through international financial markets, i.e., a drop in capital flows from the US to EMEs. Moreover,

US financial stress accounts for a large portion in emerging market economies, even at business cycle frequencies.

Since our empirical findings strongly support the view that EMEs are highly vulnerable to US financial shocks it is worth for policy makers to think about options that dampen the international transmission. In this paper we discuss two main channels for the transmission of US financial shocks: sudden stops of foreign capital inflows and a decline in export demand. We find that the trade channel is not the main driver of the sparked recessions in response to a financial stress shock. Our analysis rather points in the direction that policies should address problems related to sudden stops of foreign capital inflows. On a national level, capital controls may alleviate the problem of ceasing capital inflows. Further, we find a depreciation of the currency of EMEs. In this context debt restructuring mechanisms are vital by, e.g., lowering the exposure to foreign denominated debt (Calvo, 2007). Of course, classical policy measures such as monetary and fiscal policy provide means to cushion the effects of recessionary pressure as well. Due to the fact, that the sudden stop of capital inflows does not originate from a loss in confidence of investors, but rather because of a decrease in global investment, regulators should focus on an easing of monetary policy. Further, foreign exchange reserves can on the one hand be used to stabilize the value of the domestic currency and on the other to ease the access of foreign currency for the private sector. In light of financially constrained governments, aid provided at an international level is of vital importance. For example fast lending without conditionality which is, e.g., provided by the International Monetary Fund, reflects an important tool to bridge temporary fiscal constraints. Further, closer cooperation between regional funds and global institutions might help to coordinate resources more efficiently.

With regard to future research, one could investigate which sector of the US financial system is most responsible for the negative cross-country transmission. The present study uses a global measure of US financial conditions to highlight the general importance of financial stress for EMEs. Having presented the results of this paper, it is the next step to pin down the relative importance of *specific* US financial shocks for the emerging world. Further, theoretical research could provide insights why trade channels are inessential and deliver options to encounter the contagion through financial markets.

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Appendix 2.A Data

Table 2.A.1: Definitions and Symbols of Variables Employed in the SVAR

	Variable	Symbol	Definition
EME Sector	Real economic activity	q_t	Log of EME real GDP
	Bilateral trade	x_t	EME export / import (in %)
	Bilateral fgn. capital	b_t	Log of net accumulation of fgn. stocks
	Interest rate	i_t	EME prime lending (money market)
	Exchange rate	s_t	Log of real effective exchange rate
	Inflation	π_t	Log of EME CPI
US Sector	Financial conditions	f_t^*	US financial conditions index
	Real economic activity	q_t^*	Log of US real GDP
	Inflation	π_t^*	Log of US CPI
	Interest rate	i_t^*	US Federal Funds rate (in %)
	World commodity prices	p_t^*	Log of IMF world price index

Table 2.A.2: National Financial Conditions Index: Coverage of the US Financial System

	Financial Market	Number of Indicators
Money Markets	Repurchase Agreements	10
	Treasuries	9
	Commercial Paper	5
	Interbank Lending	4
Debt and Equity Markets	Corporate Bonds	8
	Securitized Debt	6
	Stock Markets	6
	Municipal Bonds	4
	Collateral Prices	3
Banking System	Consumer Credit Conditions	12
	Banking System Conditions	9
	Shadow Bank Assets and Liabilities	9
	Business Credit Conditions	8
	Commercial Bank Assets and Liabilities	7

Source: Brave and Butters (2011, 2012)

Table 2.A.3: Data Sources and Descriptions

Emerging Market Economies

		Economic Activity		Bilateral Trade		Bilateral Foreign Capital		Interest Rate	Exchange Rate	Inflation
		GDP	IP	US Imports	US Exports	US purchases	US sales			
BR	*Mnemonic*	BRGDP...G	BRI66..CE	USIMPCBRA	USEXCBR.A	USWSWKBRA	USWPWKBRA	BRI60P..	BRMGTWRB	BRI64...F
	Source	NS	IFS	NS (US)	NS (US)	TIC	TIC	IFS	JP Morgan	IFS
	Comment	Real GDP	Ind. Prod.	US from EME	US to EME	Fgn. stocks	Fgn. stocks	Prime lending	Real effective	CPI
CL	*Mnemonic*	CLI99BVPH	CLIPMAN.H	USIMPCCIA	USEXCCI.A	USWSWKCIA	USWPWKCIA	CLI60P..	CLMGTWRB	CLCONPRCF
	Source	IFS	NS	NS (US)	NS (US)	TIC	TIC	IFS	JP Morgan	NS
	Comment	Real GDP	Ind. Prod.	US from EME	US to EME	Fgn. stocks	Fgn. stocks	Prime lending	Real effective	CPI
KR	*Mnemonic*	KOI99BVPH	KOI66..CE	USIMPCKSA	USEXCKS.A	USWSWKKSA	USWPWKKSA	KOBANKR.	KOMGTWRB	KOI64...F
	Source	IFS	IFS	NS (US)	NS (US)	TIC	TIC	NS	JP Morgan	IFS
	Comment	Real GDP	Ind. Prod.	US from EME	US to EME	Fgn. stocks	Fgn. stocks	Prime lending	Real effective	CPI
MX	*Mnemonic*	MXGDP...D	MXI66...F	USIMPCMXA	USEXCMX.A	USWSWKMXA	USWPWKMXA	MXI60P..	MXMGTWRB	MXI64...F
	Source	NS	IFS	NS (US)	NS (US)	TIC	TIC	IFS	JP Morgan	IFS
	Comment	Real GDP	Ind. Prod.	US from EME	US to EME	Fgn. stocks	Fgn. stocks	Prime lending	Real effective	CPI
MY	*Mnemonic*	MYI99BVPH	MYI66...F	USIMPCMYA	USEXCMY.A	USWSWKMYA	USWPWKMYA	MYI60P..	MYMGTWRB	MYI64...F
	Source	IFS	IFS	NS (US)	NS (US)	TIC	TIC	IFS	JP Morgan	IFS
	Comment	Real GDP	Ind. Prod.	US from EME	US to EME	Fgn. stocks	Fgn. stocks	Prime lending	Real effective	CPI
PH	*Mnemonic*	PHGDP...D	PHIPMAN.F	USIMPCRPA	USEXCRP.A	USWSWKRPA	USWPWKRPA	PHI60P..	PHMGTWRB	PHI64...F
	Source	NS	NS	NS (US)	NS (US)	TIC	TIC	IFS	JP Morgan	IFS
	Comment	Real GDP	Ind. Prod.	US from EME	US to EME	Fgn. stocks	Fgn. stocks	Prime lending	Real effective	CPI
TH	*Mnemonic*	THI99BVPH	THIPMAN.H	USIMPCTHA	USEXCTH.A	USWSWKTHA	USWPWKTHA	THI60B..	THMGTWRB	THI64...F
	Source	IFS	NS	NS (US)	NS (US)	TIC	TIC	IFS	JP Morgan	IFS
	Comment	Real GDP	Ind. Prod.	US from EME	US to EME	Fgn. stocks	Fgn. stocks	Money market	Real effective	CPI
ZA	*Mnemonic*	SAI99BVRG	SAI66EYCE	USIMPCSFA	USEXCSF.A	USWSWKSFA	USWPWKSFA	SAI60B..	SAMGTWRB	SAI64...F
	Source	IFS	IFS	NS (US)	NS (US)	TIC	TIC	IFS	JP Morgan	IFS
	Comment	Real GDP	Ind. Prod.	US from EME	US to EME	Fgn. stocks	Fgn. stocks	Money market	Real effective	CPI

United States & World

	Financial Conditions	Economic Activity		Inflation	Interest Rate	World Commodity Prices
		GDP	IP			
Mnemonic	-	USI99BVRG	USIPTOT.G	USI64...F	USFEDFUN	WDI76NFDF
Source	Chicago FED	IFS	NS	IFS	NS	IFS
Comment	-	Real GDP	Ind. Prod.	CPI	Money market	IMF price index

Notes: Data codes from Datastream (Thomson Financial) are provided for each variable used in the analysis. Data sources are either from the National Statistics Office (NS) or the International Financial Statistics (IFS) database of the IMF. Real effective exchange rates are from JP Morgan; bilateral foreign capital flows are from the Treasury International Capital System (TIC). All data are seasonally adjusted if necessary. The time series of real GDP are interpolated to a monthly frequency using the method described in Bernanke et al. (1997).

Appendix 2.B US Financial Stress

It is important to ensure that our identified financial stress shock is indeed a shock that can be related to events in the financial sector. For this reason our shock series should clearly reflect past episodes of financial stress. Let this estimated structural innovation series be $\hat{\varepsilon}_t^{f^*}$ for $t \in \{1, \ldots, T\}$. In Figure 2.B.1 we plot the three-months moving average of the this time series $(\hat{\varepsilon}_{t-1}^{f^*} + \hat{\varepsilon}_t^{f^*} + \hat{\varepsilon}_{t+1}^{f^*})/3$. This suppresses the noise implied by serially uncorrelated innovations and allows for a clearer picture of the estimated financial stress shock series.[9]

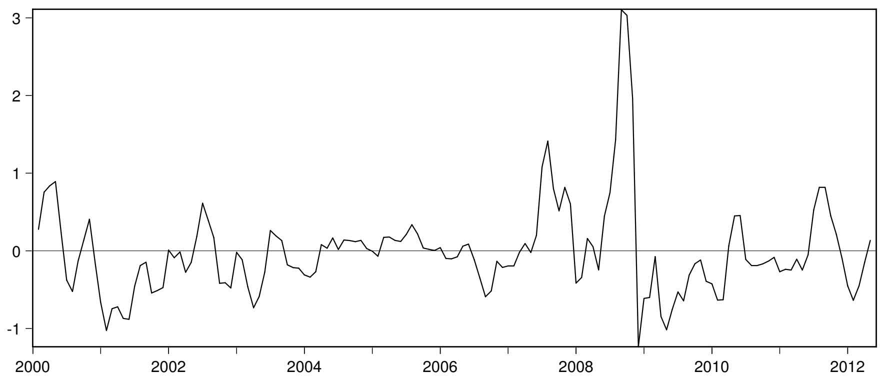

Figure 2.B.1: Estimated US Financial Stress Shock: Three-Months Moving Average

Relative to the financial conditions index, our identified shock series emphasizes times of market turmoil, i.e. strong positive deviations accentuate the events discussed in Section **??**. This is possible since our setup removes variation that is explained by e.g. recessions, booms, or other movements that are explained by the variables included in our US sector. All events discussed are clearly depicted: dot-com bubble (2000), Argentine Crisis (end 2000), "9/11" and its aftermath (2002), the global financial crisis (mid 2007), the bankruptcy of Lehman Brothers (mid 2008), the inception of the sovereign debt crisis (beginning of 2010), and the dispute over the US budget (mid 2011). Even other important events become even visible, as for instance the inception of the war on Iraq (2003) or the uncertainty caused by hurricane Katrina (mid 2005).

[9]The estimated financial stress shock series is the same for all emerging market countries since the EME variables do not enter the US block.

Appendix 2.C Impulse Response Functions

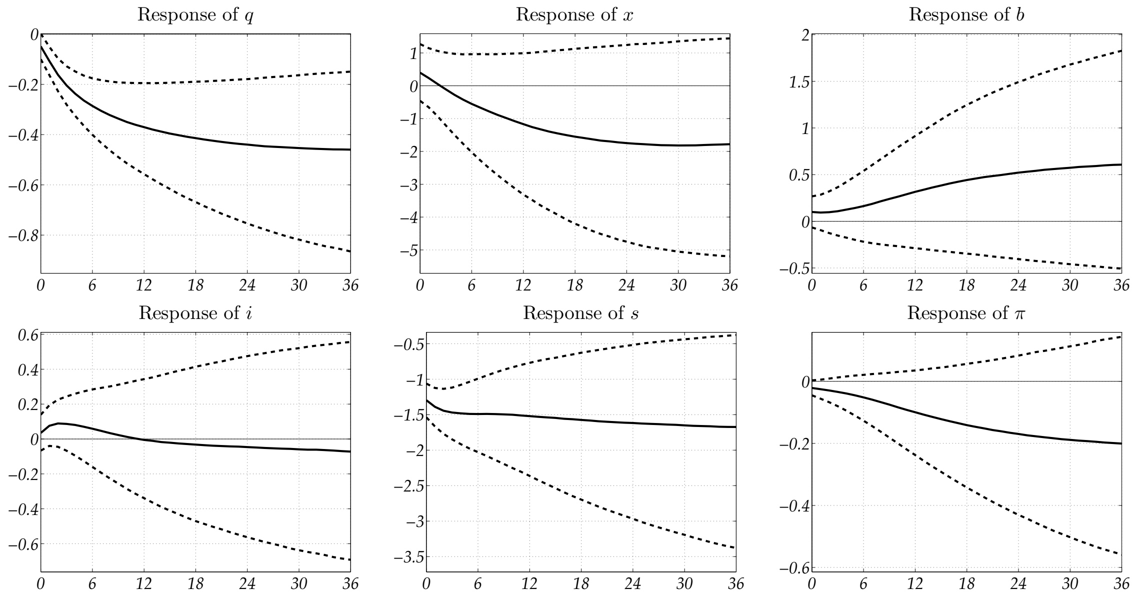

Figure 2.C.1: Response Functions of Brazil to a US Financial Stress Shock

Notes: The impulse responses are all in percentage deviations (y-axis) except for the responses of interest rates (i) and trade relations (x) that are deviations in basis points. The x-axis represents months after the shock. The dashed lines correspond to posterior 68% probability bands. q denotes log of real GDP; x exports over imports; b net accumulated foreign stocks; i interest rate; s real effective exchange rate; π log of consumer price index.

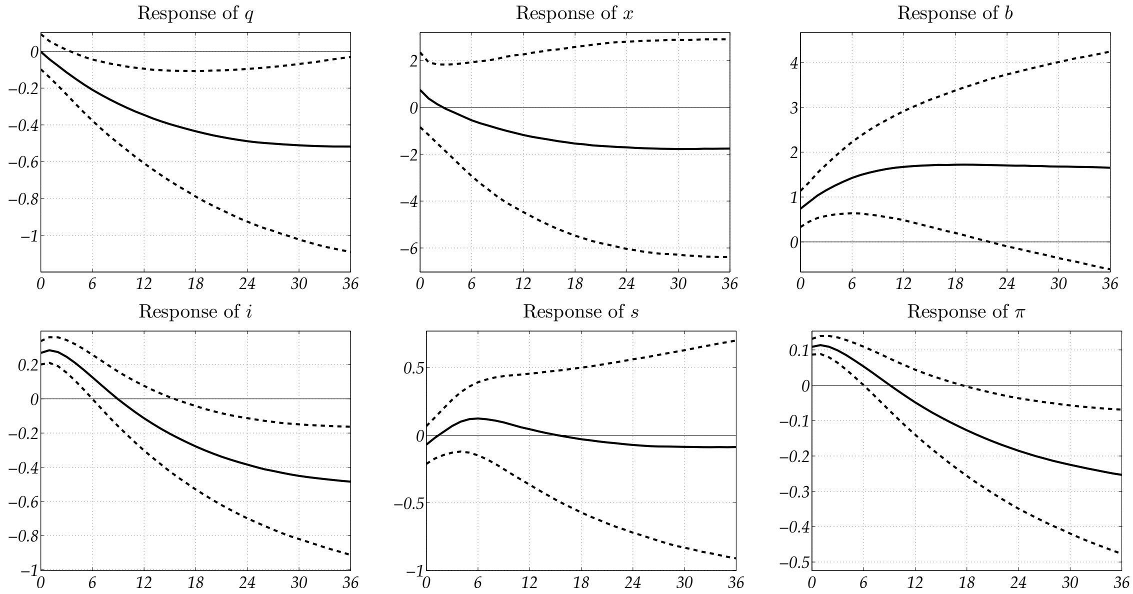

Figure 2.C.2: Response Functions of Chile to a US Financial Stress Shock

Notes: The impulse responses are all in percentage deviations (y-axis) except for the responses of interest rates (i) and trade relations (x) that are deviations in basis points. The x-axis represents months after the shock. The dashed lines correspond to posterior 68% probability bands. q denotes log of real GDP; x exports over imports; b net accumulated foreign stocks; i interest rate; s real effective exchange rate; π log of consumer price index.

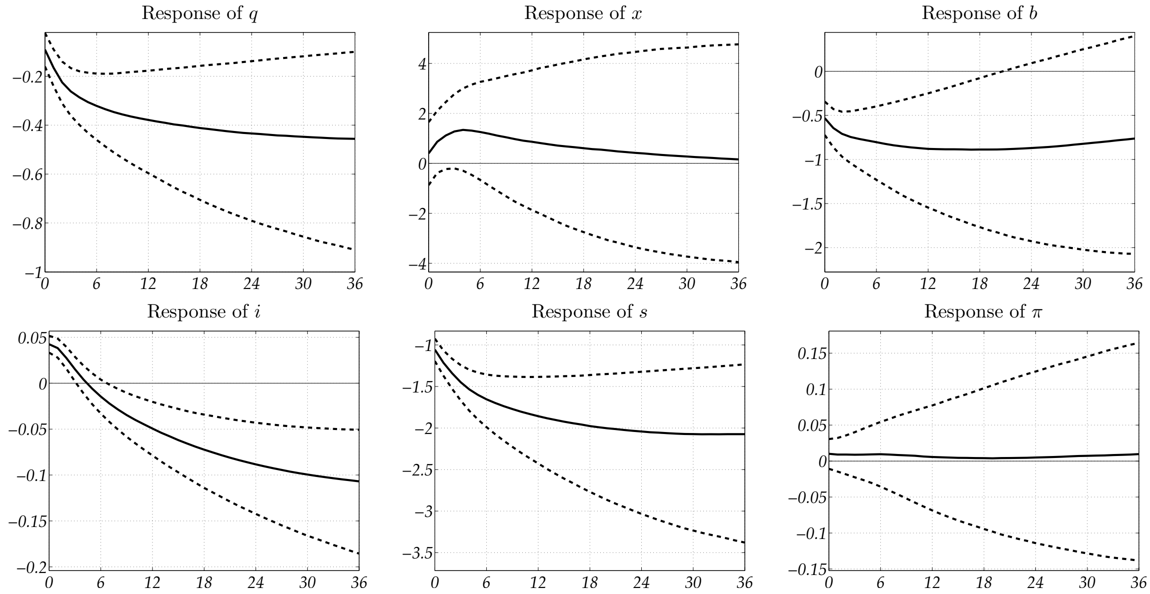

Figure 2.C.3: Response Functions of Korea to a US Financial Stress Shock

Notes: The impulse responses are all in percentage deviations (y-axis) except for the responses of interest rates (i) and trade relations (x) that are deviations in basis points. The x-axis represents months after the shock. The dashed lines correspond to posterior 68% probability bands. q denotes log of real GDP; x exports over imports; b net accumulated foreign stocks; i interest rate; s real effective exchange rate; π log of consumer price index.

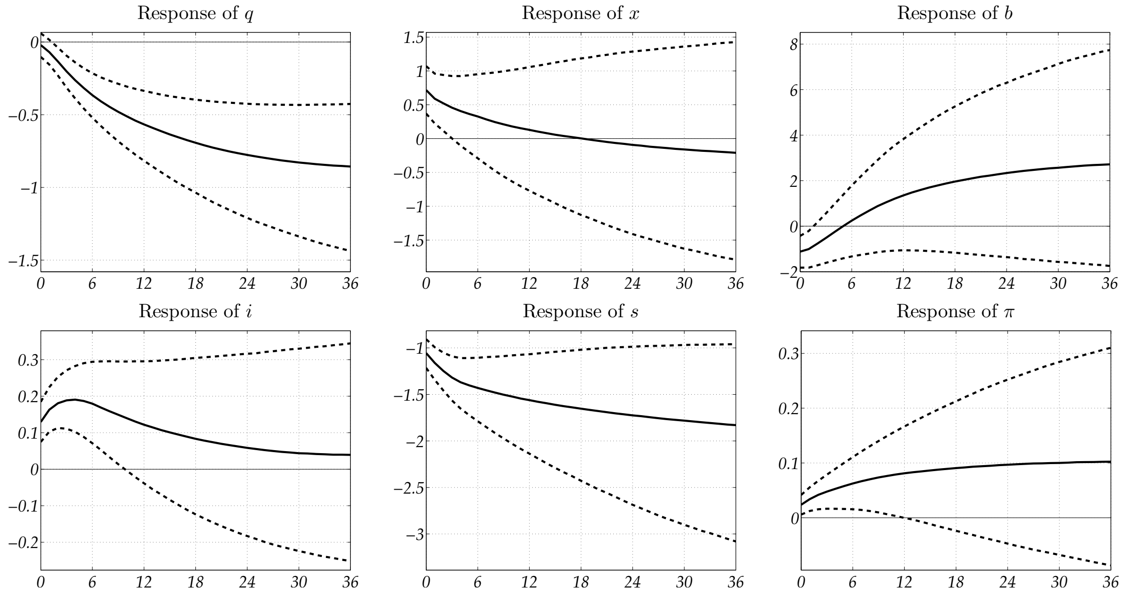

Figure 2.C.4: Response Functions of Mexico to a US Financial Stress Shock

Notes: The impulse responses are all in percentage deviations (y-axis) except for the responses of interest rates (i) and trade relations (x) that are deviations in basis points. The x-axis represents months after the shock. The dashed lines correspond to posterior 68% probability bands. q denotes log of real GDP; x exports over imports; b net accumulated foreign stocks; i interest rate; s real effective exchange rate; π log of consumer price index.

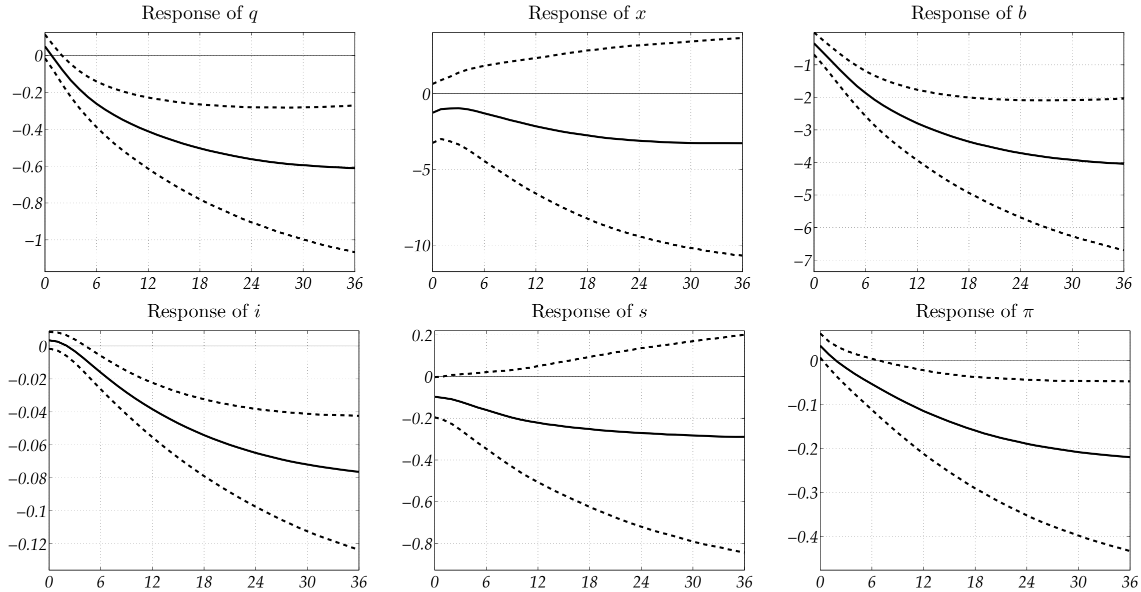

Figure 2.C.5: Response Functions of Malaysia to a US Financial Stress Shock

Notes: The impulse responses are all in percentage deviations (y-axis) except for the responses of interest rates (i) and trade relations (x) that are deviations in basis points. The x-axis represents months after the shock. The dashed lines correspond to posterior 68% probability bands. q denotes log of real GDP; x exports over imports; b net accumulated foreign stocks; i interest rate; s real effective exchange rate; π log of consumer price index.

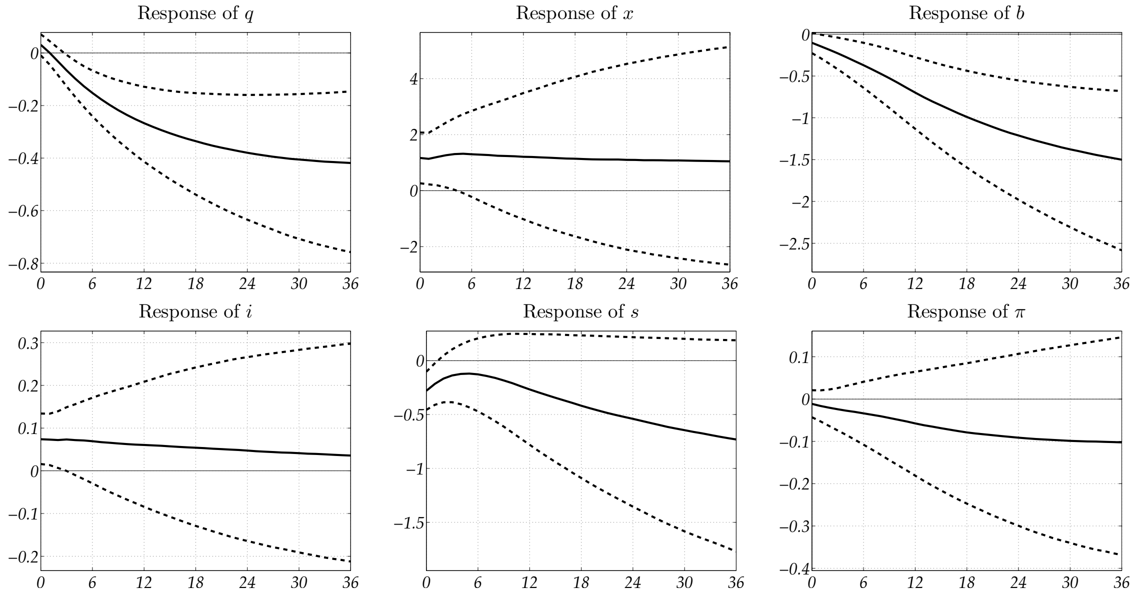

Figure 2.C.6: Response Functions of Philippines to a US Financial Stress Shock

Notes: The impulse responses are all in percentage deviations (y-axis) except for the responses of interest rates (i) and trade relations (x) that are deviations in basis points. The x-axis represents months after the shock. The dashed lines correspond to posterior 68% probability bands. q denotes log of real GDP; x exports over imports; b net accumulated foreign stocks; i interest rate; s real effective exchange rate; π log of consumer price index.

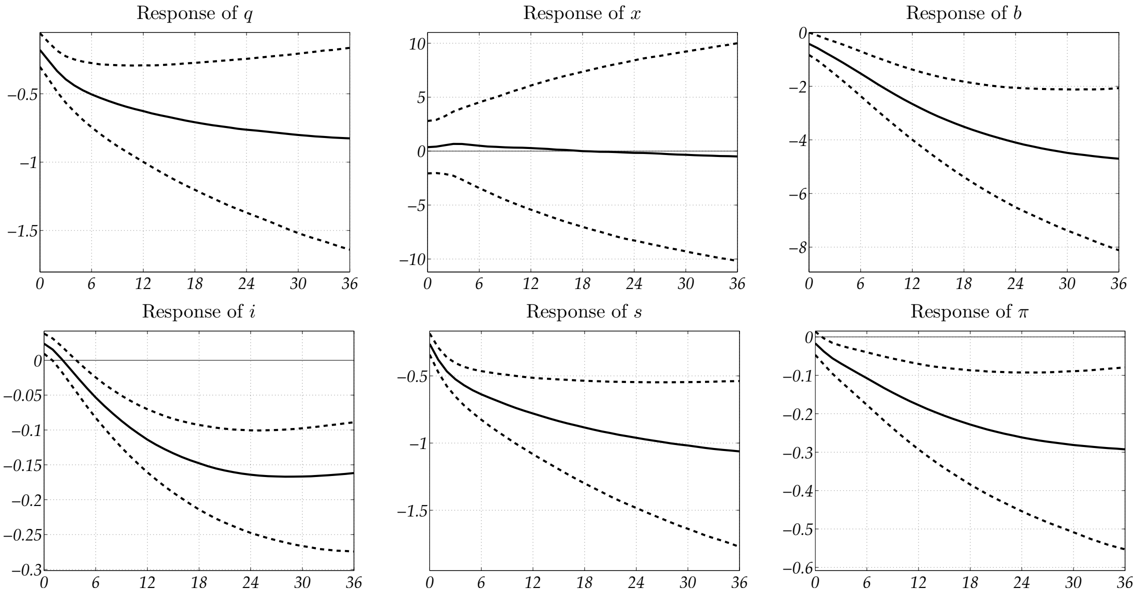

Figure 2.C.7: Response Functions of Thailand to a US Financial Stress Shock

Notes: The impulse responses are all in percentage deviations (y-axis) except for the responses of interest rates (i) and trade relations (x) that are deviations in basis points. The x-axis represents months after the shock. The dashed lines correspond to posterior 68% probability bands. q denotes log of real GDP; x exports over imports; b net accumulated foreign stocks; i interest rate; s real effective exchange rate; π log of consumer price index.

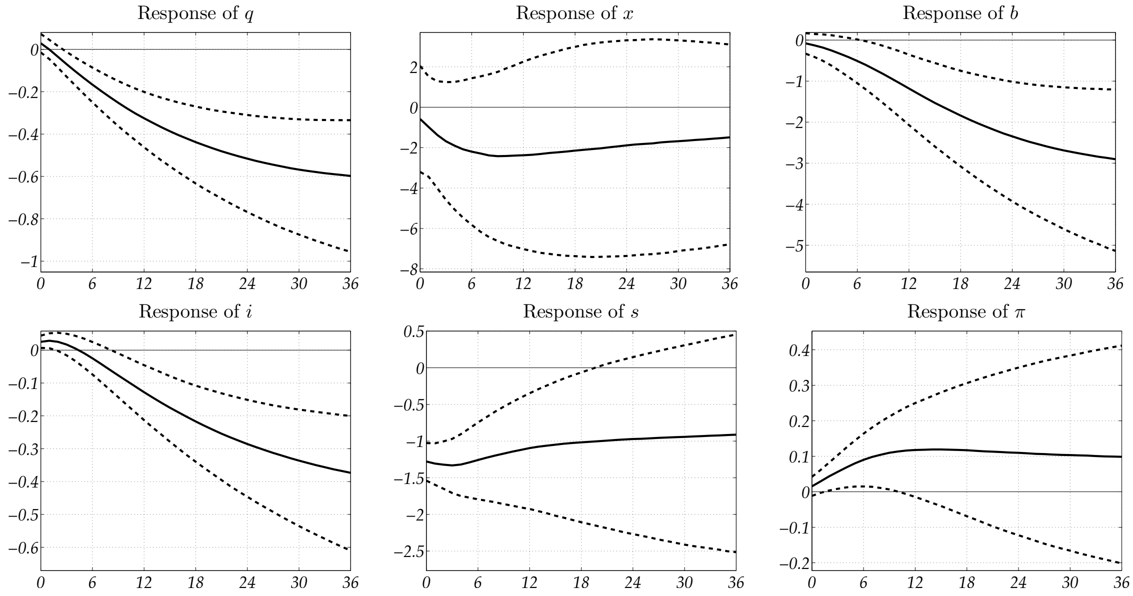

Figure 2.C.8: Response Functions of South Africa to a US Financial Stress Shock

Notes: The impulse responses are all in percentage deviations (y-axis) except for the responses of interest rates (i) and trade relations (x) that are deviations in basis points. The x-axis represents months after the shock. The dashed lines correspond to posterior 68% probability bands. q denotes log of real GDP; x exports over imports; b net accumulated foreign stocks; i interest rate; s real effective exchange rate; π log of consumer price index.

Chapter 3

Asymmetric Effects of Uncertainty over the Business Cycle: A Quantile Structural Vector Autoregressive Approach

3.1 Introduction

In the wake of the Great Depression, Keynes (1936) notes that business cycles are asymmetric and Fisher (1933) remarks that cycles may be milder depending on the state of the different macrovariables. The past Global Financial Crisis suggests equivalent conclusions. It provides firm evidence for strong asymmetries – or nonlinearities – in the correlation of macroeconomic and financial time series that seem to depend on the state of each variable in the system. This is especially evident in the case of uncertainty. The severity of the last recession is argued to be partially explained by the high level of uncertainty (e.g., Stock and Watson (2012)). That is, the state of uncertainty has been a decisive factor for the intensity of the last recession. In general, Reinhart and Rogoff (2009), Claessens et al. (2012), or Brunnermeier and Sannikov (2013) suggest that the state of the financial sector is crucial for the response of an economy to a shock. Even though, many studies point out the important negative consequences of uncertainty for the economy (see e.g., Bloom (2009), Alexopoulos and Cohen (2009), Bachmann et al. (2013), Bloom et al. (2012), Leduc and Liu (2012), Gilchrist et al. (2013), and Carrière-Swallow and Céspedes (2013)), they do not investigate the nonlinear effects related to cycles. This however is crucial, e.g., for designing policies. Policies target economies at specific phases of their cycles and should thus take these asymmetries into account.

In light of these observations, the present study aims at contributing to the literature by finding evidence for the following three questions: (1) How asymmetric are the effects of uncertainty on the US real economy over the business cycle? (2) How decisive is the phase of the financial sector for the impact of an uncertainty shock on the US real economy? (3) How does the inference over the cycle compare to the effects at the *average state* of the economy?

For the analysis of asymmetries, I propose to relate conditional quantiles of stationary macroeconomic time series to the phases of their cycle. For instance, in the case of (conditional) GDP growth, lower quantiles, i.e., lower growth rates, can rather be attributed to recessions, whereas upper quantiles, i.e., higher growth rates, can be attributed to booms. To fix ideas, consider a univariate regression in which GDP growth is explained by uncertainty, lagged by one period.[1] This relationship can be estimated at different quantiles (τ) using the methodology provided by Koenker and Bassett (1978) or at the mean via ordinary least squares (OLS). Figure 3.1.1 depicts such regression lines (at various quantiles and at the mean) and the data points of US GDP growth versus lagged uncertainty. Further, filled circles represent recession periods.[2] It can be clearly seen that the lower quantile regression lines, i.e.,

[1]For details on the definition of variables and their transformations, please see Appendix 3.C.
[2]These are as defined by the National Bureau of Economic Research.

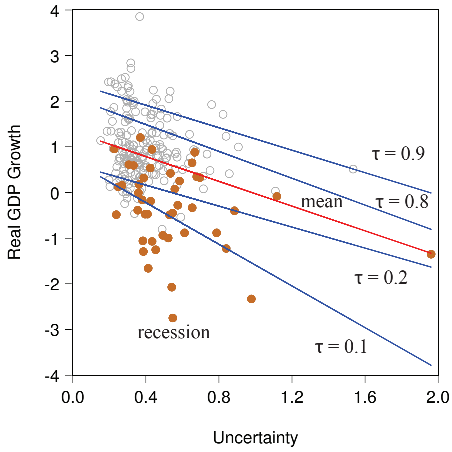

Figure 3.1.1: Scatter Plot with Regression Lines at the Mean and Different Quantiles

Note: The scatter plot shows the data points of quarterly US real GDP growth and US uncertainty lagged by one quarter for the time period 1954Q1 to 2012Q4. For details on the definition of variables see Appendix 3.C. Filled circles depict recession periods as defined by the National Bureau of Economic Research. Regression lines are as indicated for different quantiles and for the mean using ordinary least squares.

for $\tau = \{0.1, 0.2\}$ describe the dependencies during recession periods, while upper quantile regression lines $\tau = \{0.8, 0.9\}$ portray the effect of uncertainty during non-recession, i.e. growth periods. Moreover, the graph yields evidence for nonlinearities in the data as slopes for the lower quantiles differ from each other and the mean. In contrast, in the case of the upper quantiles the regression lines portray marginal effects similar to the mean. Thus, I argue that conditional quantiles capture the asymmetric dependencies over the cycle.

A study of the nonlinear dependencies within an economy requires a structural multiple equation framework, i.e., it is vital to model the interaction effects of a system of variables. Hence, I develop a framework that allows for such an analysis. It is called *Quantile Structural Vector Autoregressive* (QSVAR) model. For the formulation and estimation of the QSVAR, I propose a novel representation of the multivariate Laplace distribution that permits the joint treatment of multiple equation regression quantiles. In this, I build on the work by Koenker and Machado (1999) and Yu and Moyeed (2001) who show that the univariate Laplace distribution may be used to estimate regression quantiles. That is, in some sense, the Laplace distribution behaves to the quantile loss function as the Gaussian distribution behaves to the squared loss function.[3] Yu and Moyeed (2001) suggest Bayesian methods for estimation. This path is taken here as well.

From a methodological perspective, this paper is closely related to Cecchetti and Li (2008). The authors are the first to present a quantile vector autoregressive framework that is estimated via general methods moments. They analyze different effects

[3]The expression *in some sense* is clarified in Section 3.2.

of asset price booms and busts on the economy in two dimensional systems. The present methodology has the advantage that it can easily accommodate higher dimensional models. Through its Bayesian orientation inference is carried out directly within the sampler, while the latter avenue runs into difficulties because of nontrivial matrix differentiations. In addition, as the present methodology analyzes interdependencies over the business cycle, it is also related to Markov switching (MS)-VAR models that were first introduced by Hamilton (1989). Markov switching models assume that the economy is governed by regimes that can be related to booms or busts. The current approach differs in two important aspects. First, each variable can be defined to be at some specific state of the cycle for the analysis, i.e., the quantiles may differ across equations. The MS approach estimates the entire system at one or the other regime. Second, the present methodology estimates the system over a fine grid of the cycle, whereas the MS tool is only feasible for a small number of regimes.

I find that the effects of uncertainty shocks on the US real economy are highly asymmetric over the business cycle. The effects are significantly different from the results for an economy at the *average* state at the lower and upper quantiles.

Results reveal the strongest negative effects on the economy during recession periods. During this phase of the cycle, findings are in line with the usual interpretation of uncertainty shocks. Uncertainty is argued to induce firms to pause investments and to defer consumer spending, leading to a decrease in aggregate demand.[4] Prices fall and the monetary base shrinks, while the monetary authority lowers interest rates. During the deepest recessions uncertainty shocks contribute by 45% to the fluctuations in real GDP growth.[5] The same figure for the *average* state of the economy amounts to 10%.

Strikingly, findings indicate that the economy may experience positive effects in response to an uncertainty shock, namely during the highest boom periods. At this phase a shock to uncertainty causes positive growth in GDP, inflation, money supply, and the federal funds rate. I argue, in light of the evidence, that it represents a sensible finding. This study measures uncertainty by volatility on the stock market. Thus, the measure represents changes in the prices of shares. During strong boom phases uncertainty shocks are found to lead to a rise in these prices. Firms and consumers, hence, interpret unexpected rises in volatility as an improvement of the economic outcome. On this ground I name these unexpected changes exuberance shocks. Further, I interpret this finding as evidence for speculative bubbles. An

[4]See e.g. Romer (1990) for a discussion on the effects on consumer spending. For the impact on firms see, e.g., Bernanke (1983)

[5]The lowest quantile treated in this paper is the 10% quantile, which is here referred to as the deepest recession.

exuberance shock is highly important for fluctuations in inflation and money supply growth, which are key ingredients for the development and final burst of speculative bubbles.

At last, the state of the financial sector is decisive for the effect of an uncertainty shock if the real economy is in recession. If the financial sector is in a bad state the resulting recession is found to be stronger. In contrast, the state of the financial system is not important for an economy at boom in the short run.

The paper is structured as follows. Section 3.2 provides the reader with the basics for understanding quantile regressions and presents the multivariate Laplace distribution for multiple equation quantile regression. Section 3.3 introduces the QSVAR and outlines the sampler for its estimation. Section 3.4 depicts the empirical setup and presents the results. Section 3.5 concludes.

3.2 Quantile Regression and the Laplace Distribution

First, I give a short introduction to single equation quantile regression and highlight the link to the univariate Laplace distribution.[6] In the following, I derive the multivariate generalization of the Laplace distribution that allows for the joint treatment of multiple equation quantile regressions.

3.2.1 Introduction to Single Equation Quantile Regression

The following exposition introduces quantile regression using an autoregressive process with one lag (AR(1)), i.e., $y_t = \phi_\tau y_{t-1} + v_t$ for $t = 1, \ldots, T$, where T denotes the sample size, y_t the endogenous variable, ϕ_τ the autoregressive coefficient at quantile τ ($0 \leq \tau \leq 1$), and v_t the error term.[7] To obtain the estimated marginal effect on the dependent variable at quantile τ, i.e., $\hat{\phi}_\tau$, one needs to solve – given τ – the minimization problem

$$\underset{\phi_\tau}{\operatorname{argmin}} \sum_{t=1}^{T} \rho_\tau(y_t - \phi_\tau y_{t-1}), \qquad \text{where } \rho_\tau(v_t) = \begin{cases} v_t \cdot \tau & \text{, if } v_t \geq 0 \\ v_t \cdot (\tau - 1) & \text{, if } v_t < 0. \end{cases}$$

The loss function in the quantile framework, $\rho_\tau(v_t)$, leads to $\Pr(v_t < 0 | y_{t-1}) = \tau$. Or put differently, $Q_\tau(v_t | y_{t-1}) = 0$ where $Q_\tau(\cdot)$ yields the τ'th quantile of the respective variable.[8] This result entails that $Q_\tau(y_t | y_{t-1}) = \phi_\tau y_{t-1}$.

[6] For a thorough introduction to quantile regression please refer to Koenker (2005).
[7] Quantile Autoregression in the frequentist context is discussed by Koenker and Xiao (2006).
[8] This is a similar condition as $\mathrm{E}(v_t | y_{t-1}) = 0$ in the OLS framework.

It has already been noted that the Laplace distribution behaves to the quantile loss function in some way similar as the Gaussian distribution to the squared loss function of OLS. The Laplace density for the above example may be written as

$$f_\tau(v_t) = \tau(1-\tau)\exp\{-\rho_\tau(v_t)\}.^9 \tag{3.1}$$

The Gaussian versus OLS case is similar in the sense that maximizing the product of the densities, i.e.,

$$\underset{\phi_\tau}{\operatorname{argmax}} \prod_{t=1}^{T} f_\tau(y_t - \phi_\tau y_{t-1})$$

yields a consistent estimate $\hat{\phi}_\tau$. This result for the univariate Laplace distribution is an important finding since it enables the use of Bayesian methods for quantile regressions, as Bayesian methods require a well defined likelihood function.[10] In this context Sriram et al. (2013) show that the use of this density – even under an improper prior – leads to a consistent posterior distribution.

3.2.2 The Multivariate Laplace Distribution for Quantile Regression

This paper develops a multivariate Laplace distribution that can be used for multiple equation quantile regressions. In order to derive the formulation, it is best to begin with the general characteristic function of a univariate Laplace and derive the restrictions for univariate quantile regressions. This result can then be generalized to the multivariate setting.
The Laplace density of equation (3.1) is a special case of the general Laplace distribution. The characteristic function of this general density is given by

$$\Psi_{v_t}(s) = \frac{1}{1 + \frac{1}{2}\sigma^2 s^2 - ims},$$

where $m \in \mathbb{R}$, $\sigma \geq 0$, i is the imaginary unit, and s an arbitrary real number. m reflects the skewness parameter and σ the scale parameter. I denote the distribution

[9] Yu and Zhang (2006) provide a detailed discussion of the characteristics of the univariate Laplace density used for quantile regression.

[10] This finding spurred research on quantile regression in the Bayesian context. For instance, Alhamzawi and Yu (2013) discuss conjugate priors and variable selection. Priors are also discussed in Li et al. (2010) for the use of regularization as, e.g., via lasso. Benoit and van den Poel (2012) offer a model for quantile regression in the case of a dichotomous response variable. Geraci and Bottai (2007), Liu and Bottai (2009), Geraci and Bottai (2013), Luo et al. (2012), Reich et al. (2010), and Kobayashi and Kozumi (2012) present an approach for panel data. Chen and Gerlach (2009) present an approach that accounts for heteroskedasticity that is, e.g., present in financial data.

as $\mathcal{L}(m, \sigma)$. For further details please see Kotz et al. (2001).[11]
If one assumes that

$$m = \frac{1-2\tau}{\tau(1-\tau)} \quad \text{and} \quad \sigma^2 = \frac{2}{\tau(1-\tau)},$$

the distribution turns out to be the one presented in equation (3.1). For the proof please see Appendix 3.A. Let this restricted distribution be denoted by $\mathcal{L}(m_\tau, \sigma_\tau)$.
To extend the above result to the multivariate setting note that, following Kotz et al. (2001), the characteristic function of a general multivariate Laplace is defined as

$$\Psi_{\mathbf{v}_t}(\mathbf{s}) = \frac{1}{1 + \frac{1}{2}\mathbf{s}'\mathbf{\Sigma}\mathbf{s} - i\mathbf{m}'\mathbf{s}},$$

where $\mathbf{v}_t \in \mathbb{R}^d$, $\mathbf{m} \in \mathbb{R}^d$, $\mathbf{\Sigma}$ is a $(d \times d)$ nonnegative definite symmetric matrix, and $\mathbf{s}$ is a $(d \times 1)$ vector of arbitrary real numbers. In addition, d denotes the number of random variables. Let the general multivariate Laplace distribution be denoted by $\mathcal{L}_d(\mathbf{m}, \mathbf{\Sigma})$.
Kotz et al. (2001, p. 247) note that each component of $\mathbf{v}_t$, i.e., v_{jt} $(j = \{1, \ldots, d\})$, admits a univariate representation. This implies that the same restrictions, which are required in the univariate framework, also apply for each component v_{jt}. Additionally, it entails that each univariate Laplace may be defined for a different quantile. Thus, the elements of $\mathbf{m}$ and the diagonal elements of $\mathbf{\Sigma}$ have to fulfill the following criteria

$$m_j = \frac{1-2\tau_j}{\tau_j(1-\tau_j)} \quad \text{and} \quad \sigma_{jj}^2 = \frac{2}{\tau_j(1-\tau_j)}.$$

Let this restricted multivariate Laplace distribution be denoted by $\mathcal{L}_d(\mathbf{m}_{\boldsymbol{\tau}}, \mathbf{\Sigma}_{\boldsymbol{\tau}})$, where $\boldsymbol{\tau} = (\tau_1, \ldots, \tau_d)'$ is a $(d \times 1)$ vector of possibly different quantiles.
While the diagonal elements of $\mathbf{\Sigma}_{\boldsymbol{\tau}}$ are restricted, the off-diagonal elements of $\mathbf{\Sigma}_{\boldsymbol{\tau}}$ are not restricted. These control the covariances between the univariate asymmetric Laplace distributions.[12] The covariances can be decomposed into the product of the unrestricted correlations and the restricted variances, i.e., $\rho_{lk}\sigma_{\tau_l}\sigma_{\tau_k}$, where $l, k \in \{1, \ldots, d\}$ and $\sigma_{\tau_j} = \sqrt{\frac{2}{\tau_j(1-\tau_j)}}$. In this way, $\mathbf{\Sigma}_{\boldsymbol{\tau}}$ may be decomposed to yield

$$\mathbf{\Sigma}_{\boldsymbol{\tau}} = \mathbf{S}_{\boldsymbol{\tau}}\mathbf{R}\mathbf{S}_{\boldsymbol{\tau}}, \tag{3.2}$$

[11] In general, i.e., in the univariate as well as in the multivariate setting Kotz et al. (2001) distinguish between a symmetric and an asymmetric distribution. For quantile regression the asymmetric distribution is of interest, as the symmetric distribution only covers the case of least absolute deviation regression. The symmetric is nested in the asymmetric distribution and given in case $m = 0$.

[12] The bivariate case is discussed in Appendix 3.A.2. This example shows explicitly how the correlation between several univariate asymmetric Laplace distributions is defined.

where $\mathbf{R}$ denotes the correlation matrix with ones on the diagonal and ρ_{lk} as off diagonal elements and $\mathbf{S}_{\boldsymbol{\tau}} = \text{diag}(\sigma_{\tau_1}, \ldots, \sigma_{\tau_d})$. This representation is used in the sampler proposed in this paper.

Finally, note that the quantile restrictions lead to a Laplace distribution with a variance that is, besides the correlation structure in $\mathbf{R}$, completely defined through $\boldsymbol{\tau}$.[13] However, one might wish to relax this restriction on the variance. To this end, let $\mathbf{B}$ denote a scaling parameter, that is defined by $\mathbf{B} = \text{diag}(b_1, \ldots, b_d)$. Following Kotz et al. (2001, p. 254) it holds that $\mathbf{B}\mathbf{v}_t \sim \mathcal{L}_d(\mathbf{B}\mathbf{m}_{\boldsymbol{\tau}}, \mathbf{B}\boldsymbol{\Sigma}_{\boldsymbol{\tau}}\mathbf{B}')$.

3.3 Quantile Structural Vector Autoregressions

This paper provides a methodology for the estimation of reduced form quantile VARs. The structural model is then recovered in a second step by decomposing the covariance matrix of the error term. The reduced form VAR is given as

$$\mathbf{y}_t = \boldsymbol{\nu}_{\boldsymbol{\tau}} + \sum_{i=1}^{p} \mathbf{A}_{\boldsymbol{\tau},i}\mathbf{y}_{t-i} + \mathbf{u}_t, \text{ for } t = 1, \ldots, T, \tag{3.3}$$

where $\mathbf{y}_t = (y_{1t}, y_{2t}, \ldots, y_{dt})'$ is a $(d \times 1)$ vector of endogenous variables, $\boldsymbol{\nu}_{\boldsymbol{\tau}}$ is a $(d \times 1)$ vector of intercepts at quantiles $\boldsymbol{\tau} = (\tau_1, \ldots, \tau_d)'$, $\mathbf{A}_{\boldsymbol{\tau},i}$ for $i = 1, \ldots, p$ denotes the matrix of lagged coefficients of size $(d \times d)$ also at quantiles $\boldsymbol{\tau} = (\tau_1, \ldots, \tau_d)'$, and $\mathbf{u}_t = (u_{1t}, u_{2t}, \ldots, u_{dt})$ is a $(d \times 1)$ vector of error terms.

To obtain the estimated coefficient matrices $\hat{\mathbf{A}}_{\tau,i}$ and $\hat{\boldsymbol{\nu}}_{\boldsymbol{\tau}}$ I propose to assume

$$\mathbf{u}_t \sim \mathcal{L}_d(\mathbf{B}\mathbf{m}_{\boldsymbol{\tau}}, \mathbf{B}\boldsymbol{\Sigma}_{\boldsymbol{\tau}}\mathbf{B}'),$$

and develop in the following a sampler for its estimation.

In order to recover the structural model the covariance matrix of the error is required. Even though the assumption of a multivariate Laplace delivers consistent posteriors for $\mathbf{A}_{\boldsymbol{\tau},i}$ and $\boldsymbol{\nu}_{\boldsymbol{\tau}}$ the methodology does not directly provide an estimate for the covariance matrix of the error. However, similar to Li et al. (2012) and Cecchetti and Li (2008), the covariance matrix can be defined in the following way:

$$\boldsymbol{\Omega}_{\boldsymbol{\tau}} = (\omega_{jk}) = \left(\frac{\text{E}[(\rho_{\tau_j}(u_{jt}))(\rho_{\tau_k}(u_{kt}))]}{\text{E}[f_{u_{jt}}(0)]\text{E}[f_{u_{kt}}(0)]} \right), \text{ where } j, k \in \{1, \ldots, d\}. \tag{3.4}$$

$f_{u_{jt}}(0)$ denotes the pdf of u_{jt} evaluated at 0. For the structural model the estimated covariance matrix $\hat{\boldsymbol{\Omega}}_{\boldsymbol{\tau}}$ may then be decomposed, e.g., by the Cholesky decomposition. For details on the estimation of $\boldsymbol{\Omega}_{\boldsymbol{\tau}}$ please refer to Appendix 3.B.1.

[13] The variance of the multivariate Laplace with quantile restrictions is given by $\mathbf{m}_{\boldsymbol{\tau}}\mathbf{m}_{\boldsymbol{\tau}}' + \boldsymbol{\Sigma}_{\boldsymbol{\tau}}$.

3.3.1 Estimation Setup

In this section I first describe a location scale mixture representation of the multivariate Laplace that is exploited in the Bayesian approach of this paper. It builds on the contributions by Tsionias (2003) and Kozumi and Kobayashi (2011) that are established in the context of the univariate Laplace distribution.
The mixture representation of the multivariate Laplace permits to cast the estimation problem into a maximization problem that involves the normal distribution. Thus, common results for estimation may be applied. More specifically, Kotz et al. (2001, p. 246) note that the multivariate Laplace can be represented in the following way:

$$\mathbf{u}_t = \mathbf{B}\mathbf{m}_{\boldsymbol{\tau}} w_t + \sqrt{w_t}\mathbf{B}\boldsymbol{\Sigma}_{\boldsymbol{\tau}}^{1/2}\mathbf{z}_t,$$

where w_t represents a standard exponential random variable ($w_t \sim \mathcal{E}(1)$) and $\mathbf{z}_t$ is a d-dimensional random vector that is standard multivariate normal ($\mathbf{z}_t \sim \mathcal{N}_d(\mathbf{0}, \mathbf{I}_d)$, where $\mathbf{I}_d$ is the identity matrix of dimension d). $\boldsymbol{\Sigma}_{\boldsymbol{\tau}}^{1/2}$ represents the square root matrix $\boldsymbol{\Sigma}_{\boldsymbol{\tau}}$, that yields $\left(\boldsymbol{\Sigma}_{\boldsymbol{\tau}}^{1/2}\right)\left(\boldsymbol{\Sigma}_{\boldsymbol{\tau}}^{1/2}\right)' = \boldsymbol{\Sigma}_{\boldsymbol{\tau}}$.
This result allows to rewrite equation (3.3) to yield

$$\mathbf{y}_t = \boldsymbol{\nu}_{\boldsymbol{\tau}} + \sum_{i=1}^{p} \mathbf{A}_{\boldsymbol{\tau},i}\mathbf{y}_{t-i} + \mathbf{B}\mathbf{m}_{\boldsymbol{\tau}} w_t + \sqrt{w_t}\mathbf{B}\boldsymbol{\Sigma}_{\boldsymbol{\tau}}^{1/2}\mathbf{z}_t.$$

It follows that the conditional distribution of $\mathbf{y}_t$ given $\mathbf{A}_{\boldsymbol{\tau}}$, $\boldsymbol{\Sigma}_{\boldsymbol{\tau}}$, $\mathbf{B}$, w_t, and $\mathcal{F}_{t-1}$ is normal, where $\mathbf{A}_{\boldsymbol{\tau}}$ denotes the matrix of coefficients $(\boldsymbol{\nu}_{\boldsymbol{\tau}}, \mathbf{A}_{\boldsymbol{\tau},1}, \dots, \mathbf{A}_{\boldsymbol{\tau},p})'$ of dimension $((1 + dp) \times d)$, and $\mathcal{F}_{t-1}$ is the information set that includes all relevant past values of $\mathbf{y}_t$. The first two conditional moments of $\mathbf{y_t}$ are given by:

$$\begin{aligned}
\mathrm{E}[\mathbf{y}_t|\mathbf{A}_{\boldsymbol{\tau}}, \boldsymbol{\Sigma}_{\boldsymbol{\tau}}, \mathbf{B}, w_t, \mathcal{F}_{t-1}] &= \boldsymbol{\nu}_{\boldsymbol{\tau}} + \sum_{i=1}^{p} \mathbf{A}_{\boldsymbol{\tau},i}\mathbf{y}_{t-i} + \mathbf{B}\mathbf{m}_{\boldsymbol{\tau}} w_t = \boldsymbol{\mu}_{\boldsymbol{\tau},t} \\
\mathrm{V}[\mathbf{y}_t|\mathbf{A}_{\boldsymbol{\tau}}, \boldsymbol{\Sigma}_{\boldsymbol{\tau}}, \mathbf{B}, w_t, \mathcal{F}_{t-1}] &= w_t\mathbf{B}\boldsymbol{\Sigma}_{\boldsymbol{\tau}}\mathbf{B}' = w_t\boldsymbol{\Sigma}_{\boldsymbol{\tau}\star},
\end{aligned}$$

where $\boldsymbol{\Sigma}_{\boldsymbol{\tau}\star} = \mathbf{B}\boldsymbol{\Sigma}_{\boldsymbol{\tau}}\mathbf{B}'$. Thus, it holds that

$$\mathbf{y}_t|\mathbf{A}_{\boldsymbol{\tau}}, \boldsymbol{\Sigma}_{\boldsymbol{\tau}}, \mathbf{B}, w_t, \mathcal{F}_{t-1} \sim \mathcal{N}_d(\boldsymbol{\mu}_{\boldsymbol{\tau},t}, w_t\boldsymbol{\Sigma}_{\boldsymbol{\tau}\star}). \tag{3.5}$$

For the complete likelihood function please refer to Appendix 3.B.2.

3.3.2 Bayesian Inference

This section introduces the conditional posterior distributions of $\boldsymbol{\alpha}_{\boldsymbol{\tau}}$, $\boldsymbol{\Sigma}_{\boldsymbol{\tau}}$, w_t, and $\mathbf{B}$, which are used in the proposed Metropolis-within-Gibbs sampler. $\boldsymbol{\alpha}_{\boldsymbol{\tau}}$ denotes the column vector $\text{vec}(\mathbf{A}_{\boldsymbol{\tau}})$ of size $(d(dp+1)\times 1)$. To ease the exposition I first cast the VAR model in compact form.

$$\mathbf{y} = (\mathbf{I}_d \otimes \mathbf{X})\boldsymbol{\alpha}_{\boldsymbol{\tau}} + (\mathbf{B}\mathbf{m}_{\boldsymbol{\tau}} \otimes \mathbf{I}_T)\mathbf{w} + \left(\mathbf{B}\boldsymbol{\Sigma}_{\boldsymbol{\tau}}^{1/2} \otimes \mathbf{W}^{1/2}\right)\mathbf{z},$$

where $\mathbf{y} = \text{vec}(\mathbf{y}_1, \ldots, \mathbf{y}_T)'$ is a $(Td\times 1)$ vector of observations, $\mathbf{X} = (\mathbf{x}_1', \ldots, \mathbf{x}_T')'$ is a $(T\times(dp+1))$ matrix, where $\mathbf{x}_t = (1, \mathbf{y}_{t-1}', \ldots, \mathbf{y}_{t-p}')$ represents a $(1\times(dp+1))$ vector, $\mathbf{w} = (w_1, \ldots, w_T)'$ is a $(T\times 1)$ vector and $\mathbf{W} = \text{diag}(\mathbf{w})$ reflects a $(T\times T)$ diagonal matrix. Thus, $\mathbf{W}^{1/2} = \text{diag}(\sqrt{w}_1, \ldots, \sqrt{w}_T)$. $\mathbf{z} = \text{vec}(\mathbf{z}_1, \ldots, \mathbf{z}_T)$ denotes a $(Td\times 1)$ vector of standard multivariate normal random variables. Subsequently, the posteriors are introduced.

3.3.2.1 Conditional Posteriors of $\boldsymbol{\alpha}_{\boldsymbol{\tau}}$ and $\boldsymbol{\Sigma}_{\boldsymbol{\tau}}$

The prior is assumed to be of an independent Normal-inverse Wishart ($\mathcal{IW}$) type:[14]

$$\boldsymbol{\alpha} \sim \mathcal{N}(\underline{\boldsymbol{\alpha}}, \underline{\mathbf{V}}) \quad \text{and} \quad \boldsymbol{\Sigma} \sim \mathcal{IW}(\underline{\boldsymbol{\Sigma}}, \underline{\nu}).$$

Prior times likelihood yields the standard posterior probability density functions:[15]

$$\boldsymbol{\alpha}_{\boldsymbol{\tau}}|\mathbf{y}, \boldsymbol{\Sigma}_{\boldsymbol{\tau}}, \mathbf{B}, \mathbf{w} \sim \mathcal{N}(\overline{\boldsymbol{\alpha}}_{\boldsymbol{\tau}}, \overline{\mathbf{V}}_{\boldsymbol{\tau}}) \quad \text{and} \quad \boldsymbol{\Sigma}_{\boldsymbol{\tau}}|\mathbf{y}, \boldsymbol{\alpha}_{\boldsymbol{\tau}}, \mathbf{B}, \mathbf{w} \sim \mathcal{IW}(\overline{\boldsymbol{\Sigma}}_{\boldsymbol{\tau}}, \overline{\nu}),$$

where

$$\begin{aligned}\overline{\mathbf{V}}_{\boldsymbol{\tau}} &= [\underline{\mathbf{V}} + ((\mathbf{B}\boldsymbol{\Sigma}_{\boldsymbol{\tau}}\mathbf{B}')^{-\mathbf{1}} \otimes (\mathbf{X}'\mathbf{W}^{-\mathbf{1}}\mathbf{X}))]^{-1}\\ \overline{\boldsymbol{\alpha}}_{\boldsymbol{\tau}} &= \overline{\mathbf{V}}_{\boldsymbol{\tau}}[\underline{\mathbf{V}}^{-\mathbf{1}}\underline{\boldsymbol{\alpha}} + ((\mathbf{B}\boldsymbol{\Sigma}_{\boldsymbol{\tau}}\mathbf{B}')^{-1} \otimes \mathbf{X}'\mathbf{W}^{-\mathbf{1}})(\mathbf{y} - (\mathbf{B}\mathbf{m}_{\boldsymbol{\tau}} \otimes I_T)\mathbf{w})]\end{aligned}$$

and

$$\begin{aligned}\overline{\nu} &= \underline{\nu} + T\\ \overline{\boldsymbol{\Sigma}}_{\boldsymbol{\tau}} &= \underline{\boldsymbol{\Sigma}} + (\mathbf{B}')^{-1}(\mathbf{Y} - \mathbf{X}\mathbf{A}_{\boldsymbol{\tau}} - \mathbf{w}(\mathbf{B}\mathbf{m}_{\boldsymbol{\tau}})')'\mathbf{W}^{-1}(\mathbf{Y} - \mathbf{X}\mathbf{A}_{\boldsymbol{\tau}} - \mathbf{w}(\mathbf{B}\mathbf{m}_{\boldsymbol{\tau}})')(\mathbf{B})^{-1}.\end{aligned}$$

[14] All prior distributions are assumed to be independent of the remaining parameters. For instance, I assume for the prior of $\boldsymbol{\alpha}$ that $f(\boldsymbol{\alpha}|\boldsymbol{\Sigma}, \mathbf{B}, w_t) = f(\boldsymbol{\alpha})$. As indicated, priors do not necessarily depend on the chosen quantiles $\boldsymbol{\tau}$.

[15] The decomposition of $(\mathbf{Y} - \mathbf{X}\mathbf{A}_{\boldsymbol{\tau}} - \mathbf{w}(\mathbf{B}\mathbf{m}_{\boldsymbol{\tau}})')'\mathbf{W}^{-1}(\mathbf{Y} - \mathbf{X}\mathbf{A}_{\boldsymbol{\tau}} - \mathbf{w}(\mathbf{B}\mathbf{m}_{\boldsymbol{\tau}})')$ into $(\mathbf{Y} - \mathbf{X}\hat{\mathbf{A}}_{\boldsymbol{\tau}} - \mathbf{w}(\mathbf{B}\mathbf{m}_{\boldsymbol{\tau}})')'\mathbf{W}^{-1}(\mathbf{Y} - \mathbf{X}\hat{\mathbf{A}}_{\boldsymbol{\tau}} - \mathbf{w}(\mathbf{B}\mathbf{m}_{\boldsymbol{\tau}})')$ and $(\mathbf{A}_{\boldsymbol{\tau}} - \hat{\mathbf{A}}_{\boldsymbol{\tau}})\mathbf{X}'\mathbf{W}^{-\mathbf{1}}\mathbf{X}(\mathbf{A}_{\boldsymbol{\tau}} - \hat{\mathbf{A}}_{\boldsymbol{\tau}})$ also holds in this context.

3.3.2.2 Conditional Probability Density Function of the Latent Variable w_t

The conditional probability density of w_t is proportional to

$$f(w_t|\mathbf{y_t}, \mathbf{A}_{\boldsymbol{\tau}}, \boldsymbol{\Sigma}_{\boldsymbol{\tau}}, \mathbf{B}, \mathcal{F}_{t-1}) \propto w_t^{-d/2} \exp\left(-\frac{1}{2}\left(a_{\boldsymbol{\tau},t} w_t^{-1} + b_{\boldsymbol{\tau}} w_t\right)\right),$$

with $a_{\boldsymbol{\tau},t} = (\mathbf{y}_t - \boldsymbol{\nu}_{\boldsymbol{\tau}} - \sum_{i=1}^{p} \mathbf{A}_{\boldsymbol{\tau},i}\mathbf{y}_{t-i})'(\mathbf{B}\boldsymbol{\Sigma}_{\boldsymbol{\tau}}\mathbf{B}')^{-1}(\mathbf{y}_t - \boldsymbol{\nu}_{\boldsymbol{\tau}} - \sum_{i=1}^{p} \mathbf{A}_{\boldsymbol{\tau},i}\mathbf{y}_{t-i})$ and $b_{\boldsymbol{\tau}} = 2 + \mathbf{m}_{\boldsymbol{\tau}}'{\boldsymbol{\Sigma}_{\boldsymbol{\tau}}}^{-1}\mathbf{m}_{\boldsymbol{\tau}}$. This implies that w_t, conditional on the latter parameters, is proportional to a generalized inverse Gaussian with the following parameters:[16]

$$w_t|\mathbf{y}_t, \boldsymbol{\Sigma}_{\boldsymbol{\tau}}, \mathbf{B}, \mathbf{A}_{\boldsymbol{\tau}}, \mathcal{F}_{t-1} \sim \mathcal{GIG}\left(-d/2+1, a_{\boldsymbol{\tau},t}, b_{\boldsymbol{\tau}}\right).$$

For details on the derivation please see Appendix 3.B.3.

3.3.2.3 Conditional Posterior of B

I assume a noninformative prior for $\mathbf{B}$, i.e. let

$$f(\mathbf{B}) = \text{const.}$$

The conditional posterior of $\mathbf{B}$ then follows the likelihood of a $\mathcal{L}_d(\mathbf{B}\mathbf{m}_{\boldsymbol{\tau}}, \boldsymbol{\Sigma}_{\boldsymbol{\tau}\star})$. Following Kotz et al. (2001), it is given by:

$$\begin{aligned} &f(\mathbf{B}|\mathbf{y}, \boldsymbol{\alpha}_{\boldsymbol{\tau}}, \boldsymbol{\Sigma}_{\boldsymbol{\tau}}) \propto \\ &\prod_{t=1}^{T} \frac{2\exp\left((\mathbf{y}_t - \boldsymbol{A}_{\boldsymbol{\tau}}'\mathbf{x}_t')'\boldsymbol{\Sigma}_{\boldsymbol{\tau}\star}^{-1}\mathbf{B}\mathbf{m}_{\boldsymbol{\tau}}\right)}{(2\pi)^{d/2}|\boldsymbol{\Sigma}_{\boldsymbol{\tau}\star}|^{1/2}} \left(\frac{(\mathbf{y}_t - \boldsymbol{A}_{\boldsymbol{\tau}}'\mathbf{x}_t')'\boldsymbol{\Sigma}_{\boldsymbol{\tau}\star}^{-1}(\mathbf{y}_t - \boldsymbol{A}_{\boldsymbol{\tau}}'\mathbf{x}_t')}{2 + \mathbf{m}_{\boldsymbol{\tau}}'\boldsymbol{\Sigma}_{\boldsymbol{\tau}}^{-1}\mathbf{m}_{\boldsymbol{\tau}}}\right)^{(-d/2+1)} \\ &\qquad K_{(-d/2+1)}\left(\sqrt{(2 + \mathbf{m}_{\boldsymbol{\tau}}'\boldsymbol{\Sigma}_{\boldsymbol{\tau}}^{-1}\mathbf{m}_{\boldsymbol{\tau}})((\mathbf{y}_t - \boldsymbol{A}_{\boldsymbol{\tau}}'\mathbf{x}_t')'\boldsymbol{\Sigma}_{\boldsymbol{\tau}\star}^{-1}(\mathbf{y}_t - \boldsymbol{A}_{\boldsymbol{\tau}}'\mathbf{x}_t'))}\right), \quad (3.6) \end{aligned}$$

where $K_{(-d/2+1)}(\cdot)$ reflects the modified Bessel function of the second kind of order $-d/2+1$.

3.3.2.4 Metropolis-within-Gibbs Sampler

The sampling of the $\boldsymbol{\alpha}_{\boldsymbol{\tau}}$ coefficients and w_t is a straightforward task using a Gibbs sampler. However, the draw of the correlations, i.e., the off-diagonal elements of $\mathbf{R}$ that are represented in $\boldsymbol{\Sigma}_{\boldsymbol{\tau}}$, and the scaling factors in $\mathbf{B}$ cannot be considered as a similarly straightforward task.

[16] There are several algorithms available for the generation of random numbers from a generalized inverse Gaussian. I apply the one proposed by Devroye (2012) as it is computationally fast.

I propose to use the conditional posterior of $\boldsymbol{\Sigma_\tau}$ and standardize each draw to infer on the correlations between the variables.[17] Note that equation (3.2) yields that each draw of $\boldsymbol{\Sigma_\tau}$ can be rearranged as

$$\mathbf{R} = \mathbf{S}_{\boldsymbol{\tau}}^{\mathbf{-1}} \boldsymbol{\Sigma_\tau} \mathbf{S}_{\boldsymbol{\tau}}^{\mathbf{-1}}$$

in order to conclude on the correlations. Thereby, one achieves that the diagonal elements of $\boldsymbol{\Sigma_\tau}$ remain unchanged. This is important because quantile restrictions on the Laplace distribution have to remain fixed to obtain a consistent posterior for $\boldsymbol{\alpha_\tau}$. Having drawn the new correlation matrix $\mathbf{R}$ the covariance matrix $\boldsymbol{\Sigma_\tau}$ can be updated using equation (3.2) again.

In the case of $\mathbf{B}$, the posterior probability density function is rather complicated as the matrix appears both in the mean and the variance of the conditional distribution of $\mathbf{y_t}$ (e.g., equation (3.5)). Thus, for the draw of $\mathbf{B}$ I propose to use a random walk Metropolis-Hasting (MH) algorithm that just requires that the conditional posterior probability density function can be evaluated (see Chib and Greenberg (1995)). In contrast to the Gibbs sampler, not every draw is accepted using the MH algorithm. At each draw an acceptance probability is calculated and compared to a random draw of a uniform random variable to decide on its acceptance. If not accepted, the previous draw is taken as the new draw. The acceptance probability is derived as in the following. Given a new draw of $\mathbf{B}$, called $\mathbf{B}^*$, and the last draw $\mathbf{B}^{(j-1)}$, where $j \in \{1, \dots, N\}$, it is

$$\alpha_{\text{MH},\mathbf{B}}(\mathbf{B}^{(j-1)}, \mathbf{B}^*) = \min \left[\frac{f\left(\mathbf{B}^*|\mathbf{y}, \boldsymbol{\alpha}_{\boldsymbol{\tau}}^{(j)}, \boldsymbol{\Sigma}_{\boldsymbol{\tau}}^{(j)}, \mathbf{w}^{(j)}\right)}{f\left(\mathbf{B}^{(j-1)}|\mathbf{y}, \boldsymbol{\alpha}_{\boldsymbol{\tau}}^{(j)}, \boldsymbol{\Sigma}_{\boldsymbol{\tau}}^{(j)}, \mathbf{w}^{(j)}\right)}, 1 \right].^{18}$$

I calibrate the acceptance probability to be between 0.2 and 0.5. For a good introduction to the MH algorithm see Koop (2006).

In the following, the algorithm is depicted for the case when draws of the scaling parameters are carried out jointly. This, of course, can be broken down into separate steps to ease the calibration of the acceptance rate. Furthermore, a random walk MH algorithm may be carried out using any symmetric distribution in the innovation

[17] The other option would be to use a Metropolis-Hasting algorithm and sample the off diagonal elements of $\boldsymbol{\Sigma_\tau}$. A Gibbs sampler, however, is preferred as every draw is accepted, thus convergence is faster. Simulation studies have shown that both options provide consistent estimates.

[18] In the depiction of the acceptance probabilities the draws of the other variables are also used as conditioning variables. Variables at draw (j) or $(j-1)$ are chosen in line with the algorithm presented in this section, however, they may of course vary according to the ordering in the sampler used.

part. This paper assumes a normal distribution.[19]

Algorithm: Bayesian Quantile VAR

1. Define prior distribution for $\boldsymbol{\alpha_\tau}$ and $\boldsymbol{\Sigma_\tau}$ and set starting values $\boldsymbol{\alpha^0_\tau}$, $\boldsymbol{\Sigma^0_\tau}$ and $\mathbf{B^0}$. Set variance, c, of the random walk innovation used in the MH step.

2. Repeat for $j = 1, 2, \ldots, N$

   (a) Gibbs Step 1:
   For $t = 1, \ldots, T$:
   Draw $w_t^{(j)}|\mathbf{y}_t, \boldsymbol{\alpha_\tau}^{(j-1)}, \boldsymbol{\Sigma_\tau}^{(j-1)}, \mathbf{B}^{(j-1)}$

   (b) Gibbs Step 2:
   Draw $\boldsymbol{\alpha_\tau}^{(j)}|\mathbf{y}, \boldsymbol{\Sigma_\tau}^{(j-1)}, \mathbf{B}^{(j-1)}, \mathbf{w}^{(j)}$

   (c) Gibbs Step 3:

      i. Draw $\boldsymbol{\Sigma_\tau^{(j)}}|\mathbf{y}, \boldsymbol{\alpha_\tau^{(j)}}, \mathbf{B^{(j-1)}}, \mathbf{w^{(j)}}$

      ii. Calculate $\mathbf{R^{(j)}} = \mathbf{S_\tau^{-1}}\boldsymbol{\Sigma_\tau^{(j)}}\mathbf{S_\tau^{-1}}$

      iii. Set $\boldsymbol{\Sigma_\tau^{(j)}} = \mathbf{S_\tau}\mathbf{R^{(j)}}\mathbf{S_\tau}$

   (d) MH Step 1:

      i. Draw $\mathbf{v}_{**} \sim \mathcal{N}(\mathbf{0}, c \cdot \mathbf{I_d})$

      ii. Calculate $(b_1^*, \ldots, b_d^*)' = \left(b_1^{(j-1)}, \ldots, b_d^{(j-1)}\right)' + \mathbf{v}_{**}$

      iii. Evaluate $\alpha_{\mathrm{MH},\mathbf{B}}$

      iv. Draw $u_{**} \sim \mathcal{U}(0, 1)$

      v. If $u_{**} \leq \alpha_{\mathrm{MH},\mathbf{B}}$
      set $\left(b_1^{(j)}, \ldots, b_d^{(j)}\right)' = (b_1^*, \ldots, b_d^*)'$
      else
      set $\left(b_1^{(j)}, \ldots, b_d^{(j)}\right)' = \left(b_1^{(j-1)}, \ldots, b_d^{(j-1)}\right)'$

[19] In practice, I draw the elements of $\mathbf{B}$ separately. Thus, there are d scaling parameters, which are each adjusted automatically to satisfy the above mentioned acceptance ratio.

3.4 Nonlinear Effects of Uncertainty Shocks on the US Real Economy over the Cycle(s)

First, I detail the data, its transformations, the model setup, and the analysis as well as the identification of the structural shock. Second, I present the results of the analysis that assumes one cycle for the economy. Third, I discuss the findings on the asymmetries over the financial cycle. In each section, first the impulse response analysis and then the forecast error variance decomposition exercise are presented. A robustness analysis concludes this section.

3.4.1 Empirical Issues

Data and Transformations

To investigate the nonlinear effects of uncertainty shocks across quantiles this study includes variables that are commonly used in the analysis of financial market shocks.[20] That is, I formulate a small model of the US economy that also includes uncertainty alongside the standard variables as real economic activity, inflation, interest rates, and real money supply. The data set is of quarterly frequency and spans from 1954Q2 to 2012Q4.

Economic activity is measured by real GDP growth (Δq), inflation by growth in CPI (Δp), interest rates by changes in the effective federal funds rate (Δi), and real money supply by growth in real M2 (Δm). Uncertainty is measured by stock market volatility (u) and calculated as the sum of absolute returns of the Dow Jones Industrial index over each quarter.[21] All variables, their transformations, and their times series plots are presented in Appendix 3.C. In general, only stationary transformations of the series are included, as the derivation of quantiles for trending variables as, for instance, real GDP, is not sensible. It would imply an ordering over time and not over the different phases of the business cycle. Further, stock market volatility is converted such that lower quantiles can be attributed to recession periods

[20] See for instance Helbling et al. (2011), Meeks (2012), Hubrich and Tetlow (2012), or Fink and Schüler (2013).

[21] Studies differ strongly in the variable that is used to measure uncertainty. Apart from the measure applied in this study, Alexopoulos and Cohen (2009) construct an index on the basis of new paper articles to measure uncertainty. Bloom (2009) constructs a dichotomous index on the basis of stock market volatility that turns to one when, in response to an economic or political event, volatility rises above a certain threshold. Events are, e.g., the 9/11 terrorist attacks or the recent credit crunch during the Global Financial Crisis. Similarly, Carrière-Swallow and Céspedes (2013) measure only volatility above a certain threshold. The remaining time periods are assumed to be zero. Leduc and Liu (2012), Bachmann et al. (2013), and Bloom et al. (2012) exploit surveys on either consumers or businesses. Gilchrist et al. (2013) employ high-frequency firm-level stock market data.

and upper quantiles to booms. That is, u is multiplied by -1 to yield u^*. This entails that high levels of volatility which rather correspond to recession periods are in the lower quantiles of u^*. The other variables do not require any transformation as they are already aligned with the quantiles of GDP growth. This means that lower GDP growth tends to correspond to lower inflation, lower interest rates, and lower money supply growth.[22] In this manner, the model is set up in a way such that all the dynamics at one specific quantile reflect a similar phase of the cycle.[23]

Model Setup, Estimation, and Structural Analysis

Throughout the study, I consider a non-informative prior, so that the data is allowed to drive the estimation of the parameters. The priors are

$$\boldsymbol{\alpha} \sim \mathcal{N}(\mathbf{0}, \mathbf{I}_{d(pd+1)} \cdot 10) \qquad \text{and} \qquad \boldsymbol{\Sigma} \sim \mathcal{IW}(d, \mathbf{I}_d).$$

Due to the desire to use non-informative prior information, I am required to specify the model as parsimoniously as possible. Thus, I choose a lag length of 1.

The Metropolis-within-Gibbs sampler is set up with 15000 draws where 5000 are discarded as burn-in-draws. The convergence of the parameters is assured using trace plots.

In the structural analysis I normalize the size of the uncertainty shock across quantiles to ensure comparability. The magnitude of the shock is assumed to be one standard deviation of the volatility variable u^*. Putting this into context, the highest volatility spike during the last financial crisis was 7.5 standard deviations away from its historical average. The study considers a positive shock to risk, i.e., a rise in stock market volatility.[24] It is important to note that throughout the analysis I assume the economy to remain in the same state or quantile after the shock occurred. This represents an unrealistic assumption as a shock on a system would most likely cause an economy to change its state. Nonetheless, there is no theory that would indicate the path of this change. At last, the forecast error variance decomposition exercise uses the un-normalized decomposed covariance matrix as presented in equation (3.4). Its decomposition is discussed in the following.

[22] The objective of aligning equations with the business cycle could also be achieved differently. The model is flexible enough to specify the quantile for each equation differently. Thus, instead of multiplying a series by -1 and estimating it, e.g., at $\tau = 0.2$, one could also omit the transformation and estimate the specific equation at $\tau = 0.8$. The approach followed in this paper, however, is preferred, as the presentation of the results is more intuitive. Otherwise, the reader would have to keep in mind to read the graphs for one variable at τ and for another at $1 - \tau$, to understand the effects of each model that has been estimated.

[23] Of course, this methodology can accommodate any combination that the researcher requires as, e.g., medium GDP growth during periods of high inflation.

[24] This entails that graphs of the impulse response analyses have been re-transformed, because the variable u^* has been used in the estimation process. Here a rise signifies a decrease in volatility.

Identification and Discussion of the Structural Shock

To identify the structural shock, first, the reduced form VAR is estimated. Second, the obtained covariance matrix is decomposed using a Cholesky decomposition, which implies a recursive structure for the shocks. The ordering of the Wold causal chain for the standard variables follows the one of monetary policy VARs (see, e.g., Leeper et al. (1996) or Christiano et al. (1999)). This entails that the production sector is arranged first (economic activity, prices), then the policy sector is specified (interest rate, money). At last, I introduce the financial sector through stock market volatility. This order entails that the financial variable may be affected contemporaneously by shocks in the production and policy sector. However, an uncertainty shock does not affect the production or policy sector in the quarter of the shock. This is in line with the identification used in Gilchrist et al. (2013), who also research on the importance of uncertainty.[25]

The identification of financial shocks in general is no trivial issue. Due to the fact that financial variables are sensitive to new information and this sensitivity is not constant it is difficult to pin down what exactly is driving the structural error of the variable. Some studies in this context, e.g., Meeks (2012), Helbling et al. (2011), Eickmeier et al. (2011), use sign restrictions. However, there are no theoretical concepts that would explain how the real economy reacts to an uncertainty shock at different quantiles.

In the SVAR study by Alexopoulos and Cohen (2009) the authors use a Cholesky decomposition as well. However, the authors permit that the uncertainty shock instantaneously affects the real economy.[26] In juxtaposition, I argue that the exact opposite identification is sensible. Uncertainty is a measure related to expected future economic developments. Thus, it is important that the uncertainty shock is not related to past or contemporaneous movements in the production or policy sector. I argue that expectations are the decisive factor driving uncertainty and should, thus, be accounted for in an analysis of the latter.

3.4.2 Asymmetries over the Business Cycle

This section assumes that the economy is driven by one cycle. Thus, variables in this part of the analysis are estimated at the same conditional quantile, i.e., $\boldsymbol{\tau} = (\tau, \ldots, \tau)'$.

[25] In addition to real variables, however, the authors include other financial variables, as e.g. credit spreads. These are allowed to be contemporaneously affected by an uncertainty shock.

[26] Bloom (2009), Carrière-Swallow and Céspedes (2013), Leduc and Liu (2012) also use a Cholesky decomposition and order their uncertainty variable such that it may influence the real economy instantaneously. However, as indicated, their measure is different to the one employed in this paper. Thus, a different argument applies.

3.4.2.1 Impulse Response Analysis

This exercise reveals two important findings: (1) Responses of the US real economy to an uncertainty shock are highly asymmetric over the business cycle; especially at the extremes of the cycle. There are strong negative effects on the economy during recessions, but also weak positive effects during booms. Moving from recession to boom the negative effects decrease and then turn positive and increase. (2) Responses to an uncertainty shock over the cycle are significantly different from the responses of the Gaussian model for most quantiles. The mean model predicts effects that are within the set of effects of all estimated models at the various quantiles; mostly being around the average effect of the outcomes over the quantiles. In the following, I provide a description of the results. Subsequently, an economic interpretation is provided.

These results are portrayed in Figure 3.4.1. It shows the responses of each variable in the system to an uncertainty shock of one standard deviation that leads to a rise in volatility. Due to the transformation of u^* it is important to keep in mind that lower quantiles of this variables correspond to periods of high volatility. The left panel depicts the complete impulse responses for quantiles $\tau = 0.1$ (black) and 0.9 (gray).[27] The right panel portrays responses over the quantiles 2 quarters after the shock. These are depicted by bold (blue) lines. Further, it shows the effects that a standard Gaussian model would predict; thin (red) lines. The dotted lines refer to the 68% probability bands. Please refer to Appendix 3.D, for the complete impulse responses in comparison to the mean for specific quantiles ($\tau = \{0.1, 0.2, 0.5, 0.8, 0.9\}$).

In the case of output growth (Δq), a shock at the lowest considered quantile leads to a strong negative decline of about 0.57 percentage points (p.p.) after half a year, while it causes a positive deviation of 0.13 p.p. at the highest quantile, i.e., the lowest state of volatility. The right panel, shows that the turning point, i.e., from a negative response to a positive one lies in the upper range of the quantiles. Thus, only at the highest quantiles output growth rises in response to an uncertainty shock.[28] The effect at the mean is measured to be -0.21 p.p after two quarters. It is, thus, about three times smaller than at the lowest estimated quantile. Further, probability bands of responses for the quantiles do not cross with the mean off the center of the distribution indicating significant differences.

Inflation (Δp) responds in a similar fashion except that the responses at the upper tail of the distribution are stronger than at the lower one. Prices fall at the lower tail by 0.17 p.p., while there is a rise of about 0.33 p.p. at the upper tail after 2

[27] As quantiles are set mutually for all variables in this exercise, I report only a scalar quantile, i.e., for ease of exposition I do not report the vector of quantiles as $\boldsymbol{\tau} = (\tau, \ldots, \tau)'$.

[28] Also at $\tau = 0.85$, there is a positive deviation in response to an uncertainty shock.

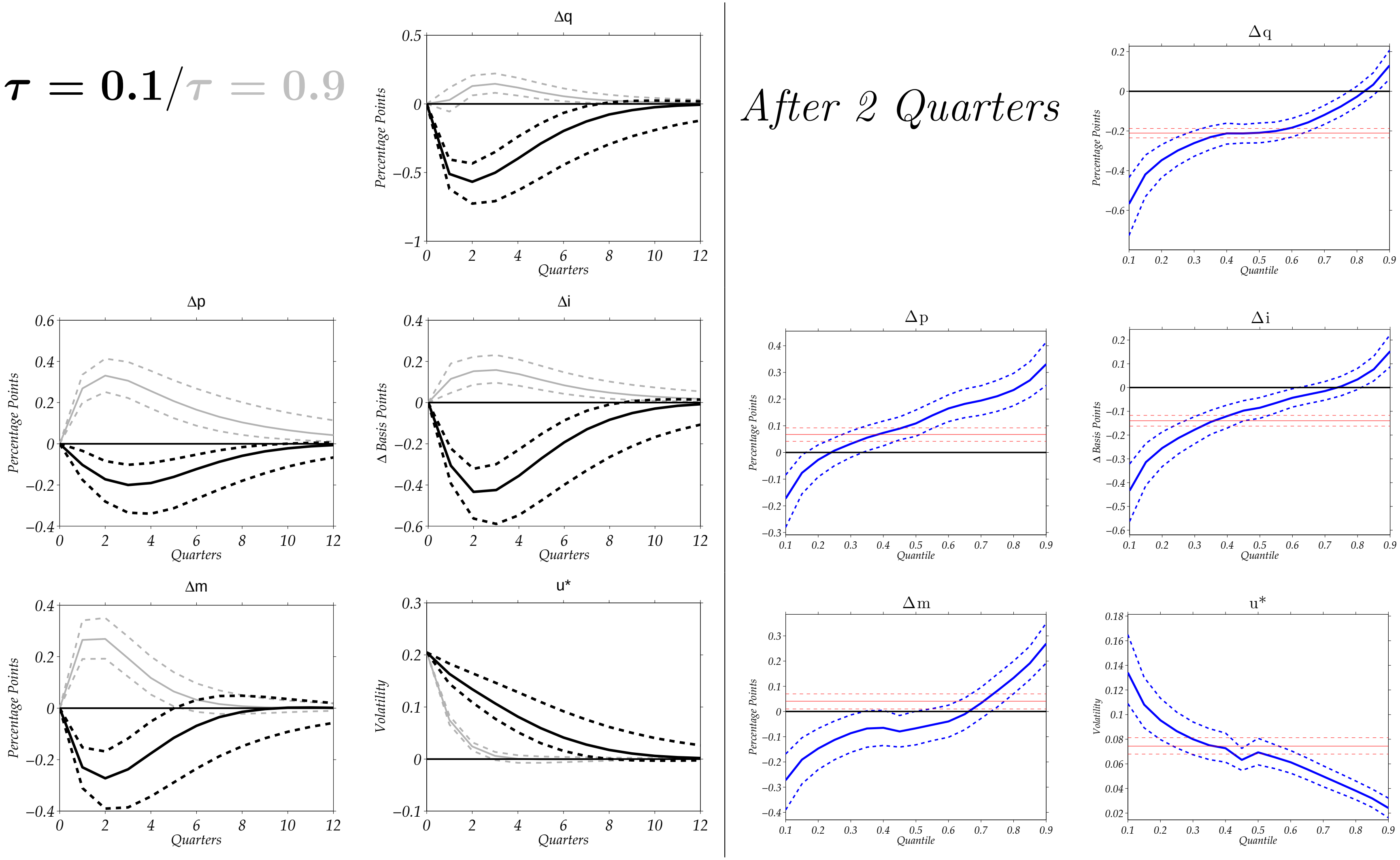

Figure 3.4.1: Response of the US Economy to an Uncertainty Shock: Left Panel: Responses at the lowest ($\tau = 0.1$) and highest ($\tau = 0.9$) quantile. Right panel: Responses After 2 Quarters Across Quantiles Compared to the Gaussian Model

Notes: The left panel depicts the complete impulse responses for quantiles $\tau = 0.1$ (black) and 0.9 (gray). The right panel portrays responses over the quantiles 2 quarters after the shock. It depicts impulse responses across quantiles (blue & thick lines) and at the mean (red & thin lines). The impulse of the uncertainty shock is normalized to one standard deviation of u*. Solid lines refer to the median impulse response obtained at each quantile. The dashed lines correspond to posterior 68% probability bands. Δq denotes real GDP growth; Δp inflation; Δi changes in the interest rate; Δm growth in money supply; u* volatility. Figures are calculated for $\tau = \{0.1, 0.15, \ldots, 0.85, 0.9\}$.

quarters. The mean response is by far smaller, 0.06 p.p. The probability bands of the models at the quantiles and the mean do not cross at lower parts, above the center, and the upper parts of the distribution.

There is also evidence for asymmetry in the response of interest rate changes (Δi) . They are lowered by about 0.43 basis point (b.p.) at quarter 2 at the lowest quantile and raised by about 0.15 b.p. at the other extreme of the distribution. The mean response only amounts to a change of -0.13 b.p. As with inflation the probability bands of the models at the quantiles and the mean do not cross at the lower and upper parts of the distribution.

Using the quantile approach, results indicate that money growth (Δm) only responds significantly to an uncertainty shock at the lowest and highest phases of the cycle (except for $\tau = 0.45$). The maximum decrease after half a year is at $\tau = 0.1$ by 0.27 p.p. The maximum increase after 2 quarters is at $\tau = 0.9$ with 0.27 p.p. as well. The effect at the mean is slightly positive and amounts to 0.04 p.p.

The response of stock market volatility (u*) is positive as assumed. Most strikingly, the persistence of the shock varies. At the lower parts of the distribution it is more persistent than at the mean, which can be explained by the phenomenon of volatility clustering during high states of volatility. Starting from $\tau = 0.65$ the shock is significantly less persistent than at the mean.

The findings during recession periods are in line with theoretical considerations. A shock to uncertainty leads firms to pause investments and hiring decisions; consumers postpone consumption. This has a negative effect on economic activity. Decreasing demand leads to downward pressure on prices and the stock of money in the economy shrinks. The monetary authority reduces interest rates in order to stimulate investments.

The decrease in negative effects of uncertainty when the economy passes from the worst recession towards periods of higher growth is also in line with theoretical considerations. On the one hand, the level of uncertainty decreases in this setup and, on the other hand, the economy itself is more sound and, thus, more immune to uncertainty.

At last, the positive effects during the highest boom periods raise some questions as they contradict the common understanding of the effects of uncertainty. Nonetheless, I argue that this finding is sensible. In light of the evidence, this shock should rather be interpreted as an exuberance shock. Investors during this phase of the cycle have highest expectations about future growth. Thus a shock to changes in the returns on the stock market is not perceived as a bad signal. In turn, output growth remains rising, inflation pressure grows, and money supply rises, while the monetary authority attempts to cool down the economy by increasing the interest rate. As discussed previously, volatility is driven by investors' expectations about the future development of the economy. Thus, this result can be supported by the latter argument. Further, this can be argued to be an empirical description of the phenomenon of speculative bubbles. At some point, even in response to a signal usually interpreted as negative, the economy remains on its growth path, which, at a certain moment, cannot be sustained by the economic fundamentals.

3.4.2.2 Forecast Error Variance Decomposition

Two important results emerge: (1) Uncertainty shocks are decisive for the US real economy. They explain up to 45% of fluctuations in GDP growth over 2 to 3 years. In general, the highest contribution of an uncertainty shock can be found during recession periods. During high phases of the economic cycle uncertainty shocks are only important for inflation and money supply growth. (2) A Gaussian model reports effects that are by far smaller. For instance, in the case of GDP growth and at $\tau = 0.1$, the contribution is more than 4 times higher (45% vs. 10%). These results support the findings of the impulse response analysis and the theoretical considerations. Uncertainty shocks in their common interpretation, i.e., in line with Bloom (2009), should have the strongest importance during recession periods where the economy is prone to instability. Their minor importance during boom phases does not contradict the hypothesis of the exuberance shock. It can be even argued to be underlined as during the highest boom phases there is an increase in the importance of the shock for fluctuations in inflation and money growth (above mean) – both representing essential variables in a build-up of a speculative bubble, a situation where we find high prices as well as high liquidity.
The results are depicted in Figure 3.4.2. It shows the quantile plots of the importance of uncertainty shocks for fluctuations in each variable of the system as measured by forecast error variance decompositions. The bold (blue) lines represent the importance of the financial shock across quantiles, while the thin (red) lines refer to the importance at the mean. The two lines in each set (bold and thin) represent the figure for different horizons. The solid line refers to the average over one year and the dashed lines the average over two to three years.
The maximum importance of an uncertainty shock for changes in real GDP (Δq) is reported to be 34% (1 year) and 45% (2-3 years) for the two horizons at quantile $\tau = 0.1$, while the estimate at the mean amounts only to 8% and 10%. Furthermore, the minimum importance is given around the highest quantiles. Thus, the importance of an uncertainty shock for GDP growth is estimated to rise for recession periods: the deeper the recession, the higher is the contribution of uncertainty.
In the case of inflation (Δp), uncertainty plays an important role at both tails of

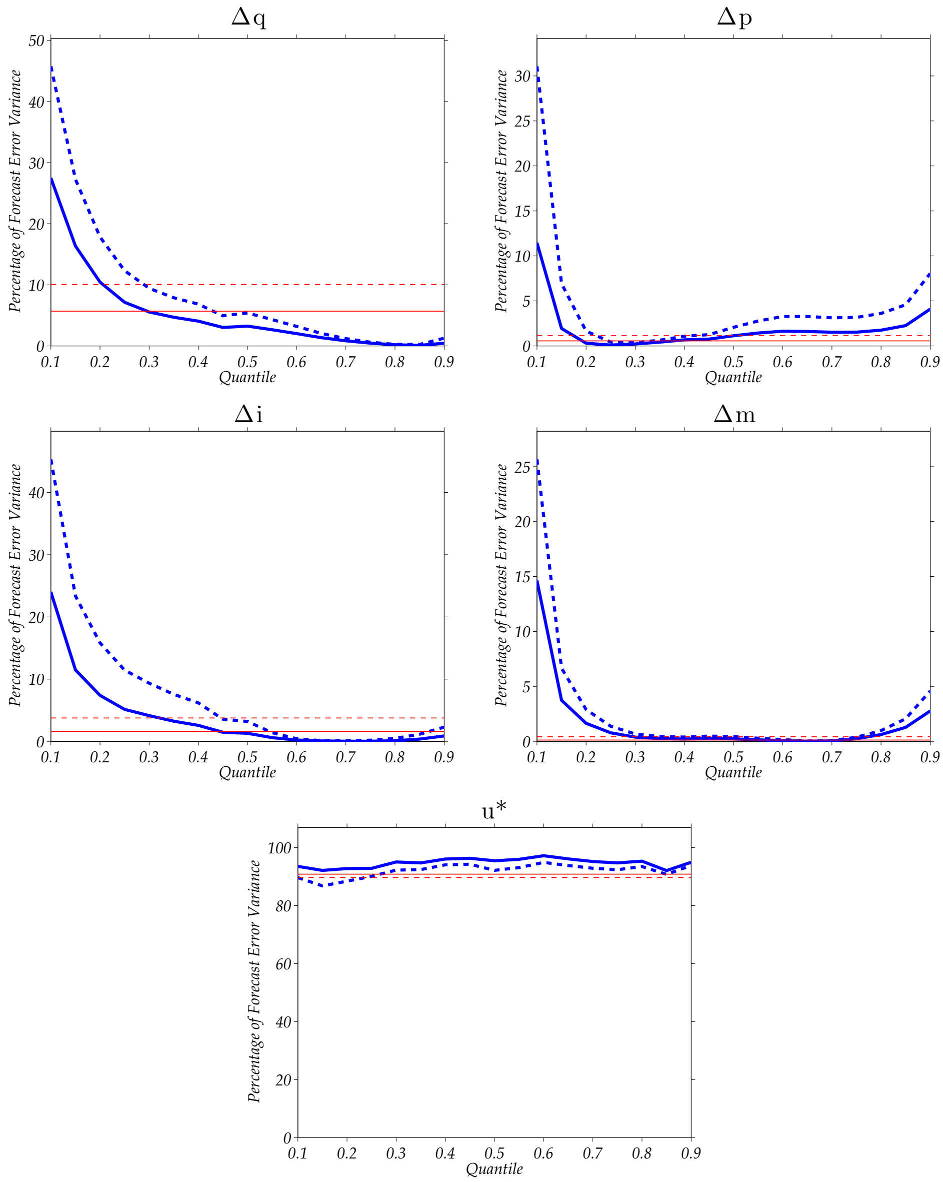

Figure 3.4.2: Contribution of Uncertainty Shocks to Fluctuations in US Economic Variables: Across Quantiles and at the Mean

Notes: The graph depicts quantile plots, where the x-axis represents the quantiles at which the specific model has been estimated and the y-axis the percentage of variance of the indicated variable explained by uncertainty shocks. The blue and thick lines represent the estimates at the quantiles. The red and thin lines represent the estimates using the Gaussian model. A solid line refers to the average forecast error variance between 1 and 4 quarters (1st year). A dashed line refers to the average from 5 to 12 quarters (2nd and 3rd year). Δq denotes GDP growth; Δp inflation; Δi changes in interest rates; Δm growth in money supply; u* the transformed variable of stock market volatility. Figures are calculated for $\tau = \{0.1, 0.15, \ldots, 0.85, 0.9\}$.

the distribution. However, the highest magnitudes are revealed during the deepest recession ($\tau = 0.1$) with 14% and 31% for the two horizons. From the center of the distribution to the upper quantiles the importance remains higher than the one estimated by the Gaussian model, which is about 1% at both horizons. The highest importance during booms is 5 and 8% at quantile $\tau = 0.9$.

Furthermore, there is evidence that the contribution of uncertainty shocks to changes in interest rates (Δi) has a similar structure than in the case of GDP growth; almost no importance during boom phases and an increasing importance at the lower the quantile. The maximum importance is found at the lowest quantile, which is 30% and 45%. The mean figures are 2% and 4%.
The contribution of uncertainty shocks to fluctuations in money supply growth (Δm), on the other hand, has a similar structure as found for inflation. In both tails the contributions are important, however, they are strongest during recession periods. The strongest effects are found at the lower tail with 18% and 26% for the two horizons. The mean figures amount only to 0.2% and 0.4%. The importance at the highest quantile is 3 and 5%.
At last, the importance of an uncertainty shock for stock market volatility (u*) is fairly stable across the distribution and remains at most parts higher than the one obtained using the Gaussian model. The importance is very high. Thus, other shocks of the system are not important for explaining fluctuations in stock market volatility.

3.4.3 Asymmetries over the Financial Cycle: Economy at Bust and Boom

This section analyzes the interaction of the cycle of the real economy and the financial cycle. The cycle of the real economy is fixed in this setup. More specifically, I analyze the asymmetric effects of the financial cycle for an economy in a recession ($\tau = 0.2$) and during a boom ($\tau = 0.8$). Putting it differently the vector $\boldsymbol{\tau}$ is assumed to be $(0.2, 0.2, 0.2, 0.2, \tau_5)'$ during the recession phase and $(0.8, 0.8, 0.8, 0.8, \tau_5)'$ during the boom phase. τ_5 is then allowed to vary to represent the financial cycle. I do not present the results for the strongest recessions and booms ($\tau = 0.1, 0.9$) to emphasize that asymmetries of the financial cycle are not only important at the most extreme tails of the distribution of the economy.

3.4.3.1 Impulse Response Analysis

Two results stand out: (1) For an economy in recession the state of the financial system (good or bad) is important. There is a stronger recession when the financial system is also at a bad state. E.g., the response of GDP growth to an uncertainty shock is more than twice as persistent if the financial system is at a bad state. (2) For an economy at boom the state of the financial system does not seem to be crucial in the short run. In the long run, the exuberance shock is more pronounced if the financial system is at a bad state. If the financial system is at a bad state the behavior of the economy is explosive. This could be argued to provide further evidence for speculative bubbles. It leads to the case that the developments in the real economy cannot be sustained by fundamentals. A burst of a speculative bubble, thus, becomes more likely. However, results in the long run have to be taken with caution. According to the findings it can be assumed, for instance in the last case, that the economy remains at a boom, while the financial sector is at the worst considered state. This would not remain. The cycles would converge, i.e., each sector would follow a path of phases until the financial and business cycle reflect the same state of the economy.

Figure 3.4.3 illustrates these impulse responses. The left panel depicts the responses to an uncertainty shock for an economy in a recession period $\tau = 0.2$ and the right panel shows the responses for the boom period $\tau = 0.8$. Each graph has two different sets of impulse responses. The gray ones refer to responses where the financial system is at a good state (low volatility, $\tau = 0.9$). The black ones show the case where the financial system is at a bad state (high volatility, $\tau = 0.1$). It, thus, compares the effects of an uncertainty shock in situations when the financial system is in its best and its worst state.

Economy at Bust: The effect of a shock on GDP growth dies out twice as fast (1 1/2 year vs. more than 3 years) if the financial system is in a good state. Similar results hold for changes in interest rates. The reaction of the monetary authority is stronger and more persistent than if the financial system is in a good state. Responses of inflation and money supply do not differ significantly. Here, responses during a bad state of the financial system are reported to have higher variance. While the median response is different, the probability bands mostly overlap. The response of volatility indicates a highly persistent shock during bad states and a less persistent shock during good states.

Economy at Boom: Responses in the short run are reported to be very similar, i.e., the state of the financial system does not seem to matter. However, in the long run shocks that occur in a bad financial state lead to an explosive behavior of the responses in the case of inflation, interest rate changes, money supply growth, and volatility. Thus it can be argued that the general notion of an exuberance shock does not depend on the state of the financial system. However, the magnitude and persistence seems to be important. A system with explosive behavior will end up faster in a burst of a speculative bubble than a system that still returns to an equilibrium.[29]

[29] An analysis where $\boldsymbol{\tau} = (0.9, 0.9, 0.9, 0.9, 0.1)'$, that is where the best and worst states of the economy and the financial system are estimated together, yields a similar result. The only difference is that in this setup the entire economy, i.e., also GDP growth, explodes in the positive direction.

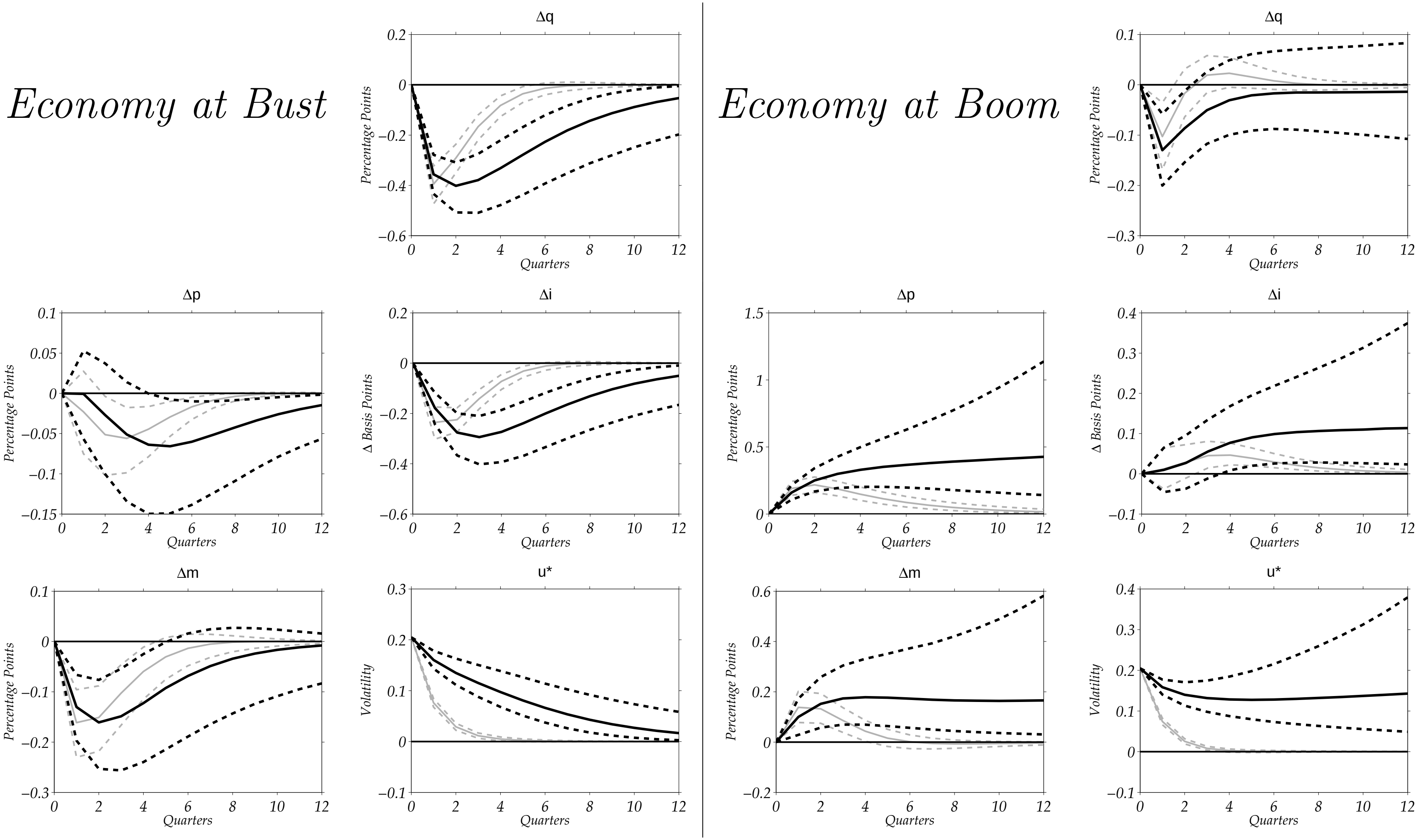

Figure 3.4.3: Response of the US Economy to an Uncertainty Shock During a Bust and Boom: Shock at $\tau_5 = 0.1$ and at $\tau_5 = 0.9$

Notes: The graph depicts the responses to an uncertainty shock. The left panel depicts an economy at $\tau = 0.2$, i.e., a recession and the right panel an economy at $\tau = 0.8$, i.e., a boom phase. The black lines describe the responses to a financial shock at $\tau_5 = 0.1$ and the gray lines portray the responses to a financial shock at $\tau_5 = 0.9$. The dashed lines correspond to posterior 68% probability bands. Δq denotes GDP growth; Δp inflation; Δi changes in interest rates; Δm growth in money supply; u* the transformed variable of stock market volatility.

3.4.3.2 Forecast Error Variance Decomposition

Two results stand out: (1) Uncertainty shocks have higher importance during a bad state of the financial cycle (2) Uncertainty is most important for GDP growth and changes in interest rates during recession, while it explains the highest fraction for inflation and money supply growth during booms. This again supports the hypothesis of the exuberance shock, as the variables involved in the build-up of speculative bubbles are most affected by uncertainty.
Figure 3.4.4 portrays the forecast error variance decompositions where stock market volatility is estimated over different phases of its cycle. The remaining variables of the US economy remain either at a recession period $\tau = 0.2$ or boom phase 0.8. As in the previous exercise the left panel shows the former and the right panel the latter setup. Again estimates are compared against the Gaussian model (thin lines). In addition, the percentage contribution is reported for the two horizons: average over one year (solid lines), and average over two and three years (dashed lines).
As noted, in general, i.e. across variables and states of the economy, a financial system in a bad state has a higher contribution for fluctuations in the real economy than a financial system in a good state. A financial shock in a bad state has higher importance for GDP growth and interest rates during recession periods than if the economy is in a good state. For GDP the difference is about 50% to about 4.5% (even smaller than at the mean) and for interest rates it is about 46% to 15% for the long horizon. In the case of inflation and money supply it is exactly the opposite. For an economy at boom an uncertainty shock in a bad state has stronger effects than the same shock for an economy at bust. The difference is about 45% to 7.5% for inflation and 28% to 12% for money supply growth over the longer time horizon. In the case of volatility the analysis depicts again a fairly stable contribution. Just in the case of a boom economy and a bad financial system other shocks in the system are found to have some importance for fluctuations in stock market volatility.

3.4.4 Robustness Analysis

In the following two kinds of robustness checks are conducted.[30] First, I include stock returns in the model of the US economy and, second, I analyze the effects of uncertainty on the German real economy as it shares similar characteristics with the

[30] As a third robustness check I consider a shock to monetary policy, i.e., an unexpected rise in the changes of interest rates, in order to see whether the findings about the uncertainty shock are model or data driven. At first sight, e.g., in the case of the high importance of an uncertainty shock during recession periods for all variables, the results might suggest that this represents an artefact of the model. However, the pattern of a monetary policy shock is different to that of an uncertainty shock. This outrules the possibility that the outcomes are model driven. Further details are available upon request from the author.

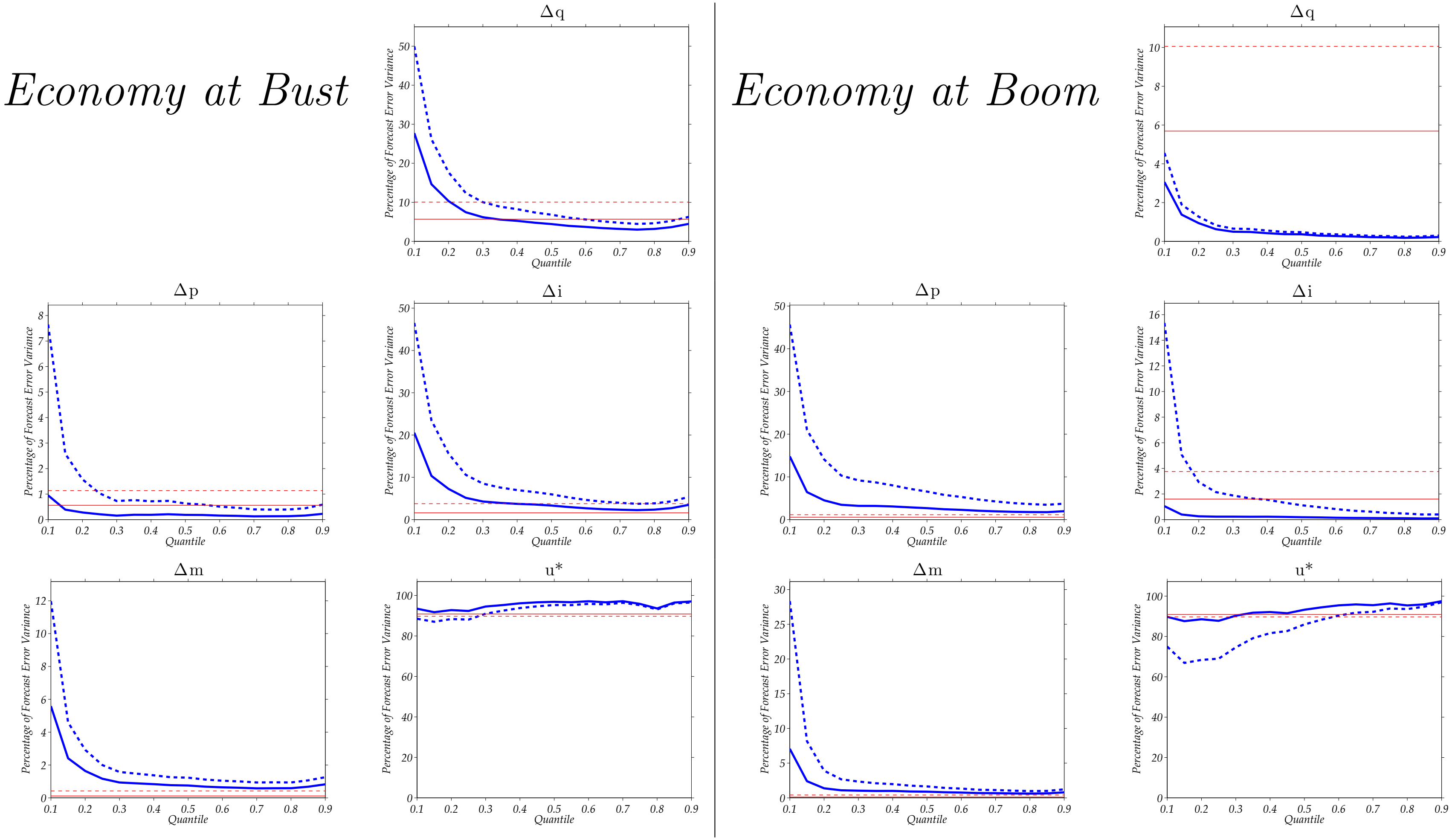

Figure 3.4.4: Contribution of Uncertainty Shocks to Fluctuations in US Economy at Bust ($\tau = 0.2$) and at Boom ($\tau = 0.8$)

Notes: The graph depicts quantile plots, where the x-axis represents the quantiles of the financial cycle τ_5 at which the specific model has been estimated and the y-axis the percentage of variance of the indicated variable explained by uncertainty shocks. The blue and thick lines represent the estimates at the quantiles. The red and thin lines represent the estimates using the Gaussian model. A solid line refers to the average forecast error variance between 1 and 4 quarters (1st year). A dashed line refers to the average from 5 to 12 quarters (2nd and 3rd year). Δq denotes GDP growth; Δp inflation; Δi changes in interest rates; Δm growth in money supply; u* the transformed variable of stock market volatility. Figures are calculated for $\tau = \{0.1, 0.15, \ldots, 0.85, 0.9\}$.

US economy.

3.4.4.1 Including Stock Returns

In light of the evidence that an economy may experience a positive development in response to an uncertainty or exuberance shock, it is of interest how the stock market develops in response to such a shock. If it was an exuberance shock, one should see a rise in stock returns.
Results are depicted in Appendix 3.E.1 and the exact definition of the variable that measures stock returns is shown in Appendix 3.C.[31] I introduce the variable stock returns into the model such that it may be affected by the uncertainty shock contemporaneously.
Most importantly, the results support my interpretation of the exuberance shock. An economy in its highest phase, i.e., $\tau = 0.9$, experiences a rise in the returns on the stock market in response to a shock. After one quarter the returns rise by about 1.9 p.p. In contrast, in a recession the stock market falls by about 1.3 p.p. With respect to the importance of an uncertainty shock for fluctuations in stock returns, findings indicate a higher contribution during recessions – where the highest contribution is at $\tau = 0.15$ with about 21% for both horizons.

3.4.4.2 German Economy

This section aims at finding further evidence for the asymmetric effects of uncertainty shocks. If it was a general phenomenon one should find equivalent results for countries that share similar characteristics. Especially with regard to the exuberance shock a robustness check should be most insightful as it contradicts common knowledge on uncertainty. For this analysis I consider the German economy.
I model the German economy using the equivalent variables as in the US case. Stock market volatility is constructed using the DAX. Please see Appendix 3.C for details on the data. Due to the shorter availability of the data the starting date of the analysis is now 1970Q2 (1954Q2 in the case of the US). Nonetheless, the other parts of the analysis as for instance lag length and priors remain unchanged to the previous analysis. Results are depicted in Appendix 3.E.2.
Assuming *one cycle for the economy*, the impulse response analysis reveals a strong negative development of the German economy in response to an uncertainty shock. Further, this analysis also reveals a positive effect on the economic outcome during

[31] I present the results for the setup that assumes one cycle for the economy. On the one hand, this is sufficient to provide insights into the meaning of the shock during a boom phase and, on the other, I avoid making assumptions on how the business and financial cycle converge. Phases of different macrovariables will not stay *orthogonal* to each other for a prolonged period of time.

the highest boom phases. Again, responses for the tails of the distribution are shown to be significantly different from the Gaussian estimates. The forecast error variance decomposition analysis reveals a similar pattern for recession periods – even though stronger than for the US in the case of inflation, interest rates, and money – however, all contributions of uncertainty shocks are close to zero for boom periods. Considering the effect of an uncertainty shock along its *financial cycle* there is an equivalent pattern for an economy at bust. Only in case of GDP growth and interest rate changes, the response to an uncertainty shocks ebbs off faster than in the case of the US. For Germany the state of the financial system also seems to be crucial for developments of inflation; contrary to the case of the US in both scenarios (good and bad state of financial system). For a shock during boom phases, the state of the financial system does not seem to have an effect, as anyways the responses are insignificant. Only at the highest state of the economy, I obtain the same results as in the US, that the state of the financial system only matters for the size of the positive deviation.[32] The variance decompositions, again reveal a similar pattern, just that the importance of an uncertainty shock is in general higher for an economy at bust than for an economy at boom (i.e., also for inflation and money supply, which is different compared to the US). For a booming economy the importance is below the mean importance, except for money supply, for most quantiles.
Overall, I conclude that the previous results are supported. Asymmetries over the business cycle and the financial cycle are an important characteristic of the German economy. There is also evidence for an exuberance shock. Of course, slight differences in the results to the US emerge. However, apart from obvious differences between the countries as e.g. institutions, in this setup differences can possibly be attributed to the sample period.

3.5 Concluding Remarks

This paper sheds light on the asymmetric effects of uncertainty on the US real economy. To provide evidence I argue that conditional quantiles may be related to the different phases of the business cycle. Building on this, I construct a novel methodology that allows for an analysis of one or more cycles - the quantile structural vector autoregressive model. For its estimation, I introduce a new representation of the multivariate Laplace distribution and propose a sampler for the estimation of the parameters.
The analysis provides evidence for the existence of strong asymmetries over the business and financial cycles. The asymmetries appear in many parts of the dis-

[32]Results are not shown but can be obtained from the author on request

tribution, mostly in the tails of the distribution, different from estimates provided by a Gaussian model. I find evidence that the commonly known uncertainty shock has two different effects on the outcome of the economy. During recession periods these are highly negative which is in line with theoretical considerations. However, the effects are also found to be positive during the highest boom phases. I interpret this shock as an exuberance shock as the stock market is affected positively as well. An exuberance shock entails a rise in equity prices. This can be argued to constitute empirical evidence for the phenomenon of speculative bubbles, as unexpected changes on the stock market leads to positive growth. This is supported by the result that prices and money are strongly determined by uncertainty shocks during boom phases, which are key ingredients in the build-up of speculative bubbles. At last, the state of the financial sector is decisive for the effect of an uncertainty shock if the real economy is in recession. If the financial sector is in a bad state the resulting recession is found to be stronger. In contrast, the state of the financial system is not important for an economy at boom in the short run.

The present study underlines the important changes in the dependencies over the cycles. Future research should, thus, provide further evidence for asymmetries over the cylce considering different shocks to the economy. Moreover, the framework should deliver important insights into cross-country spill-overs; especially considering the international differences in the phases of the cycles.

With regard to the methodology, there are also open questions left for future research. The use of different priors, maybe varying across quantiles, might be considered. Furthermore, it still remains unclear whether the approach to derive the structural model is best. Possibly one can estimate the contemporaneous relations directly from the multivariate Laplace distribution. Additionally, the methodology could be extended to deal with non-standard innovations, e.g. for the analysis of higher frequency financial data.

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Appendix 3.A Laplace Distribution and Quantile Restrictions

3.A.1 Quantile Restrictions for the Univariate Laplace Density

Assume v_t is Laplace distributed, i.e.,

$$f_\tau(v_t) = \tau(1-\tau)\exp\{-\rho_\tau(v_t)\}, \text{ where } \rho_\tau(v_t) = \begin{cases} v_t \cdot \tau & \text{, if } v_t \geq 0 \\ v_t \cdot (\tau - 1) & \text{, if } v_t < 0. \end{cases}$$

Then the following has to hold for the characteristic function:

$$\begin{aligned} \Psi_{v_t}(s) &= E[\exp(isv_t)] \\ &= \int_{-\infty}^{\infty} \exp(isv_t) f_\tau(v_t) dv_t \\ &= \int_{-\infty}^{0} \tau(1-\tau)\exp(isv_t + (1-\tau)v_t)dv_t + \int_{0}^{\infty} \tau(1-\tau)\exp(isv_t - \tau v_t)dv_t \\ &= \tau(1-\tau)\left(\frac{1}{is + (1-\tau)} + \frac{1}{p - is}\right) \\ &= \frac{1}{1 + \frac{1}{\tau(1-\tau)}s^2 - i\frac{1-2\tau}{\tau(1-\tau)}s} \end{aligned}$$

The characteristic function as defined in Kotz et al. (2001) is

$$\Psi_{v_t}(s) = \frac{1}{1 + \frac{1}{2}\sigma^2 s^2 - ims}.$$

Thus the restrictions required are

$$m = \frac{1-2\tau}{\tau(1-\tau)} \quad \text{and} \quad \sigma^2 = \frac{2}{\tau(1-\tau)}.$$

3.A.2 Bivariate Laplace Distribution with Quantile Restrictions

Following Kotz et al. (2001), the bivariate characteristic function may be written as follows:

$$\Psi(s_1, s_2) = \frac{1}{1 + \frac{\sigma_{\tau_1}^2 s_1^2}{2} + \rho_{12}\sigma_{\tau_1}\sigma_{\tau_2}s_1 s_2 + \frac{\sigma_{\tau_2}^2 s^2}{2} - im_{\tau_1}s_1 - im_{\tau_2}s_2},$$

where the five parameters have to satisfy $m_{\tau_1} \in \mathbb{R}, m_{\tau_2} \in \mathbb{R}, \sigma_{\tau_1} \geq 0, \sigma_{\tau_2} \geq 0, \rho_{12} \in [-1, 1]$, and ρ_{12} denotes the correlation coefficient.

As can be seen, the bivariate Laplace can be thought of as two univariate Laplace distributions that are linked through ρ_{12}, the correlation coefficient.[33]

Appendix 3.B Quantile Structural Vector Autoregression and Bayesian Inference

3.B.1 Estimation of Covariance Matrix

The following discusses briefly how the covariance matrix

$$\boldsymbol{\Omega}_{\boldsymbol{\tau}} = (\omega_{jk}) = \left(\frac{\mathrm{E}[(\rho_{\tau_j}(u_{jt}))(\rho_{\tau_k}(u_{kt}))]}{\mathrm{E}[f_{u_{jt}}(0)]\mathrm{E}[f_{u_{kt}}(0)]}\right), \text{ where } j,k \in \{1,\dots,d\},$$

may be calculated. Given the parameter estimates $\hat{\mathbf{A}}_{\boldsymbol{\tau},i}$ and $\hat{\boldsymbol{\nu}}_{\boldsymbol{\tau}}$ one obtains $\hat{\mathbf{u}}_{\mathbf{t}}$ in the standard way, i.e., $\hat{\mathbf{u}}_{\mathbf{t}} = \mathbf{y}_t - \hat{\boldsymbol{\nu}}_{\boldsymbol{\tau}} - \sum_{i=1}^{p} \hat{\mathbf{A}}_{\boldsymbol{\tau},i}\mathbf{y}_{t-i}$.
Following, the terms (i) $\mathrm{E}[(\rho_{\tau_j}(u_{jt}))(\rho_{\tau_k}(u_{kt}))]$ and (ii) $\mathrm{E}[f_{u_jt}(0)]$ can be replaced with their sample estimates. (i) is estimated by

$$\frac{1}{T}\sum_{t=1}^{T}(\tau_j - I(u_{jt} < 0))(\tau_k - I(u_{kt} < 0)).$$

(ii) refers to the probability density of u_{jt} evaluated at the point zero. It is obtained using a kernel density estimator on the residuals $\hat{u}_{jt}$ using a Gaussian kernel, again, evaluated at zero.

3.B.2 The Conditional Likelihood Function of y

Additionally to the definitions in Section 3.3, let $\boldsymbol{\mu}_{\boldsymbol{\tau}} = \mathrm{vec}((\boldsymbol{\mu}_{\boldsymbol{\tau},1},\dots,\boldsymbol{\mu}_{\boldsymbol{\tau},T})') = (\mathbf{I}_d \otimes \mathbf{X})\boldsymbol{\alpha}_{\boldsymbol{\tau}} + (\mathbf{B}\mathbf{m}_{\boldsymbol{\tau}} \otimes \mathbf{I}_T)\mathbf{w}$. The complete likelihood of $\mathbf{y}$, i.e., for all observations $1,\dots,T$, may be written as

$$f(\mathbf{y}|\boldsymbol{\alpha}_{\boldsymbol{\tau}}, \boldsymbol{\Sigma}_{\boldsymbol{\tau}}, \mathbf{w}, \mathbf{B}) = \frac{1}{(2\pi)^{dT/2}}|\boldsymbol{\Sigma}_{\boldsymbol{\tau}\star}\otimes\mathbf{W}|^{-1/2}\exp\left[-\frac{1}{2}(\mathbf{y}-\boldsymbol{\mu}_{\boldsymbol{\tau}})'(\boldsymbol{\Sigma}_{\boldsymbol{\tau}\star}\otimes\mathbf{W})^{-1}(\mathbf{y}-\boldsymbol{\mu}_{\boldsymbol{\tau}})\right].$$

3.B.3 Derivation of the Conditional Posterior of w_t

Let $w \sim \mathcal{E}(1)$ and $\mathbf{y} \sim \mathcal{L}_d(\mathbf{m}, \boldsymbol{\Sigma})$. In order to show that the kernel of the $f(w|\mathbf{y})$ is proportional to that of a generalized inverse Gaussian distribution recall that the conditional density is obtained through

$$f(w|\mathbf{y}) = \frac{f(\mathbf{y}|w)f(w)}{f(\mathbf{y})}.$$

[33] However, as Kotz et al. (2001) note, even in the symmetric case, i.e., $m_{\tau_1} = 0$ and $m_{\tau_2} = 0$, when the random variables are uncorrelated, i.e., $\sigma_{\tau_1}\sigma_{\tau_2}\rho_{12} = 0$, they are not independent.

It has been shown that $f(\mathbf{y}|w)$ has a multivariate normal pdf, i.e.,

$$f(\mathbf{y}|w) = (2\pi)^{-d/2}|w\mathbf{\Sigma}|^{-1/2} \exp\left(-\frac{1}{2}(\mathbf{y}-\mathbf{m}w)'(w\Sigma)^{-1}(\mathbf{y}-\mathbf{m}w)\right)$$

Furthermore, $f(w) = \exp(-w)$. Neglecting $f(\mathbf{y})$ and the invariant terms of $f(\mathbf{y}|w)$,

$$\begin{aligned} f(w|\mathbf{y}) &\propto w^{-d/2} \exp\left(-\frac{1}{2}(\mathbf{y}-\mathbf{m}w)'(w\mathbf{\Sigma})^{-1}(\mathbf{y}-\mathbf{m}w) - w\right) \\ &= w^{-d/2} \exp\left(-\frac{1}{2}\left(\frac{\mathbf{y}'\mathbf{\Sigma}\mathbf{y}}{w} - \mathbf{y}'\mathbf{\Sigma}\mathbf{m} - \mathbf{m}'\mathbf{\Sigma}\mathbf{y} + w\mathbf{m}'\mathbf{\Sigma}\mathbf{m}\right) - w\right) \\ &\propto w^{-d/2} \exp\left(-\frac{1}{2}\left((\mathbf{y}'\mathbf{\Sigma}\mathbf{y})w^{-1} + (2+\mathbf{m}'\mathbf{\Sigma}\mathbf{m})w\right)\right). \end{aligned}$$

The probability density function of a generalized inverse Gaussian denoted by $\mathcal{GIG}(\lambda, \chi, \psi)$, with $\lambda = -(d/2)+1$, is given by

$$f(x|\lambda,\chi,\psi) = \frac{(\psi/\chi)^{\lambda/2}}{2K_\lambda(\sqrt{\chi\psi})} x^{\lambda-1} \exp\left\{-\frac{1}{2}(\chi x^{-1} + \psi x)\right\},$$

where $K_\lambda(\cdot)$ reflects the modified Bessel function of the second kind.
Hence,

$$f(w|\mathbf{y}) \propto \mathcal{GIG}(-d/2+1, \mathbf{y}'\mathbf{\Sigma}\mathbf{y}, 2+\mathbf{m}'\mathbf{\Sigma}\mathbf{m}).$$

Appendix 3.C Data

Table 3.C.1: Data Sources, Descriptions, and Transformations

Variable	Symbol	Base Variable	Transformation	QC	Freq.	Conversion	Code
Real Economic Activity Growth	Δq	Real GDP	Log differences	-	Q	-	USGDP...D
Inflation	Δp	CPI All Items	Log differences	-	M	End of period	USCONPRCE
Change in Interest Rates	Δi	Federal Funds	differences	-	M	Average	USFEDFUN
Real Money Supply Growth	Δm	Money Supply M2	Constant prices Log Differences	-	M	End of period	USMS2...B
Stock Market Volatility	u*	Dow Jones Industrials	Absolute value of log differences	-1	D	Sum of observations	DJINDUS(PI)
GDP Deflator		Chain-Type Price Index	-	-	Q	-	USGDP..CE
Robustness: *Stock Return*							
Stock Returns	r	Dow Jones Industrials	Log Differences	-	D	End of Quarter	DJINDUS(PI)
Robustness: *Germany*							
Real Economic Activity Growth	Δq	Real GDP	Constant prices Log Differences	-	Q	-	BDGDP...B
Inflation	Δp	CPI All Items	Log differences	-	M	End of period	BDCONPRCF
Interest Rate	Δi	Discount/Short Term EUR Repo	-	-	M	Average	BDPRATE.
Real Money Supply Growth	Δm	Money Supply M2	Constant prices Log Differences	-	M	End of period	BDM2....B
Stock Market Volatility	u*	DAX 30	Absolute value of log differences	-1	D	Sum of observations	DAXINDX(PI)
GDP Deflator		GDP Deflator	-	-	Q	-	BDQNA057E

Notes: QC denotes quantile conversion, i.e., how transformed variables are converted to align the quantiles with the business cycle. *D, M, Q* refers to daily, monthly, quarterly frequency respectively. 'Real Money' is obtained by dividing by 'GDP deflator'. Data codes from Datastream (Thomson Financial) are provided for each variable used in the analysis. All data are seasonally adjusted when necessary. In the robustness analysis GDP and Money Supply are converted into real variables using the GDP deflator indicated.

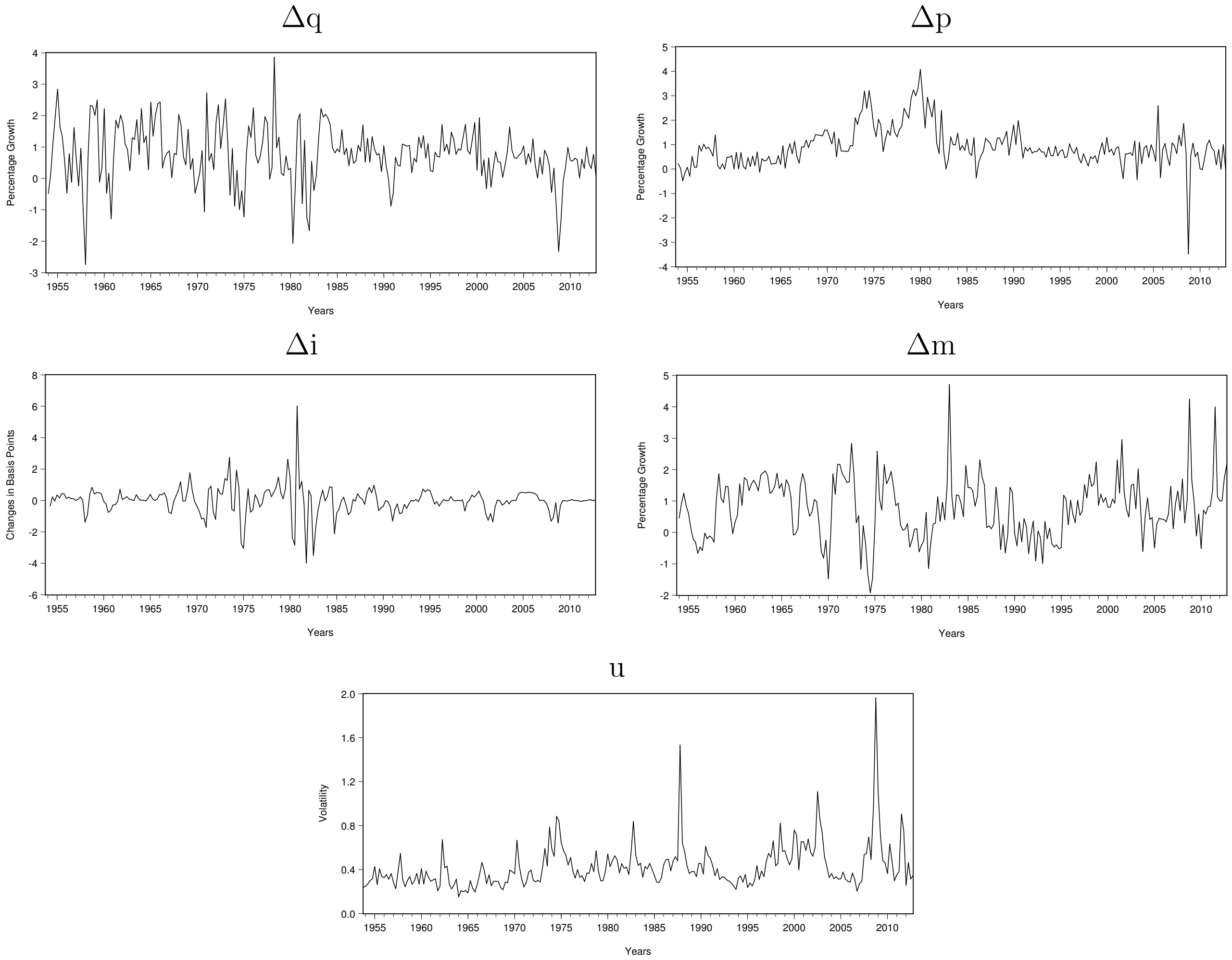

Figure 3.C.1: Time Series Graphs of US Economy

Notes: Δq denotes GDP growth, Δp inflation, Δi changes in interest rates, Δm growth in money supply, and u represents the untransformed measure of stock market volatility. The main analysis is conducted using $u^* = -u$. For further details on the variables see Table 3.C.1.

Appendix 3.D Complete Impulse Responses

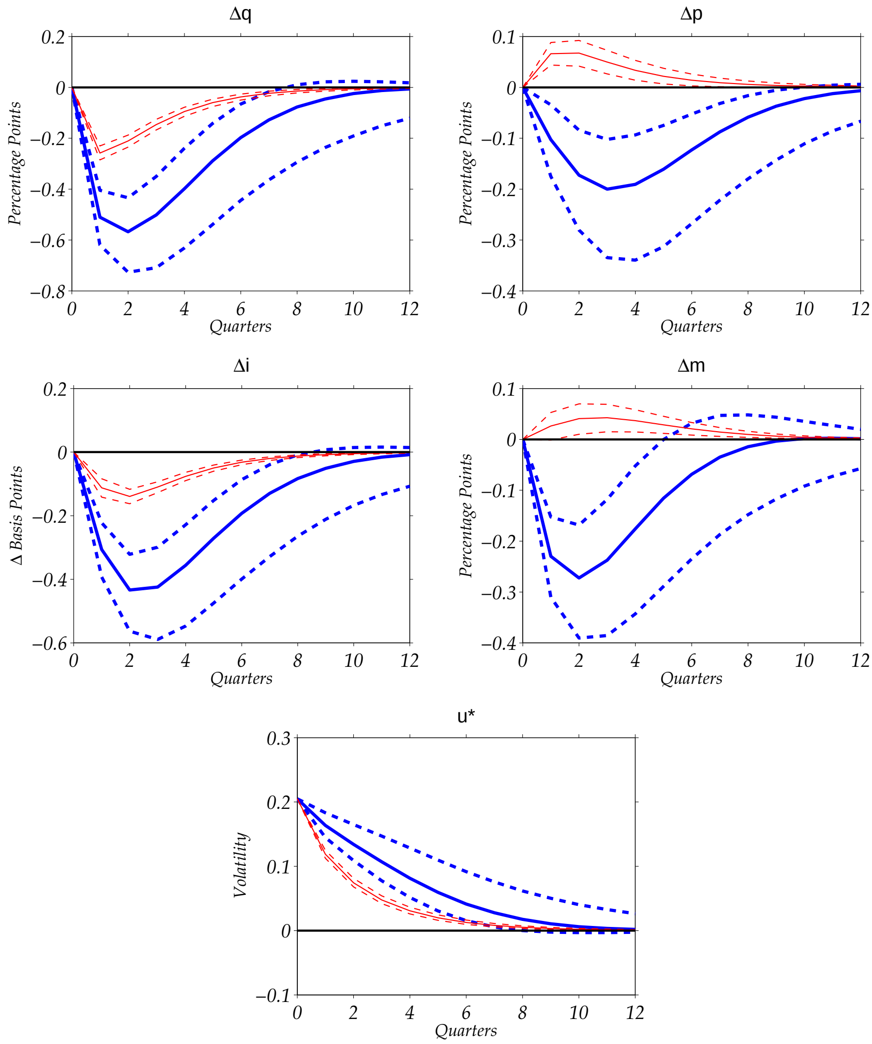

Figure 3.D.1: Response to Uncertainty Shock at $\tau = 0.1$

Notes: The graph depicts impulse responses at the quantile (τ) indicated (blue & thick lines) and at the mean (red & thin lines). Solid lines refer to the median impulse response. The dashed lines correspond to posterior 68% probability bands. Δq denotes real GDP growth; Δp inflation;Δi changes in interest rates; Δm growth in money supply; u* stock market volatility. The x-axis measures quarters, where the shock occurs in quarter zero.

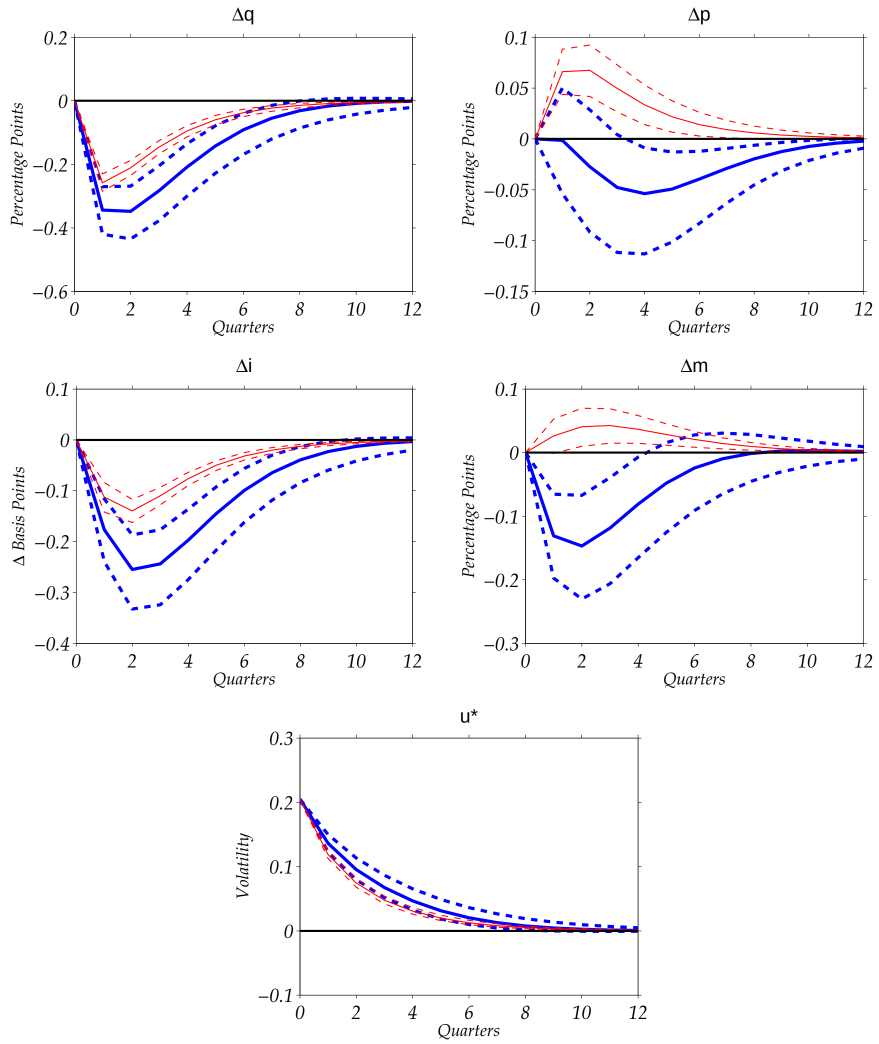

Figure 3.D.2: Response to Uncertainty Shock at $\tau = 0.2$

Notes: The graph depicts impulse responses at the quantile (τ) indicated (blue & thick lines) and at the mean (red & thin lines). Solid lines refer to the median impulse response. The dashed lines correspond to posterior 68% probability bands. Δq denotes real GDP growth; Δp inflation;Δi changes in interest rates; Δm growth in money supply; u* stock market volatility. The x-axis measures quarters, where the shock occurs in quarter zero.

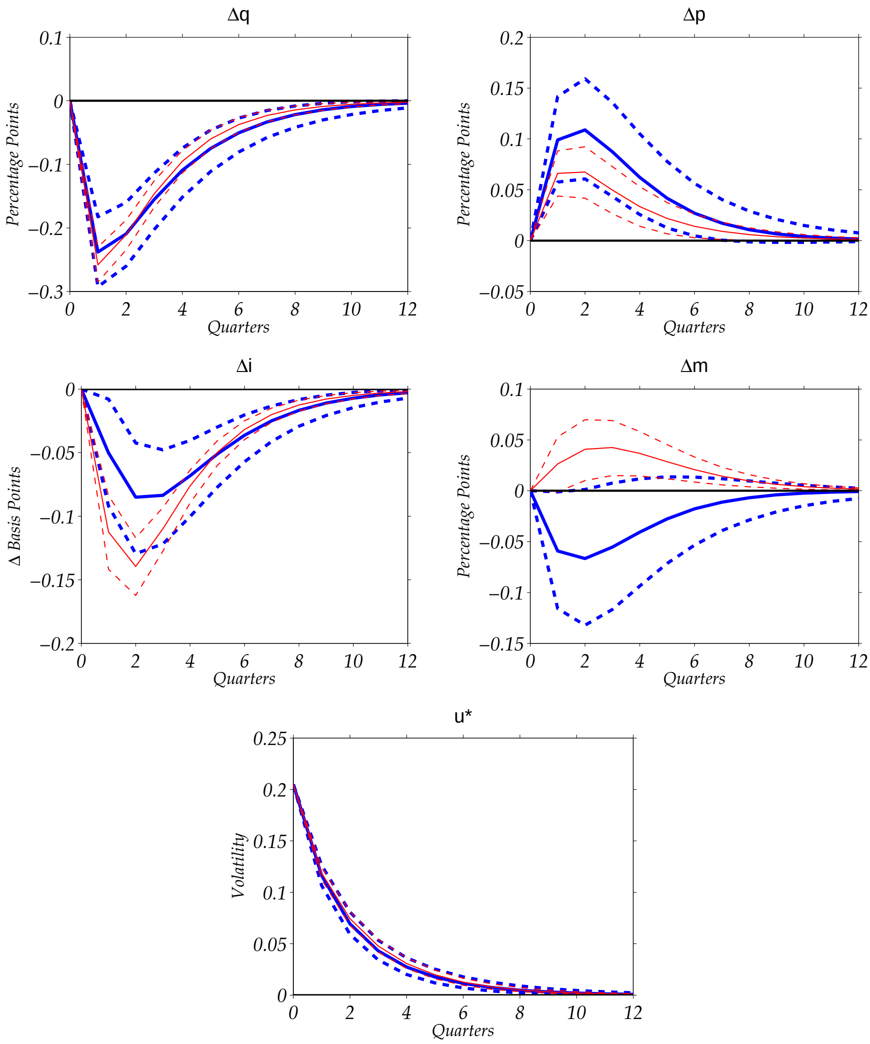

Figure 3.D.3: Response to Uncertainty Shock at $\tau = 0.5$

Notes: The graph depicts impulse responses at the quantile (τ) indicated (blue & thick lines) and at the mean (red & thin lines). Solid lines refer to the median impulse response. The dashed lines correspond to posterior 68% probability bands. Δq denotes real GDP growth; Δp inflation;Δi changes in interest rates; Δm growth in money supply; u* stock market volatility. The x-axis measures quarters, where the shock occurs in quarter zero.

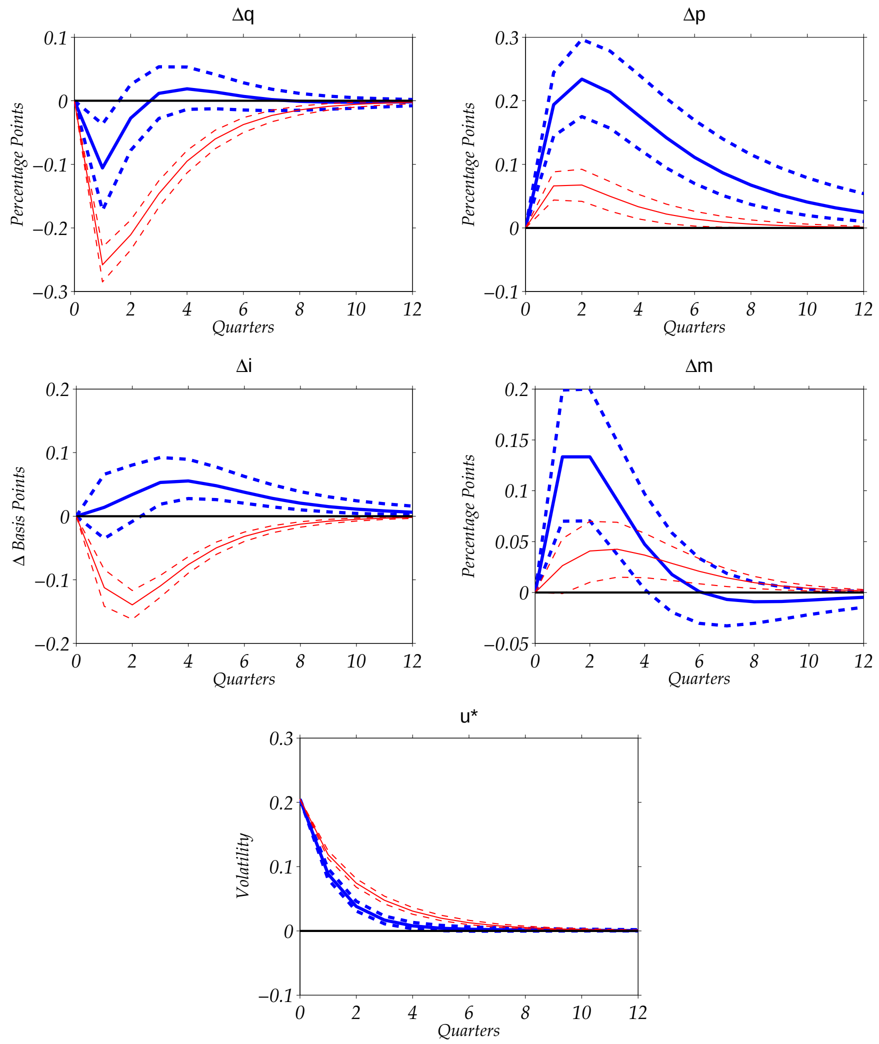

Figure 3.D.4: Response to Uncertainty Shock at $\tau = 0.8$

Notes: The graph depicts impulse responses at the quantile (τ) indicated (blue & thick lines) and at the mean (red & thin lines). Solid lines refer to the median impulse response. The dashed lines correspond to posterior 68% probability bands. Δq denotes real GDP growth; Δp inflation;Δi changes in interest rates; Δm growth in money supply; u* stock market volatility. The x-axis measures quarters, where the shock occurs in quarter zero.

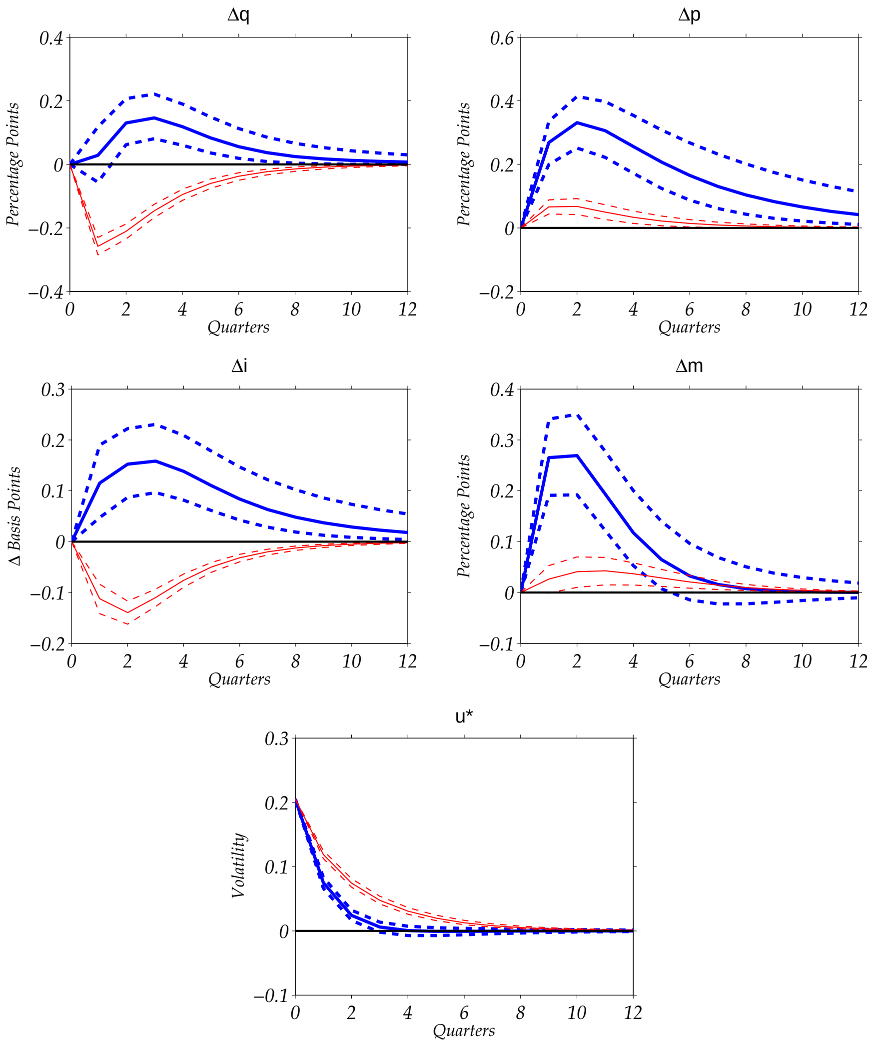

Figure 3.D.5: Response to Uncertainty Shock at $\tau = 0.9$

Notes: The graph depicts impulse responses at the quantile (τ) indicated (blue & thick lines) and at the mean (red & thin lines). Solid lines refer to the median impulse response. The dashed lines correspond to posterior 68% probability bands. Δq denotes real GDP growth; Δp inflation;Δi changes in interest rates; Δm growth in money supply; u* stock market volatility. The x-axis measures quarters, where the shock occurs in quarter zero.

Appendix 3.E Robustness Analysis

3.E.1 Stock Returns

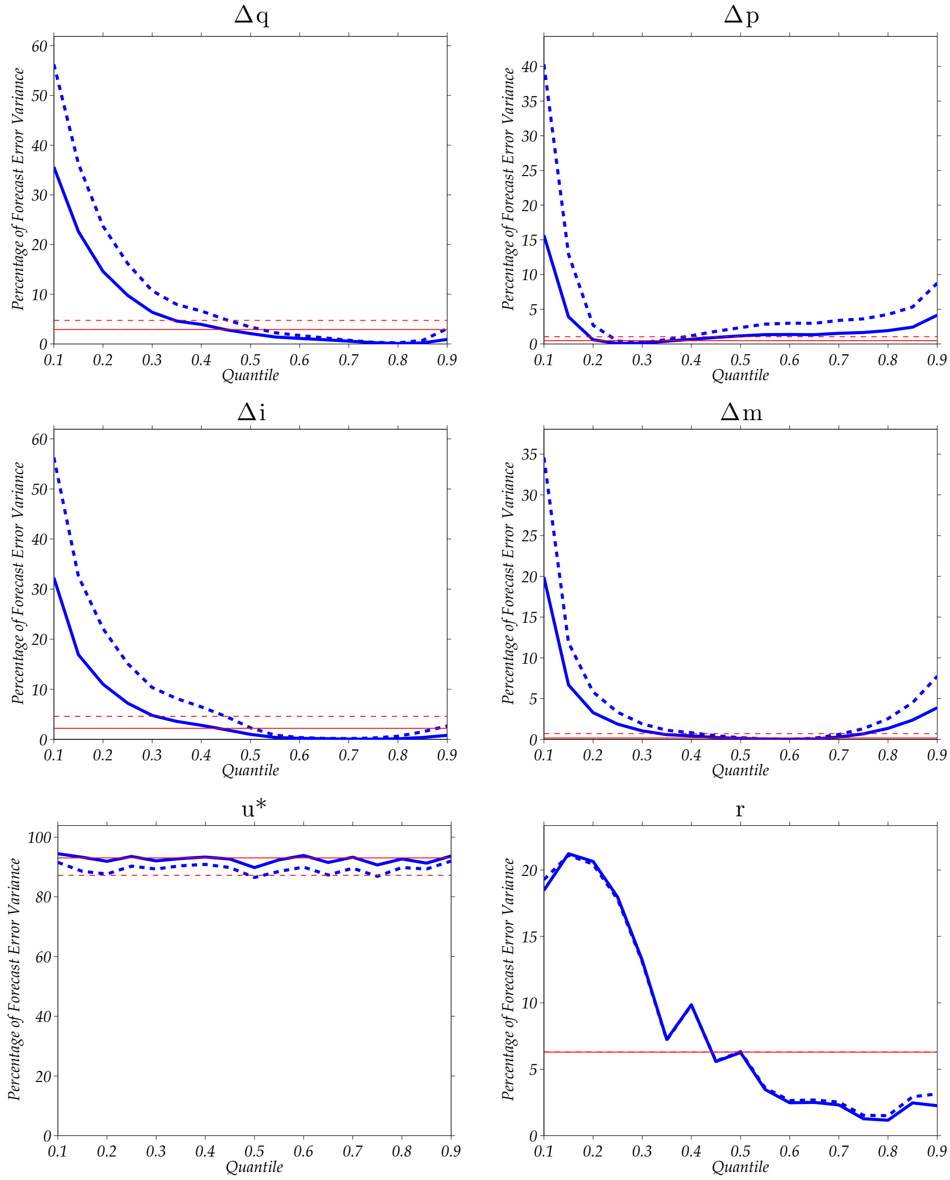

Figure 3.E.1: Contribution of Uncertainty Shocks to Fluctuations in US Economic Variables Including Stock Returns: Across Quantiles and at the Mean

Notes: The graph depicts quantile plots, where the x-axis represents the quantiles at which the specific model has been estimated and the y-axis the percentage of variance of the indicated variable explained by uncertainty shocks. The blue and thick lines represent the estimates at the quantiles. The red and thin lines represent the estimates using the Gaussian model. A solid line refers to the average forecast error variance between 1 and 4 quarters (1st year). A dashed line refers to the average from 5 to 12 quarters (2nd and 3rd year). Δq denotes GDP growth; Δp inflation; Δi changes in interest rates; Δm growth in money supply; u* the transformed variable of stock market volatility; r the stock return. Figures are calculated for $\tau = \{0.1, 0.15, \ldots, 0.85, 0.9\}$.

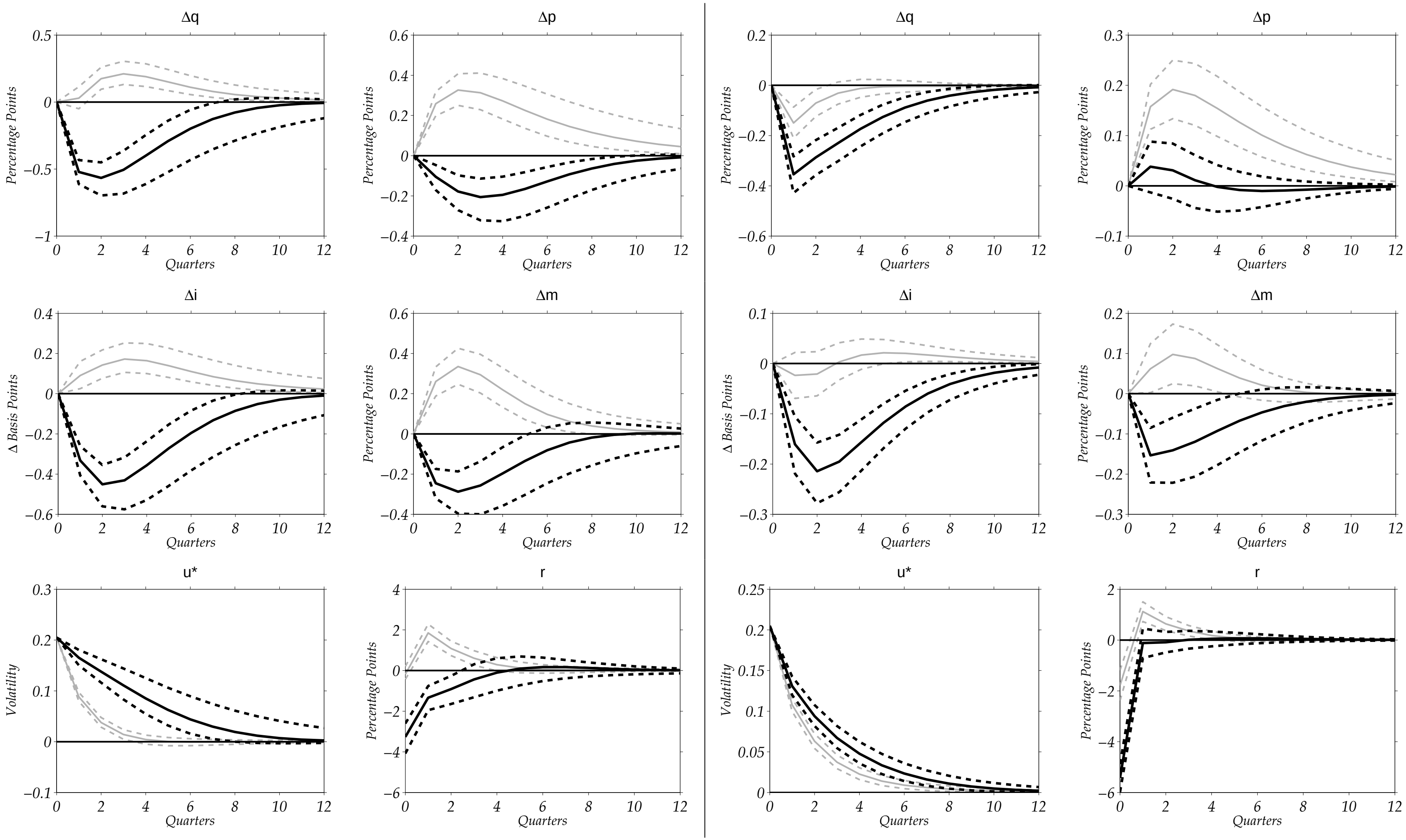

Figure 3.E.2: Response of the US Economy Including Stock Returns to an Uncertainty Shock: Left Panel: Responses at $\tau = 0.1$ (black) and $\tau = 0.9$ (gray). Right panel: Responses at $\tau = 0.3$ (black) and $\tau = 0.7$ (gray)

Notes: The left panel depicts the complete impulse responses for quantiles $\tau = 0.1$ (black) and 0.9 (gray). The right panel portrays the complete impulse responses for quantiles $\tau = 0.3$ (black) and 0.7 (gray). The impulse to uncertainty is normalized to one standard deviation of u*. Solid lines refer to the median impulse response obtained at each quantile. The dashed lines correspond to posterior 68% probability bands. Δq denotes real GDP growth; Δp inflation; Δi changes in the interest rate; Δm growth in money supply; u* volatility; r stock returns. Figures are calculated for $\tau = \{0.1, 0.15, \ldots, 0.85, 0.9\}$.

3.E.2 Germany

3.E.2.1 Asymmetries over the Business Cycle

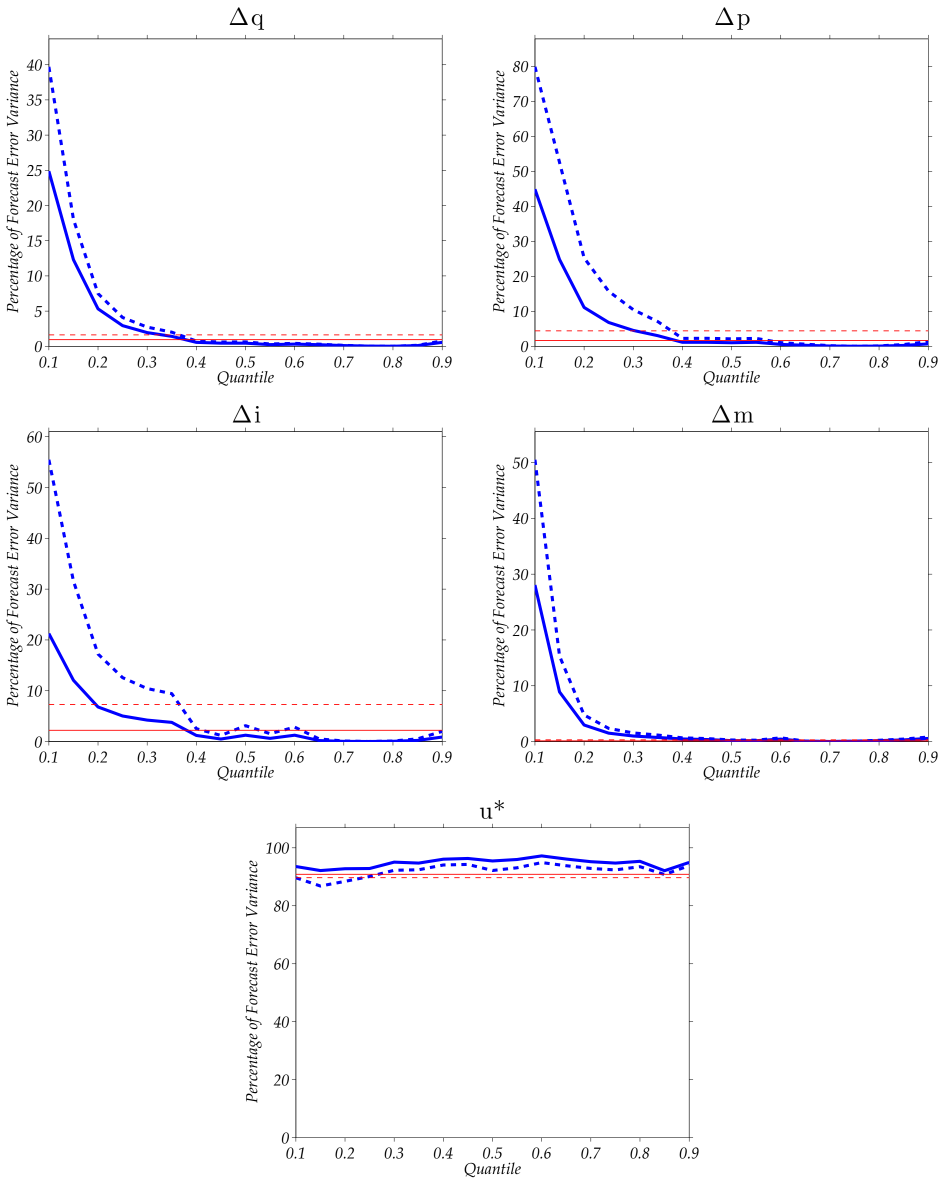

Figure 3.E.3: Contribution of Uncertainty Shocks to Fluctuations in German Economic Variables: Across Quantiles and at the Mean

Notes: The graph depicts quantile plots, where the x-axis represents the quantiles at which the specific model has been estimated and the y-axis the percentage of variance of the indicated variable explained by uncertainty shocks. The blue and thick lines represent the estimates at the quantiles. The red and thin lines represent the estimates using the Gaussian model. A solid line refers to the average forecast error variance between 1 and 4 quarters (1st year). A dashed line refers to the average from 5 to 12 quarters (2nd and 3rd year). Δq denotes GDP growth; Δp inflation; Δi changes in interest rates; Δm growth in money supply; u* the transformed variable of stock market volatility. Figures are calculated for $\tau = \{0.1, 0.15, \ldots, 0.85, 0.9\}$.

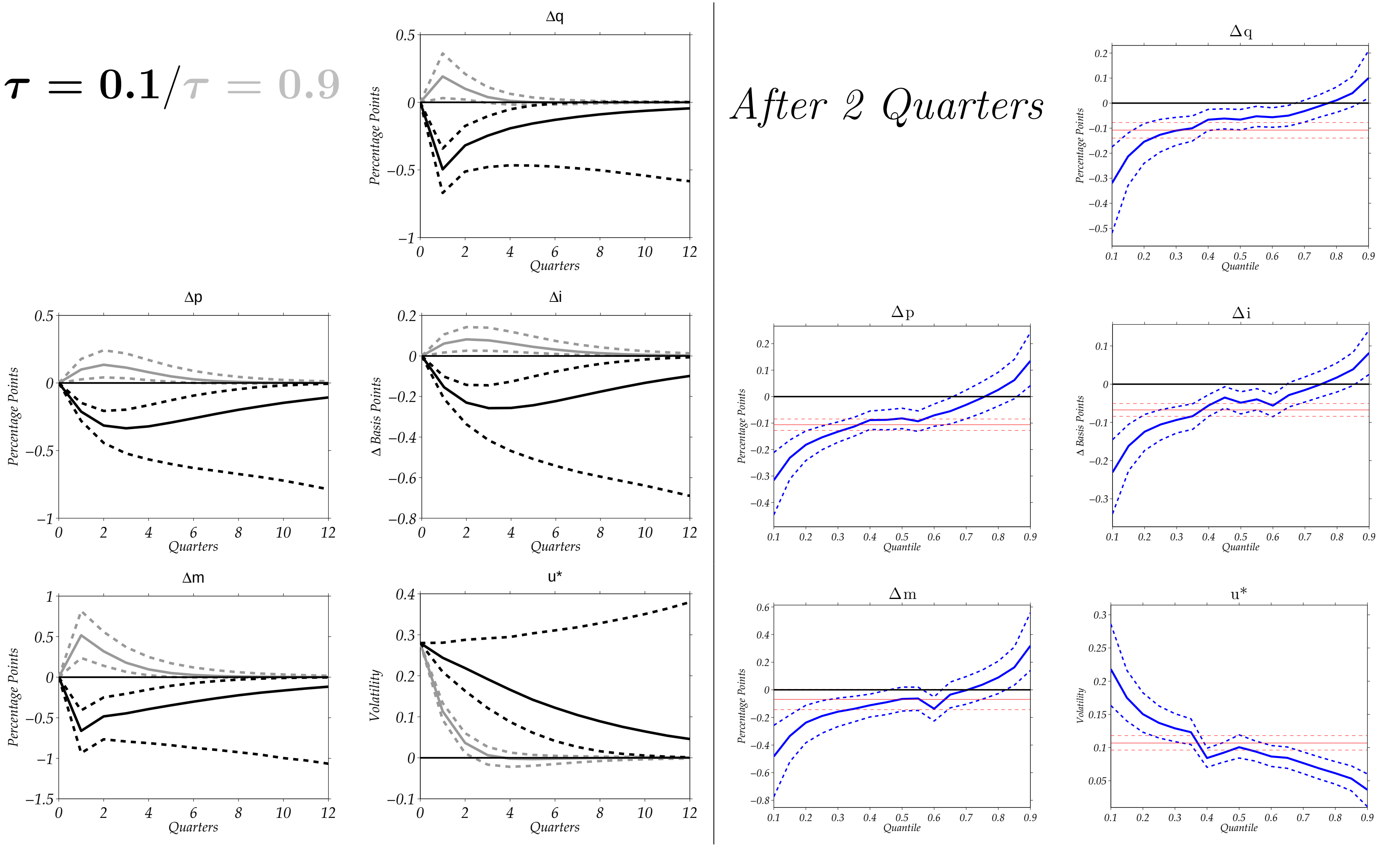

Figure 3.E.4: Response of the German Economy to an Uncertainty Shock: Left Panel: Responses at the lowest ($\tau = 0.1$) and highest ($\tau = 0.9$) quantile. Right panel: Responses After 2 Quarters Across Quantiles Compared to the Gaussian Model

Notes: The left panel depicts the complete impulse responses for quantiles $\tau = 0.1$ (black) and 0.9 (gray). The right panel portrays responses over the quantiles 2 quarters after the shock. It depicts impulse responses across quantiles (blue & thick lines) and at the mean (red & thin lines). The impulse to uncertainty is normalized to one standard deviation of u*. Solid lines refer to the median impulse response obtained at each quantile. The dashed lines correspond to posterior 68% probability bands. Δq denotes real GDP growth; Δp inflation; Δi changes in the interest rate; Δm growth in money supply; u* volatility. Figures are calculated for $\tau = \{0.1, 0.15, \ldots, 0.85, 0.9\}$.

3.E.2.2 Asymmetries over the Financial Cycle: Economy at Bust and Boom

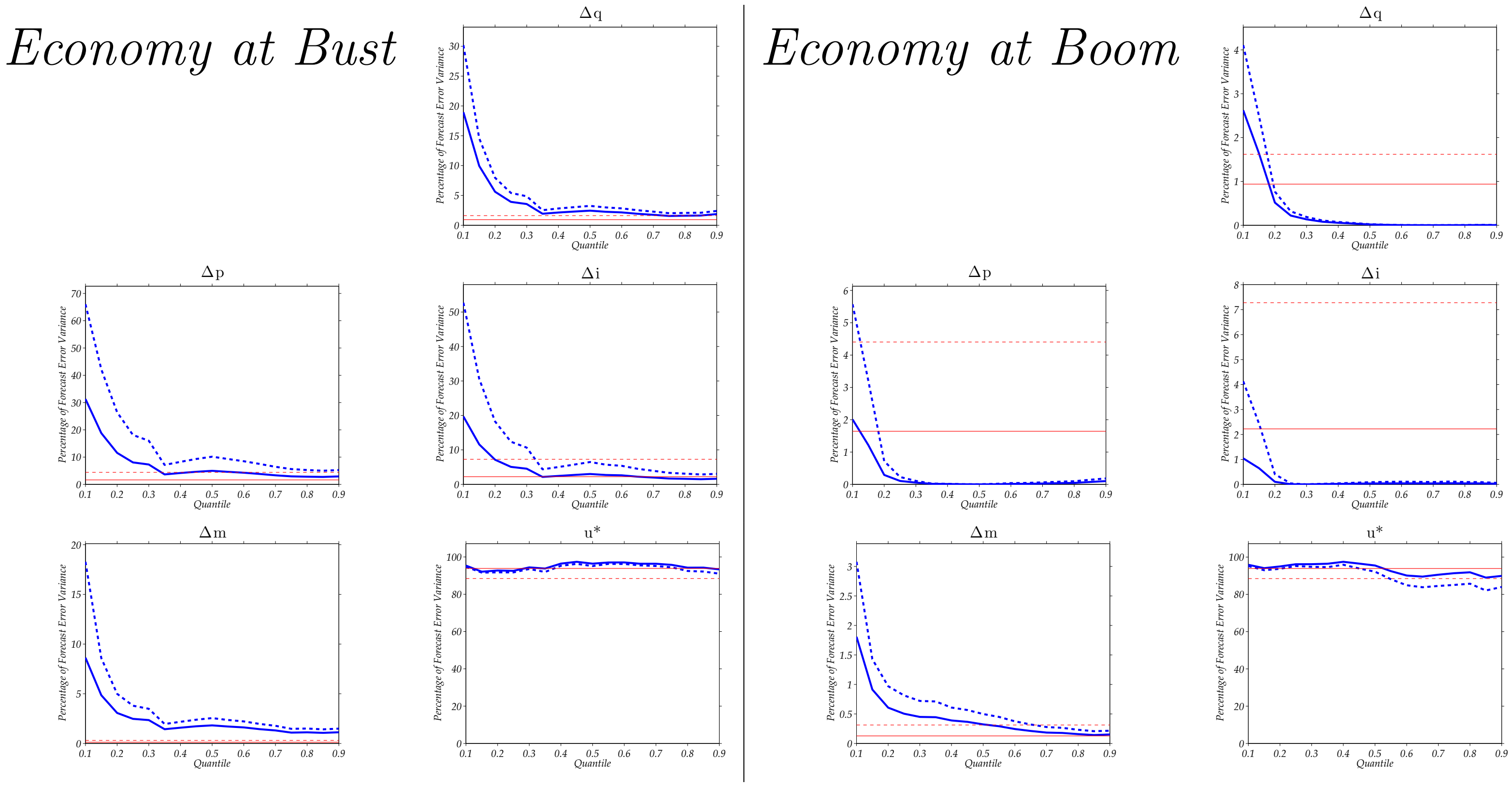

Figure 3.E.5: Contribution of Uncertainty Shocks to Fluctuations in the German Economy at Bust ($\tau = 0.2$) and at Boom ($\tau = 0.8$)

Notes: The graph depicts quantile plots, where the x-axis represents the quantiles of the financial cycle τ_5 at which the specific model has been estimated and the y-axis the percentage of variance of the indicated variable explained by uncertainty shocks. The blue and thick lines represent the estimates at the quantiles. The red and thin lines represent the estimates using the Gaussian model. A solid line refers to the average forecast error variance between 1 and 4 quarters (1st year). A dashed line refers to the average from 5 to 12 quarters (2nd and 3rd year). Δq denotes GDP growth; Δp inflation; Δi changes in interest rates; Δm growth in money supply; u* the transformed variable of stock market volatility. Figures are calculated for $\tau = \{0.1, 0.15, \ldots, 0.85, 0.9\}$.

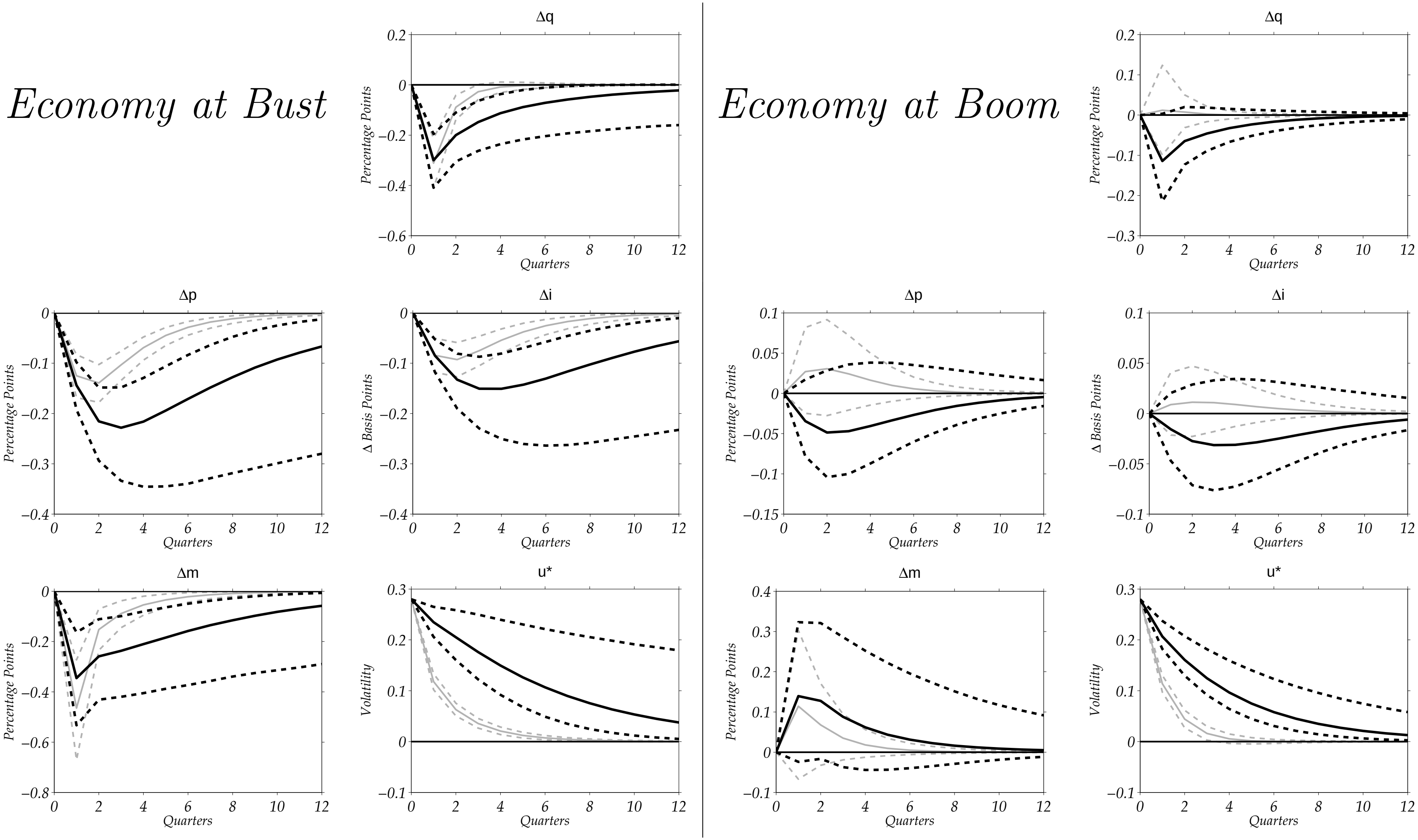

Figure 3.E.6: Response of the German Economy to an Uncertainty Shock During Bust and Boom: Shock at $\tau_5 = 0.1$ and at $\tau_5 = 0.9$

Notes: The graph depicts the responses to an uncertainty shock. The left panel depicts an economy at $\tau = 0.2$, i.e., a recession and the right panel an economy at $\tau = 0.8$, i.e., a boom phase. The black lines describe the responses to a financial shock at $\tau_5 = 0.1$ and the gray lines portray the responses to a financial shock at $\tau_5 = 0.9$. The dashed lines correspond to posterior 68% probability bands. Δq denotes GDP growth; Δp inflation; Δi changes in interest rates; Δm growth in money supply; u* the transformed variable of stock market volatility.

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Eigenabgrenzung

Kapitel 1 entstammt einer gemeinsamen Arbeit mit Herrn Adrian Alter (Universität Konstanz). Meine individuelle Leistung bei der Erstellung dieser Arbeit beträgt 50%.

Kapitel 2 entstammt einer gemeinsamen Arbeit mit Herrn Fabian Fink (Universität Konstanz). Meine individuelle Leistung bei der Erstellung dieser Arbeit beträgt 50%.

Ich versichere hiermit, dass ich Kapitel 3 ohne Hilfe Dritter verfasst habe.