Unconventional Identification in Vector Autoregressive Models: Empirical Essays on Credit, Risk and Uncertainty

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To Anna.

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Berlin, July 2015 *Maximilian Podstawski*

Abstract

The toolkit of identification strategies for structural vector autoregressive (SVAR) models has been constantly expanded since their introduction by Sims (1980). Recently, the literature has introduced methods of achieving identification by combining zero and sign restrictions (Mountford and Uhlig, 2009), using the heteroscedasticity properties of the structural shocks (Rigobon, 2003; Lanne and Lütkepohl, 2008) and exploiting information contained in external instruments (Stock and Watson, 2012; Mertens and Ravn, 2013). This thesis deploys those newly established methods of identification to address a variety of research questions that have arisen in the aftermath of the recent economic and financial crisis. The research questions, which fall within the domain of credit, risk and uncertainty, are addressed in four independent chapters.

The first chapter, based on joint work with Christoph Große Steffen, analyzes the relationship between macroeconomic uncertainty and risk aversion, together with their role for the pricing of sovereign debt. A theoretical model of sovereign default is used to separate the effects of risk aversion and uncertainty for bond prices. We find that investors' risk aversion is positively affected by an increase in uncertainty, pointing toward uncertainty constituting a root cause for changes in risk attitudes. Building a structural VAR identified via heteroscedasticity, we decompose credit default swaps (CDS) for Spain and Italy into three shocks: fundamental risk, risk aversion, and uncertainty. We find that shocks to macroeconomic uncertainty (1) significantly increase international investors' risk aversion, in line with the predictions of the theoretical model; (2) have a significant and economically relevant impact on sovereign financing premia; (3) account for a share in sovereign CDS of up to 25 basis points at the onset of the European sovereign debt crisis, quantitatively comparable to the effect of increased risk aversion during this period.

The second chapter, based on joint work with Anton Velinov, analyzes the impact of changes in sovereign bond holdings in the banking sector on the risk position of the sovereign. The theoretical literature is inconclusive on whether changes in bank exposure towards the domestic sovereign have an adverse effect on the sovereign risk position via a *diabolic loop* in the sovereign-bank nexus or reduce perceived default risk by acting as a *disciplinary device* for the sovereign. We empirically analyze the impact of exogenous changes in bank exposure on the risk position of the sovereign within a Markov switching structural vector autoregressive in heteroscedasticity (MSH-SVAR) framework for a set of EMU countries. We add to the methodological literature by allowing for regime dependent shock transmissions according to the volatility state of the financial system. Finding support for both, a stabilizing and a destabilizing effect, we document a clear clustering among the country sample: Rising bank exposure increased default risk for the EMU periphery, but decreased credit risk for the core EMU countries during times of financial stress.

The third chapter analyzes the drivers of current account imbalances in the European Monetary Union. Against the backdrop that current account imbalances have been a decisive feature of the European banking and sovereign debt crisis, this chapter investigates the drivers of euro area current accounts — their divergence and subsequent rebalancing — within a structural model that accommodates potential regime changes upon the introduction of the common currency and the onset of the financial crisis. It is found that domestic demand shocks account for a substantial fraction in the current account deficits of EMU periphery countries in the run-up to the crisis — the mirror image of Germany's foreign demand driven surplus. While supply side factors also explain part of the current account deficits in Italy, Spain and Portugal in the years before the crisis, shocks to price competitiveness or foreign demand played a minor role for those economies. The adjustment subsequent to the financial crisis was borne partly by a contraction in demand in the economies running deficits, but is also due to adverse supply shocks implying lower growth perspectives.

The fourth chapter, based on joint work with Michele Piffer, proposes a new instrument to identify the impact of uncertainty shocks in a SVAR model with external instruments. We construct the instrument for uncertainty shocks by exploiting variations in the price of gold around selected events. The events capture periods of changes in uncertainty unrelated to other macroeconomic shocks. The variations in the price of gold around such events provide a measure correlated with the underlying uncertainty shocks, due to the perception of gold as a safe haven asset. The proposed approach improves upon the recursive identification of uncertainty shocks by not restricting only one structural shock to potentially affect all variables in the system. Replicating Bloom (2009), we find that the recursive approach underestimates the effects of uncertainty shocks and their role in driving monetary policy.

Keywords: Structural vector autoregression, Identification, Heteroscedasticity, Sign restrictions, External Instruments, Sovereign debt, Risk, Uncertainty, Sovereign-bank interlinkages, Capital flows, Current accounts.

JEL Classification: C32, D80, E43, G01, H63, F32, F45.

Zusammenfassung

Das Instrumentarium zur Identifikation von strukturellen Vektorautoregressiven Modellen ist seit deren Einführung durch Sims (1980) stetig gewachsen und zuletzt um neue Ansätze erweitert worden. Zu diesen neuen Identifikationsstrategien gehört die Kombination von Ausschluss- und Vorzeichenrestriktionen (Mountford and Uhlig, 2009), die Verwendung der Heteroskedastizitätseigenschaften in den zugrundeliegenden Daten (Rigobon, 2003; Lanne and Lütkepohl, 2008), sowie die Nutzung von externen Instrumenten (Stock and Watson, 2012; Mertens and Ravn, 2013). Diese Dissertation verwendet diese neuen Identifikationsstrategien, um in vier unabhängigen Aufsätzen Forschungsfragen zu untersuchen, die im Zuge der jüngsten Finanz- und Wirtschaftskrise auf die Forschungsagenda gerückt sind.

Der erste Aufsatz basiert auf einem Fachartikel mit Christoph Große Steffen und analysiert den Zusammenhang zwischen makroökonomischer Unsicherheit und Risikoaversion sowie deren Rolle für die Bepreisung von Staatsanleihen. Im Rahmen eines theoretischen Modells zeigen wir, dass sowohl steigende Risikoaversion als auch zunehmende ökonomische Unsicherheit die Finanzierungsprämie des Staates erhöhen. Dabei steigt die Finanzierungsprämie mit der ökonomischen Unsicherheit aufgrund eines direkten Effekts, der Unsicherheitsprämie, und eines indirekten Effekts, da auch die Risikoaversion mit zunehmender Unsicherheit steigt. In einer empirischen Analyse auf der Grundlage eines strukturellen Vektorautoregressiven Modells, das über die Heteroskedastizität in den Daten identifiziert wird, zerlegen wir die Prämien von Kreditausfallversicherungen für Spanien und Italien in drei strukturelle Schocks: Fundamentales Ausfallrisiko, Risikoaversion und makroökonomische Unsicherheit. Wir zeigen, dass Unsicherheitsschocks (1) die Risikoaversion internationaler Investoren signifikant erhöhen, (2) die Finanzierungsprämien in einem ökonomisch relevanten Maßsteigern und (3) zu Beginn der Europäischen Staatsschuldenkrise zu einem Finanzierungsaufschlag von bis zu 25 Basispunkten — vergleichbar mit dem Effekt der Veränderung in der Risikoaversion in diesem Zeitraum — auf die Kreditausfallversicherung führen.

Der zweite Aufsatz, der auf einem Fachartikel mit Anton Velinov basiert, untersucht empirisch den Effekt von Veränderungen in den Volumina von Staatsanleihen, die im heimischen Bankensektor gehalten werden, auf die Risikoposition des Staates. Aus der theoretischen Literatur leiten sich widersprüchliche Aussagen über den erwarteten Effekt ab: Eine zunehmende Exponiertheit des Bankensektors könnte entweder über einen *Teufelskreis* der Risikoansteckung zwischen Staat und Bankensektor zum Anstieg des Ausfallrisikos des Staates führen, oder aber zu einer Reduktion des Ausfallrisikos, da die Exponiertheit des heimischen Bankensektors als *disziplinierendes Element* auf den Staat wirkt. Zur Untersuchung des empirischen Zusammenhangs entwickeln wir ein Markov-Switching-Modell, das endogen zwischen einem Regime mit niedriger Volatilität und einem Regime mit hoher Volatilität wechselt und dabei Veränderungen in der Transmission von Schocks zwischen den

Regimen zulässt. Wir dokumentieren die Existenz von destabilisierenden Effekten, die von einer zunehmenden Exponiertheit des heimischen Bankensektors ausgehen insbesondere in Spanien, Portugal und Italien, aber auch von stabilisierenden Effekten in Frankreich, Deutschland, den Niederlanden und Österreich in Phasen größerer Volatilität auf den Finanzmärkten.

Der dritte Aufsatz untersucht die Treiber von Leistungsbilanzungleichgewichten in der Europäischen Währungsunion (EWU), die ein maßgebliches Merkmal der Europäischen Banken- und Staatsschuldenkrise waren. Zur Analyse entwickele ich ein strukturelles Modell für Deutschland, Italien, Spanien und Portugal, das über eine Kombination aus Ausschluss- und Vorzeichenrestriktionen identifiziert wird und den Strukturbrüchen zum Eintritt in die Währungsunion und zum Beginn der Finanz- und Wirtschaftskrise von 2008/09 Rechnung trägt. Das Modell verweist darauf, dass Nachfrageschocks zu den wesentlichen Treibern der Leistungsbilanzdefizite von Italien, Spanien und Portugal gehören, während spiegelbildlich die Auslandsnachfrage ursächlich ist für die deutschen Leistungsbilanzüberschüsse in den ersten Jahren der Währungsunion. Während angebotsseitige Schocks ebenfalls eine Rolle spielen, scheinen weder exogene Veränderungen der preislichen Wettbewerbsfähigkeit noch der Auslandsnachfrage die Leistungsbilanzen in den Defizitländern belastet zu haben. Die plötzliche Anpassung der Leistungsbilanzpositionen in der Folge der Krise wurde von einer Kontraktion der Nachfrage in den Defizitländern aber auch von angebotsseitigen Schocks und entsprechend geringeren Wachstumserwartungen getragen.

Der vierte Aufsatz basiert auf einem Fachartikel mit Michele Piffer. In dem Aufsatz entwickeln wir ein neues Instrument zur Identifikation von Unsicherheitsschocks in einem strukturellen Vektorautoregressiven Modell auf der Grundlage der Veränderung des Goldpreises zu ausgewählten Ereignissen. Diese Ereignisse sind so gewählt, dass sie in einem Zusammenhang mit Veränderungen ökonomischer Unsicherheit stehen, nicht aber zu anderen makroökonomischen Schocks. Wir argumentieren, dass die Veränderung des Goldpreises zu diesen Ereignissen mit den zugrundeliegenden, unbeobachtbaren Unsicherheitsschocks korreliert, da Gold unter Anlegern als sichere Anlage gilt. Die Identifikation von Unsicherheitsschocks mittels des vorgeschlagenen externen Instruments hat gegenüber dem in der Literatur verbreiteten rekursiven Identifikationsschema den Vorteil, dass sie nicht nur einem einzelnen Schock erlaubt, kontemporär sämtliche Variablen im System zu beeinflussen. Impuls-Antworten und Varianzzerlegungen der Prognosefehler verweisen darauf, dass die Effekte von Unsicherheitssschocks auf die Volkswirtschaft durch das rekursive Identifikationsschema unterschätzt werden.

Schlagworte: Strukturelle Vektor Autoregression, Identifikation, Heteroskedastizität, Vorzeichen-Restriktionen, Externe Instrumente, Staatsschulden, Risiko, Unsicherheit, Kapitalflüsse, Leistungsbilanzen.

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List of Abbreviations

AIC Akaike Information Criterion
ARCH Autoregressive conditional heteroscedasticity
BIC Bayesian Information Criterion
CBOE Chicago Board Options Exchange
CDS Credit default swaps
CRRA Constant relative risk aversion
ECB European Central Bank
EFSF European Financial Stabilization Facility
EMU European Monetary Union
ERM European exchange rate mechanism
ESM European Stability Mechanism
FEVD Forecast error variance decomposition
GDP Gross domestic product
HARA Hyperbolic absolute risk aversion
i.e. id est
IR Impulse response
LR Likelihood ratio
LTRO Long Term Refinancing Operations
MFI Monetary financial institution
MS Markov switching
MS-SVAR Markov-switching structural vector autoregression
MSH-VAR Markov-switching in heteroscedasticity vector autoregression
OECD Organisation for Economic Co-operation and Development
OMT Outright Monetary Transactions
SMP Securities Markets Programme
SVAR Structural vector autoregression
TFP Total factor productivity
VAR Vector autoregression
VIX CBOE volatitlity index

Overview

Since their introduction by Sims (1980) vector autoregressions (VARs) have become the workhorse model for empirical macroeconomists. The use of VAR models for structural analysis is contingent on additional identifying assumptions imposed on the model. Imposing sufficient additional structure on reduced form VAR models allows to uncover unobservable structural shocks and trace their effect throughout the system modeled in the vector autoregressive setup, say, the economy or the financial system. The identification of economically interpretable, uncorrelated shocks constitutes the main challenge in deploying structural vector autoregressions (SVARs) in order to move from correlation to causation for the analysis of structural economic dynamics.

The toolkit of identification strategies for SVARs has constantly grown over the past decades. Researchers have been using zero restrictions on impact or on the long-run effects of structural shocks on economic variables, as well as set identification approaches, such as sign, shape and magnitude restrictions. More recently, the methodological literature on identification of VARs has established new methods of achieving identification by combining zero and sign restrictions (Mountford and Uhlig, 2009), using the heteroscedasticity properties of the structural shocks (Rigobon, 2003; Lanne and Lütkepohl, 2008) and exploiting information contained in external instruments (Stock and Watson, 2012; Mertens and Ravn, 2013).

This thesis deploys these unconventional and newly established methods of identification to address a variety of research questions that have arisen in the aftermath of the recent economic and financial crisis. The research questions, which fall within the domain of credit, risk and uncertainty, are addressed in four independent chapters. In particular, the thesis (1) investigates the determinants of sovereign financing premia during the financial and sovereign debt crisis exploiting the heteroscedasticity in the structural shocks for identification, (2) analyses the linkage between sovereign risk and banking sector exposure using heteroscedasticity to assess the identifying restrictions imposed, (3) investigates the structural determinants of credit flows within the European Monetary Union based on shocks identified with a combination of long-run and sign restrictions, and (4) assesses the macroeconomic effects of uncertainty shocks identified based on a novel external instrument that is proposed.

The first chapter, based on joint work with Christoph Große Steffen, analyzes the relationship between macroeconomic uncertainty and risk aversion, together with their role for the pricing of sovereign debt. A theoretical model of sovereign default is used to separate the effects of risk aversion and uncertainty for bond prices. We find that investors' risk aversion is positively affected by an increase in uncertainty, pointing toward uncertainty constituting a root cause for changes in risk attitudes. Building a structural VAR identified via heteroscedasticity, we decompose credit default swaps (CDS) for Spain and Italy into three shocks: fundamental risk, risk aversion, and uncertainty. We find that shocks to macroeconomic uncertainty (1) significantly increase international investors' risk aversion, in line with the predictions of the theoretical model; (2) have a significant and economically relevant impact on sovereign financing premia; (3) account for a share in sovereign CDS of up to 25 basis points at the onset of the European sovereign debt crisis, quantitatively comparable to the effect of increased risk aversion during this period.

This chapter contributes to the literature along different dimensions. Firstly, it shows theoretically and empirically that increases in uncertainty rises investors risk aversion, pointing toward uncertainty constituting a root cause for changes in risk attitudes. Secondly, we introduce a novel high frequency measure of economic uncertainty by applying the methodology put forward by Jurado et al. (2015) to a large set of equity returns. Thirdly, we propose an identification of fundamental risk, risk aversion, and uncertainty shocks that makes use of the data properties following Rigobon (2003) and Lanne and Lütkepohl (2008) and the forecast error variance of the endogenous variables in the SVAR model in order to label the shocks. We confirm the labeling based on the heteroscedasticity pattern of the structural shocks obtained. Fourthly, we quantify the share in sovereign yields over the most recent period of financial and fiscal distress in the euro area.

The second chapter, based on joint work with Anton Velinov, analyzes the impact of changes in sovereign bond holdings in the banking sector on the risk position of the sovereign. The theoretical literature is inconclusive on whether changes in bank exposure towards the domestic sovereign have an adverse effect on the sovereign risk position via a *diabolic loop* in the sovereign-bank nexus or reduce perceived default risk by acting as a *disciplinary device* for the sovereign. We empirically analyze the impact of exogenous changes in bank exposure on the risk position of the sovereign within a Markov switching structural vector autoregressive in heteroscedasticity (MSH-SVAR) framework for a set of EMU countries. We add to the methodological literature by allowing for regime dependent shock transmissions according to the volatility state of the financial system. Finding support for both, a stabilizing and a destabilizing effect, we document a clear clustering among the country sample: Rising bank exposure increased default risk for the EMU periphery, but decreased credit risk for the core EMU countries during times of financial stress.

This chapter contributes to the literature along two dimensions. Firstly, we empirically investigate the impact of bank exposure on sovereign credit risk (and hence, overall financial stability) in the euro area. As far as we are aware, this issue is not yet investigated from an empirical perspective, even though the role of bank exposure is at the center of an intense policy debate. Secondly, this chapter makes a methodological contribution to the existing MSH-SVAR literature (see for instance Herwartz and Lütkepohl, 2014) by allowing for regime dependent shock transmission along the lines of Bacchiocchi and Fanelli (2015). Here, the appeal of the model extension is that it allows to identify regime dependent impacts of increases in exposure on the risk positions of the sovereign sector.

The third chapter analyzes the drivers of current account imbalances in the European Monetary Union. Against the backdrop that current account imbalances have been a decisive feature of the European banking and sovereign debt crisis, this chapter investigates the drivers of euro area current accounts — their divergence and subsequent rebalancing — within a structural model that accommodates potential regime changes upon the introduction of the common currency and the onset of the financial crisis. It is found that domestic demand shocks account for a substantial fraction in the current account deficits of EMU periphery countries in the run-up to the crisis — the mirror image of Germany's foreign demand driven surplus. While supply side factors also explain part of the current account deficits in Italy, Spain and Portugal in the years before the crisis, shocks to price competitiveness or foreign demand played a minor role for those economies. The adjustment subsequent to the financial crisis was borne partly by a contraction in demand in the economies running deficits, but is also due to adverse supply shocks implying lower growth perspectives.

The contribution of this chapter is twofold. Firstly, it adds to the literature by putting forward a structural analysis of the drivers of EMU current accounts, integrating the competing hypotheses into one coherent structural framework. This is — to the best of my knowledge — the first paper deploying a structural empirical model in order to investigate the drivers of EMU current accounts. Secondly, it proposes a modeling approach that accounts for potential structural breaks, while being parsimonious on the data. Such an approach is well suited for analyses confronted with few observations in relatively short regimes, as it is the case with the EMU before and after the financial crisis.

The fourth chapter, based on joint work with Michele Piffer, proposes a new instrument to identify the impact of uncertainty shocks in a SVAR model with external instruments. We construct the instrument for uncertainty shocks by exploiting variations in the price of gold around selected events. The events capture periods of changes in uncertainty unrelated to other macroeconomic shocks. The variations in the price of gold around such events provide a measure correlated with the underlying uncertainty shocks, due to the perception of gold as a safe haven asset. The proposed approach improves upon the recursive identification of uncertainty shocks by not restricting only one structural shock to potentially affect all variables in the system. Replicating Bloom (2009), we find that the recursive approach underestimates the effects of uncertainty shocks and their role in driving monetary policy.

The contribution of this chapter is to propose a new instrument to identify the impact of uncertainty shocks in a SVAR model with external instruments. We improve upon existing proxies for uncertainty shocks (Stock and Watson, 2012; Carriero et al., 2015) by constructing a proxy variable that is not restricted to a dummy variable or an *ad hoc* measure based on the residuals of an autoregressive model of variables capturing uncertainty. To the best of our knowledge, our paper is the first one to study uncertainty shocks using the dynamics of the price of safe haven assets around selected events.

Chapter 1

Risk And Uncertainty in Sovereign Debt Markets[1]

1.1 Introduction

Over the course of the European sovereign debt crisis of 2009-2012, affected governments in the euro area faced financial conditions in international capital markets that seemed to be inconsistent with public debt sustainability. In this context, a growing strand of empirical literature shows that public debt of distressed countries was priced at levels that cannot be explained by macroeconomic fundamentals alone.[2] Instead, a common explanation for the unexplained part in European bond returns was found to be strong variation in investors' risk aversion.[3]

We argue that macroeconomic uncertainty affects investors asset pricing decisions in two distinct ways: via a first order effect in form of an ambiguity premium and via a second order effect by increasing investors risk aversion. While it is well understood from the macroeconomic literature that risk aversion varies with changes in wealth and the level of habit persistence in consumption,[4] this paper introduces macroeconomic uncertainty as an additional source of variation in investors' risk aversion. In particular, we show theoretically and empirically that an increase in the level of macroeconomic uncertainty raises investors' effective risk aversion. Thereby, the results are pointing toward uncertainty constituting a root cause for changes in risk attitudes. The empirical findings are part of the research effort attempting

[1] This chapter is based on an article that is joint work with Christoph Große Steffen.

[2] See, among others, Aizenman et al. (2013), Grauwe and Ji (2012), or D'Agostino and Ehrmann (2014).

[3] Hagen et al. (2011) and Bernoth and Erdogan (2012) document a sharp increase in risk aversion. See a detailed discussion below.

[4] The role of wealth for risk aversion was elicited in the classic work by Arrow (1963) and Pratt (1964). Constantinides (1990) and Campbell and Cochrane (1999) made seminal contributions to the analysis of habit. However, Brunnermeier and Nagel (2008) find no evidence of a wealth effect on risk aversion in the micro data.

to understand the deterioration in financing conditions for European sovereigns. We find that macroeconomic uncertainty explains a relevant share in the sovereign financing premia.

To explore the different nature of risk and uncertainty for the pricing of sovereign debt, we use a consumption-based asset pricing model with optimal sovereign default. In this model of a small open economy that exists for two periods, a sovereign government is rolling over its accumulated stock of government debt. It cannot commit to repay its debt in the final period. It will do so depending on the realization of aggregate productivity. However, the law of motion of the aggregate productivity state is risky and uncertain, similar to the case in Ilut and Schneider (2014). More precisely, uncertainty enters in the form of ambiguity, which reflects the nature of uncertainty we are interested in and which contrast with the analysis of volatility. As a result of ambiguity about the macroeconomic fundamental, the payoffs from holding government debt turn out to be ambiguous, too. International investors purchase the government debt. Their preferences have two features. First, they exhibit constant relative risk aversion (CRRA) preferences with habit persistence in the level of consumption. This yields variation in the intertemporal elasticity of substitution in consumption that affects investors' risk aversion, depending on the level of habit persistence (Chetty and Szeidl, 2005). Second, investors exhibit preferences that make them sensitive toward the uncertainty surrounding the future aggregate productivity realization. Specifically, we let investors be ambiguity averse according to the maxmin-model of Gilboa and Schmeidler (1989). As a result of multiple priors regarding the possible law of motion for productivity, maxmin preferences make investors act under their worst case prior. We use the model to pin down analytically the three components, fundamental risk, risk aversion and uncertainty, in the arising asset pricing equation for defaultable government debt, which we subsequently identify in an empirical model.

Further, we show on the microeconomic level at the backdrop of the preference structure of investors in the model that a rise in uncertainty increases risk aversion. This is a result from the interaction between a change in the worst case prior of investors in response to a level-shift in uncertainty and decreasing aversion to risk in wealth, a property that arises from external habit persistence in consumption. As investors expect with higher uncertainty lower levels of surplus consumption in the future, they tend to be more risk averse today. This mechanism is not described previously in the literature. We derive the conditions for the main mechanism in a parametrized setting within the maxmin-model.[5] In the empirical part, we provide evidence for the implied testable implication that an increase of macroeconomic uncertainty is followed by a significant rise in an aggregate measure of risk aversion, as predicted by the model. Thereby, macroeconomic uncertainty is found to be a root cause for risk attitudes more generally.

Based on the decomposition of sovereign financing premia of our theoretical model, we analyze the role of macroeconomic uncertainty for the pricing of sovereign debt empirically in a structural vector autoregressive (SVAR) model. Given the lack of identifying restrictions provided by economic theory, we exploit the statistical properties of the data in order to identify three shocks: A fundamental risk shock, a risk aversion shock, and an uncertainty shock. We deploy the structural model to empirically assess the relevance of macroeconomic uncertainty for the pricing of Spanish and Italian sovereign debt, decomposing their financing premia in contributions from the three shocks considered. We find that shocks to macroeconomic uncertainty have a significant impact on sovereign yields. They make up for close to 30 basis points in credit default swaps (CDS) at the onset of the European sovereign debt crisis, while their role diminishes as the sovereign debt crisis unfolds. Our model provides evidence for macroeconomic uncertainty to play a comparable role for the pricing of sovereign credit risk as time varying risk aversion. By jointly analyzing the effects of risk aversion and uncertainty, we achieve a comprehensive empirical identification of these two closely related concepts, which are often not clearly separated in the literature.

On the empirical side, this paper makes three contributions. Firstly, we propose a novel high frequency measure of economic uncertainty. To this end, we apply the methodology put forward by Jurado et al. (2015) to a large set of Spanish and Italian equity returns. As a result, we obtain a weekly time series that reflects the underlying economic uncertainty faced by investors, entrepreneurs, and employees alike. Secondly, we propose an identification of fundamental risk, risk aversion, and uncertainty shocks within a Markov-switching structural vector autoregressive

[5] We leave the generalization of this result with respect to different modeling approaches to ambiguity in the $\alpha-$maxmin expected utility framework (Ghirardato et al., 2004) and in the smooth ambiguity framework (Klibanoff et al., 2005) for future research

(MS-SVAR) model that makes use of the data properties following Rigobon (2003) and Lanne and Lütkepohl (2008). Such a statistical identification approach is particularly helpful as economic theory does not offer any structural restrictions that facilitate the disentanglement of risk aversion from uncertainty shocks. We label the statistically identified shocks by investigating their contribution to the forecast error variance of the endogenous variables in the SVAR model and confirm the labeling based on the heteroscedasticity pattern of the shocks. Thirdly, we quantify the share in sovereign yields over the most recent period of financial and fiscal distress in the euro area and find that uncertainty shocks account for a relevant share in the financing premium of the countries considered.

Relation with the literature. On the theoretical side, this paper is closely related with a small literature that analyses the interaction of risk aversion and ambiguity aversion. Cherbonnier and Gollier (2015) analyse how the attitude towards risk, specifically the property of *decreasing aversion* in wealth in an Arrow-Pratt sense, is affected by the introduction of ambiguity aversion. They show that this property is robust to the introduction of ambiguity aversion in the form of the maxmin-model if preferences feature decreasing concavity and are of the HARA-type[6], i.e. linear in absolute risk aversion. Alary et al. (2013) find that the willingness to pay for self-insurance is, under certain conditions, higher if there is ambiguity aversion on top of risk aversion. They further extend their analysis to the case of self-protection which assumes that the level of ambiguity can be affected through effort, an assumption which we do not have in our setting.

Our findings are, moreover, related to the finance literature that explains the equity premium and risk free rate puzzle through the joint presence of risk and uncertainty. Maenhout (2004) documents that robust control preferences increase the coefficient of relative risk aversion of an investor with Duffie-Epstein-Zin preferences, thereby leading to *environment-specific* effective risk aversion. Similarly, Trojani and Vanini (2004) describe that portfolio decisions of ambiguity averse investors can be observationally equivalent to decisions made by investors with higher levels of risk aversion. Since with robust control preferences the amount of required robustness is endogenously determined, this framework does not allow for the anal-

[6] This property holds for the majority of utility functions used in the macroeconomic literature.

ysis of exogenous variations in the level of uncertainty that are independent of the fundamental state, as is the focus of this paper.

Further, this paper is related to models of sovereign default that analyze the role of investor preferences for pricing of government debt. Lizarazo (2013) shows how the introduction of risk aversion makes the pricing of sovereign debt sensitive toward investors' stock of accumulated wealth. Borri and Verdelhan (2010) introduce time-varying risk aversion through habit persistence in the utility function. Große Steffen (2015) analyses the effects of ambiguity aversion in a quantitative model of sovereign default. This paper is distinct in that it combines ambiguity aversion, risk aversion and habit persistence in consumption on the side of investor preferences. We show that all three elements are necessary to obtain an effect of uncertainty on risk aversion. Thereby, we achieve a clear separation of the concepts of risk and uncertainty in an encompassing framework and study their interactions.

The empirical results of this paper are related to a growing literature on the determinants of sovereign yields. While Laubach (2009), Borgy et al. (2011) and Hilscher and Nosbusch (2010) find evidence for an important role of fiscal variables on government bond yields in US, European and emerging market data, respectively, fundamentals fall short in explaining the deterioration in sovereign financing conditions. There are a number of explanations put forward in the existing literature for this overpricing of risk during the global financial crisis and the subsequent European sovereign debt crisis.

Most prominently, several papers investigate the time variation in investors' risk perception as an explanation of diverging European sovereign spreads. Barrios et al. (2009), Sgherri and Zoli (2009) and Caceres et al. (2010) empirically analyze the determinants of European sovereign yield spreads during the financial crisis and find evidence for increased global risk aversion in combination with macroeconomic fundamentals to be important drivers for the rise in yield spreads. Hagen et al. (2011) find that markets turned more sensitive toward fiscal measures after the collapse of Lehman Brothers. Bernoth and Erdogan (2012) also find evidence for time-varying coefficients that determine the impact of fiscal variables for the pricing of sovereign debt and for investors' risk aversion in a semi-parametric approach. Arghyrou and Kontonikas (2012) argue that the European sovereign debt crisis was in fact a currency crisis that diverted into markets for sovereign bonds. They find that during the crisis markets started pricing an international risk factor and macro-fundamentals on a country-by-country basis and report evidence for a contagion of European economies originating in Greece. According to D'Agostino and Ehrmann (2014), time varying risk appetite of investors can explain some increase in European bond yields, but it still falls short of explaining the rise seen in French and Italian data over the crisis period. They conclude that observed yields are due to an overpricing of risk or possible concerns about redenomination of currencies. Further, Aizenman et al. (2013) and Haan et al. (2014) refer to overpricing in selected member countries of the euro area using cross-country panel data approaches. In a study of risk premia in the CDS market Amato (2005) decomposes the spreads into a default component and a risk premium component. He finds the latter to be highly volatile, supporting the view that changing risk attitudes are important for fluctuations in asset prices. Focusing on the decomposition of sovereign CDS for an extensive set of developed and emerging market economies, Longstaff et al. (2011) find that the risk premium represents about one third of the spreads.

Next to time varying risk aversion additional explanations for excessive bond spreads have put forward. One strand of literature argues that the exit from the currency union would expose counterparties to the risk of redenomination into a new currency. Kriwoluzky et al. (2014) use a structural macroeconomic model with exogenous probabilities of regime changes to decompose the sovereign yield of Greece. They find that the exit risk can explain up to 10 percent in Greek bond yields. De Santis (2015) exploits the difference between credit default swap (CDS) contracts denominated in euro and US dollar to identify the redenomination risk contained in European sovereign yields. He finds that up to 50 percent in Spanish yield spreads could be explained by changes in redenomination risk. As another explanation, Favero and Missale (2012) and Beirne and Fratzscher (2013) look into the role of cross-country contagion. Both papers find only a minor role for contagion over the course of the European sovereign debt crisis. Recently, Bocola and Dovis (2015) argue that non-fundamental self-fulfilling default expectations due to future inefficient roll-over crises have been at play. Based on their structural model of optimal sovereign default with sun-spot rollover crises and an endogenous maturity structure, they find that the non-fundamental share in Italian bond spreads was important during 2011.

The paper is structured as follows. The next section develops a small scale structural model in order to study the relation between macroeconomic uncertainty and the pricing of sovereign debt and motivate the following empirical analysis. Section 1.3 outlines the empirical setup for the analysis of economic uncertainty for sovereign financing premia. The data set is introduced in Section 1.4. This section also discusses in greater detail the construction of a high frequency index of macroeconomic uncertainty. Section 1.5 presents the empirical model used to analyze the relevance of uncertainty shocks for the pricing of sovereign debt, before results are presented in Section 1.6. Section 1.7 concludes.

1.2 A theoretical model

In this section, we develop a parsimonious model in which investors hold defaultable government debt. The aggregate level of productivity is assumed to be uncertain. We consider exogenous changes in the level of uncertainty and investors' risk aversion. The objective is to study the effects of theses two shocks in a unified framework for the pricing of risky and ambiguous government debt, motivating the decomposition of the sovereign yield spread in fundamental risk, time varying risk aversion, and uncertainty shocks. While the level of uncertainty is fully exogenous in this setting, one main result of the model is that risk aversion is partly affected by changes in macroeconomic uncertainty.

1.2.1 Environment

We start with a simple two-period dynamic model of optimal sovereign default in a production economy. Let there be a small open economy over two periods, $t = 1, 2$. The economy is populated by three different agents: a representative household, a government, and a representative international investor.[7] The innovation lies in modeling the preference structure of international investors more exhaustively. Specifically, international investors are assumed to be simultaneously risk averse and ambiguity averse. Further, variation in the degree of relative risk aversion arises from habit persistence in consumption (Constantinides, 1990; Borri and Verdelhan, 2010).

[7] Figure 1.C.8 gives an overview of the timing of events in the model.

Household. The household produces a final tradeable good y_t with constant labor input l while taking as given the aggregate level of productivity z_t, thus $y_t = e^{z_t}F(l)$. The law of motion for aggregate productivity z_t is subject to risk and uncertainty and will be specified below. The household derives utility from consumption in each period, given by a quadratic utility function:

$$u(c_1, c_2) = \sum_{t=1}^{2} \left(c_t - \frac{\psi}{2}(c_t)^2 \right)$$

Final goods cannot be stored and therefore consumption is given by aggregate final good production net of government transfer payments or lump sum taxation, τ_t. Thus, the household is respecting a set of period t budget constraints of the form

$$c_1 = y_1 - \tau_1,$$
$$c_2 = y_2 - \tau_2$$

Government. The government is a benevolent planner. Given limitations of private households to save or access international financial markets for consumption smoothing, the government provides an optimal tax- and transfer schedule that smoothes private consumption, which are given by

$$\tau_1 = q_1 B_2 - B_1,$$
$$\tau_2 = -B_2.$$

In particular, the government may borrow from international investors in the form of one-period discount bonds, denoted by B_t. It enters the period $t = 1$ with the previously accumulated stock of debt B_1. Importantly, the government cannot commit to repay the debt when it becomes due in period t. Instead, it takes an optimal default decision. Default is a binary choice, denoted by $\delta_t \in \{0, 1\}$. When defaulting, the government suffers from an exogenous penalty, which comes in the form of a loss on aggregate output:

$$g(y) = \left\{ \begin{array}{lll} \hat{y} & \text{if} & z_t = z^h \\ y & \text{if} & z_t = z^l \end{array} \right\}$$

The penalty function $g(y)$ is pro-cyclical. The lower aggregate output, the lower is the output-loss conditional on defaulting. As a result and depending on the exact specification, default becomes more likely in times of below average production, thus during recessions, as shown by Arellano (2008).

Technology and uncertainty. The formalization of uncertainty closely follows Große Steffen (2015).[8] In order to keep the model as parsimonious as possible, the productivity parameter z_t is assumed to feature two states, $z_t \in \left\{z^l, z^h\right\}$, with $z^h > 0$ and $z^l < 0$. We think of these two states as being sufficient in introducing risk and uncertainty about the future fundamental state of the economy. The values of z_t can be interpreted as recessions and booms, respectively. For simplicity, let aggregate productivity at $t = 1$ be deterministic and taking the lower value, $z_1 = z^l$. However, productivity at $t = 2$ is *uncertain* and can take either the low or the high value. This is decided from the realization of a random draw of the stochastic variable x, which is uniformly distributed on the interval (x^*_{lb}, x^*_{ub}), i.e. $x \sim \mathcal{U}(x^*_{lb}, x^*_{ub})$. If the draw exceeds the threshold variable $\bar{x}$, the high productivity level realizes, thus $z_2 = z^h$. Agents know the threshold value $\bar{x}$ and that x is drawn from a uniform distribution. Thereby, future productivity is stochastic, hence *risky*. Additional uncertainty in the form of *ambiguity* enters into the law of motion of aggregate productivity. Specifically, we assume that the exact upper and lower bounds (x^*_{lb}, x^*_{ub}) of the distribution of x are unknown. In order to form expectations about the realization of future productivity, agents have multiple priors about these two parameters, which are specified next.

We assume that there is an exogenous realization of uncertainty that pins down the set of prior beliefs about the true data generating process. Specifically, agents are assumed to have *a priori* information about parameters of the distribution, denoted by $\tilde{x}^p_{lb}$ and $\tilde{x}^p_{ub}$. Then, an uncertainty realization from a known uniform distribution $a \sim \mathcal{U}(0, \bar{a})$ pins down the set of prior beliefs about the true probabilistic model $\mathcal{U}(x^*_{lb}, x^*_{ub})$ as a symmetric interval around the *a priori* given parameters $\tilde{x}^p_{lb}$ and $\tilde{x}^p_{ub}$ according to

$$supp^p(\mathcal{U}) \in \mathcal{P} = \begin{cases} x^p_{lb} \in [\tilde{x}_{lb} - a, \tilde{x}_{lb} + a] \\ x^p_{ub} \in [\tilde{x}_{ub} - a, \tilde{x}_{ub} + a]. \end{cases} \tag{1.1}$$

[8] This approach to modeling uncertainty is based on Ilut and Schneider (2014), adjusted to the simplified set-up described here.

The productivity process is illustrated in Figure 1.C.9 in the form of a stylized bet over the ambiguous process of the stochastic variable x.

1.2.2 Consumption-based asset pricing

Government debt is purchased by a unit mass of identical international investors. This Section presents a consumption-based asset pricing model with two assets, risky and uncertain government debt and a riskfree asset. The novelty here is to modify the preferences of investors such that changes in risk aversion and the level of uncertainty regarding future productivity simultaneously matter for the portfolio decision of investors, and ultimately for the pricing of government debt in this framework. This is achieved by extending the standard dynamic asset pricing model (Samuelson, 1969) in two directions, habit persistence in consumption and ambiguity aversion.

We follow Campbell and Cochrane (1999) with their specification of external habit persistence in the form of the difference between current and past aggregate consumption. Including this approach to habit in the constant relative risk aversion (CRRA) utility function yields time variation in risk aversion through non time separability of preferences.[9] Specifically, investors exhibit the following utility function:

$$\upsilon(c_t^*, h_t) = \frac{(c_t^* - h_t)^{1-\gamma} - 1}{1-\gamma}$$

with consumption c_t^*, the level of habit persistence h_t, and γ denoting the coefficient of risk aversion. Given the reduced time horizon in the analysis of two periods, we assume that the habit parameter h_t is fully exogenous and not determined by the history of aggregate consumption. Specifically, the habit parameter can take two values, $h_t \in \left\{h^l, h^h\right\}$. For simplicity, let $h_2 = h^l$. Here, we are mainly interested in the effects of a change in relative risk aversion in the initial period $t = 1$, which depends on the level of surplus consumption. We can then proceed by defining the surplus consumption ratio of the investor as $\phi_t \equiv (c_t^* - h_t)/c_t^*$, such that the

9 There are alternative approaches to modeling habit persistence in the literature. In Abel (1990; 1999), utility is redefined as $\upsilon(c^*/h_t)$, which yields constant degree of risk aversion.

coefficient of relative risk aversion is given by

$$\eta_t = -\frac{c_t^* \upsilon_{cc}(c_t^*, h_t)}{\upsilon_c(c_{t,}^* h_t)} = \gamma \frac{c_t^*}{c_t^* - h_t} = \frac{\gamma}{\phi_t}. \tag{1.2}$$

Next, we describe the maxmin-model following Gilboa and Schmeidler (1989) that is used to allow for ambiguity aversion on the side of international investors.[10] Be reminded that investors, confronted with the fact that the support of the uniform distribution of the random variable x determining the level of productivity in period $t = 2$ is ambiguous, exhibit a set of multiple-priors regarding the support of the distribution which is determined by an exogenous realisation of uncertainty, as shown in equation (1.1). Then, international investors maximize their expected utility over two periods conditional on each prior in the set, and act according to the worst case outcome.[11] This approach leads to distorted probabilities in expectations, which are denoted by E_t^p. The optimization problem of the representative international investor consists of an consumption-savings decision c_1^* and a portfolio decision that determines the fraction α, which is invested in government debt. Formally, the investor's problem takes the form:

$$\max_{\{c_1^*, \alpha\}} \min_{\{supp^p(\mathcal{U} \in \mathcal{P})\}} \upsilon(c_1^*, h_1) + \beta E_t^p[\upsilon(c_2^*, h_2)] \tag{1.3}$$

$$\text{s.t.} \qquad W_2 = (1 + R_{p,2})(W_1 - c_1^*)$$

$$R_{p,2} = \alpha(R_t - R_f) + R_f$$

where β is the investor's discount factor, $R_{p,t}$ denotes the returns from the portfolio consisting of a risk-free asset with returns R_f and government debt with returns R_t. Initial investor's wealth is given by the pre-determined portfolio $W_1 = B_1 + S_1 R_f$, where S_1 denotes the risk-free asset and B_1 the amount of accumulated government debt. The payoffs from holding the risk-free asset and government debt from the perspective of the ambiguity averse international investor are R_f and $E_t^p[1 - \delta_t + 1]$, respectively.

[10] To focus on the main mechanism, we assume that only investors are ambiguity averse, which implies that households and the government are ambiguity neutral.

[11] The formation of a worst case prior is a result of the axiom of strict ambiguity aversion in Gilboa and Schmeidler (1989).

Then, the first order conditions to the investors problem with respect to consumption and investment decisions amount to

$$\lambda_t = (c_t^* - h_t)^{-\gamma} - h_t \tag{1.4}$$

$$q^f = \beta \min_{\{supp^p(\mathcal{U} \in \mathcal{P})\}} E_t^p \left[\frac{\lambda_{t+1}}{\lambda_t} \right] \tag{1.5}$$

$$q_t = \beta \min_{\{supp^p(\mathcal{U} \in \mathcal{P})\}} E_t^p \left[\frac{\lambda_{t+1}}{\lambda_t} (1 - \delta_{t+1}) \right] \tag{1.6}$$

The first equation reflects the optimal consumption-savings decision with λ_t denoting the shadow price on the budget constraint. Optimal investment in the risk-free asset and government debt yield the standard asset pricing conditions, where returns and asset prices are related according to $R_f \equiv (q^f)^{-1}$, and $R_t \equiv (q_t)^{-1}$.

Thus, how does ambiguity aversion affect the asset pricing condition for sovereign debt? In order to disentangle the effects of risk and uncertainty on the pricing of sovereign debt in (1.6), let us define the covariance evaluated under the worst case prior as

$$cov^p(\lambda_{t+1}, (1 - \delta_{t+1})) \equiv E_t^p \left[\lambda_{t+1}(1 - \delta_{t+1}) \right] - E_t^p \left[\lambda_{t+1} \right] E_t^p \left[1 - \delta_{t+1} \right] \tag{1.7}$$

Here, we loosely follow Epstein and Schneider (2010), who show that in the classic mean-variance portfolio choice problem, ambiguity averse investors consider uncertainty in the covariance matrix of assets for their decision. The evaluation of the covariance under the worst case prior is necessary in the here presented consumption-based asset pricing model as well as the underlying uncertainty is related to the fundamental state of the economy.

Thus, using the definition of the covariance under ambiguity and dropping the minimization operator to simplify the notation, we can rewrite the asset pricing condition for government debt as

$$q_t = \beta \frac{cov^p \left[\lambda_{t+1}, (1 - \delta_{t+1}) \right]}{\lambda_t} + \beta \frac{E_t^p[\lambda_{t+1}] E_t^p[1 - \delta_{t+1}]}{\lambda_t}$$

Now, substituting in the definition of the risk-free rate, the bond pricing condition can be rewritten as

$$q_t = \beta \frac{cov^p\left[\lambda_{t+1}, (1-\delta_{t+1})\right]}{\lambda_t} + q^f\left(1 - E_t^p[\delta_{t+1}]\right). \tag{1.8}$$

The second term in the asset pricing condition for government bonds (1.8) is well known in the literature and captures the first order effect of uncertainty for the pricing decision of ambiguity averse international investors (Epstein and Wang, 1994). Higher uncertainty leads to a more pessimistic worst case prior, hence to a higher default expectation $E_t^p[\delta_{t+1}]$.

The first term of condition (1.8) is more interesting for the present analysis. It contains a risk-premium that is negative. Intuitively, if default is expected to happen and $(1-\delta_{t+1}) \rightarrow 0$, then this affects negatively the wealth of the international investor in the consecutive period, W_{t+1}, along with her consumption level. This, in turn, pushes up the marginal utility for future consumption, $\upsilon_{c(t+1)}$, which leads to the conclusion that $cov^p[\upsilon_{c(t+1)}, (1-\delta_{t+1})] < 0$. The lower asset price given from the covariance-term makes borrowing for the government more costly.[12]

Further, condition (1.8) implies a second order effect of uncertainty on the pricing of government debt that only arises when risk aversion and ambiguity aversion are jointly present in investor preferences. In particular, the covariance-term is affected by worst case prior beliefs about the repayment of government debt in the final settlement period.

There are two counteracting effects from uncertainty on the risk premium that must be considered. On the one hand is the expected cash flow under the worst case prior lower than under subjective expected utility due to the distorted probabilities, such that $E_t^p[1-\delta_{t+1}] < E_t[1-\delta_{t+1}]$. On the other hand is the expectation for marginal utility of consumption in the consecutive period higher under the worst case prior, such that $E_t^p[\lambda_{t+1}] > E_t[\lambda_{t+1}]$. This is the case since a higher probability of default of the government on its outstanding bonds will make consumption more

[12] As we know from the definition of the covariance,

$$cov[\lambda_{t+1}, (1-\delta_{t+1})] = E_t\left[\lambda_{t+1}(1-\delta_{t+1})\right] - E_t\left[\lambda_{t+1}\right] E_t\left[1-\delta_{t+1}\right].$$

For the covariance to exist, both its elements need to be stochastic variables. In fact, both arguments are dependent on the exogenous variables of the model, which are given by TFP (z_2), uncertainty (a) and eventually habit (h), see Figure 1.C.8.

valuable. The overall effect of ambiguity aversion on the covariance term is therefore *a priori* unclear. The next Section discusses the effects arising from interactions between risk aversion and ambiguity aversion in detail.

1.2.3 Interaction of uncertainty with risk aversion

How does ambiguity aversion affect the covariance term of international investors? In order to discuss the differences between an ambiguity averse investor and the case without uncertainty, let us first define the operator E_t as the expectation under the assumption that the investor is ambiguity neutral. In the Gilboa-Schmeidler model of ambiguity aversion, this can be compared to a situation where the level of realized uncertainty is zero, $a = 0$. This case is typically understood as the standard assumption in the subjective expected utility paradigm. Therefore, we use it as a useful benchmark to illustrate the effects of uncertainty and ambiguity aversion in the model.

Disentangling the risk premium and the ambiguity premium is further complicated by the fact that the interaction between ambiguity aversion and uncertainty leads to higher risk aversion.[13] To show this, we first restate the result of decreasing aversion in *wealth* provided by Cherbonnier and Gollier (2015). They find that decreasing aversion to risk in wealth is maintained in the maxmin model if and only if the utility function u exhibits decreasing concavity.[14] Further, they state that there are three conditions that guarantee that decreasing risk aversion also leads to higher demand for the risky asset conditional on higher wealth.[15] These are (i) preferences are of the HARA type (*hyperbolic absolute risk aversion*), (ii) preferences feature decreasing concavity, and (iii) the coefficient of risk aversion is positive, thus $\gamma > 0$.

The first two conditions are satisfied under the chosen framework of CRRA utility with external habit persistence in consumption. This can be seen from relative risk aversion in the model as defined in equation (1.2). The third condition is fulfilled if one assumes a risk averse investor, which requires $\gamma > 0$ in the calibration. We are now able to state the main result regarding the interaction from ambiguity aversion and risk aversion in the model in the following proposition:

[13] A related finding was presented in Alary et al. (2013), where the authors show that ambiguity aversion, under certain conditions, leads to a higher willingness to pay for self-insurance.
[14] See Proposition 1 in Cherbonnier and Gollier (2015).
[15] See Proposition 4 in Cherbonnier and Gollier (2015).

Proposition 1. *Suppose that investors are ambiguity averse according to the maxmin-model. Suppose further that utility features hyperbolic absolute risk aversion (HARA) and decreasing concavity with a positive coefficient of risk aversion. Then, an increase in uncertainty from a_1 to a_2 with $a_1 < a_2$ leads to higher risk aversion.*

Proof. We need to show that the following condition holds:

$$-\frac{u''(E_t^{p,1}[W_2])}{u'(E_t^{p,1}[W_2])}E_t^{p,1}[W_2] < -\frac{u''(E_t^{p,2}[W_2])}{u'(E_t^{p,2}[W_2])}E_t^{p,2}[W_2],$$

Using the notation of relative risk aversion from equation (1.2), this condition can be rewritten as

$$E_t^{p,1}[\eta_{t+1}] = \frac{\gamma}{E_t^{p,1}[\phi_{t+1}]} < \frac{\gamma}{E_t^{p,2}[\phi_{t+1}]} = E_t^{p,2}[\eta_{t+1}].$$

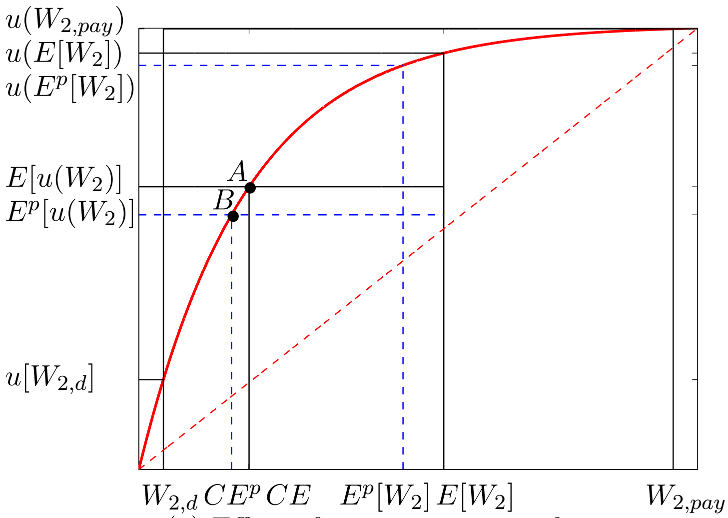
Given that expected surplus consumption under the worst case prior is decreasing in uncertainty, or $\partial E_t^p[\phi_{t+1}]/\partial a < 0$, this condition is fulfilled, such that the following relationship holds:

$$\frac{\partial E_t^p[\eta_{t+1}]}{\partial a} > 0 \tag{1.9}$$

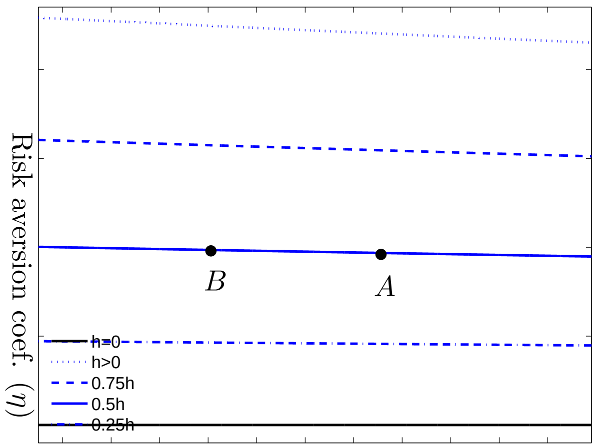
□

The content of Proposition 1 is illustrated in Figure 1.2.1(a) and Figure 1.2.1(b). First, see the wealth of the investor in period $t = 2$ under default and repayment ($W_{2,d}$, $W_{2,pay}$), along with the expected utility of the international investor.[16] If uncertainty is positive ($a > 0$), then the investors' expected utility changes from $E_t[\upsilon(W_2)]$ to $E_t^p[\upsilon(W_2)]$. Due to the first-order effect of uncertainty through ambiguity aversion, expected utility is moving from point A to point B. It is through the presence of habit persistence in consumption that introduces decreasing aversion such that this change in the level of uncertainty is accompanied by an increase in risk aversion of the investor. Figure 1.2.1(b) highlights that there is a linear relationship between risk aversion η and uncertainty a in the depicted case, which is a consequence of the HARA type of preferences used in this setting.

[16] A further detailed illustration of each of these investors' characteristics is provided in the Appendix 1.B.



(a) Effect of uncertainty on risk aversion



(b) Coefficient of relative risk aversion (η)

Figure 1.2.1: Risk aversion and ambiguity aversion

In the next section, we provide a numerical example in order to give an illustration of the different effects that uncertainty and risk imply for the pricing of government debt.

1.2.4 Numerical illustration

We solve the model numerically in order to illustrate the two different effects of risk aversion and uncertainty. Figure 1.2.2 contains the results of various calibrations.

First, we assume that investors are risk neutral and are not exposed to uncertainty ($\gamma = a = 0$). This would imply that the government can borrow within the risky borrowing region at a constant price given by $q_t = (1 - \pi^{z_l})/(1 + r^f)$. Note that the probability of default in this simple model collapses to the probability of a low productivity state (π^{z_l}). Since there is no penalty in the low productivity state, the government will default for sure in this state.

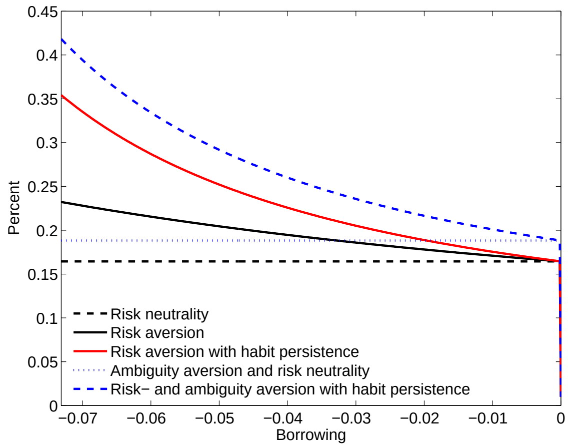


Figure 1.2.2: Bond returns from the model under risk aversion and ambiguity

Next, introducing risk aversion makes investors charge a risk premium for holding risky government debt that increases in the investors' exposure. Habit persistence in consumption increases the risk premium, which is a well established result in the literature (Campbell and Cochrane, 1999).

The novel part in this model is to combine risk aversion with ambiguity aversion. As illustrated in equation (1.2.2), introducing ambiguity aversion and habit persistence gives two effects. First, there is the well-known first-order effect of ambiguity on the pricing of risky asset which is characterized by the upward shift in the curve that characterizes the yields on government debt. Second, there is a second-order effect of ambiguity aversion that leads to a stronger increase in the yields on sovereign debt due to a higher level of risk aversion from the worst case prior from equation (1.8).

1.3 Empirical setup

The remainder of the paper, building upon the model outlined above, is concerned with the empirical assessment of the effect of economic uncertainty on the pricing of sovereign debt. Let us rewrite equation (1.8) such that the decomposition in fundamental risk, risk aversion and uncertainty on the government bond price becomes more evident. We use the property that for positive values of uncertainty we always have $E_t[\delta_{t+1}] < E_t^p[\delta_{t+1}]$, where E_t denotes the rational expectations operator of an ambiguity neutral investor, as discussed in the previous section. Expanding equation (1.6) with ambiguity neutral expectations, the asset pricing condition for risky and ambiguous government debt holding can be decomposed into four distinct components as

$$q_t = \quad q^f - \underbrace{\left(q^f E_t[\delta_{t+1}]\right)}_{\text{fundamental risk}} + \underbrace{\frac{\beta}{\lambda_t} cov(\cdot)}_{\text{risk premium}} \; + \underbrace{\frac{\beta}{\lambda_t}\left\{cov^p(\cdot) - cov(\cdot)\right\} + q^f\left(E_t[\delta_{t+1}] - E_t^p[\delta_{t+1}]\right)}_{\text{uncertainty premium}}, \tag{1.10}$$

where $cov(\cdot) = cov(\lambda_{t+1}, (1 - \delta_{t+1}))$ and $cov^p(\cdot) = cov^p(\lambda_{t+1}, (1 - \delta_{t+1}))$. Equation (1.10) is our point of departure for taking the model to the data. Note that the model implies financing premia to increase in fundamental risk, risk aversion, and uncertainty. Further, the bond price is inversely related to the yield. We make use of a trivariate Markov-switching in heteroscedasticity vector autoregressive model (MSH-VAR) containing a measure of the sovereign financing premium as well as measures of aggregate risk aversion and macroeconomic uncertainty and model the sovereign yield driven by the three (unobservable) terms in equation (1.10): a fundamental risk shock, a risk aversion shock and an uncertainty shock. Finally, we decompose the sovereign financing premium requested by market participants into contributions from these three shocks. In addition we use the model to evaluate the response of the measure of risk aversion to an uncertainty shock as an empirical assessment of the validity of Proposition 1.

The choice of model has the advantage of allowing to make use of the statistical properties of the data in order to identify the shocks of interest following the identification procedure pioneered by Rigobon (2003). In the context of VAR models, the properties of the data allow for the identification of orthogonal structural shocks within the model under certain conditions (Lanne and Lütkepohl, 2008). Making use of the statistical properties of the data for identification of orthogonal shocks is particularly helpful as economic theory does not provide a set of restrictions — neither exclusion restrictions on the short or long run effects matrix nor more agnostic sign, shape or magnitude restrictions — that would enable us to disentangle the three shocks of interest: a fundamental risk shock, a risk aversion shock, and a macroeconomic uncertainty shock.

While the statistical properties of the data help to uncover orthogonal shocks that are unique up to sign and column rotations from the model, they do not deliver any labeling of the shocks that would make them economically interpretable. Based on the assumption that the identification approach provides a vector of economic shocks, our strategy to label the set of shocks is twofold. Firstly, we draw on the information contained in the forecast error variance decomposition: The shocks explaining most of the variance in the risk aversion and the uncertainty measure are labeled risk aversion shock and uncertainty shock, respectively. The remaining shock, expected to dominate the variation in the financing premium, is labeled the fundamental risk shock. Secondly, in order to further back the economic interpretation of the shocks we follow the more narrative approach by Rigobon (2003) and exploit patterns in the series of the structural shocks uncovered from the MSH-SVAR model for a consistency check of the labeling. The two subsequent sections discuss details of the construction of the uncertainty index and the remainder of the data set as well as the specification of the MSH-SVAR in further detail before turning to the results.

1.4 Data

This section provides an overview of the data used in the subsequent analysis. It discusses in greater detail the construction of the uncertainty index and the measure of aggregate risk aversion, as well as describes the vector of exogenous variables — mainly related to unconventional monetary policy action — that are controlled for in the empirical analysis.

The vector of endogenous variables consists of a proxy for the sovereign financing premium, a measure of aggregate risk aversion, and an uncertainty proxy. The analysis covers Italy and Spain, two countries that exhibited a particularly strong deterioration in their sovereign financing conditions throughout the financial and sovereign debt crisis. Neither received any financial assistance from the European Financial Stabilization Mechanism (EFSM) or its successor, the European Stability Mechanism (ESM), that could potentially distort the estimation of the effect running from the uncertainty in the economy to the pricing of sovereign debt, discussed in Section 1.2. Limited by the availability of data, the sample spans from 2004 to 2015.[17] We use data of weekly frequency in order to average out noise in higher frequency, for example daily data, and to make the estimation of the model computationally feasible. Figure 1.C.11 in the Appendix 1.C plots the endogenous variables in the VAR model explained in detail below.

We proxy for the sovereign financing premium with credit default swaps (CDS), following Aizenman et al. (2013). CDS, usually traded over-the-counter, are derivatives that function similar to credit insurances. The seller of a CDS insures the buyer against the default of the creditor such that the price of CDS mirrors the financing premium of the underlying asset over a safe asset. The advantage of using CDS rather than yield spreads on sovereign bonds is that the CDS markets usually are more liquid and, hence, deliver more accurate measures of financing premia (Longstaff et al., 2011). Fontana and Scheicher (2010) find that price discovery for Spanish and Italian sovereign debt actually takes place in the sovereign CDS markets rather than in sovereign bond markets during the financial crisis. We obtain sovereign CDS data for Spain and Italy at five year maturity from Bloomberg.

1.4.1 A high frequency measure of macroeconomic uncertainty

In the construction of a measure of economic uncertainty, we face two main challenges. Firstly, the empirical model relies on the identification of different volatility regimes, which requires sufficient number of observations. As we aim at decomposing sovereign financing premia over the course of the recent period of fiscal stress, there is a natural limit to the number of available observations. A solution is to aim for a high frequency measure. Secondly, as the concept of uncertainty implemented in the theoretical model in Section 1.2 refers to the production outlook specific to

[17] The limiting factor is the availability of sovereign credit defaults swaps data at weekly frequency. The sample spans from 01/12/2004 for Italy and 04/12/2004 for Spain to 04/20/2015 and includes 589 (Italy) and 576 (Spain) weekly observations.

the economy, the measure should be country specific and talk about the uncertainty of the production outlook.

In the construction of a high frequency, country specific, measure of economic uncertainty we follow the approach proposed by Jurado et al. (2015) in order to construct a proxy for country specific economic uncertainty.[18] They extract an uncertainty proxy at monthly frequency from a large dataset of macroeconomic variables by determining the common variation in the unforcastable component of those data. Their procedure involves three steps. In a first step forecast errors are obtained based on conditional mean forecasts from factor augmented autoregressive models. In a second step stochastic volatility in the forecast errors allows the extraction of uncertainty of variable y_j at time t for horizon h of a single series, which is defined by

$$\mathcal{U}^y_{j,t}(h) \equiv \sqrt{E\left\{[y_{jt+h} - E\left(y_{j,t+h}|I_t\right)]^2\,|I_t\right\}},$$

where I_t denotes the information available at time t. A crucial assumption in their setup is that every series in the dataset features time varying volatility, which generates the time variance in uncertainty. In a third step the uncertainty estimates for the single variables in the dataset are aggregated to an economy-wide index of uncertainty. Appendix 1.A provides a more detailed description of the construction of the uncertainty index in Jurado et al. (2015).

As we are aiming at a higher frequency, we depart from their approach in the use of the underlying dataset and apply their methodology to a large dataset of equity returns in order to construct a country specific high frequency measure of economic uncertainty.[19] The construction of the fundamental macroeconomic uncertainty measure builds upon a large set of weekly equity return data (total return index) from Thomson Reuters Datastream covering 1492 equity return index series

[18] Unfortunately, there is no stock market implied volatility available for Spain and Italy. Alternative measures, such as the disagreement or subjective uncertainty of professional forecasters would be a natural candidate for uncertainty regarding the production outlook, but are only available at lower, that is, monthly frequency.

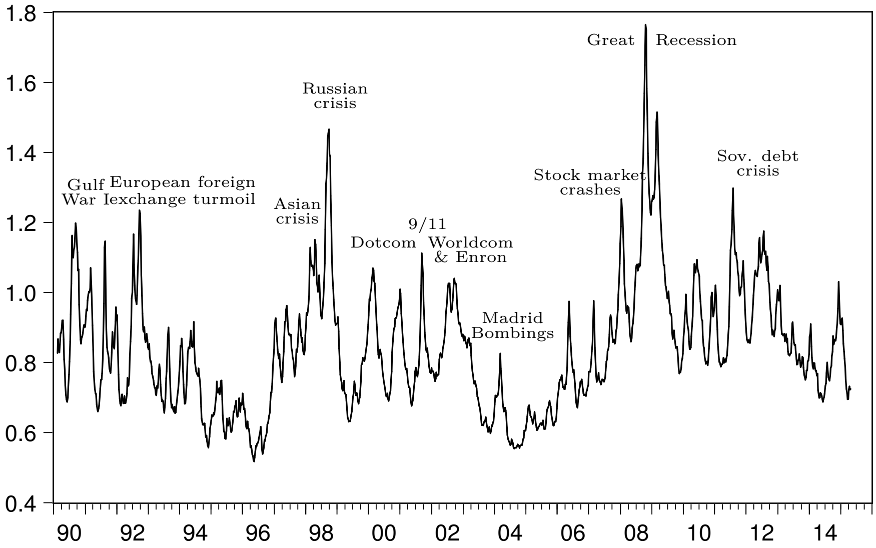
[19] Jurado et al. (2015) argue that the construction of an uncertainty measure for macroeconomic data needs to take into account the forecastable component in macroeconomic data and deploy diffusion index forecasts for this purpose. Accounting for the forecastable component in equity returns may seem less urgent, given that equity returns are harder to forecast than macroeconomic time series. However, Ludvigson and Ng (2007) document that diffusion index models, as the one used in the construction of forecast errors here, provide forecasts for equity returns that are superior to using simple historical averages.

for Spain and 1928 for Italy.[20] This dataset contains many degenerate series, as certain stocks are not traded continuously or traded only for a short period within the sample. We therefore remove all series that are either not traded or not present in the market for more than one third of the sample. In addition we control for equity splits and other outliers by removing observations associated with changes in the index above four standard deviations. After cleaning the dataset and filling the remaining gaps by means of a dynamic factor model along the lines of Schumacher and Breitung (2008), the dataset compiles 201 and 543 equity return series for Spain and Italy, respectively.

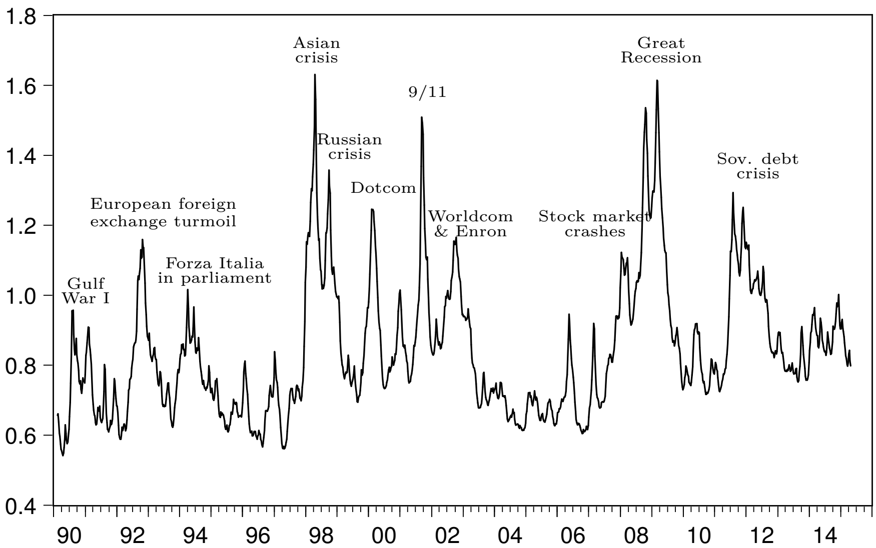
The high frequency measures of economic uncertainty for Spain and Italy for the period from 1990 to 2015 are plotted in Figure 1.4.3. The figure also provides an interpretation regarding the events underlying a peak in the economic uncertainty. Both indexes clearly indicate their largest peaks in economic uncertainty around the most recent financial crisis in the years 2008 and 2009, but also around the Asian and Russian crises around 1998, while for Italy the rise in uncertainty surrounding the sovereign debt crisis 2011/2012 is more pronounced than for Spain. Economic uncertainty in both countries seems to be driven by the same global or regional events, with a few exceptions, among them the Madrid train bombings of 2004.

Figure 1.C.10 in the Appendix 1.C plots the high frequency uncertainty measures for Spain and Italy against stock market volatilities and the low frequency macroeconomic uncertainty measures based on monthly macroeconomic data. This type of comparison is particularly informative as we deploy similar data as the former and the same methodology as the latter. While the stock market volatility exhibits numerous large and significant jumps throughout the sample, but low persistence, the low frequency macroeconomic uncertainty peaks only once significantly at the onset of the financial crisis and is quite persistent. The measure proposed here, resembles those properties rather well, although it is constructed based on equity data: It features much stronger persistence than the stock market volatility and exhibits two significant peaks, the larger one at the onset of the financial crisis in late 2008 and one during the unfolding of the sovereign debt crisis in 2011.

[20] The total return index is a better measure of the performance of a stock and its underlying company in that it includes not only the capital gain on the stock, but also returns related to dividend payments, the value of rights issues, special dividends, and stock dilutions.



(a) Spain



(b) Italy

Figure 1.4.3: Weekly uncertainty index based on the method by Jurado et al. (2015) applied to a large dataset of equity returns.

Table 1.4.1 compares the constructed high frequency measure of macroeconomic uncertainty (aggregated to monthly frequency) to a number of alternative indicators of economic uncertainty at lower frequencies, that is, to (1) a measure of the degree of disagreement of professional forecasters,[21] (2) a low frequency macro data uncertainty index that we construct from a set of 51 monthly macro series for Spain and 84 monthly macro series for Italy; and (3) the news based policy uncertainty index provided by Baker et al. (2013) and weekly realized stock market volatility.[22] The aggregated high frequency measures correlate significantly with the set of alternative measures at lower frequency and the realized stock market volatility. The lowest correlation is found with the policy uncertainty measure. As it aims at capturing a somewhat different concept of uncertainty related to political decision processes, the lower correlation seems plausible and expected.

Table 1.4.1: Correlation of our uncertainty measure with alternative measures

	Spain	Italy	sample
Forecast Disagreement	0.46***	0.33***	2007M01 — 2014M08
Uncertainty based on monthly macro data	0.37***	0.46***	1990M07 — 2015M05
Policy uncertainty index (Baker et al., 2013)	0.27***	0.33***	1997/2001M1 — 2015M05
Realized stock market volatility	0.65***	0.66***	2000W1 — 2015W19
Uncertainty measure (Spain)	1	0.81***	1990M02 — 2015M05

Notes: The weekly uncertainty measure based on equity returns is aggregated to monthly frequency where necessary for comparison. *** Indicates significance at the 1 percent level.

The validity of the constructed measure as a high frequency indicator of macroeconomic uncertainty critically depends on the closeness of the link between equity markets and the real economy. We argue that under the assumption of efficient markets our equity based measure of economic uncertainty reflects the fundamental macroeconomic uncertainty in the economies, for investors, entrepreneurs, employees and other stakeholders of the considered companies alike.

Overall we take the strong and significant correlation among our high frequency uncertainty measure and alternative uncertainty measures together with the evi-

[21] Forecast disagreement captures the interdecile range of the distribution of point forecasts over GDP growth provided by a panel of professional forecasters, where the data is taken from Consensus Economics and Focus Economics.

[22] Realized stock market volatility is taken from the Oxford-Man Institute's 'realized library' and aggregated to weekly frequency by averaging.

dence from the graphical comparison in Figure 1.C.10 as reassuring in that we well capture economic uncertainty at weekly frequency.

1.4.2 A measure of risk aversion

In order to construct a measure of risk aversion of (international) investors, we borrow from the recent literature that computes the variance premium from options implied volatility indexes (Bollerslev et al., 2009, 2011; Bekaert et al., 2013; Bekaert and Hoerova, 2014). Option implied volatility indexes, for example, the CBOE volatility index (VIX), may be decomposed into one part capturing expected market volatility and a second part capturing risk aversion. We make use of such a decomposition in order to obtain a proxy for the risk aversion of international investors, as discussed in the model framework in Section 1.2. We base our measure of global risk aversion on the VIX, the options implied volatility index of the S&P500. We follow Bekaert et al. (2013) in constructing forecasts for the realized volatility based on a linear model incorporating the squared VIX and the past realized variance as predictors.[23] As in Bekaert et al. (2013), we winsorize the data prior to the estimation.[24] The difference between the squared VIX and the estimated conditional variance constitutes the proxy for risk aversion among international investors.

1.4.3 Exogenous controls

The vector of exogenous control variables in the MSH-VAR model contains the short term US nominal interest rate in order to control for global opportunity costs, bid-ask spreads controlling for time varying liquidity premia and a range of non-standard monetary policy measures, as we want to make sure our estimates are not affected by the extraordinary monetary policy action taken during the sample period. The monetary policy measures include dummy variables for the announcements of the Securities Markets Programme (SMP), the Long Term Refinancing Operations (LTROs) and the Outright Monetary Transactions (OMT) as well as variables capturing the

[23] The data on realized variances for five minute windows is taken from the Oxford-Man Institute's 'realized library'.

[24] Winsorization eliminates outliers in the distribution by replacing values in the tails with those of the respective percentiles. The underlying data, that is the VIX and realized stock market volatility, are winsorized at the one percent level.

volumes of their implementation[25]. The CDS Bid-Ask Spread is computed from bid and ask prices according to the formula $spread = \frac{p^{ask} - p^{bid}}{(p^{ask}+p^{bid})/2}$. Sources are Thomson Reuters Datastream, the ECB for data on unconventional monetary policy, and Bloomberg for the CDS prices, the bid-ask spreads are based upon.

1.5 The MSH-SVAR

The reduced form VAR model used for the empirical analysis is described by

$$\begin{aligned} y_t = \nu + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} \\ + \Gamma_0 x_t + \Gamma_1 x_{t-1} + \cdots + \Gamma_n x_{t-n} + \Xi d_t + u_t \ , \end{aligned} \tag{1.11}$$

where y_t is the vector of K endogenous variables, x_t contains the N exogenous variables and A_i's and Γ_j's are matrices that hold the respective coefficients with $i = 1, \ldots, p$ and $j = 1, \ldots, n$. ν is a vector of constant terms and d_t holds the L dummy variables with Ξ being its respective coefficient matrix. u_t represents the vector of reduced form error terms with $E[u_t] = 0$ and $E[u_t u_t'] = \Sigma_u(S_t)$. In addition we assume that the conditional distribution of u_t is normal, hence, $u_t|S_t \sim \mathrm{N}(0, \Sigma_u(S_t))$, that is, following Lanne et al. (2010) and Lütkepohl and Netšunajev (2014) the distribution of the reduced form error term is assumed to depend on a discrete Markov process S_t that can take on M values representing different regimes, $S_t \in \{1, \ldots, M\}$. While the model allows for Markov switching in the covariance of the residuals the parameters governing the first moments of the model are restricted to be constant over the sample.

The uncorrelated structural shocks, given by ε, map into the reduced form residuals as

$$u_t = B\varepsilon_t, \tag{1.12}$$

via the matrix B of impact effects (see Lütkepohl, 2005, Chapter 9). Since the distribution of the residuals is governed by a Markov process, we have $\mathrm{var}(u_t|S_t) = \Sigma_u(S_t) = B\Lambda(S_t)B'$ with $E[\varepsilon_t] = 0$ and $E[\varepsilon_t \varepsilon_t'] = \Lambda(S_t)$. $\Lambda(S_t)$ is a diagonal matrix

[25] We include volumes for the SMP and LTROs with 6-12 and 36 months maturity as additional exogenous variables.

satisfying the orthogonality condition of the structural shocks. The variances, i.e. the diagonal elements, in the first state are normalized to unity, such that $\Lambda(1) = I_K$.

The assumption on the constancy of B may be challenged and newer literature is adopting more flexible models with state dependent impact matrices (Bacchiocchi and Fanelli, 2015; Podstawski and Velinov, 2016). However, the feature of interest in the current setup is the ability to make use of the statistical properties of the data in order to identify a set of structural shocks, rather than the analysis of a potential state dependency of the shock transmission that could be introduced into the model via a regime switching structural impact matrix B.

Given the assumption on the constancy of the structural impact matrix B, the setup allows — assuming that the diagonal elements of Λ are distinct (Lanne et al., 2010) — for the uncovering of a set of orthogonal structural shocks from the reduced form VAR model that are consistent with the statistical properties of the data. Given distinct diagonal elements in the covariance matrix of the structural shocks, the structural impact matrix B is unique up to sign and column permutations.

We exploit this feature of the MSH-VAR setup for the identification of the structural shocks of interest. As mentioned above, making use of the statistical properties of the data for identification of a set of structural shocks is particularly helpful in cases where economic theory does not provide a set of restrictions that is suited to identify of the shocks of interest.

Under the assumption that the conditions for identification via heteroscedasticity are met by the models — an assumption that we address in the subsequent section — the MSH-SVAR model leaves us with three orthogonal shocks, ε_1, ε_2 and ε_3. These shocks need to be labeled and, hence, endowed with economic interpretation. We turn to this issue in Section 1.6.2.

1.6 Results

This section presents the results from the MSH-SVAR model for Spain and Italy. Based on information criteria for the linear model, we introduce two lags for the Italian model and three for the Spanish model. In order to keep the model parsimonious and since we mainly use the state switching property of the model for the purpose of identification, we resort to choosing two states for the Markov process.[26] Before turning to the analysis of the impulse responses and the historical decomposition, we report the state probabilities of the Markov process and a number of results related to the identification of the shocks.

1.6.1 State probabilities

The smoothed state probabilities provide a first assessment of the suitability of the specified MSH-VAR model. Figure 1.6.4 reports the state probabilities for the high volatility state for the Spanish and Italian model.

Both models indicate a state switches around 2007/2008, capturing the emergence of the financial crisis. The Markov-switching model identifies a low volatility state roughly before default of Lehman Brothers and a high volatility state afterwards, in which both economies remain for the remainder of the sample. The state probabilities clearly reflect the heteroscedasticity pattern in the data (see Figure 1.C.11 in the Appendix 1.C). All three endogenous variables exhibit low volatility in the period up to 2007 and higher volatility afterwards.

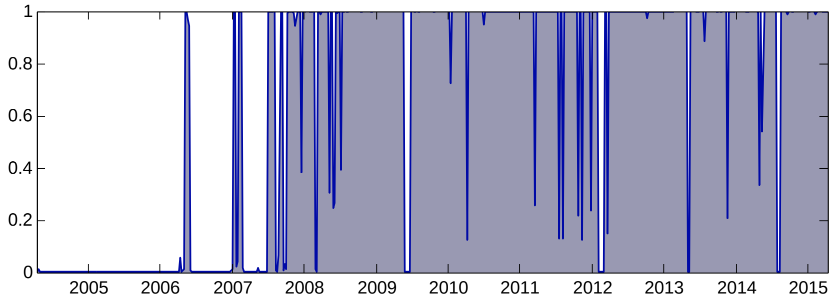
Figure 1.C.12 in the Appendix 1.C plots the reduced form residuals and the standardized reduced form residuals from both MSH-VAR models. The standardization takes into account the two volatility regimes, and allows for an informal assessment of the fit of the model. Formally, the vector of standardized residuals $\hat{u}_t^z$ is computed by

$$\hat{u}_t^z = \hat{\Sigma}_{t|t-1}^{-1/2}\hat{u}_t,$$

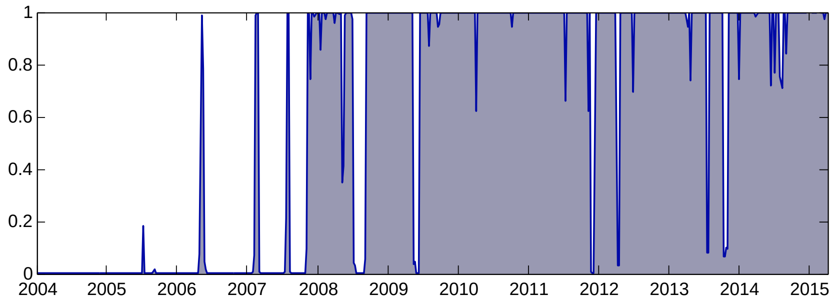
where $\hat{u}_t$ is the vector of estimated residuals and $\hat{\Sigma}_{t|t-1}^{-1/2}$ is the estimated variance covariance matrix of the residuals based on the information up to $t-1$, i.e. $\hat{\Sigma}_{t|t-1}^{-1/2} = \sum_{m=1}^{M} \hat{P}(s_t = m|Y_{t-1})\Sigma_m$.

The distinct heteroscedasticity pattern present in the non standardized residuals is tempered substantially by the standardization, indicating the model's success in capturing the heteroscedasticity in the residuals. Although higher order MSH-

[26] We attempt to investigate the data's preferences for higher order Markov-switching models by estimating the MSH-SVAR with three and four states. Maximizing the likelihood becomes increasingly more complicated with an increasing number of states. Given the sufficiency of two states to identify the three shocks in the model, we resort to two states for the Markov process.



(a) Spain



(b) Italy

Figure 1.6.4: Smoothed state probabilities for the high volatility state

VAR models may capture even more of the heteroscedasticity pattern, we conclude that the above state probabilities resemble the recent crisis dynamics, i.e. the heteroscedasticity pattern in the data, in a convincing manner. Next, we discuss issues related to the identification of the model and move from the reduced form to the structural model.

1.6.2 Identification

In a MSH-VAR model with two states the reduced form variances may be decomposed such that $\Sigma_{u1} = BB'$ and $\Sigma_{u2} = B\Lambda_2 B'$, where $\Lambda_2 = diag(\lambda_{21}, \ldots, \lambda_{2K})$, and all diagonal elements are positive. In order to make use of the statistical properties for the identification of the structural shocks we require the λ_{2i}s representing the variances of the structural shocks to be distinct (Herwartz and Lütkepohl, 2014; Lanne et al., 2010).

Table 1.6.2: Relative variances of structural shocks in the high volatility regime

	λ_{21}	λ_{22}	λ_{23}
ES	5246.125 (10.845)	23.471 (4.807)	5.543 (0.750)
IT	1339.912 (14.847)	13.881 (1.969)	2.877 (0.533)

Notes: Standard errors in parentheses.

Table 1.6.2 reports the estimated relative variances of the structural shocks, λ_{2i}, for both models for the second state. Recall that the variances of the structural shocks are normalized to unity for the first state, i.e. $m = 1$. Clearly, the second state is the one exhibiting higher volatility and, indicating turbulent or crisis times. The point estimates indicate reasonable distance between the λ_{2i}s taking into account the size of their standard errors. Overall, the point estimates and standard errors of the λ_{2i}s strongly indicate that identification is achieved based on the properties of the data.

1.6.3 Labeling the uncorrelated shocks

So far we have identified a set of three orthogonal structural shocks — ϵ_1, ϵ_2 and ϵ_3 — that we would like to label as fundamental risk, risk aversion and uncertainty shocks in order to make them economically interpretable. For the labeling we make use of the fact that proxies for two of the structural shocks we aim to identify are included in the vector of endogenous variables. We label the shock with the maximum contribution to the forecast error variance of the risk aversion proxy to be the risk aversion shock and the one with the maximum contribution to the forecast error variance of the uncertainty measure to be the uncertainty shock. The remaining structural shock is labeled fundamental risk shock. Table 1.C.3 and 1.C.4 report the forecast error variance decomposition (FEVD) for the first state at different horizons and allow a clear labeling based on the rational discussed above. We use the FEVD for the first state as it is the normal or non-crisis state within the setup, however, the labeling would be exactly the same if we took into account the higher relative variances of the second state in the FEVD.

Figure 1.C.13 in the Appendix 1.C plots the three structural shocks and provides an opportunity for a further assessment of the labeling based on the forecast error variance decompositions. The dynamics of the shocks look quite similar among the models: The fundamental risk shock exhibits highest volatility during the sovereign debt crisis emerging around 2011/12 and has a very distinct pattern of heteroscedasticity. The risk aversion shock exhibits the strongest impulses during the unfolding of the financial crisis in 2008 — a pattern also found by Guiso et al. (2013) based on survey data of customers of Italian banks and in line with the general notion of countercyclical risk aversion (Cohn et al., 2015). In addition, this pattern seems to match the dynamics of alternative proxies for risk aversion such as the Baa-Aaa corporate bond spread provided by Moody's, which similarly jumps during this time period. Finally, the uncertainty shock is less clustered among the time dimension than the other two, but still exhibits phases of higher volatility during both, the financial crisis and the European sovereign debt crisis broadly in line with the literature on economic uncertainty (Bloom, 2014). Overall the dynamics of the structural shocks strongly support the labeling based on the forecast error variance contributions.

In addition to the labeling of the structural shocks the FEVD provides first insights into the role of the three shocks for the sovereign financing premium. Clearly, the fundamental risk shock dominates the variations in CDS, but risk aversion and uncertainty shocks make up for a substantial share of the variation in CDS in both models, increasing in the forecast horizon. Also note that the risk aversion measure seems to contain a significant uncertainty component. We take this as first evidence of an impact of uncertainty shocks on investors' risk aversion in line with the predictions of Proposition 1. As opposed to that, the uncertainty measure seems rather well described by its own shock — and less affected by the fundamental risk and the risk aversion shock — judged by the forecast error variance decomposition.

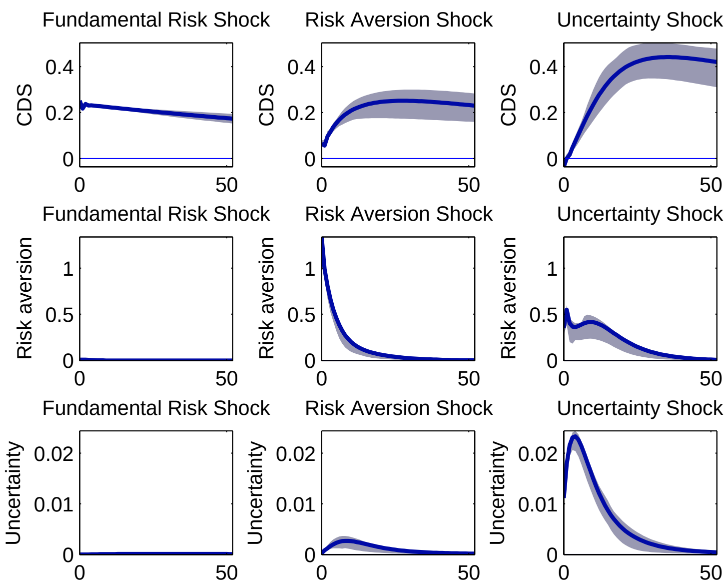
Based on the identification and the labeling of the structural shocks, we turn to the impulse responses analysis and the historical decomposition of the financing premia in the subsequent sections.

1.6.4 Impulse responses

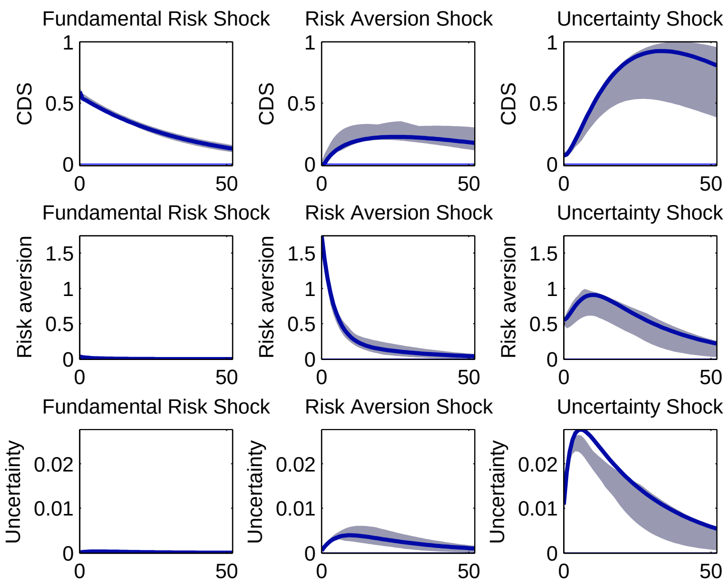
Impulse responses from both models are plotted in Figure 1.6.5. Confidence sets are based on a fixed design wild bootstrap in order to re-sample without corrupting the heteroscedasticity properties of the data.[27] The responses of the CDS spreads are in line with the theoretical prediction of the model presented in Section 1.2. All three shocks, the fundamental risk shock, the risk aversion shock, and the uncertainty shock impact positively on the CDS, increasing the borrowing cost for the sovereign. Among the three shocks, the fundamental risk shock has the largest short run impact on the sovereign financing cost, followed by the uncertainty and the risk aversion shock — in line with the findings from the forecast error variance decomposition in Tables 1.C.3 and 1.C.4 in the Appendix 1.C. At longer horizons, the uncertainty shock impacts sovereign financing costs even stronger than the fundamental risk shock in the low volatility regime, although the fundamental risk shock becomes by far the strongest driver of sovereign CDS in the high volatility regime plotted in Figure 1.C.14 in the Appendix 1.C. Note that qualitatively the impulse responses in the first regime and the second regime are identical by construction. The only difference stems from the higher variances of the structural shocks that scales up the set of impulses.

Quantitatively a one standard deviation uncertainty shock increases CDS by 0.5 to 1 basis points in the first regime of the MSH-SVAR model and between 1 and 1.5 basis points in the second regime. The effect of a uncertainty shock on CDS is somewhat comparable to that of a risk aversion shock, both with a somewhat larger impact in the high volatility regime. A fundamental risk shock of one standard deviation, however, has an impact effect of about 20 basis points in the high volatility regime, clearly dominating the risk aversion and uncertainty shocks. Overall the impulse responses for both economies are qualitatively and quantitatively very similar. They only feature slight differences in the persistence of the responses of the CDS to the three shocks.

[27] For further details on the bootstrapping procedure see Podstawski and Velinov (2016). Brüggemann et al. (2016) argue that block bootstrapping would be superior to wild bootstrapping approaches, because the latter fails to correctly replicate the fourth moments structure of the residuals. Against the backdrop of minor distortions for the point wise confidence bands, we follow the literature and deploy a wild bootstrapping to obtain confidence bands.



(a) Spain



(b) Italy

Figure 1.6.5: Impulse responses with 68% confidence intervals based on 1000 bootstrap replications, low volatility state

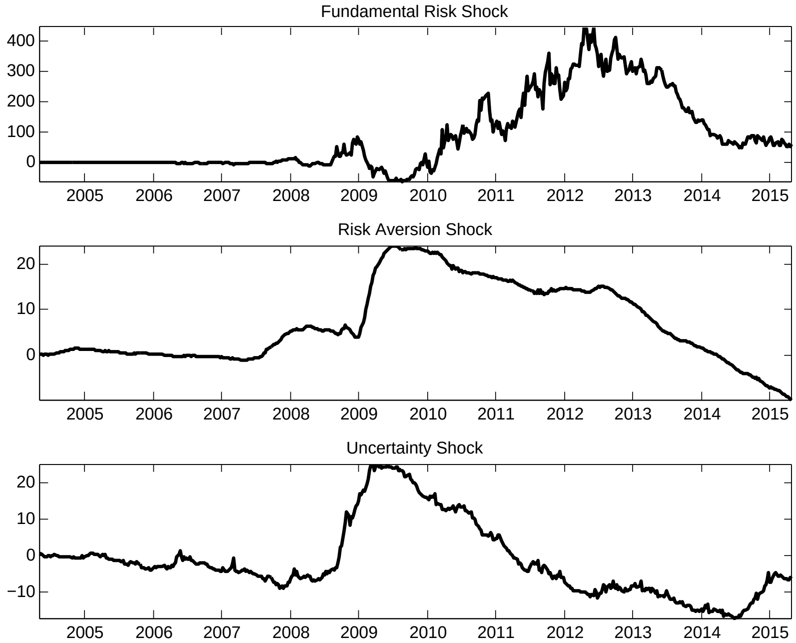
The impulse response also allow for empirically assessing the prediction of Proposition 1; that is — given ambiguity averse investors with preferences further featuring varying relative risk aversion in wealth, and thus ambiguity — a positive response of investors' risk aversion to uncertainty shocks. Indeed, in both models we find a strong positive response of the measure of risk aversion to uncertainty shocks. This is in line with the large fraction of the forecast error variance of the risk aversion measure driven by uncertainty shocks. We take this as strong evidence in support of Proposition 1.

1.6.5 Historical decomposition

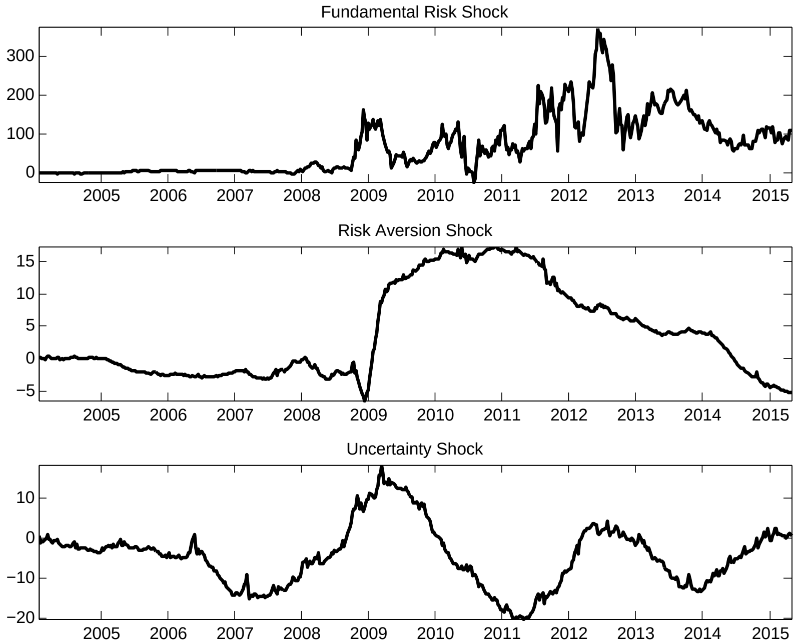
In order to assess the contributions of the three shocks to sovereign CDS, we conduct a historical decomposition based on the structural shocks. The series of structural shocks is constructed based upon equation (1.12) using the structural impact matrix B and the observable reduced form residuals. The Wald decomposition of the model described by equation (1.5) allows for expressing the endogenous variables at time t as a linear combination of initial values and structural shocks in the past according to

$$\begin{aligned} y_t - \widehat{\nu} &= \sum_{i=0}^{t-1} \widehat{\phi}_i \widehat{u}_{t-i} + \widehat{A}_1 y_0 + \ldots + \widehat{A}_p y_{-p+1} \\ &= \sum_{i=0}^{t-1} \widehat{\phi}_i \widehat{B} \widehat{\varepsilon}_{t-i} + \widehat{A}_1 y_0 + \ldots + \widehat{A}_p y_{-p+1}, \end{aligned}$$

where $\widehat{\phi}_i$ is the matrix of estimated impulse response coefficients $\widehat{\phi}_i = \sum_{j=1}^{i} \widehat{\phi}_{i-j} \widehat{A}_j$ with $i = 1, 2, \ldots$, $\widehat{\phi}_0 = I_K$ and $\widehat{A}_j = 0$ for $j > p$ (see Lütkepohl, 2005, Chapter 2) and we ignore the deterministic and exogenous terms in equation (1.5) that are not relevant for the impulse responses. The historical decomposition of the sovereign CDS variable into the three structural shocks is reported in Figure 1.6.6. It clearly supports the hypothesis of risk aversion and uncertainty shocks being relevant drivers of sovereign financing premia, notwithstanding the fact that fundamental risk shocks account for by far the largest share in CDS spreads, especially in later stages of the sovereign debt crisis.



(a) Spain



(b) Italy

Figure 1.6.6: Historical decomposition of sovereign CDS of Italy and Spain

The decomposition indicates large positive contributions of both increased risk aversion and uncertainty to the financing premium of the Spanish and the Italian sovereign. Shocks to economic uncertainty make up for up to about 25 basis points in Spanish CDS spreads and 15 basis points in Italian CDS spreads, playing quantitatively a similar role to changes in investors risk aversion. The Spanish sovereign faced an increase in CDS of up to 25 basis points driven by an increase in risk aversion. Similarly, the Italian financing premium increased by up to 15 basis points due to rising risk aversion among international investors.

Our findings are in line with the literature that documents a crucial role of time variations in risk aversion for the pricing of sovereign debt.[28] Barrios et al. (2009) argue that general risk perception and its interaction with macroeconomic fundamentals are strong driving forces of yield spreads in the euro area. Sgherri and Zoli (2009) provide evidence that 15 to 30 basis points of the increase in Spanish and Italian yield spreads from late 2008 to early 2009 are attributable to increased risk aversion. Similarly, Caceres et al. (2010) find a positive contribution from global risk aversion to changes in Spanish yield spreads during 2009 but not for changes in Italian yield spreads.

While the sharp increase in financing premia for the sovereigns was fueled by risk aversion and uncertainty at the onset of the sovereign debt crisis, the picture is different for later stages of the crisis. Compared to the large contribution by fundamental risk shocks, there is only a minor impact from risk aversion and uncertainty shocks on sovereign financing premia, especially in 2012 when market participants became increasingly concerned about redenomination risk. This form of risk refers to the exit of member countries from the monetary union and the redenomination of their public and private liabilities. As we do not explicitly account for this specific form of exchange rate risk, it is part of the fundamental risk shock identified in our setup. In line with the large share of fundamental risk driving CDS upward during 2012, De Santis (2015) finds that close to half of the sovereign yield spreads were accounted for by redenomination risk in the first quarter of 2012.

[28] Note that we do not decompose CDS into a default-risk component and a risk premium, as do, for example, Longstaff et al. (2011), who find about one third of the CDS spread to be associated with the risk premium. Instead we assess the effects of changes in the risk aversion over time, against the backdrop of a steady-state risk aversion in the VAR model considered.

Overall, we find clear evidence in support of a channel running from macroeconomic uncertainty to sovereign financing premia discussed in Section 1.2: Exogenous variations in uncertainty increase sovereign yields and make up for a non-negligible share in sovereign CDS. At the onset of the sovereign debt crisis in the euro area uncertainty shocks accounted for up to 15 basis points in Italian and up to 25 basis points in Spanish CDS spreads, an effect that is quantitatively comparable to the premium originating in rising risk aversion among international investors in the context of the global financial crisis.

1.7 Conclusion

In this paper we theoretically and empirically separate the effects of risk and uncertainty in the pricing of risky assets using the example of sovereign debt markets.

First, we build a simple model of optimal sovereign default that allows us to distinguish between the effects of risk aversion and uncertainty aversion for the pricing of risky government debt. In order to arrive at an analytical decomposition of the price for public debt, we assume that the investor is (i) risk averse, (ii) ambiguity averse, and (iii) has habit persistence in consumption. We show that risk aversion and ambiguity aversion lower bond prices and, hence, increase sovereign yields. Further, the model features an endogenous relationship between uncertainty and risk aversion: An increase in uncertainty affects the worst case prior of ambiguity averse agents, which feeds into higher levels of risk aversion.

Second, we take this theoretical decomposition of prices for government debt to the data. In order to jointly analyze the contributions from risk aversion and uncertainty for the financing premia faced during the European sovereign debt crisis empirically, we set up a structural VAR model and exploit the statistical properties of the data in order to identify three shocks: A fundamental risk shock, a risk aversion shock, and an uncertainty shock. Within this framework, we assess the relevance of risk aversion and macroeconomic uncertainty as drivers of the pricing of sovereign debt for Spain and Italy. We find that shocks to macroeconomic uncertainty (1) significantly increases international investors' risk aversion, in line with the predictions of the theoretical model; (2) have a significant impact on sovereign yields; (3) make up for a non-negligible share in Spanish and Italian sovereign yield spreads of up to 25 basis points at the onset of the sovereign debt crisis that is quantitatively comparable to the effect of increased risk aversion during this period.

The results underline the relevance of macroeconomic uncertainty for the determination of asset prices and as a potential amplifier during times of economic crises. The theoretical and empirical connection between macroeconomic uncertainty and risk aversion documented in this paper might be an interesting avenue for future research.

1.A Construction of the uncertainty measure

The following summary is based upon Jurado et al. (2015, Section 3.1), which the reader is referred to for further details. Recall that uncertainty of variable y_j at time t for horizon h of a single series defined by

$$\mathcal{U}^{y}_{j,t}(h) \equiv \sqrt{E\left\{\left[y_{jt+h} - E\left(y_{j,t+h}|I_t\right)\right]^2 |I_t\right\}}.$$

Assume that X_{it} contains the set of predictors used for forecasting and is representable by the following factor structure

$$X_{it} = \Lambda_i^{F\prime} F_t + e_{it}^X,$$

where F_t contains the latent factors, Λ_t the loadings and e_{it}^X the idiosyncratic errors. Forecasts for the series y_t are conducted using the following factor augmented autoregressive model

$$y_{jt+1} = \phi_j^y(L)y_{jt} + \gamma_j^F(L)\hat{F}_t + \upsilon^y_{jt+1},$$

where $\phi_j^y(L)$ and $\gamma_j^F(L)$ are polynomials in the lag operator L, $\hat{F}_t$ are estimates of F_t. The one-step-ahead prediction errors for each variable y_j and each factor F_t are allowed to feature time varying volatility, i.e. $\upsilon^y_{jt+1} = \sigma^y_{jt+1}\epsilon^y_{jt+1}$ and $\upsilon^F_{kt+1} = \sigma^F_{kt+1}\epsilon^F_{kt+1}$, an assumption that is crucial for the time variation in uncertainty. The forecasts $E\left[y_{jt+h}|I_t\right]$ are obtained from the factor augmented autoregressive (FAVAR) model, written in companion form as

$$\begin{pmatrix} \mathcal{F}_t \\ Y_{jt} \end{pmatrix} = \begin{pmatrix} \Phi^F & 0 \\ \Lambda_j' & \Phi_j^Y \end{pmatrix} \begin{pmatrix} \mathcal{F}_{t-1} \\ Y_{jt-1} \end{pmatrix} + \begin{pmatrix} \mathcal{V}_t^F \\ \mathcal{V}_{jt}^Y \end{pmatrix},$$

or written more compactly as

$$\mathcal{Y}_{jt} = \Phi_j^{\mathcal{Y}} \mathcal{Y}_{jt-1} + \mathcal{V}_{jt}^{\mathcal{Y}},$$

where $\mathcal{F}_t$ collects the factors and additional predictors used for forecasting, Y_{jt} represents the set of variables that are to be forecasted, $\Lambda_j'$and Φ_j^y are collections of the coefficients in the matrix polynomial lag operators from the single factor augmented forecasting model. The optimal forecast is given by the conditional mean

$$E_t\mathcal{Y}_{jt+h} = (\Phi_j^{\mathcal{Y}})^h \mathcal{Y}_{jt}$$

and the forecast error variance at horizon $h = 1$ is given by

$$\Omega_{jt}^{\mathcal{Y}} = E_t(\mathcal{V}^{\mathcal{Y}}_{jt+1}\mathcal{V}^{\mathcal{Y}\prime}_{jt+1}).$$

In order to obtain the expected forecast uncertainty of a single variable y_{jt+h}based on the information set at time t, we select a single entry of the forecast error variance matrix $\Omega^{\mathcal{Y}}_{jt}$ using $\mathbb{1}_j$ as a selection vector with unity as its jth element and zeros elsewhere

$$\mathcal{U}^{y}_{j,t}(1) = \sqrt{\mathbb{1}_j' \Omega^{\mathcal{Y}}_{jt} \mathbb{1}_j} \ .$$

Finally, aggregate uncertainty is computed as the average of the individual forecast uncertainties

$$\mathcal{U}^{y}_{t}(1) = \frac{1}{N_y} \sum_{j=1}^{N_y} \mathcal{U}^{y}_{j,t}(1) \ .$$

1.B Risk and uncertainty attitudes

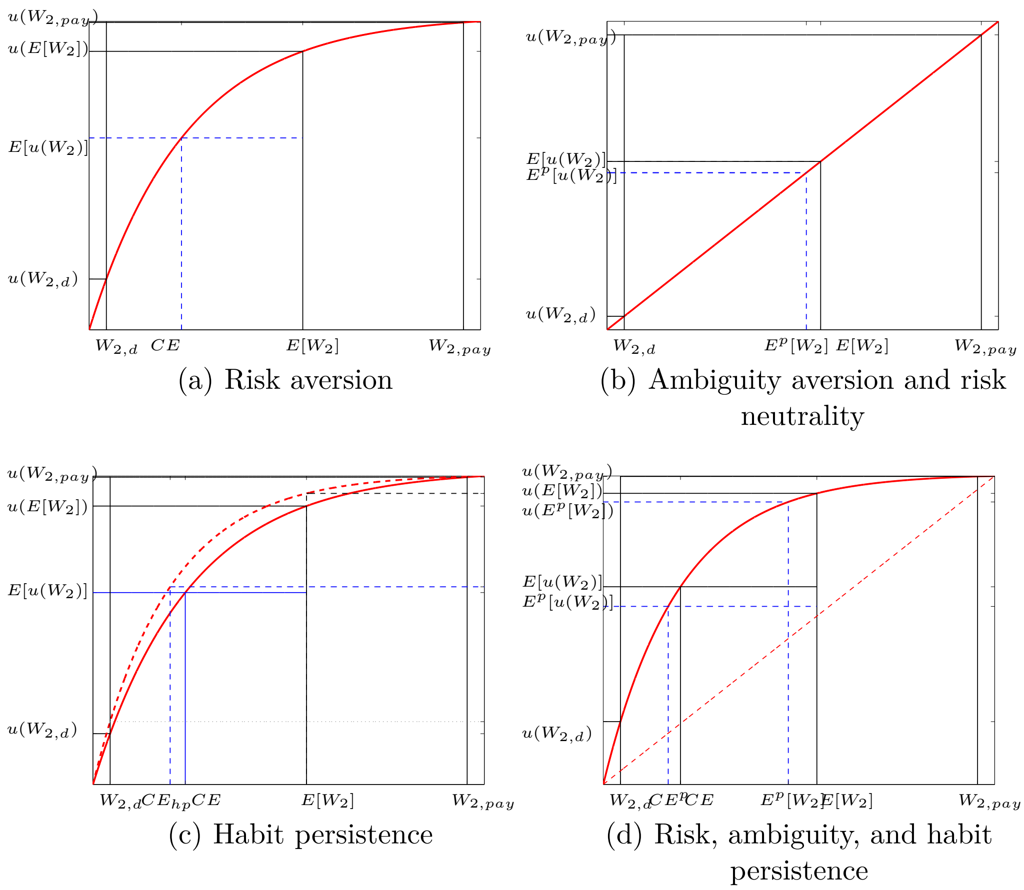
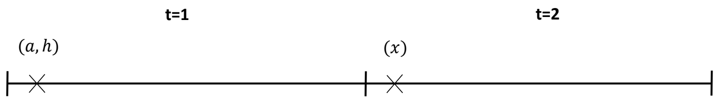


Figure 1.B.7: Risk attitudes, utility on y-axis and wealth on x-axis wherever not noted otherwise.

1.C Tables and figures

Figure 1.C.8: Timing of events in default model



t=1	t=2
exogenous realisations	
- uncertainty, a	- productivity:
- habit, h	$\rightarrow$ x is drawn
	$\rightarrow$ z_2 becomes known
domestic economy	
- default decision, δ_1	- default decision, δ_2
- borrowing, B_2	- taxes/transfers, τ_2
- taxes/transfers, τ_1	- production, y_2
- production, y_1	- consumption, c_2
- consumption, c_1	
foreign investor	
- portfolio choice, (θ)	- consumption, c_2^*
$\rightarrow$ risky lending, B_2	
$\rightarrow$ risk-free lending, S_2	
- consumption, c_1^*	

Figure 1.C.9: Simultaneously risky and uncertain bet on sovereign bonds

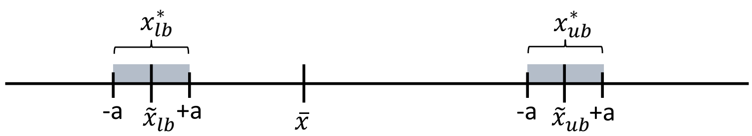
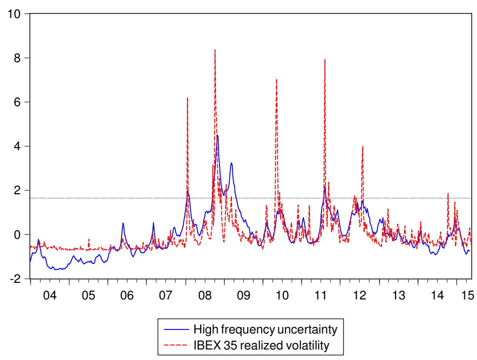


Table 1.C.3: Forecast error variance decomposition from the MSH-SVAR for Spain (low volatility state)

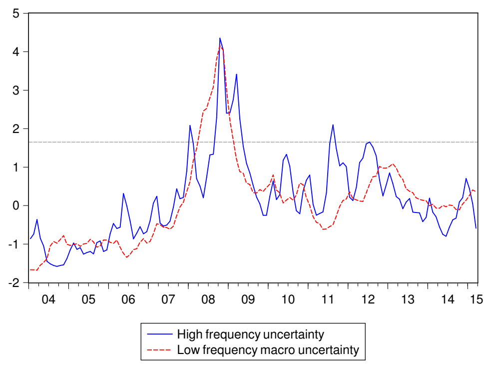
Variable	Horizon	ε_1	ε_2	ε_3
CDS	1	**0.92**	0.06	0.02
	5	**0.82**	0.15	0.03
	10	**0.60**	0.24	0.16
	20	**0.35**	0.25	0.40
Risk Aversion	1	0.00	**0.94**	0.06
	5	0.00	**0.83**	0.17
	10	0.00	**0.74**	0.26
	20	0.00	**0.63**	0.37
Uncertainty	1	0.00	0.00	**1.00**
	5	0.00	0.00	**1.00**
	10	0.00	0.01	**0.99**
	20	0.00	0.02	**0.98**

Table 1.C.4: Forecast error variance decomposition from the MSH-SVAR for Italy (low volatility state)

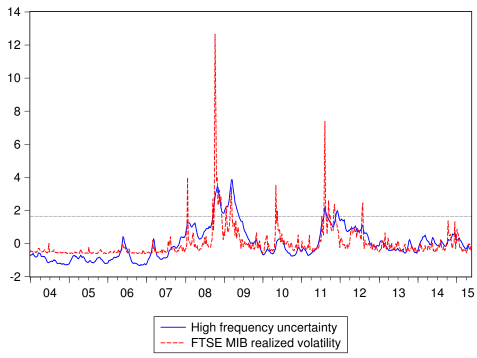
Variable	Horizon	ε_1	ε_2	ε_3
CDS	1	**0.99**	0.00	0.01
	5	**0.93**	0.01	0.06
	10	**0.75**	0.04	0.22
	20	**0.41**	0.06	0.54
Risk Aversion	1	0.00	**0.91**	0.09
	5	0.00	**0.79**	0.21
	10	0.00	**0.61**	0.39
	20	0.00	**0.42**	0.58
Uncertainty	1	0.00	0.00	**1.00**
	5	0.00	0.01	**0.99**
	10	0.00	0.02	**0.98**
	20	0.00	0.02	**0.98**



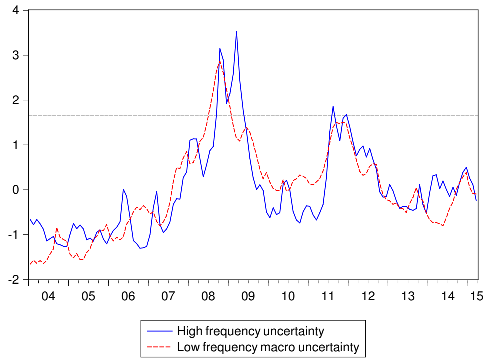
(a) Spain, comparison with stock market volatility



(b) Spain, comparison with low freq. macro uncertainty

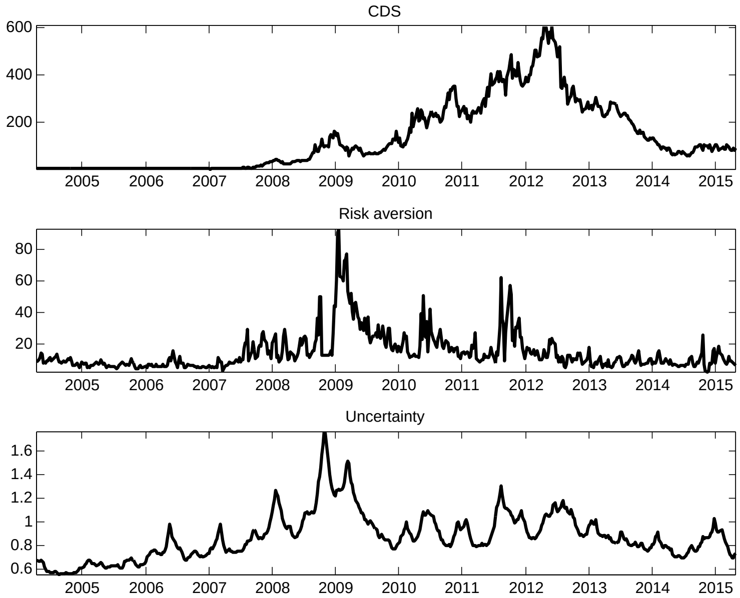


(c) Italy, comparison with stock market volatility

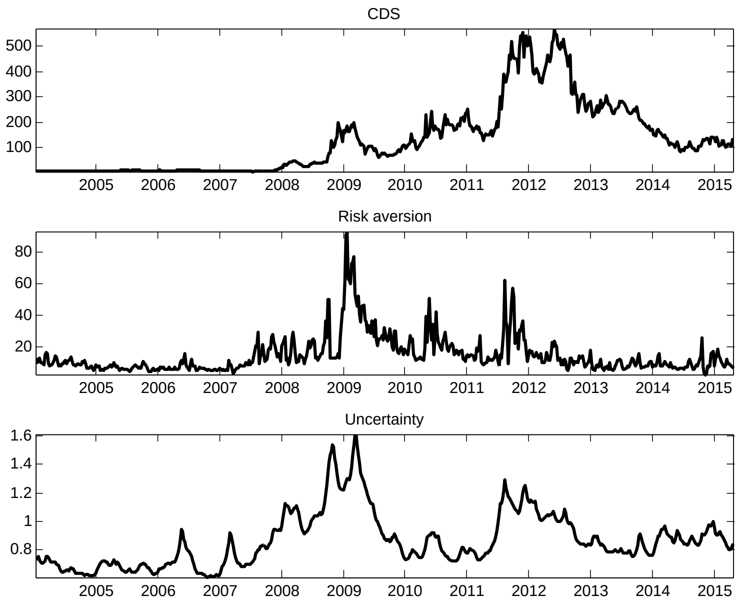


(d) Italy, comparison with low freq. macro uncertainty

Figure 1.C.10: Comparison of weekly uncertainty measure with realized stock market volatility and low frequency macroeconomic uncertainty, data standardized and horizontal dashed line indicating 1.65 standard deviations.

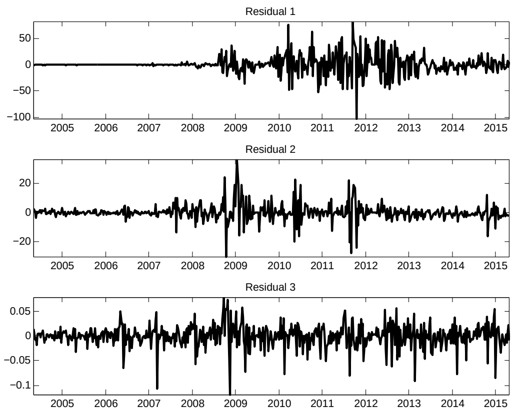


(a) Spain

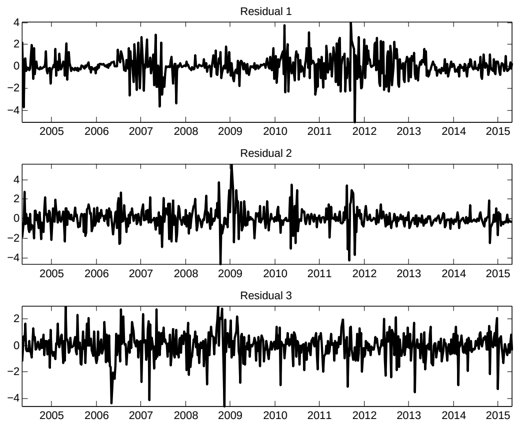


(b) Italy

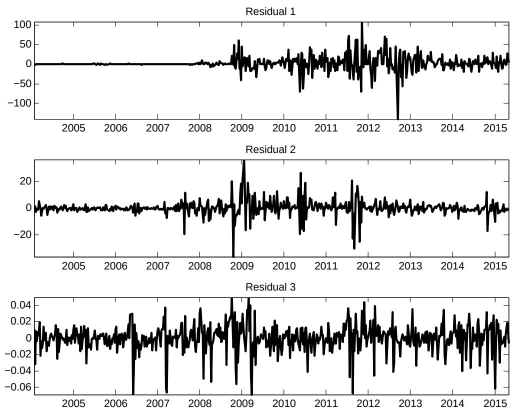
Figure 1.C.11: Endogenous variables entering the MSH-VAR models



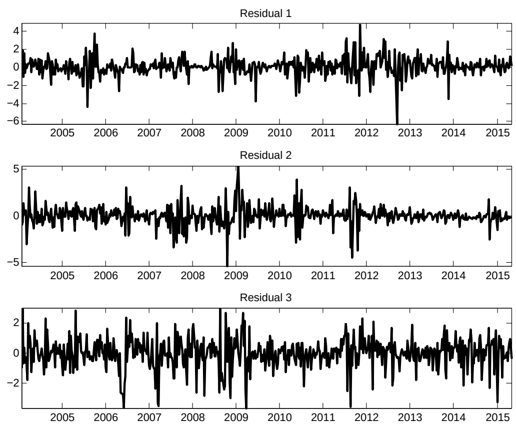
(a) Spain, residuals



(b) Spain, standardized residuals

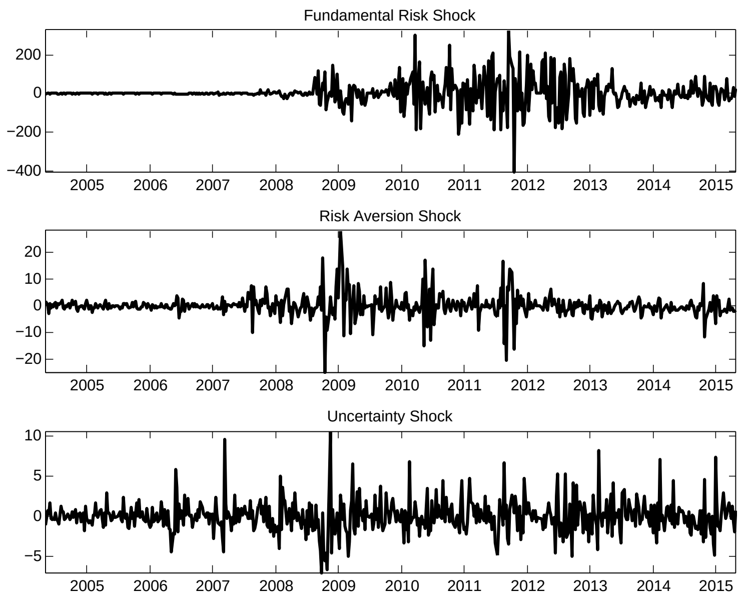


(c) Italy, residuals

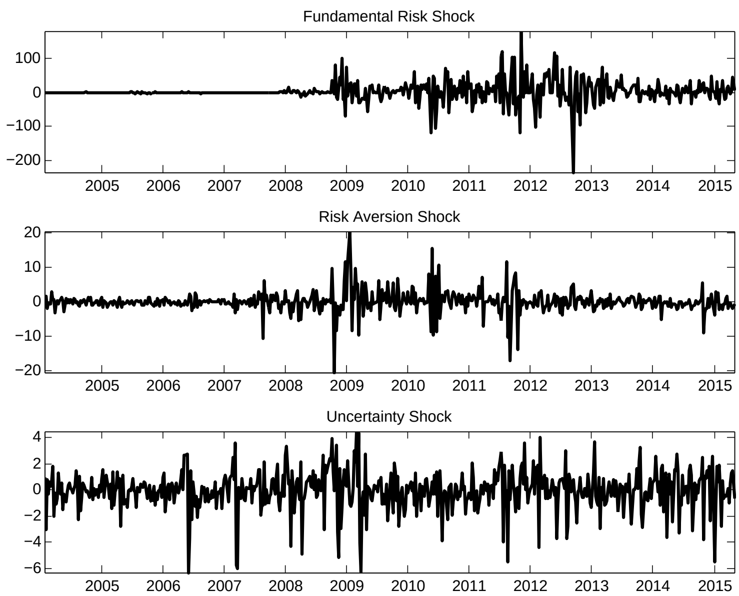


(d) Italy, standardized residuals

Figure 1.C.12: Residuals and standardized residuals from the MSH-SVAR models

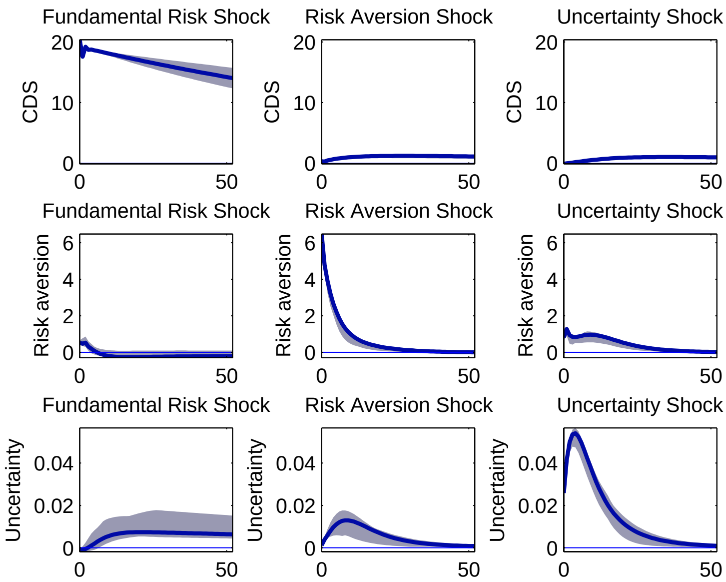


(a) Spain

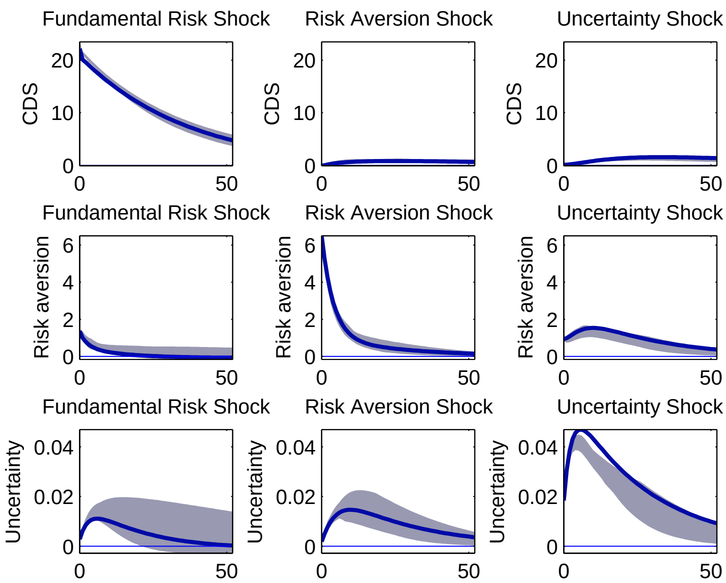


(b) Italy

Figure 1.C.13: Structural shocks uncovered from the MSH-SVAR models



(a) Spain



(b) Italy

Figure 1.C.14: Impulse responses MSH-SVAR models with 68% confidence intervals based on 1000 bootstrap replications, high volatility state

Chapter 2

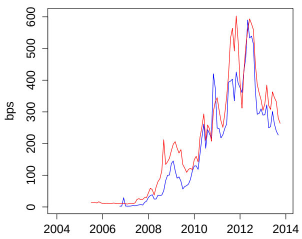
The State Dependent Impact of Bank Exposure on Sovereign Risk[1]

2.1 Introduction

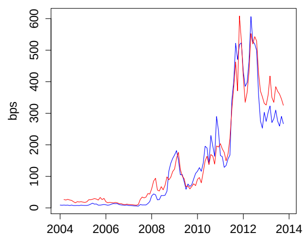
The most recent financial and European debt crises dealt a heavy blow to the financial stability of both governments and institutions alike. Throughout these crises two distinct phenomena were observed: First, sovereign and bank sector risk rose sharply and appear to move closely together. Second, the volume of domestic government debt held by the banking sector (which we will refer to as exposure in the following) has increased heavily (see Figure 2.1.1).

The role of bank exposure on financial stability is experiencing a lively debate in the literature. However, the literature appears to provide conflicting conclusions regarding the effect of increased domestic government debt holdings by banks on the government's credit risk. In their seminal paper on the sovereign-bank nexus, Brunnermeier et al. (2011) point out that high exposure potentially increases the risk positions of both the sovereign and its domestic banking system, via a so-called *diabolic loop*. They argue that speculation about the solvency of either of the two sectors would affect the risk position of the other, thus feeding back into a higher default risk for the first. Therefore, increases in exposure make twin crises (banking and sovereign) more likely and, thus, increase the probability of sovereign default. In contrast, the literature on sovereign default argues that bank exposure can act as a *disciplinary device* for the sovereign. Gennaioli et al. (2014) and Engler and Große Steffen (2016) show in the framework of theoretical models that a default is more costly to the sovereign if a relevant share of public debt is held by the domestic banking system. This triggers a credit crunch, thus reducing economic activity and worsening the sovereign's budget prospects. Due to costs of default increasing in the

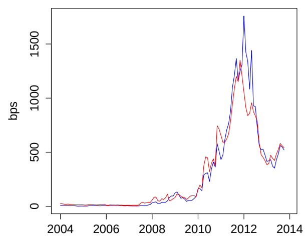
[1] This chapter is based on an article that is joint work with Anton Velinov.



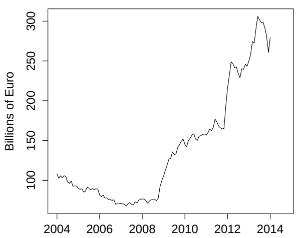
(a) CDS, Spain



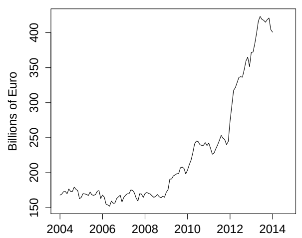
(b) CDS, Italy



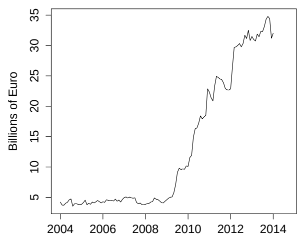
(c) CDS, Portugal



(d) Exposure, Spain



(e) Exposure, Italy



(f) Exposure, Portugal

Figure 2.1.1: Government (blue) and banking sector (red) credit default swaps (CDS) in selected euro area countries (Source: Datastream) and banking sector exposure toward domestic sovereign in the Euro zone (Source: ECB).

domestically held share of public debt, they claim that default risk on government debt falls with rising exposure. These two somewhat contradicting hypotheses from the sovereign-bank nexus and sovereign defaults literature are discussed in greater detail in Section 2.2.

In this paper we investigate the impact of exposure on sovereign risk from an empirical perspective for eight euro area economies. In particular, we aim to determine which of the competing hypotheses has more support in the data. We investigate this issue within a Markov Switching Structural Vector Autoregressive in heteroscedasticity (MSH-SVAR) framework. Such models are well suited for the purpose of our analysis for several reasons. Firstly, from Figure 2.1.1 it is apparent that the data display structural breaks, occurring around crisis periods. Such periods can be thought of as being different states of nature, which are arguably well modelled with the Markov switching methodology (see for instance Hamilton, 1989). Our model is capable of endogenously determining different volatility states and, therefore, depicts crises as periods of increased volatility (see Velinov and Chen, 2015). Secondly, the heteroscedastic feature of our model allows us to test structural identifying restrictions as, for instance, in Lanne et al. (2010) and others (see Section 2.5). This is of particular interest as there are no restrictions that are well established in the literature that we can make use of to identify the structural model. Thirdly, the theoretical literature this empirical investigation is built upon implicitly differentiates between states of the economy and the financial system when deriving implied effects of bank exposure on sovereign risk. The sovereign-bank nexus literature, on the one hand, mainly refers to twin crises of banks and sovereigns during a phase of financial turmoil. The disciplinary mechanism underlying the argument in the sovereign default literature, on the other hand, is also likely to gain importance with rising financial distress as market participants may increase awareness and monitoring efforts regarding the sovereign's creditor decomposition. The model used in this paper, therefore, extends the classical Markov-switching in heteroscedasticity framework to allow for state dependent contemporaneous impact effects and shock transmission.

This paper contributes to the literature along two dimensions. Firstly, we empirically investigate the impact of bank exposure on sovereign credit risk (and hence, overall financial stability) in the euro area. As far as we are aware, this issue is not yet investigated from an empirical perspective, even though the role of bank exposure is at the center of an intense policy debate. Pockrandt and Radde (2012) identify a range of regulatory incentives fostering the large observed increases in bank exposure and argue that they should be repealed in order to break the link between risk positions in both sectors. This development is particularly pronounced in times of ample liquidity in the banking sector (see Shambaugh, 2012), which was the case due to the European Central Bank's (ECB) unconventional monetary policy. Another explanation linking exposure to policy actions is provided by Merler and Pisani-Ferry (2012), who see persuasion by politicians as driving the purchase of sovereign debt by domestic banks. Given that the drivers of banking sector exposure identified in the literature are to a large extent at the discretion of policy makers, this renders the subject of investigation as highly policy relevant.

Secondly, we make a methodological contribution to the existing MSH-SVAR literature (see for instance Herwartz and Lütkepohl, 2014) by allowing for regime dependent shock transmission along the lines of Bacchiocchi and Fanelli (2015). The existing literature makes the implicit assumption that changes in observed volatility are solely attributable to the variance of structural shocks. This is a strong assumption and there is no clear reason to believe that the shock transmission should remain unaffected if an economy, for instance, enters a state of financial turmoil. In this paper the appeal of our model extension is that it allows us to identify regime dependent impacts of increases in exposure on the risk positions of the sovereign sector.

Based on the MSH-SVAR model, we find empirical support for the identifying restriction imposed on the system in order to identify the two shocks of interest, an exposure shock and a risk shock. Overall, our findings from the model with state invariant shock transmission point toward a destabilizing effect running from bank exposure to sovereign default risk in line with the literature on the sovereign-bank nexus. Impulse responses from models that allow for state dependent shock transmission, however, reveal a more differentiated picture. While the reaction of sovereign credit risk to changes in bank exposure is found to be particularly strong during turbulent times for the EMU periphery countries, it acts as a stabilizing device for a cluster of countries that were less affected by the crisis, supporting the theoretical predictions by the literature on sovereign defaults.

The remainder of the paper is structured as follows. The next section revisits the sovereign-bank nexus and sovereign defaults literature, deriving the hypotheses that we empirically investigate. Section 2.3 introduces the data. In Section 2.4, we discuss the MSH-SVAR models and identification scheme used. Section 2.5 tests the identifying restriction using the data, presents smoothed state probabilities and assesses the hypotheses based on impulse responses. Finally, Section 2.6 concludes.

2.2 Literature and hypotheses

This section revisits two strands of literature that form the basis for competing hypotheses regarding the impact of bank sector exposure[2] on sovereign default risk. We begin by discussing the so-called sovereign-bank nexus literature, leading to a *diabolic loop* hypothesis. We then turn to the sovereign defaults literature, leading to a *disciplinary device* hypothesis. Finally, we conclude the section with the derivation of a third hypothesis, emphasizing the regime dependency of the relationship between bank exposure and sovereign risk.

Literature on the sovereign-bank nexus

As evident from Figure 2.1.1, there is a clear tendency for the credit risk of banks and their respective sovereigns to move together. This phenomenon triggered a large strand of literature investigating the linkages between both sectors, establishing a *diabolic loop* of risk contagion (Brunnermeier et al. (2011)). We refer to this as the sovereign-bank nexus literature. A number of channels that connect both sectors together are identified. In what follows we discuss both directions separately, first the channels of contagion from the banking sector to the sovereign and then vice versa.

There are two main mechanisms identified as being responsible for potential contagion from the banking sector to the sovereign. Firstly, there is the credit supply channel. If the financial conditions of the banking sector were to deteriorate, banks may react by reducing credit supply to the real economy. This would lead to an economic slowdown or a deepening of an existing recession, which might severely harm the sovereign's tax base. The worsened fiscal position would reduce the sovereign's credit worthiness and, consequently, increase its default risk. Secondly, risks stemming from the banking sector might spill over to the national government via implicit bailout guarantees or, in a later stage, by explicit state promises (Ejsing and Lemke, 2011; Alter and Schüler, 2012; Kallestrup et al., 2013).

In the other direction, from the government to its banking sector, there is also risk contagion. It may take one of the following four channels. Firstly, given that banks generally hold non-negligible amounts of public debt, an increase in the per-

[2] Note from Section 2.1 that we refer to exposure as the volume of national government debt held by the domestic banking sector.

ceived likelihood of sovereign default would weaken the balance sheet positions of the banking sector. Angeloni and Wolff (2012), Buch et al. (2013) and De Bruyckere et al. (2013) provide evidence for the so-called portfolio channel during the European debt crisis. Secondly, a reduction of the market value of sovereign bonds has a direct negative impact on the funding conditions of banks, which use the bonds as collateral for refinancing operations (Kiyotaki and Moore (2005) and Kaminsky et al. (2003)); this is known as the collateral channel. Thirdly, Brown and Dinc (2011) and Demirgüç-Kunt and Huizinga (2010) point toward a guarantee channel: As soon as public debt default risk rises, government bank bailout and guarantee schemes become less worthy, which increases banking sector risk. Finally, Arezki et al. (2011) identify a sovereign rating channel. Since many rating agencies use public debt ratings as a ceiling for the private entities within an economy, a reduction in the sovereign rating may in turn lead to a reduction in the private rating.

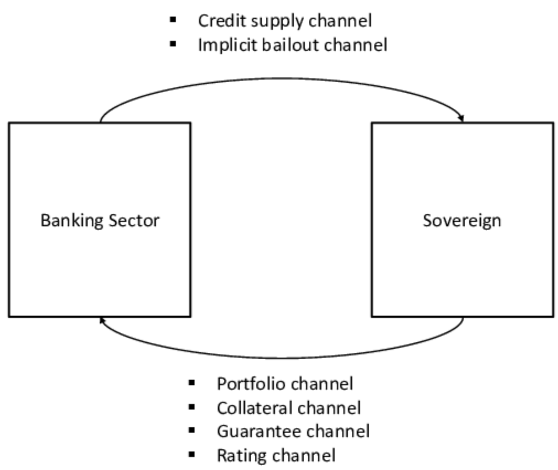


Figure 2.2.2: Transmission channels and diabolic loop according to the sovereign bank nexus literature.

The channels of contagion noted above are summarized in Figure 2.2.2. Given that risk spillovers work in both directions via a number of different channels, Acharya et al. (2014) and Rieth and Fratzscher (2014) among others, empirically identify a two way feedback between sovereign risk and bank risk. The paths of contagion outlined above result from domestic sovereign bond holdings by the banking sector, which hence lie at the core of the sovereign-bank nexus.

A measure to break the so called *diabolic loop* would have to target the amount of sovereign bonds held by banks: If the banks would hold less or no sovereign bonds, the link between financial and sovereign credit risk would become a lot weaker or vanish completely (Pockrandt and Radde, 2012). Conversely, increases in exposure intensify the link between the two sectors, thus making twin crises more likely and, consequently, increasing the probability of sovereign default. Summing up, the literature on the sovereign-bank nexus implies that banking sector exposure to the domestic sovereign should generally have a destabilizing effect on the economy. Hence, we derive the following hypothesis based on this literature.

Hypothesis I (diabolic loop): Increases in bank sector exposure raise sovereign default risk via a diabolic loop of risk contagion.

Literature on sovereign defaults

Aside from the sovereign-bank nexus literature, another strand of literature related to this paper is on sovereign defaults. As opposed to private debt, where creditor rights in most countries are strong, it is not easy to enforce claims against governments in a similar manner. Therefore, sovereign debt can only exist because a default is costly to the government as the damage to the domestic economy (through the financial system) erodes the tax base. Borensztein and Panizza (2009) find that banking crises and credit crunches driven by debt defaults are particularly costly to the sovereign. The severity of such costs depends mainly on the extent of bank sector exposure.

Losses from default are more severe if debt is held by the domestic banking system. Gennaioli et al. (2014) set up a model of sovereign default in which government defaults are costly because of the adverse effect on domestic banks' balance sheets. Consequently, their model predicts that sovereign default probability decreases in banking sector exposure. In addition, they find panel econometric evidence for sovereign defaults being less likely, the more exposed the domestic banking sector is. Similarly, Kohlscheen (2010) and Van Rijckeghem and Weder (2004) find governments are less likely to default on domestic creditors than foreign ones. Based on this line of reasoning, Engler and Große Steffen (2016) argue that incentives for sovereign default originate in wealth transfers by defaulting on foreign held debt. The fundamental point from this strand of literature is that bank exposure can act as a *disciplinary device* for the sovereign. Such a device would lead to a lower perceived sovereign default risk when more domestic debt is held by the banking system.

On a related point, the sovereign default literature helps explain the sharp increase in bank exposure observed in Figure 2.1.1. In particular, Broner et al. (2014) argue that sovereign bonds deliver a higher expected return to domestic creditors than to foreign creditors. Given that debt default is more costly to the sovereign if its debt is held domestically, government bonds offer a higher expected return to domestic creditors, especially during turbulent times. Therefore, public debt crises trigger a buy up of bonds by domestic creditors – most importantly banks.

Overall, the sovereign default literature points toward bank sector exposure acting as a *disciplinary device*. In other words, the greater the exposure of the domestic banking system, the less likely the government is to default on its debt. We formulate this in the following hypothesis.

Hypothesis II (disciplinary device): Increases in bank sector exposure raise the cost of default for the sovereign and, therefore, decrease sovereign default risk.

State dependency

From the above noted literature we further observe a certain degree of state dependence in the relation of bank exposure and sovereign risk. Given that the focus of the sovereign-bank nexus literature is on times of financial distress, we expect the *diabolic loop* mechanism to be particularly pronounced during those times. Financial market participants, for example, may become aware of a critically close linkage between banks and sovereigns, particularly during times of financial turmoil.

Similarly, bank exposure may have a stronger disciplinary effect during times of fiscal stress. This could be due to rising awareness of the role of creditor composition for sovereign default decisions by market participants. By engaging in a closer monitoring of the debt composition, market participants are more likely to incorporate the degree of home bias in sovereign bond holdings in their credit risk assessment. During tranquil times with low default risk, however, such a mechanism might play only a minor role for the assessment of sovereign risk by financial markets.

It should be noted that there is no reason to assume that changes in exposure of domestic banks should even have a similar impact in terms of the sign across states. Increases in bank exposure may, for instance, have a stabilizing effect during tranquil times disciplining the sovereign, while acting as a destabilizing force during turbulent times in which the diabolic loop becomes dominant. We account for these considerations in our empirical setup.

In order to take into account the potential state dependence in the relationship of bank exposure and sovereign risk, we formulate the following third hypothesis.

Hypothesis III (state dependency): The effect of bank sector exposure on sovereign credit risk is state dependent and particularly pronounced during times of financial turmoil.

In what follows, we evaluate the hypotheses derived from the literature within a Markov Switching Structural Vector Autoregressive in heteroscedasticity (MSH-SVAR) framework. We test Hypothesis I and II by means of a state invariant shock transmission model (see Section 2.4.1.1). In order to test Hypothesis III we use a regime dependent shock transmission model (see Section 2.4.1.2). In the next section we briefly discuss how we construct our data set.

2.3 Data

Our analysis covers eight euro area economies. Three of which – Italy, Portugal and Spain – were hit hard by the European banking and sovereign debt crisis. The remaining five countries we investigate are Austria, Belgium, France, Germany and The Netherlands. These countries were less affected by the European banking and sovereign debt crisis, with Germany even being considered a so-called safe haven. We use monthly frequency data ranging from 2006:1 to 2014:1 for most countries. For Spain, The Netherlands and France the data start in 2006:10.

Our data consist of sovereign credit default swaps (CDS^{Sov}) and the log difference of bank sector exposure (ΔExp). Data on CDS with five year maturity is obtained from Thomson Reuters Datastream. CDS are a commonly used proxy for sovereign credit risk as they insure the buyer against the potential loss from loan default.[3] We

[3] Note that the price of CDS may be decomposed in the probability of default and the loss given default. Those components contribute to CDS prices approximately in a multiplicative manner. Throughout this paper we follow the convention in the literature of using time variation in CDS as a proxy for the variations in default probability, implicitly assuming the loss given default to remain constant over time.

measure changes in banks' exposure by the growth rate of the index of notional stocks of domestic public bonds held by the financial sector.[4] An important feature of this series is that it is cleaned from effects of reclassification, revaluation, and exchange rate movements. Thus, changes in the level of this measure capture changes of the volume of bonds held on banks' balance sheets. Data on bank sector bond holdings is taken from the European Central Bank (ECB) Statistical Data Warehouse. All data is end of period data, i.e. from the last trading day in each month.

In addition, we collect a battery of exogenous control variables. These include total bonds issued by the government[5] (to control for the scaling of total public debt), industrial production (as a control for potential business cycle effects), banking sector equity (as an indicator of banks' stability), stock market indices (to account for asset price developments), and a dummy variable for the announcement of the outright monetary transactions (OMT) in June 2012.[6] The data for the control variables also stem from the ECB Statistical Data Warehouse and Thomson Reuters Datastream.

2.4 The model

This section describes the theoretical aspects of the models we use to test the hypotheses outlined in Section 2.2. It begins with a description of the general Markov

[4] The index of notional stocks is superior to the simple balance sheet item as it is not clear whether balance sheet items are reported by book value or by market value. The ECB's manual on monetary financial institutions (MFI) balance sheet statistics remains imprecise on this issue (ECB, 2012, p. 74): "*The ECB's preference is that in balance sheet reporting MFIs should present asset and liability positions at current market values or a close equivalent to market values (fair values), while accepting that in practice MFIs may continue to use local accounting rules requiring valuation other than current market values.*" This assumption might introduce some distortions in the estimation of structural shocks, given that those might not reflect movements in the volume of the bond holdings but rather underlying price movements. However, since we use the index of notional stocks for the balance sheet data, the adjustments should clean the data with respect to these considerations.

[5] We use a geometrically interpolated quarterly series to obtain a monthly frequency.

[6] In addition, we consider further control variables, such as the VIX volatility index, the spread of BBB and AAA rated corporate bonds, the announcement dates for the securitized market programme (SMP) and of the (very) long term refinancing operations ((V)LTRO) (to control for global risk appetite and the ECB's unconventional monetary policy). However, we find them to be insignificant in most cases and, hence, exclude them from the vector of exogenous variables. We also attempt to control for hedging efforts by banks toward sovereign default risk, but found such data not to be available.

Switching Vector Autoregressive (MS-VAR) model, then introduces two modeling approaches for the MS Structural VAR in heteroscedasticity (MSH-SVAR) model — with and without a regime dependent shock transmission. It describes how the structural shocks are identified and ends with a short note on bootstrapping.

2.4.1 MS-VAR

We consider the following reduced form MS-VAR(p) model

$$\begin{aligned} y_t = \nu(S_t) \quad &+ \quad A_1(S_t)y_{t-1} + A_2(S_t)y_{t-2} + \cdots + A_p(S_t)y_{t-p} \\ &+ \quad \Gamma_0(S_t)x_t + \Gamma_1(S_t)x_{t-1} + \cdots + \Gamma_n(S_t)x_{t-n} + D(S_t)z_t + u_t, \end{aligned} \tag{2.1}$$

where y_t is a $(K \times 1)$ vector of endogenous variables. In our case, $y_t = [CDS^{Sov}, Exp]'$ (hence, $K = 2$). Further, x_t is a vector of N exogenous variables, A_i's $(K \times K)$ and Γ_j's $(K \times N)$ are parameter matrices with $i = 1, \ldots, p$ and $j = 1, \ldots, n$, where n does not necessarily equal p. z_t is a vector of J dummy variables with a $(K \times J)$ coefficient matrix D and ν is a $(K \times 1)$ vector of constant terms. Finally, u_t is a $(K \times 1)$ vector of reduced form error terms with $E[u_t] = 0$ and $E[u_t u_t'] = \Sigma_u(S_t)$. In addition, we assume (for estimation purposes) that u_t is normally and independently distributed conditional on a given state, hence,

$$u_t | S_t \sim \text{NID}(0, \Sigma_u(S_t))^7. \tag{2.2}$$

All of the coefficient matrices are potentially governed by a first order discrete valued Markov process, S_t, that can take on M different values, $S_t = 1, \ldots, M$. In Section 2.5.1 we determine which parameters are allowed to switch by means of information criteria.

The structural errors are related to the reduced form errors as

$$u_t = B\varepsilon_t, \tag{2.3}$$

where B is a $(K \times K)$ matrix of instantaneous effects (see Lütkepohl, 2005, Chapter 9) and ε is a vector of structural errors. We now consider two modeling ap-

[7] The unconditional distribution of u_t can take on a wide range of distributions (see Hamilton, 1994, Chapter 22).

proaches for equation (2.3); a state invariant and state dependent B matrix. In addition, we discuss how we identify the structural shocks in both model specifications — which we label as a sovereign risk shock, (ε_{risk}) and an exposure shock, (ε_{exp}).

2.4.1.1 Invariant instantaneous impact matrix

The state invariant approach is given in equation (2.3). In order to capture periods of different heteroscedasticity, we assume that $E[\varepsilon_t] = 0$ and $E[\varepsilon_t \varepsilon_t'] = \Lambda(S_t)$, a diagonal matrix, and that $\Lambda(1) = I_K$. Hence, $\text{var}(u_t|S_t) = B\Lambda(S_t)B' = \Sigma_u(S_t)$.

With this specification we use the following identification restriction

$$\begin{pmatrix} u_1 \\ u_2 \end{pmatrix} = \begin{pmatrix} b_{11} & 0 \\ b_{21} & b_{22} \end{pmatrix} \begin{pmatrix} \varepsilon_{risk} \\ \varepsilon_{exp} \end{pmatrix}. \tag{2.4}$$

This implies that a sovereign risk shock instantaneously effects both variables, sovereign CDS and bank exposure, while a bank exposure shock has no instantaneous impact on sovereign CDS. As noted in Section 2.3, we use end of period data for all endogenous variables and bank exposure data is published about two to four weeks after the respective month has ended. Hence, at the end of a respective period there is no contemporaneous information on bank exposure available to market participants. This means that a shock to bank exposure would not be known to the market instantaneously, which justifies a zero contemporaneous restriction.[8]

The restriction in equation (2.4) may be formally tested using over-identifying restrictions stemming from the heteroscedasticity in the data (see for instance Lanne et al., 2010; Herwartz and Lütkepohl, 2014; Velinov and Chen, 2015). In particular, it is necessary for the diagonal elements of at least one of the $\Lambda(S_t), S_t = 2, \ldots, M$ matrices to be distinct. If that is the case then the B matrix is identified up to changes in sign and column ordering. Any additional restrictions on B then become over-identifying and can be tested. Note that for a model with two states, we are left with five unknowns (three elements of B and two of $\Lambda(2)$), which are related to

[8] Even without actual information on bank exposure, analysts might try and build expectations about shifts in bank balance sheets based on other information available to the market. However, we argue that such expectation building is accounted for by the autoregressive structure of the reduced form VAR model.

the six unique variance parameters from $\Sigma_u(1)$ and $\Sigma_u(2)$. Hence, the model would be over-identified and the zero restriction could be tested.[9]

2.4.1.2 State dependent instantaneous impact matrix

The second modeling approach considers a state dependent B matrix, which, following Bacchiocchi and Fanelli (2015), is given as

$$B(S_t) = B^{INV} + Q(S_t). \tag{2.5}$$

Here B^{INV} is a $(K \times K)$ matrix of state invariant instantaneous effects and $Q(S_t)$ is a $(K \times K)$ matrix of varying instantaneous effects for a given state, with $Q(1) = 0$, a matrix of zeros. Note that with this approach we have $\mathrm{var}(u_t|S_t) = B(S_t)B(S_t)' = \Sigma_u(S_t)$ (see equation (2.2)), hence, $E[\varepsilon_t \varepsilon_t'] = I_K$ (naturally, $E[\varepsilon_t] = 0$).

This state dependent instantaneous impact model allows impulse responses (IRs) to vary over regimes according to the contemporaneous impacts of a shock. Therefore, the model has sufficient degrees of freedom to investigate the third hypothesis, which posits state dependent signs of the impulse responses.

To identify the structural shocks (ε_{risk} and ε_{exp}) in the state dependent instantaneous effects model, we use the same restriction on B^{INV} as given in Equation (2.4). In addition, we allow some of the elements of $Q(S_t), S_t > 1$ to vary. Formally, we use the following matrix specification of Equation (2.5)

$$B^{INV} = \begin{pmatrix} b_{11} & 0 \\ b_{21} & b_{22} \end{pmatrix} \; , \quad Q(1) = \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix} \quad \text{and} \quad Q(S_t) = \begin{pmatrix} q_{11}(S_t) & q_{12}(S_t) \\ 0 & 0 \end{pmatrix} \forall S_t > 1 \; . \tag{2.6}$$

This means that the upper right element, $b_{12}(S_t)$ of $B(S_t)$, is unrestricted for $S_t > 1$, or, in other words, for high volatility states (see Section 2.5.2).

We use the specification in equation (2.6) for several reasons. Firstly, over the course of the most recent crises market participants have become more sensitive toward potential risk contagion between banks and sovereigns. This has arguably induced closer monitoring than before. We, therefore, feel more comfortable only imposing the restriction for the lower volatility state. Note that in order to achieve identification within this setup the two lower elements of $B(S_t)$ remain invariant

[9] The pair of elements of $\Lambda(2)$ need to be distinct so that $\Sigma_u(1) \neq \Sigma_u(2)$ (recall, $\Lambda(1) = I_2$).

across states, imposing the assumption that risk shocks and exposure shocks have the same effect on bank exposure across states. Secondly, we need to provide the model with enough flexibility so as to investigate the third hypothesis. Put differently, if we keep the zero restriction in all states, the responses we are interested in (namely those of sovereign CDS toward exposure shocks) remain invariant up to scaling.

Finally, we assure that the necessary and sufficient conditions for (local) identification of the model are satisfied, given the set of restrictions that we impose.[10]

2.4.2 Estimation and Bootstrapping

We now discuss parameter estimation for both types of model specifications, with and without a state invariant B matrix, and we briefly describe how we test the identifying restriction in equation (2.4). This section concludes with a note on bootstrapping.

The model parameters in equation (2.1) are estimated by means of the expectation maximization (EM) algorithm (see Hamilton, 1994, Chapter 22). To estimate the parameters of the state invariant B matrix in equation (2.3) and of $\Lambda(S_t), S_t > 1$, we use a similar algorithm as that described in (Velinov and Chen, 2015, Appendix). The model with state dependent B matrix in (2.5) is estimated based on the following concentrated out log likelihood function in the maximization step of the EM algorithm

$$\begin{aligned} l(B^{INV}, Q(2), Q(3)\ldots, Q(M)) &= \frac{1}{2}\sum_{m=1}^{M}\Bigg[\widehat{T}_m \log(\det(B(m)B(m)')) \\ &+ \operatorname{tr}\bigg((B(m)B(m)')^{-1}\sum_{t=1}^{T}\widehat{\xi}_{mt|T}\widehat{u}_t\widehat{u}_t'\bigg)\Bigg], \end{aligned}$$

[10] In order to check the rank condition we follow Bacchiocchi and Fanelli (2015) and check whether the $K(K+1)\times a$ matrix given by

$$(I_2 \otimes D_K^*)\begin{pmatrix} (B\otimes I_K) & 0_{K^2\times K^2} \\ (B+Q)\otimes I_K & (B+Q)\otimes I_K \end{pmatrix}\begin{pmatrix} S_B & S_I \\ 0_{K^2\times a_C} & S_Q \end{pmatrix}$$

has full column rank (see Bacchiocchi and Fanelli, 2015, equation (27)), where a is the number of free parameters in the structural impact matrices B and Q, S_B, S_Q and S_I summarize the linear restrictions on B, Q and cross-restrictions on B and Q, respectively, and D_K^* is the Moore-Penrose inverse of the duplication matrix D. We draw 10,000 matrices from the uniform distribution on the interval between -10 and 10 and find the rank condition satisfied for every draw.

where $\xi_{mt|T}, m = 1, \ldots, M, t = 1, \ldots, T$ are the model smoothed probabilities and $T_m = \sum_{t=1}^{T} \xi_{mt|T}$. The remaining parameters are defined as in equation (2.1). The hat denotes estimated parameters.

Once the EM algorithm has converged, standard errors of the point estimates of the parameters are obtained through the inverse of the negative of the Hessian matrix evaluated at the optimum. With the standard errors in hand, we use Wald tests to determine whether the pairwise parameters of at least one of the $\Lambda(S_t), S_t = 2, \ldots, M$ matrices are distinct. As noted in Section 2.4.1.1, if that is the case then the B matrix is identified up to changes in sign and column ordering. Hence, any additional restrictions as in equation (2.4) become over-identifying and can be tested by means of a Likelihood Ratio (LR) test.

Finally, we would like to mention the theoretical aspects of the bootstrapping procedure we use for generating confidence bands for our impulse responses (see Section 2.5.3). In particular, given the heteroscedastic nature the data,[11] classical residual based bootstrap techniques may be problematic in generating reliable confidence intervals for impulse responses (IRs). Any re-sampling scheme needs to preserve the second order characteristics of the data. We therefore, use a fixed design wild bootstrap according to $u_t^\star = \varphi_t \widehat{u}_t$, where φ_t is a random variable, independent of y_t following a Rademacher distribution. In other words, φ_t is either 1 or -1 with a 50% probability. Davidson and Flachaire (2008) show that using the Rademacher distribution for wild bootstrapping is superior to the two-point distribution proposed by Mammen (1993), even if the residuals are not symmetrically distributed.[12]

2.5 Results

This section presents the empirical results of both models (see Section 2.4.1.1 and Section 2.4.1.2) for eight euro area countries. Impulse responses (IRs) are presented to assess the three hypotheses. The section starts with a discussion of the model specification and smoothed probabilities.

[11] ARCH tests strongly indicate the presence of heteroscedasticity in the data.
[12] See MacKinnon (2014) for a further discussion of Wild bootstrap auxiliary distributions.

2.5.1 Model selection

In our analysis we consider two-state Markov Switching Structural Vector Autoregressive in heteroscedasticity (MSH-SVAR) models. The use of two states is for several reasons. Firstly, due to a limited number of observations, we prefer parsimonious model specifications. Secondly, two states are sufficient to formally test the identifying restriction imposed on the model (see Section 2.4.1). Thirdly, provided one state is interpretable as a tranquil and the other as a crisis state, two states suffice for testing the third hypothesis that refers to a state dependent shock transmission. Finally, a third state would mainly pick up outliers, rendering the parameters for this state difficult to estimate due to few observations.

We follow the literature on MS-VAR models and select the lag order of the endogenous variables, p (see equation (2.1)), based on the linear VAR model. To keep the models as parsimonious as possible we follow the Bayesian information criterion (BIC) and choose one lag for Spain, Italy, Portugal, Belgium and Germany and two lags for France, The Netherlands and Austria. In addition, we set $n = p$, that is we use the same lag length for the exogenous variables.

Table 2.5.1 reports information criteria for different specifications regarding the linearity of the model. Clearly, non-linear models are preferred over linear specifications, according to log-likelihoods and information criteria. For Spain, Germany, The Netherlands and Austria, the AIC favors models with more parameters switching. For the remainder of the countries both criteria indicate models without switching slope parameters. Based on our preference for parsimonious model specifications, we opt for the more restrictive BIC. In all cases except for Spain it strongly favors a model structure with only switching covariance matrices. Therefore, we use a Markov Switching Structural Vector Autoregressive in heteroscedasticity (MSH-SVAR) model for all countries considered.[13] Such a specification is in line with the findings from ARCH tests for conditional heteroscedasticity in the data. These tests strongly reject the null hypothesis of no heteroscedasticity.

[13] Given the approximative nature of the likelihoods of the MS-VAR models that the information criteria are based upon, they should not be viewed as providing a strict guideline, but rather as well informed indications towards a preferred specification.

Table 2.5.1: Log-Likelihood, Akaike and Bayesian information criteria for model selection based on a Markov-switching model with two states and different sets of switching parameters

		linear	$\Sigma(S_t)$	$\Sigma(S_t)$, $\nu(S_t)$	$\Sigma(S_t)$, $A_i(S_t)$	$\Sigma(S_t)$, $A_i(S_t)$, $\nu(S_t)$
	LogLik	-711.32	-686.68	-675.47	-673.73	-662.5
Spain	AIC	1476.64	1435.36	**1418.93**	1419.47	1436.99
	BIC	1542.9	1511.81	**1502.78**	1508.24	1575.09
	LogLik	-746.53	-694.57	-693.87	-717.26	-692.83
Italy	AIC	1547.06	**1451.14**	1455.73	1506.53	1497.67
	BIC	1616.3	**1530.64**	1542.92	1598.85	1641.27
	LogLik	-949.09	-862.5	-860.98	-860.36	-862.16
Portugal	AIC	1952.17	**1786.99**	1787.95	1790.73	1834.32
	BIC	2021.41	**1866.49**	1872.57	1880.48	1975.36
	LogLik	-693.04	-636.75	-635.91	-634.87	-641.23
Belgium	AIC	1440.08	**1335.51**	1337.81	1339.73	1392.46
	BIC	1509.31	**1415**	1422.44	1429.48	1533.5
	LogLik	-686.54	-599.23	-597.03	-596.13	-558.91
Germany	AIC	1427.08	1260.46	1260.06	1262.26	**1227.82**
	BIC	1496.32	**1339.95**	1344.69	1352.02	1368.86
	LogLik	-616.46	-564.19	-560.77	-560.59	-549.93
France	AIC	1294.92	1198.39	**1197.53**	1209.19	1227.86
	BIC	1371	**1287.77**	1294.58	1321.56	1391.31
	LogLik	-638.26	-590.87	-591.34	-597.65	-574.17
Netherlands	AIC	1338.51	**1251.74**	1258.67	1283.3	1276.34
	BIC	1414.6	**1337.24**	1351.49	1390.78	1432.67
	LogLik	-721.48	-641.64	-640.66	-630.2	-624.78
Austria	AIC	1504.96	1353.27	1357.32	**1348.4**	1377.56
	BIC	1584.45	**1442.66**	1454.36	1460.77	1541.01

Notes: $\Sigma(S_t)$ – only covariance matrix switching; $\Sigma(S_t)$, $\nu(S_t)$ – covariance matrix and intercept switching; $\Sigma(S_t)$, $A_i(S_t)$ – covariance matrix and slope parameters switching; $\Sigma(S_t)$, $A_i(S_t)$, $\nu(S_t)$ – all reduced form parameters switching

2.5.2 Smoothed state probabilities

Figure 2.5.3 plots the smoothed probabilities of state 2, the high volatility state, for all eight countries based on the MS model with the state invariant instantaneous impact matrix.[14] Clearly, each MS model is well capable of capturing the crisis phases, which are always indicated as being in state 2.[15]

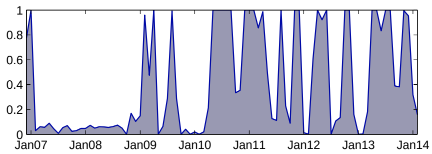
The upper four Panels of Figure 2.5.3 show the countries that were affected somewhat more by the crisis (Spain, Portugal, Italy and Belgium). Their smoothed probabilities appear to be relatively stable. The lower four Panels of the figure show the more stable countries (France, Germany, The Netherlands and Austria), where Germany was even regarded as a safe haven during the European debt crisis. The smoothed probabilities of Germany, The Netherlands and Austria show more volatile patterns. This is likely attributable to less volatility in data, making both states not very different from each other.

In order to test the identifying restriction in equation (2.4), we first need to determine whether the pairwise diagonal elements of $\Lambda(2)$ are distinct (see Section 2.4.1.1 and Section 2.4.2). Table 2.5.2 clearly shows that this is the case according to Likelihood Ratio (LR) tests (the null hypothesis is $\lambda_{11}(2) = \lambda_{22}(2)$).[16] This means that all of the estimated models are over-identified since $\Sigma(1) \neq \Sigma(2)$. Table 2.5.3 summarizes the LR tests of the validity of the over-identifying restriction on the matrix of structural impact parameters B. The null hypothesis is B, as in equation (2.4), i.e. $b_{12} = 0$, versus the alternative of an unrestricted B matrix. The imposed restriction is not rejected by the data, except in the case of the Spanish model. We consider this result as a strong signal in support of our identifying assumption and proceed with testing the hypotheses formulated in Section 2.2. Since most elements of $\Lambda(2)$

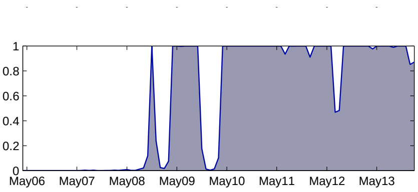
[14] Note that the smoothed state probabilities for the model with a state dependent instantaneous impact matrix look quite similar, but are not identical.

[15] Note that the states are not directly comparable among different countries. For instance, volatility may be higher in the second state for some countries than for others indicating that they were hit more strongly by the crisis.

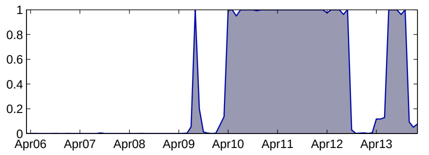
[16] We follow the literature on identification via heteroscedasticity regarding the assumptions on the asymptotic distribution of the test statistic. It should be noted, however, that according to personal communication with Helmut Lütkepohl recent research finds the assumptions for the asymptotic distributions of the test statistic to be not quite correct. Therefore, these tests should be interpreted with some caution. Tentative evidence indicates that the LR statistic for a bivariate VAR model has an asymptotic $\chi^2(2)$ distribution under the null. Based on the critical values of the $\chi^2(2)$ distribution the test would indicate identification. In addition, the (bootstrapped) IRs stemming from the models identified via heteroscedasticity do not indicate any lack of identification since error bands are well behaved.



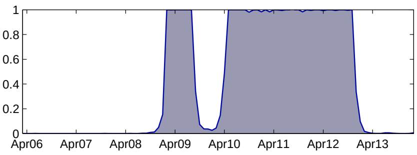
(a) Spain



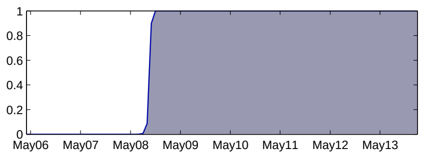
(b) Portugal



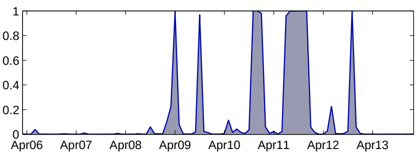
(c) Italy



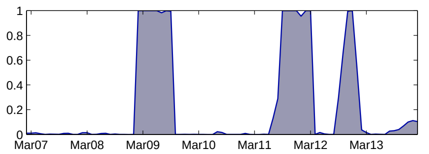
(d) Belgium



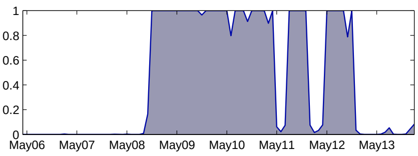
(e) France



(f) Germany



(g) Netherlands



(h) Austria

Figure 2.5.3: Smoothed probabilities from the Markov switching VAR models with invariant structural impact matrices

are larger than unity (i.e. the volatility of the first state), we refer to the second state as the crisis state.[17]

Table 2.5.2: Diagonal elements of $\Lambda(2)$ with standard errors in parentheses. Likelihood Ratio test for distinct elements of $\Lambda(2)$. The null hypothesis is $\lambda_{11}(2) = \lambda_{22}(2)$.

	Spain	Italy	Portugal	Belgium	Germany	France	Netherlands	Austria
λ_1	54.13	185.05	188.12	62.68	14.33	130.87	36.73	136.86
	(17.77)	(6.01)	(23.00)	(50.35)	(5.91)	(6.05)	(5.67)	(139.80)
λ_2	0.19	1.89	5.89	0.99	79.84	1.95	0.05	10.23
	(0.09)	(0.83)	(2.47)	(0.31)	(13.41)	(0.53)	(0.02)	(4.09)
LogLik	-590.71	-696.08	-690.97	-655.06	-609.08	-890.41	-664.2	-602.65
χ^2	28.62	12.8	55.84	55.79	6.91	53.72	36.89	26.85
p-value	0	0	0	0	0.01	0	0	0

Table 2.5.3: Likelihood ratio test of the restriction in equation (2.4) versus an unrestricted B matrix.

	Spain	Italy	Portugal	Belgium	Germany	France	Netherlands	Austria
Restr.	-687.78	-694.57	-862.5	-636.75	-599.23	-564.19	-590.87	-641.64
Unrestr.	-681.77	-694.53	-862.49	-636.31	-599.2	-563.85	-590.63	-641.63
χ^2	12.01	0.09	0.01	0.89	0.06	0.69	0.48	0.01
p-value	0	0.76	0.91	0.34	0.8	0.41	0.49	0.93

2.5.3 Impulse Responses

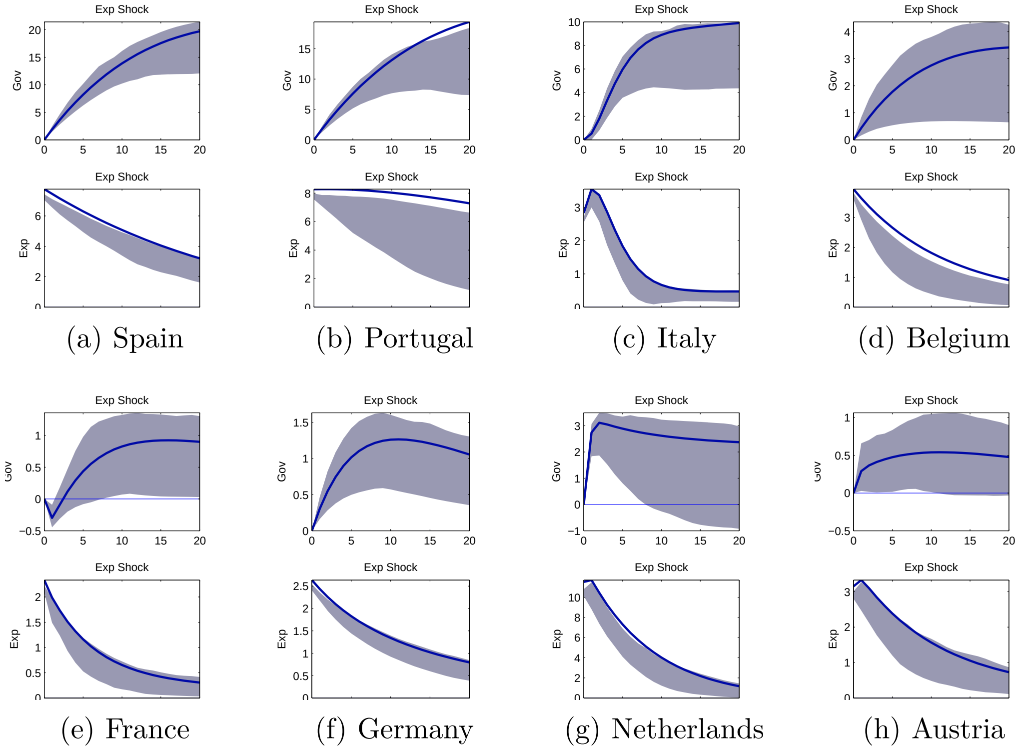
We turn to impulse response (IR) analysis to formally test the hypotheses outlined above. We evaluate Hypotheses I and II using the state invariant B model, since they do not refer to a regime dependent shock transmission. We assess Hypothesis III by means of the regime dependent B model.

2.5.3.1 State invariant B impulse responses

Figure 2.5.4 reports the IRs in state 1 of sovereign CDS to a positive one standard deviation exposure shock. Note, the IRs of state 2 are the same in shape, sign and

[17] Note that we are mainly interested in λ_1, the CDS volatility in the second state, which is always greater than one (see Table 2.5.2).

significance, only differing in the scaling on the vertical axis. All countries exhibit a significant increase in credit risk as a response to a shock in bank exposure.



(a) Spain (b) Portugal (c) Italy (d) Belgium

(e) France (f) Germany (g) Netherlands (h) Austria

Figure 2.5.4: State invariant B impulse responses of sovereign CDS to an exposure shock with 68% confidence intervals based on 1000 bootstrap replications

The overall responses are not only statistically significant, they are also economically significant. The countries in the upper panel of the figure that were hit harder by the sovereign debt crisis exhibit particularly strong responses. For instance, the model indicates an increase in CDS of up to 10 basis points for Italy and more than 20 basis points for Spain and Portugal. In addition, for those countries, the responses do not show signs of mean reversion at the 20 month horizon plotted in the figure. Whereas for Germany, The Netherlands and Austria the IRs also show longer lasting impacts, but with a clear reversion toward mean after a couple of months.

Overall, we conclude that the results from models with state invariant structural impact matrices seem to point strongly toward the *diabolic loop* story (Hypothesis

I), thereby, rejecting competing Hypothesis II, the *disciplinary device* mechanism hypothesis.

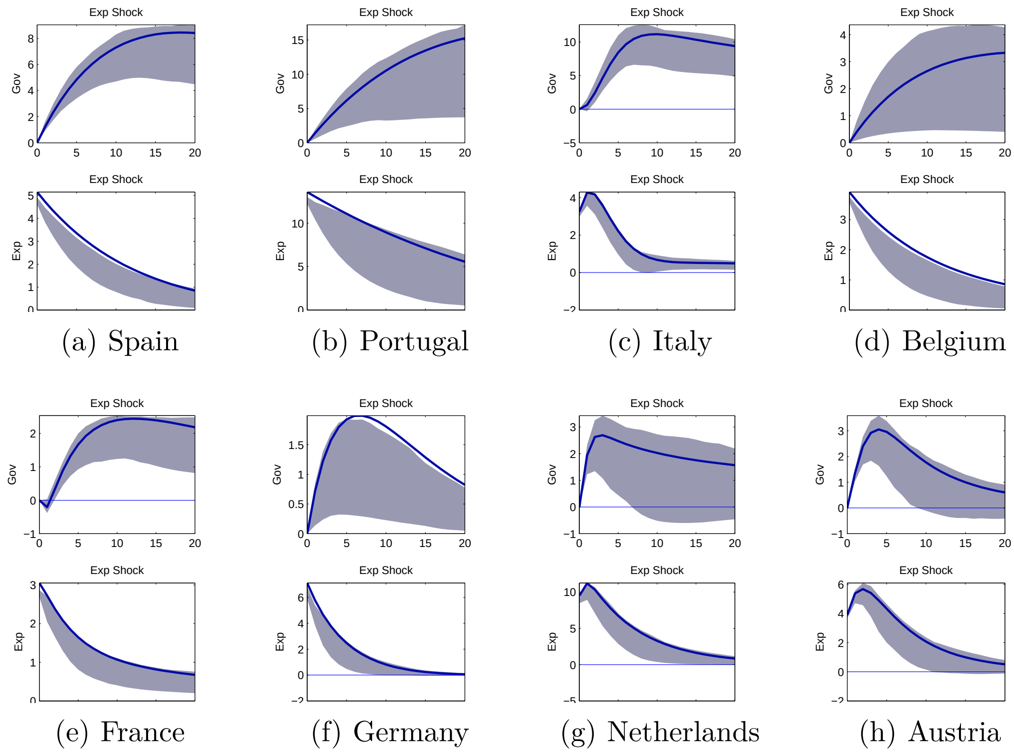
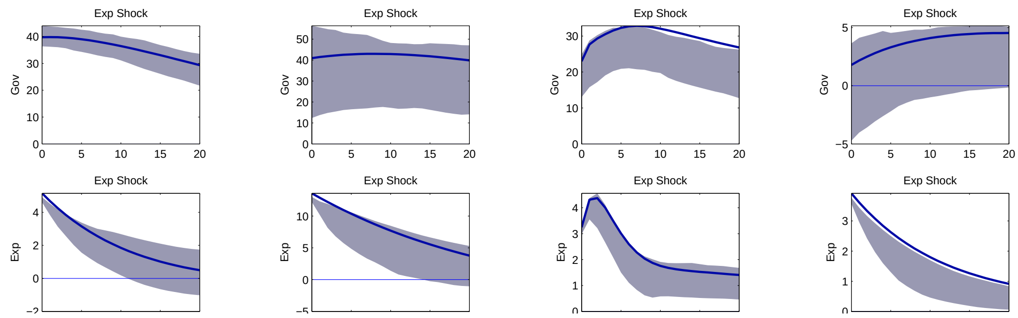


Figure 2.5.5: State dependent B impulse responses of sovereign CDS to an exposure shock for the low volatility state with 68% confidence intervals based on 1000 bootstrap replications

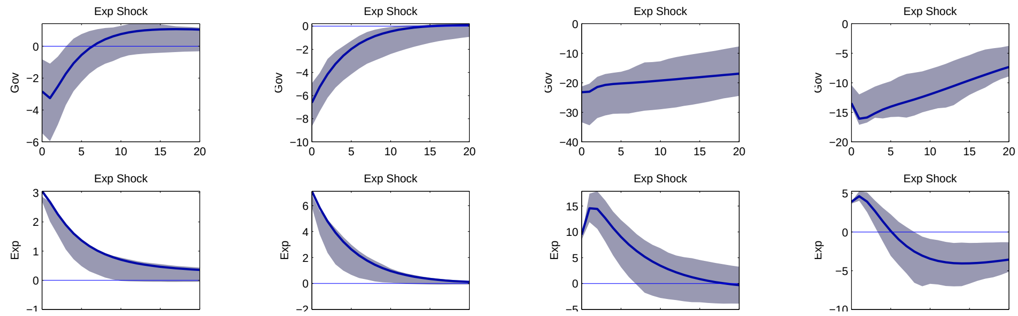
2.5.3.2 State dependent B impulse responses

We now turn to the state dependent B model results in order to investigate Hypothesis III. These allow for contemporaneous reactions of the sovereign CDS markets to changes in banks' balance sheets (i.e. increases in bank exposure toward the sovereign, during crises times). Figure 2.5.5 and Figure 2.5.6 plot these IRs for the low and high volatility states, respectively. Note, that for tranquil times, the contemporaneous restriction still holds, identifying the exposure shock as argued in Section 2.4.1.2.

A number of findings arise from Figure 6. Firstly, the IRs of state 1, the tranquil state, are qualitatively very similar to the ones from the state invariant B model.



(a) Spain (b) Portugal (c) Italy (d) Belgium



(e) France (f) Germany (g) Netherlands (h) Austria

Figure 2.5.6: State dependent B impulse responses of sovereign CDS to an exposure shock for the high volatility state with 68% confidence intervals based on 1000 bootstrap replications

This is as expected, given that the identification has not changed for the tranquil state. Secondly, for state 2, the crisis state, the impact responses plotted in Figure 2.5.6 are all different from zero — due to the higher degree of freedom in estimating the impact matrix. Finally, the impulse responses portray a clear clustering of the countries, dividing them by the sign of the impact response into a group that was hit hard by the crisis and a group with sovereign finances less affected by the crisis.

Sovereign credit risk rises strongly in Spain, Portugal and Italy in response to an exposure shock. The impulse responses exhibit a clear pattern of regime dependence and point toward a strong *diabolic loop* effect at play in the crisis hit countries. On impact, an increase in exposure of one standard deviation leads to a jump of between 20 and 40 basis points in credit default swaps. There is no evidence of bank exposure acting as a *disciplinary device* for these countries in either regime.

The effect runs in the opposite direction for the countries less affected by financial distress during the sovereign debt crisis: Increased bond holdings in the domestic banking sector reduce sovereign credit risk in France, Germany, The Netherlands and Austria. This evidence indicates that domestic bond holdings may have a disciplining effect on some governments. Given the clear clustering of the countries, this may be related to the room for maneuver that is left for governments to take home bias in bond holdings into account in their decision process.

Overall, the state dependent B model partly supports the findings from the state invariant model and points toward a *diabolic loop* at play for the sample of crisis countries, Spain, Italy and Portugal. For these economies there seems to be positive feedback between risk in the banking sector and sovereign risk running via sovereign bonds held by domestic banks. While this effect is rather small and, thus, economically less relevant in tranquil times, it seems to be particularly pronounced during crisis times — in line with the predictions of the sovereign-bank nexus literature.

However, we also identify a stabilizing effect during times of financial distress running from bank exposure to sovereign risk for the group of core countries, France, Germany, The Netherlands and Austria, thus supporting the *disciplinary device* hypothesis. This may be due to a rising awareness of the degree of bank exposure to sovereign risk and, hence, its consequences for public default during turbulent times. Indeed, there is a body of literature documenting how increased awareness of fundamentals determined sovereign risk during the European public debt crisis (Bekaert et al., 2011; Beirne and Fratzscher, 2013; D'Agostino and Ehrmann, 2014).

In summary, the results based on the state dependent B model point toward a strong regime dependence (Hypothesis III) and the existence of both a stabilizing and a destabilizing effect (Hypotheses I and II) running from bank exposure to sovereign risk. A drawback of our modeling approach is that there is no leeway to draw conclusions on the economic factors that determine which of the two effects — *diabolic loop* or *disciplinary device* — dominate. While this may be related to factors like the awareness by markets of economically significant sovereign default risk in the first place and subsequent room for maneuver on the side of the sovereign to react to changes in the structure of its creditors, we leave it to future research to investigate these determinants.

2.6 Conclusion

During the European debt crisis, banks heavily increased their domestic bond holdings. The theoretical literature remains inconclusive as to whether increasing exposure has an adverse effect on the risk positions of the domestic sovereign via a *diabolic loop* or whether it reduces perceived credit risk by acting as a *disciplinary device* for the sovereign.

In this paper we analyze the impact of exogenous changes in bank exposure on the risk positions of the sovereign within a Markov Switching Structural Vector Autoregressive in heteroscedasticity (MSH-SVAR) framework. We add to the methodological literature by allowing for regime dependent shock transmissions according to the state of the financial system.

The MSH-SVAR model captures higher volatility phases during the crisis periods in a plausible manner. Based on Likelihood Ratio tests, the imposed short-run restriction that is used for identification of a bank exposure shock is widely accepted.

There is strong evidence for the existence of a destabilizing effect running from bank exposure to sovereign default risk in the countries hardest hit by the crisis, namely Spain, Italy and Portugal. This effect is particularly pronounced during phases of financial turmoil and supports the hypothesis of bank exposure being a key ingredient of a *diabolic loop* mechanism. On the other hand, we find a stabilizing effect from increased bank exposure during turbulent times for the countries less hit by the crisis, namely France, Germany, The Netherlands and Austria. This points toward exposure potentially acting as a *disciplinary device* in line with the sovereign defaults literature.

While the findings underpin the importance of efforts to break the sovereign-bank nexus by reducing the home bias in sovereign bond holdings, regulators should also take into account the potentially stabilizing force of exposure of the banking sector toward sovereign risk. Future research should investigate the determinants of the effect running from bank exposure to sovereign risk, leading to an adverse effect for some sovereigns and a stabilizing one for others.

Chapter 3

What drives EMU current accounts? — A time varying structural VAR approach

3.1 Introduction

Significant macroeconomic imbalances evolved in the European Monetary Union (EMU) during the run-up to the financial and subsequent European sovereign debt crisis, ultimately becoming a defining feature of the crisis. They became particularly apparent in the form of steadily diverging current accounts within the monetary union. Subsequent to the crisis there has been considerable external adjustment underway in those countries that were at the center of the sovereign debt crisis, at the cost of the build up of significant internal imbalances in form of sluggish growth and high unemployment.

Various authors pointed toward private indebtedness and persistent current account deficits with their impact on the stability of the countries' banking systems and sovereign solvency as being at the roots of the European banking and sovereign debt crisis.[1] This triggered an intense debate in academic and policy circles on the drivers of the current accounts within EMU and, hence, the set of appropriate policies and institutional reforms.

Despite the widespread consensus that financial integration through a reduction in risk premia and, thus, borrowing costs within EMU set the stage for the pronounced

[1] Among others, excessive current account deficits are associated with intensifying the adverse effect of poor fiscal positions on sovereign financing premia (Barrios et al., 2009; IMF, 2010; Gros, 2011) as well as the banking system and the real economy (Lane and Pels, 2012; Kang and Shambaugh, 2016)

divergent macroeconomic development[2] the channels through which it fed into the current account positions of the member countries are discussed controversially in the literature. Fundamentally, the competing views — discussed in more detail in Section 3.2 — attribute the large current account deficits before the crisis to convergence on the supply side, changes in price competitiveness or to demand distortions.

(a) current account by GDP (b) net savings, private sector (c) net savings, public sector

(d) real. interest rates (e) GDP, growth rate (f) Inflation

Figure 3.1.1: Selected macro variables during EMU period by cluster (dashed blue line = core cluster, solid red line = periphery cluster) with vertical lines indicating the start of EMU and the onset of the financial crisis (Source: Ameco and OECD)

All three above hypotheses are potentially in line with the stylized facts[3] presented in Figure 3.1.1: While the current account divergence was clearly driven by private

[2] Various authors relate financial integration within EMU to the observed pattern of capital flows within the currency union (see Langedijk and Roeger, 2007; Fagan and Gaspar, 2008; Siena, 2012, among others).

[3] Figure 3.1.1 plots GDP weighted averages of the two clusters. Clustering is undertaken based on the current account position relative to GDP from 1999 to 2008 applying the k-means algorithm.

sector developments rather than public borrowing, it was accompanied by persistent gross domestic product (GDP) growth differentials, diverging price competitiveness and differentials in real interest rates that emerged at the entry into EMU. After the crisis hit external imbalances rapidly unwound and current accounts reached levels close to external balance accompanied by a strong rebound in the savings rate in the deficit countries. Policies aiming to support the rebalancing mainly focused on restoring price competitiveness by means of internal devaluation, accompanied by structural reforms in labor and product markets in those countries formerly running large deficits (Kang and Shambaugh, 2016). However, given the lingering recessions in deficit countries and their cyclical effect on the current accounts, it is an open question of whether imbalances may return with growth eventually picking up (Tressel and Wang, 2014).

Although the three hypotheses outlined above are in line with the stylized facts, simultaneity does not imply causality and the hypotheses differ substantially with regards to the set of appropriate policy responses and institutional reforms to overcome existing and preventing the build-up of future external and internal macroeconomic imbalances. However, the empirical literature investigating the emergence and rebound of EMU current account deficits focuses on exploring correlations often in reduced form panel frameworks (see Jaumotte and Sodsriwiboon (2010); Barnes (2010); Belke and Dreger (2013); Lane and Pels (2012); Schnabl and Wollmershäuser (2013); Atoyan et al. (2013); Tressel and Wang (2014) among others). This is partly due to the small number of observations that cover the period of interest with structural breaks in the data potentially occurring at the entry into monetary union and with the onset of the financial crisis.

This paper builds a structural model of EMU current accounts that accommodates potential breaks along the sample while being as parsimonious as possible on the data. The model is used to investigate the validity of the partly competing hypotheses on the drivers of EMU current accounts that are mainly assessed in reduced form frameworks in the literature. Structural shocks driving EMU current accounts are identified based on a combination of sign and long-run restrictions — a price competitiveness shock, a domestic supply shock, a domestic demand and a

The periphery cluster consists of Greece, Ireland, Italy, Portugal, Slovenia, Slovakia and Spain. The core cluster consists of Austria, Belgium, Finland, France, Germany and the Netherlands. See Holinski et al. (2012) for a similar approach.

foreign demand shock — in order to investigate the role of these structural drivers for the divergence and subsequent rebalancing of EMU current accounts. The small sample problem is circumvented by making use of a battery of Chow-type-tests and allowing for time variation only in a subset of model parameters rendering the model to potentially exhibit regime dependent shock transmission.

It is found that domestic demand shocks account for a substantial fraction in the current account deficits of EMU periphery countries, while Germany's surplus was driven by foreign demand - the mirror image of the former development. While supply side factors also played a role in explaining current account deficits in Italy, Spain and Portugal in the years before the crisis, shocks to price competitiveness and foreign demand played a minor role for those economies. The adjustment subsequent to the financial crisis was born partly by a contraction in demand in the economies running deficits, but is also due to adverse supply shocks implying lower growth perspectives.

The contribution of this paper is twofold. Firstly, the paper adds to the literature by putting forward a structural analysis of the drivers of EMU current accounts, integrating the competing hypotheses into one single coherent structural framework. This is — to the best of my knowledge — the first paper deploying a structural empirical model in order to investigate the drivers of EMU current accounts. Secondly, it proposes a modeling approach that accounts for potential structural breaks, while being parsimonious on the data. Such an approach is well suited for analyses confronted with few observations in relatively short regimes, as it is the case with the EMU before and after the financial crisis.

The paper is organized as follows. Section 3.2 discusses the literature and existing hypotheses on drivers of EMU current account imbalances. Section 3.3 sets up a time varying structural VAR model in order to account for structural breaks in the sample and discusses the identification strategy uncovering price competitiveness, domestic demand, domestic supply and foreign demand shocks. Section 3.4 discusses the results and Section 3.5 concludes.

3.2 Literature

The dynamics of EMU current account imbalances have received sizable attention with the unfolding of the European banking and sovereign debt crisis. The literature established a close link between external indebtedness and the severity of the crisis in affected economies. Barrios et al. (2009) find that large current account deficits amplify the impact of deteriorated public finances on government bond spreads, while the IMF (2010) concludes that current account deficits are correlated with higher sovereign credit default swap (CDS) spreads. Gros (2011) argues that foreign debt, that is accumulated current account deficits, formed the underlying problem for the solvency of the euro area countries. Lane and Pels (2012) see the current account imbalances at the core of the crisis, having contributed to the economic contraction and severely damaged the banking system. Kang and Shambaugh (2016) find that large current account deficits and the extent of the subsequent rebalancing are the best predictors of sharp economic contraction during the crisis.

A large body of research investigates the divergence of EMU current accounts. Despite the widespread consensus that the changes in the institutional setting - common monetary policy, fixed exchange rates and hence a convergence of refinancing costs - set the stage for diverging external positions within the monetary union, the mechanisms at play are discussed controversially in the literature. The views differ fundamentally in that they attribute the divergence either to the supply side, changes in price competitiveness or demand side distortions.

Following the convergence hypothesis, the current account imbalances emerged as the result of an increased investment in those economies catching up within the monetary union. The convergence allowed the economies that were catching up to borrow against future growth, consistent with the intertemporal theory of the current account (Obstfeld and Rogoff, 1995). According to this hypothesis financial integration and the elimination of exchange rate risks resulting in the convergence of nominal interest rates fueled the convergence process (Blanchard and Giavazzi, 2002). While several authors find evidence pointing toward the validity of this hypothesis (Lane and Pels, 2012; Ca'Zorzi and Rubaszek, 2012; Schmitz and Von Hagen, 2011), it is challenged by others (Barnes et al., 2010; Holinski et al., 2012).

A second strand of the literature sees the development of the price competitiveness at the roots of the current account divergence (Arghyrou and Chortareas, 2008).

With the introduction of the common currency two main (external) adjustment mechanisms came to an end: flexible exchange rates and autonomous monetary policy. Shifts in relative prices, triggered by idiosyncratic shocks or the heterogeneous reaction to one common shock in absence of sufficient adjustment mechanisms, lie at the root of the diverging current accounts according to this view. Belke and Dreger (2013) find evidence pointing toward movements in relative prices, driven by excessive nominal wage growth in deficit countries, being at the center of the divergence.

A different line of reasoning suggests that the current account imbalances are part of an overall macroeconomic divergence due to the mode of operation of the real interest rate channel within a monetary union. Walters (1990) argues, with reference to the European Exchange Rate System (ERM), that fixed nominal exchange rates and liberalized capital markets within a group of economies that is heterogeneous with respect to their inflation rates would create an inherently unstable system. With the convergence of nominal interest rates, inflation differentials would materialize in real interest rate differentials, stimulating both, domestic demand and inflation dynamics, in high inflation countries. This spiral of demand and inflation pressure also leads to an appreciation of the real exchange rate and a deterioration of the current account (Mongelli and Wyplosz, 2009). Following this line of arguments, the current account divergence can be traced back to mismatched monetary policy (Wyplosz, 2010) and domestic demand booms potentially amplified by the real interest rate channel (Wyplosz, 2013).

Finally, it is argued that asymmetric trade shocks also contributed to the build-up of imbalances while the increased capital flows within the EMU allowed them to persist (Chen et al., 2013).

The external adjustment subsequent to the unfolding of the financial crisis came at the cost of significant and persistent internal imbalances (Kang and Shambaugh, 2016). Although some structural adjustment has taken place in former deficit countries (Tressel et al., 2014), it remains an empirical question of whether external imbalances will return with growth eventually picking up (Tressel and Wang, 2014). However, in order to evaluate the process of rebalancing, it is critical to understand the structural source of the imbalances.

3.3 The model

This section sets up a time varying structural model of EMU current accounts, mapping the hypotheses outlined above into a set of four structural shocks, a domestic supply shock, a competitiveness shock, a domestic demand shock and a foreign demand shock, in order to investigate their contribution to the emergence and unwinding of the EMU current account imbalances. This section first introduces the reduced form VAR and the identification strategy of the structural shocks before turning to the specification of the model.

3.3.1 Time varying VAR

The economies modeled in this paper have experienced two distinct structural breaks since the course of the past decades. Firstly, the introduction of the monetary union in 1999 and, secondly, the global financial crisis and the subsequent sovereign debt crisis in 2008/9. Both events had a critical impact on the external imbalances within the monetary union: In the aftermath of the introduction of the common currency the external imbalances started to build up while the financial crisis induced a rapid adjustment process. In what follows, a time varying VAR model is set up accounting for the potential structural breaks in the data.

The $K \times 1$ vector Y_t contains four variables, namely the consumer price inflation π_t, a measure of economic activity Δy_t, the current account by GDP ca_t and a short term interest rate r_t.
The reduced form VAR model is given by

$$Y_t = \psi D_t + A_1 Y_{t-1} + \ldots + A_p Y_{t-p} + u_t,\ t = 1, \ldots, T\ , \tag{3.1}$$

where u_t is a 4 dimensional white noise process with positive definite covariance matrix Σ_u, A_j for $j = 1, ..., p$ are the 4×4 coefficient matrices, p is the lag order of the VAR, D_t is a vector capturing the deterministic components of the model, ψ_t is the matrix of respective coefficients and T is the sample length. Writing the system more compactly using $\Pi := [\psi, \mathbf{A}]$, where $\mathbf{A} := [A_1, \ldots, A_p]$ and $Z_t := (D_t', Y_{t-1}', \ldots, Y_{t-p}')$

gives

$$Y_t = \Pi Z_t + u_t,\ with\ E(u_t u_t') = \Sigma_u\ .$$

Now, consider two structural changes in the model occurring at T_{B1} and T_{B2}, in our case in the last period before the introduction of the Euro and at the onset of the financial crisis given by the collapse of Lehman Brothers, so that

$$Y_t = \Pi(t) Z_t + u_t,\ E(u_t u_t') = \Sigma_u(t)\ ,$$

where

$$\Pi(t) := \Pi_1 \cdot \mathbb{1}(t \leq T_{B1} + \Pi_2 \cdot \mathbb{1}(T_{B1} < t \leq T_{B2}) + \Pi_3 \cdot \mathbb{1}(T_{B2} < t)$$
$$\Sigma_u(t) := \Sigma_{u,1} \cdot \mathbb{1}(t \leq T_{B1}) + \Sigma_{u,2} \cdot \mathbb{1}(T_{B1} < t \leq T_{B2}) + \Sigma_{u,3} \cdot \mathbb{1}(T_{B2} < t)\ ,$$

with $\Pi_1 := [\psi_1, \mathbf{A_1}]$, $\Pi_2 := [\psi_2, \mathbf{A_2}]$, $\Pi_3 := [\psi_3, \mathbf{A_3}]$ and $\mathbb{1}(\cdot)$ is an indicator function.

Given the setup of the model with two structural breaks there are potentially many parameters to be estimated based on relatively short samples — even given the availability of monthly data for the variables considered. Section 3.3.3 addresses the issue of model specification and attempts to search for a balance in accommodating structural breaks, on the one hand, and keeping the model as parsimonious as possible, on the other.

After the reduced form model is put into place, the following section will proceed by bringing outside information into play in order to identify four structural shocks, namely a price competitiveness shock, a domestic demand shock, a domestic supply shock and a foreign demand shock.

3.3.2 Identification

The structural VAR system associated with the reduced form is given by

$$u_t = B(t)\epsilon_t\ ,$$

where ϵ_t are the structural shocks obtained by a linear transformation of the reduced form errors u_t and $B(t) := B_1 \cdot \mathbb{1}(t \leq T_{B1}) + B_2 \cdot \mathbb{1}(T_{B1} < t \leq T_{B2}) + B_3 \cdot \mathbb{1}(T_{B2} < t)$, that is, the structural parameter matrix B is allowed to be time varying. Normalizing the variances of the structural innovations for both regimes to one, i.e. assuming $E(\epsilon_t \epsilon_t') = \Sigma_\epsilon = I_K$ gives

$$\Sigma_u(t) = E\left[u_t u_t'\right] = E\left[B(t)\epsilon_t \epsilon_t' B(t)'\right] = B(t)B(t)' \ .$$

Note that an alternative way of mapping the variation in the variance covariance matrix of the reduced form residuals Σ_u into the structural model would be to allow for time variation in the variances of the structural shocks Σ_ϵ. Letting instead the structural impact matrix $B(t)$ depend on the current regime allows for variation in the impulse responses across regimes. However, both approaches are observationally equivalent transformations of the reduced form model.[4]

In order to integrate the partly competing hypotheses regarding the drivers of current account fluctuations within the monetary union outlined above into the model, four structural shocks to the economy summarized by the VAR system are identified: (1) A price competitiveness shock, ϵ_t^{comp}, to account for exogenous movements in relative prices driving the current accounts; (2) a domestic demand shock, ϵ_t^{dd}, capturing both, exogenous increases in demand due to, say, preference shocks and to monetary policy shocks; (3) a domestic supply shock, ϵ_t^{ds}, to capture potential convergence; and (4) a foreign demand shock, ϵ_t^{fd}, that captures exogenous shifts in foreign demand for the goods exported by the respective economy.

The identification approach follows Canova and De Nicolo (2002) and Uhlig (2005) by imposing sign restrictions on the impulse responses of selected variables. In the following, shocks are identified by restricting the impact responses, that is the signs of the elements of $B(t)$. Table 3.3.1 summarizes the sign restrictions imposed to identify the four respective shocks. Note that all shocks are normalized to have an adverse effect on the current account.

A price competitiveness shock within a monetary union leads to an increase in inflation that is associated with no decrease of interest rates. A domestic demand shock is defined as increasing economic activity and inflation while the response of the interest rate remains unrestricted. This specification of the demand shock is

[4] See Bacchiocchi and Fanelli (2015) for a discussion of modeling approaches of regime dependent variance covariance matrices in SVAR models

Table 3.3.1: Sign restrictions for impulse responses

	ϵ_t^{comp}	ϵ_t^{dd}	ϵ_t^{ds}	ϵ_t^{fd}
inflation π_t	$\uparrow$	$\uparrow$	$\downarrow$	$\downarrow$
economic activity y_t	$\star$	$\uparrow$	$\uparrow$	$\downarrow$
current account ca_t	$\downarrow$	$\downarrow$	$\downarrow$	$\downarrow$
interest rate r_t	$\uparrow$	$\star$	$\uparrow$	$\downarrow$

a stand in for exogenous shocks driving demand. The restrictions imposed cover standard preference driven demand shocks, but also expansionary monetary policy shocks, given that the instantaneous response of the interest rate remains unrestricted. A domestic supply shock impacts inflation negatively, increases production and does not involve a decrease of interest rates, while the current account is restricted to depreciate — in accordance with the literature that ascribes imbalances to economic convergence discussed above. Finally, a foreign demand shock is defined as leading to a depreciation of the current account, accompanied by a reduction in inflation and economic activity and, again, no increase in the policy rate.

By and large, the restrictions on the reaction of inflation, economic activity and the interest rate for the identification of the two demand and the supply shock reflect those backed by a broad range of models, whereas those on the current account are consistent with the literature on external imbalances within the monetary union discussed above. On the contrary the price competitiveness shock is rather unconventional to macroeconomic models as prices tend to be understood as being determined endogenously. However, as shifts in price competitiveness are discussed prominently as a source of macroeconomic imbalances within the monetary union, structural shocks to price competitiveness are considered in the SVAR. Intuitively, it may be thought of as an exogenous change in the structure or strength of trade unions or the utility of worker's leisure that is orthogonal to the other shocks considered and, thus, moves relative prices in an exogenous manner. Strictly speaking, it is poorly identified for the period before monetary unification as the nominal exchange rate is not modeled in the VAR, and should be interpreted with caution for this regime.

Imposing sign restrictions is not sufficient for the set of shocks to be properly identified, since the price competitiveness shock cannot be disentangled from the domestic demand shock based on the sign restrictions defined in Table 3.3.1. In the absence of additional identifying information those shocks would not be distinct. Such additional information is induced by imposing a single long-run restriction (Blanchard and Quah, 1989), i.e. forcing the response of economic activity to a domestic demand shock to be zero in the long-run as indicated in Table 3.3.2.

Table 3.3.2: Long-run restrictions for impulse responses

	ϵ_t^{comp}	ϵ_t^{dd}	ϵ_t^{ds}	ϵ_t^{fd}
inflation π_t	$\star$	$\star$	$\star$	$\star$
economic activity y_t	$\star$	0	$\star$	$\star$
current account ca_t	$\star$	$\star$	$\star$	$\star$
interest rate r_t	$\star$	$\star$	$\star$	$\star$

Intuitively speaking, the restrictions are implemented as follows: Various structural impact parameter matrices $\tilde{B}$ that are consistent with $\Sigma_u = \tilde{B}\tilde{B}'$ are randomly drawn and rotated such that they fulfil the single zero long-run restriction. Out of these, all matrices matching the sign restrictions are kept while the remaining matrices are dismissed until a sufficient number of models satisfying the restrictions is collected.

More formally, following Binning (2013), the algorithm for combining short- and long-run restrictions with sign restrictions in underidentified models to consists of following four steps that are repeated until M models matching the sign and zero restrictions are collected.[5]

1. An initial matrix of structural parameters B determined by a Cholesky decomposition of Σ_u is estimated, assuring the orthogonality of the structural shocks, such that $\Sigma_u = BB'$.

2. Therefore let $N = QR$ be the QR-decomposition of an independently drawn standard normal $K \times K$ matrix N, where Q is an orthogonal rotation matrix,

[5] The results in this paper are based upon 1000 candidate models matching the sign and zero restrictions, i.e. $M = 1000$.

i.e. $QQ' = I$ (Rubio-Ramirez et al., 2010). The rotation matrix Q is post-multiplied to the initial matrix of structural parameters B in order to obtain a random rotation of B. Now $\tilde{B} = BQ$ is a random rotation of the initial structural parameter matrix, where

$$\Sigma_u = \tilde{B}\tilde{B}' = B\underbrace{QQ'}_{=I}B' \ .$$

3. Zero restrictions are imposed on the long-run impact matrix $\tilde{\Xi}_\infty = (I_K - A_1 - \ldots - A_p)^{-1}\tilde{B}$. In order to achieve this, the long-run impact matrix $\tilde{\Xi}_\infty$ is rotated such that the long-run restrictions are met. This is accomplished by post-multiplying an appropriately defined Givens rotation matrix[6] G to the long-run impact matrix, i.e. $\bar{\Xi}_\infty = \tilde{\Xi}_\infty G$, such that $\bar{\Xi}_\infty$ satisfies the imposed long-run restrictions.

4. In a final step, the structural parameter matrix $\bar{B} = \tilde{B}G = BQG$ is used for the construction of impulse responses and the model is dismissed if the specified sign restrictions are not met.

Following Peersman (2005) and Barnett and Straub (2008), in order to take into account both, the estimation uncertainty of the reduced form model and the identification uncertainty, the model is bootstrapped and the covariance matrix Σ_u is reestimated after each draw. By imposing sign restrictions based on the numerical algorithm above, in particular by drawing candidate matrices from the uniform Haar prior, methods that are essentially Bayesian in nature are introduced into the otherwise frequentist setup. It should be noted that, while similar numerical algorithms are widely applied in the empirical literature that imposes sign restrictions for structural identification, their theoretical properties have not been thoroughly investigated. In fact, for the Bayesian setup Baumeister and Hamilton (2015) have recently emphasized potential drawbacks due to additional restrictions implicitly imposed on the structural parameters by using a uniform prior to set identify sign restricted models.

[6] The Givens matrices assuring that the zero restriction of the model under consideration are met is constructed via Algorithm 5.1.3 in Golub and Van Loan (2012).

Given the underidentified system with one long-run restriction and a number of sign restrictions, resulting in a set of models satisfying the specified restrictions, the challenge of summarizing the information contained in the impulse responses arises. A number of strategies to handle this issue are suggested. Uhlig (2005) makes use of pointwise median impulse responses in order to capture the central tendency of the impulse responses. However, summarizing set identified models using the pointwise medians has been criticized as they may represent information about shocks that stem from different models (Fry and Pagan, 2011; Kilian and Murphy, 2012; Inoue and Kilian, 2013). Indeed, pointwise median impact responses are likely to represent a structural impact matrix B that is inconsistent with the assumption of orthogonal structural shocks, as the different impact responses may stem from different rotations and thus different structural models.

This would be particularly problematic for the decomposition conducted in Section 3.4 that uses the estimates of the impulse response functions in order to assess the cumulative influence of the different shocks on the variables over time. Therefore, this paper follows the suggestion by Fry and Pagan (2011) of using closest to median impulse responses. This approach retains the notion of median responses being an appropriate summary of the set of models, while assuring that impulse responses are produced by a single model and thus are consistent with one another.[7]

3.3.3 Data and model specification

In order to bring the model to the data, it has to be specified in terms of the time variation of the parameters and the lag structure. The set of countries under consideration consists of three EMU member states running current account deficits after the onset of the monetary union, Italy, Spain and Portugal on the one hand and Germany, running surpluses in the aftermath of the launch of EMU, on the other hand. The exogenous break dates are set to the introduction of the common

[7] It should be noted that the 'closest to median impulse responses' still suffer from the criticism that the median of a vector valued variable does not exist, questioning the overall appropriateness of the median impulse responses as a measure of central tendency in the impulse responses. Inoue and Kilian (2013) propose using the modal model together with the highest-posterior density credible set in order to summarize the information contained in impulse responses estimated by Bayesian techniques. On the downside, the highest-posterior density credible set, however, faces the flaw of having no mass as it is a collection of impulse responses, each stemming from a single model with zero mass.

monetary policy in 1999M1, and the onset of the global financial crisis in 2008M9, given by the month in which Lehman Brothers collapsed, while the sample starts in 1986M1 (1989M8 for Portugal) and ends in 2015M5.

Data on consumer price inflation and industrial production as a monthly proxy for economic activity are taken from the OECD. The interest rate included in the model is a combination of the ECB shadow rate taken from Wu and Xia (2014) which accounts for unconventional monetary policy measures from 2009 onward, and the short term interest rate taken from the OECD for the periods prior to the shadow rate data. Data on current accounts relative to GDP is also taken from the OECD database. As it is only published at quarterly frequency the dynamics within one quarter are interpolated using the Chow-Lin procedure (Chow and Lin, 1971) based on the dynamics of the monthly trade balance. The first two variables enter in year-on-year log differences in order to account for seasonal unit roots, especially in the consumer price index, the latter two in levels. See Figure 3.A.4 for a descriptive plot of the data. Based on information criteria a lag length of one is chosen for the estimation of the reduced form models.[8]

The model, introduced in Section 3.3, potentially allows for full variability of the parameters over the two exogenously identified regimes. However, given the length of time series data for the three separate regimes, it is desirable to keep the model as parsimonious as possible in terms of time variation. In order to isolate a specification that accommodates potential structural breaks between regimes on the one hand, while making use of the entire sample information for the estimation of as many parameters as possible on the other hand, a number of Chow type tests of different model specifications is conducted. The specification of choice for the following analysis will be the one among those not rejected by the Chow test that is most parsimonious in terms of parameters to be estimated.

Following Candelon and Lütkepohl (2001), who show that Chow tests are size distorted in small samples and in particular overreject the null, bootstrapped versions of the test statistics are used for inference on the parameter stability. Table 3.3.3 reports the p-values from bootstrapped and asymptotic Chow type tests against

[8] The lag length of the VAR model is set according to the mode of lag lengths chosen by the Akaike, the Schwarz (Bayesian) and Hannan-Quinn information criterion for models with a lag length up to 12. The information criteria are determined on the entire sample of data under the assumption of linearity of the model, i.e. no breaks in the coefficients.

the alternative of full time variability over the two regimes against different null hypotheses.

Table 3.3.3: Chow type tests against the alternative of full time variability of the model, p-values based on 1000 bootstraps and on asymptotic critical values

	null			Germany		Italy		Spain		Portugal	
#	ψ	$\mathbf{A}$	Σ_u	bootst.	asympt.	bootst.	asympt.	bootst.	asympt.	bootst.	asympt.
1	C	C	C	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	S(t)	C	C	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
3	C	S(t)	C	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
4	C	C	S(t)	0.086	0.029	0.134	0.054	0.129	0.073	0.000	0.000
5	S(t)	S(t)	C	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
6	C	S(t)	S(t)	0.212	0.008	0.792	0.336	0.636	0.138	0.045	0.000
7	S(t)	C	S(t)	0.008	0.016	0.020	0.016	0.233	0.395	0.000	0.000

Notes: 'C' indicates constancy of the respective parameter matrix, 'S(t)' indicates state dependence over the regimes.

Clearly, the tests indicate breaks in the system at the entry into monetary union and the beginning of the great recession,[9] as the null of constancy of all parameters is rejected for the entire set of countries based on both, the asymptotic and the bootstrapped Chow tests. Also note that all null hypotheses that are not rejected based on p-values close to zero, namely specification 4, 6 and 7 in Table 3.3.3, allow for the variance covariance matrix to be regime dependent. Out of those, the specification including regime dependent deterministic parameters, ψ, (line 7 in Table 3.3.3) is rejected at conventional levels of significance for Germany, Italy and Portugal.

The rather parsimonious model with constant deterministic parameters, ψ, constant parameters in the matrix of slope coefficients, $\mathbf{A}$, and state dependency only in the reduced form covariance matrix, Σ_u, (line 4 in Table 3.3.3) seems to sufficiently accommodate the structural breaks for the majority of the countries considered, that is Germany, Italy and Spain. Although the Portuguese data representing the

[9] Table 3.3.3 reports only those test results of the null hypotheses that assumes both structural breaks to be given. In addition the same battery of tests is conducted assuming that the data exhibits only one of the two potential breaks. All those tests indicated the model with three regimes to be strongly preferred by the data.

smallest economy in the country sample seems to prefer a more complicated model structure, we resort from using different setups for the set of countries. Hence, this specification will serve as model of choice for the remainder of the paper.

3.4 Results

This section employs the outlined setup in order to assess how the monetary unification has changed the transmission and propagation of shocks in the economies and what has been driving the current account fluctuations in the EMU countries considered in the run-up to the most recent crisis and during the subsequent adjustment. The analysis resorts to a comparison of impulse response functions to tackle the former and to forecast error variance and historical decompositions of the current accounts to investigate the latter issue.[10]

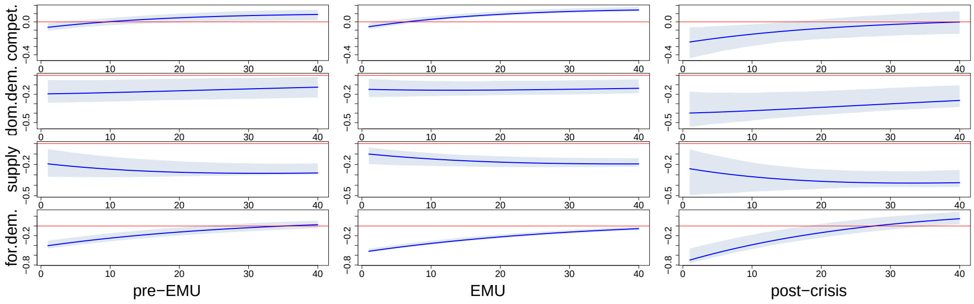
3.4.1 Impulse responses

Figures 3.A.5 to 3.A.8 in the Appendix 3.A plot the impulse responses of the four economies to a price competitiveness shock, a domestic demand shock, a domestic supply shock and a foreign demand shock for the three regimes, i.e. the period in the run-up to monetary unification (pre-EMU regime), the period of monetary union before the crisis (EMU regime) and after the financial crisis (crisis regime).

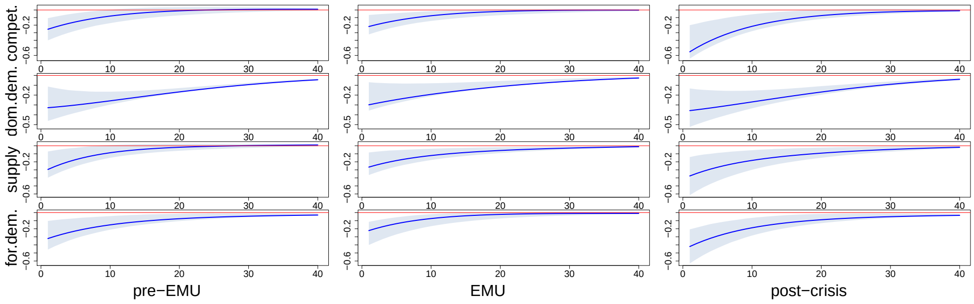
The reactions of the economies to the four shocks are in line with expectations (by construction) in terms of their sign but also regarding the magnitude of the responses. A few patterns emerge regarding the comparison between the regimes.

Firstly, the impulse responses support the findings from the Chow tests on structural breaks. Especially the response of the monetary authority to domestic and foreign demand shocks seems to be rather distinct among the regimes. Note that the model is restricted to time invariant slope coefficients such that the only degree of freedom stems from the impact responses while the shape is the same across regimes due to time invariant slope coefficients (see Section 3.3.3).

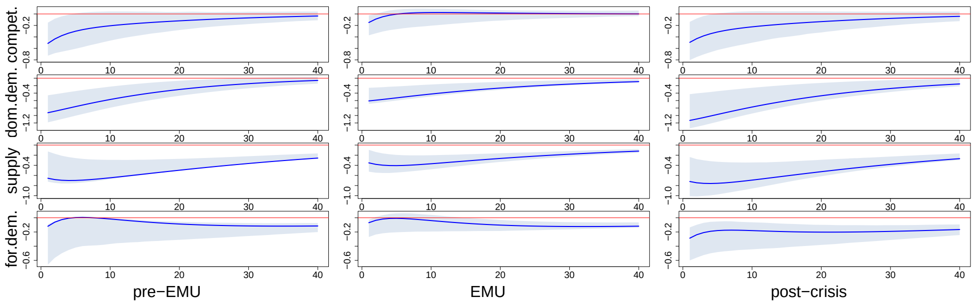
[10] The results presented in this section are robust toward moving around the break dates considered, dropping observations at the beginning and the end of the sample and estimating the VAR specification in levels or in monthly growth rates.



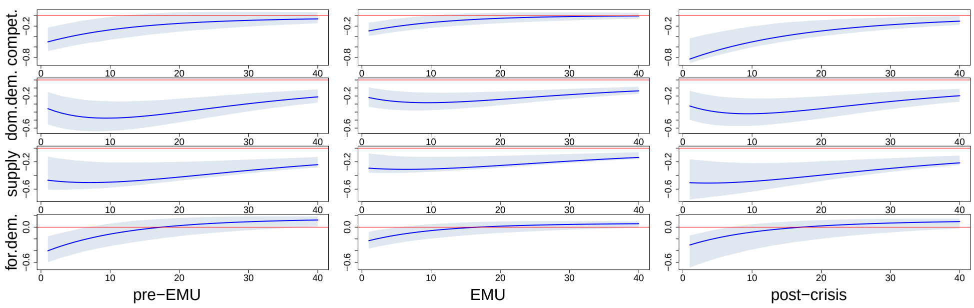
(a) Germany



(b) Italy



(c) Portugal



(d) Spain

Figure 3.4.2: Impulse responses of the current account to the four structural shocks across countries and regimes, 68 percent bootstrapped confidence intervals

Secondly, the rather tranquil phase between monetary unification and the beginning of the great recession exhibits the lowest magnitudes of impulse responses of the economies, while the turbulent post crisis period seems to be associated with a stronger transmission of shocks, on the one hand, and higher uncertainty in the estimation of the models, on the other hand.

Thirdly, comparing the pre-EMU state with the EMU state before the onset of the crisis, significant differences in impulse responses occur largely with respect to the nominal variables, that is prices and interest rates. Monetary policy reacts less to the country specific shocks (see for example the impulse response of the interest rate to a domestic supply shock), as one would expect given that it targets the euro area as an aggregate, while prices are also less sensitive to the shocks, potentially reflecting the integration into the single European market (see for example the impulse response of the inflation rate to domestic demand shocks).

Finally, the interest rate reaction to demand shocks delivers some insight into the nature of and source of the demand shocks identified. Recall that the restrictions imposed on the demand shock do not rule out that these shocks are induced by loose monetary policy being a stand in for both, preference and monetary policy driven demand booms. The impulse responses to a demand shock in the German model indicate that monetary policy is counteracting the shock by increasing the policy rate. In the deficit countries evidence points toward procyclical monetary policy in the pre-EMU regime. After the establishment of EMU, the picture is mixed. In Italy, impact responses are insignificant, while in Spain and Portugal demand shocks are still associated with decreasing policy rates. This may point toward monetary policy either being a source of demand distortions in this country or falling short on counteracting them.

Figure 3.4.2 plots the responses of the current accounts to the identified structural shocks over the three different regimes in a compact manner. As discussed above, the EMU period exhibits the most moderate shock transmission across regimes, while the transmission of shocks seems to be most pronounced in the crisis period. However, the changes in shock transmission are hardly significant. Please note that those results remain, even if the slope coefficients are allowed to be state dependent, and, hence, are not an artefact of the chosen specification. The impulse responses from models with time-varying slope coefficients as in model 6 of Table 3.3.3 are plotted in Figure 3.A.9 to Figure 3.A.11 in the Appendix 3.A.

Overall, the impulse responses point toward the great recession to have been a more pronounced game changer for the economies considered than the institutional transformation accompanying European monetary unification. In addition the evidence from the impulse response analysis indicates that the frequency of shocks rather than a stronger transmission of shocks has been lying at the roots of divergent current accounts in the run up to the crisis. On the contrary, the subsequent rebalancing may have been supported by stronger transmission of shocks to the current account.

Comparing the different structural shocks, domestic demand and supply seem to have the most persistent effects on the external balance across countries and regimes, while price competitiveness and foreign demand shocks are shorter lived. The supply shock response points toward intertemporal smoothing along the lines of Obstfeld and Rogoff (1995) rather than intratemporal effects running via the trade channel being at play. The competitiveness shock, being the one with least support by theoretical models, seems to find limited support by the data for Italy, Portugal and Spain, while the responses of the German current account to the competitiveness shock may cast some doubt on the identification of this shock.

3.4.2 Variance decomposition

Table 3.4.4 reports the decomposition of forecast error variances of the current account into components stemming from the four structural shocks and sheds light on their importance for the dynamics of EMU current accounts.

Although the impulse responses are rather homogeneous across countries, the error variance decomposition indicates substantial differences. For Germany with its export driven economy, foreign demand is the main driver of the variation in the current account, most notably during the EMU regime. After the financial crisis hit, domestic shocks in demand and supply gain importance, with exogenous movements in competitiveness playing only a minor role.

The variance decomposition for the Italian model exhibits rather balanced contributions by the different shocks. Domestic demand accounts for about two thirds in the variance of the Italian current account before the crisis, followed by supply

Table 3.4.4: Forecast error variance decomposition of the current account across countries and regimes

country	regime	horiz.	structural shocks compet.	dom. dem.	supply	for. dem.
Germany	pre-EMU	1	0.02	0.16	0.15	0.67
		10	0.01	0.19	0.26	0.55
		20	0.01	0.20	0.37	0.43
	EMU	1	0.01	0.07	0.03	0.88
		10	0.00	0.10	0.07	0.83
		20	0.02	0.13	0.12	0.74
	crisis	1	0.08	0.21	0.08	0.64
		10	0.07	0.26	0.14	0.52
		20	0.06	0.31	0.23	0.41
Italy	pre-EMU	1	0.18	0.3	0.24	0.28
		10	0.13	0.43	0.17	0.26
		20	0.11	0.5	0.14	0.25
	EMU	1	0.19	0.35	0.27	0.19
		10	0.15	0.44	0.26	0.15
		20	0.13	0.48	0.25	0.13
	crisis	1	0.41	0.17	0.19	0.24
		10	0.35	0.25	0.18	0.22
		20	0.32	0.29	0.18	0.21
Spain	pre-EMU	1	0.33	0.17	0.29	0.21
		10	0.22	0.30	0.37	0.10
		20	0.17	0.35	0.41	0.06
	EMU	1	0.31	0.18	0.32	0.2
		10	0.19	0.31	0.41	0.09
		20	0.13	0.37	0.45	0.06
	crisis	1	0.6	0.09	0.22	0.08
		10	0.50	0.17	0.29	0.04
		20	0.42	0.22	0.32	0.03
Portugal	pre-EMU	1	0.17	0.55	0.27	0.01
		10	0.09	0.5	0.41	0.00
		20	0.08	0.45	0.47	0.00
	EMU	1	0.04	0.71	0.24	0.01
		10	0.01	0.64	0.35	0.00
		20	0.01	0.6	0.39	0.01
	crisis	1	0.12	0.6	0.24	0.04
		10	0.07	0.57	0.33	0.03
		20	0.06	0.53	0.38	0.03

and foreign demand shocks. Exogenous shifts in competitiveness explain less than a fifth of the variance before the crisis, but become more important thereafter.

Similarly, the Spanish model is mainly driven by domestic factors in the first two regimes, especially at longer horizons. However, after the the Spanish economy was hit by the crisis, shifts in competitiveness become rather important and explain about half of the variation in the Spanish current account. As opposed to that foreign demand plays not much of a role.

Portugal's current account is the one in the sample that is most independent of international factors such foreign demand and price competitiveness, but heavily driven by domestic factors. About 90 per cent of the variation in the Portuguese current account is accounted for by domestic demand and supply shocks, with most weight being on the demand side.

Overall, domestic drivers seem to become more important at longer horizons, reflecting partly the stronger persistence of those shocks. During the EMU regime, domestic demand seems to be a candidate for a strong driver of the deficits countries' current accounts, while supply side effects were also important. On the contrary the variation in the German current account is mainly explained by foreign demand shocks, potentially being the mirror image of the expansion of domestic demand in the other EMU economies. Competitiveness does not seem to be a explaining much of the EMU current accounts during the phase of divergence, but becomes somewhat more important in Italy and Spain after the onset of the financial crisis.

3.4.3 Historical decomposition

In order to investigate the relative importance of the four different shocks and, thus, allow to assess the hypotheses discussed in Section 3.2, a historical decomposition of EMU current accounts is considered. At each point in time, the current account is decomposed into contributions from the structural shocks of the model in order to assess their respective relevance for the evolution of the EMU current accounts.

The historical decomposition is based on the reduced form model in equation (3.1) and takes into account the time variance in the structural impact matrix $B(t)$. Using the moving average representation of the VAR, the endogenous variables may be expressed as a linear combination of initial values and structural shocks. Formally, the historical decomposition is given by

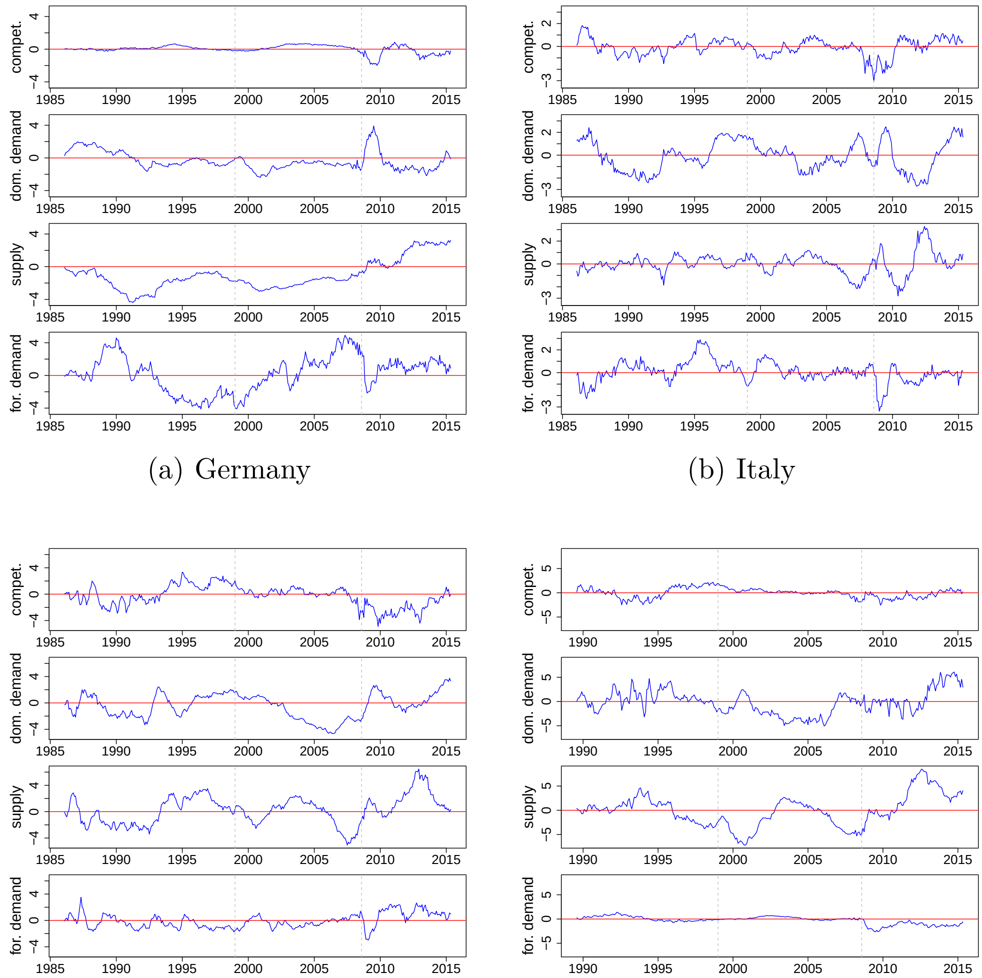
$$
\begin{aligned}
y_t - \widehat{\mu} &= \sum_{i=0}^{t-1} \widehat{\phi}_i \widehat{u}_{t-i} + \widehat{A}_1 y_0 + \ldots + \widehat{A}_p y_{-p+1} \\
&= \sum_{i=0}^{t-1} \widehat{\phi}_i \widehat{B} \widehat{\varepsilon}_{t-i} + \widehat{A}_1 y_0 + \ldots + \widehat{A}_p y_{-p+1},
\end{aligned}
$$

where y_t is the vector of endogenous variables, $\widehat{\mu}$ is the estimated vector of constant parameters, $\widehat{B}(t)$ is, again, the regime dependent structural impact matrix and ϕ_i is the matrix of estimated impulse response coefficients $\widehat{\phi}_i = \sum_{j=1}^{i} \widehat{\phi}_{i-j} \widehat{A}_j$ with $i = 1, 2, \ldots$, $\widehat{\phi}_0 = I_K$ and $\widehat{A}_j = 0$ for $j > p$ (see Lütkepohl, 2005, Chapter 2).[11]

Figure 3.4.3 plots historical decompositions of the current account for Germany, Italy, Spain and Portugal based on the estimated time varying structural VAR models. Those decompositions quantify the cumulated impact of the structural shocks on the endogenous variables. Thereby they indicate what portion of the deviation from the unconditional mean or steady state of the variable within the model is due to the occurrence of the different structural macroeconomic shocks. Those empirical steady states are derived entirely on statistical grounds and have no notion of sustainability of the current account position attached to it. The empirical steady state levels based on the estimated VAR models differ quite substantially from zero and cluster the countries into one surplus country, Germany with a steady state current account relative to GDP of 4.80 and the group of deficit countries Italy, Spain and Portugal with steady state current account levels of $-.44$, -2.93 and -6.32, respectively. As a note of caution it should be emphasized that the starting point of a decomposition might matter quite substantially even in the case of stationary processes. Resilient inference should be based on periods some distance away from the starting point only (Lütkepohl, 2011). We therefore plot the historical decompositions for the entire sample, but resort from drawing inference based on the pre-EMU sample using it as a burn in period.

Common to all four EMU economies is the strong hit to the current account stemming from a drop in foreign demand after the unfolding of the financial crisis. This drop in demand for exports was counteracted by a contraction of domestic

[11] Note that due to the model specification in Section 3.3.3 the matrix of estimated impulse response coefficients $\widehat{\phi}_i$ is time invariant.



(a) Germany (b) Italy

(c) Spain (d) Portugal

Figure 3.4.3: Historical Decomposition of selected EMU current accounts

demand reducing the imports. Overall this mirrors the well documented collapse of trade during the global financial crisis (Chor and Manova, 2012).

Despite this common feature the historical decompositions exhibit a rather distinct pattern, clustering Germany in one group and the three deficit countries in another. The upward trend of the German current account since monetary unification is driven by two structural factors: a steady increase in foreign demand up to the crisis, in line with the findings of export demand driven German surpluses in Kollmann et al. (2014), and a change in supply side factors potentially reflecting a lowering of the long term growth prospects. Although price competitiveness contributes positively to the current account in the first years of monetary unification up to the crisis, the structural model does not identify exogenous movements in relative prices as an important factor in explaining the Germany current account surplus. Similarly, domestic demand also plays a minor role over the sample with the exception of the demand contraction during the financial crisis related recession.

The Spanish, Portuguese and Italian current account deficits were driven by demand shocks subsequent to entry into EMU. This is particularly pronounced in the case of Spain and Portugal, which ran the largest deficits among the country sample and could be an indication of the real interest rate channel being at play, given the relatively high initial inflation rates in these countries at the onset of EMU.[12] Subsequently, in the years before the crisis unfolds, supply shocks become a relevant factor in explaining negative deviations of the current account in all three countries. This may reflect overoptimistic growth expectations in these countries in the years prior to the crisis (Lane and Pels, 2012).

Neither foreign demand nor price competitiveness shocks contribute systematically positive or negative to the current account. It should be noted, however, that in Italy and Spain exogenous movements in prices unrelated to demand or supply effects contribute quite negatively to the level of the current account immediately before the crisis hit. This may be attributable to the overheating of those economies in the period before the crisis hit.

Following the crisis, considerable adjustment has been underway in those countries that had build up significantly negative net foreign asset positions before the crisis emerged. Rebalancing in those countries was driven by both, demand and supply side adjustments, while, in addition, the adverse effects of past shocks to price competitiveness have diminished in Italy and Spain. This reflects the fact that import compression bears the majority of external adjustment and is in line with the finding in Atoyan et al. (2013) and Tressel and Wang (2014). While the deficit countries have undergone severe adjustments in their current account positions, this is not the case for Germany where the current account remains at historically high levels. However, the large positive contribution of sluggish demand to the current

[12] Note that demand shocks in this paper include those induced by loose monetary policy given that the sign restrictions leave the policy rate unrestricted.

account balances in Italy, Spain and Portugal at the current edge suggest that external imbalances may build up as soon as growth returns.

Overall, the current account deterioration in the deficit countries Italy, Spain and Portugal was driven by demand side developments in the early years of EMU, whereas supply shocks played some role in the years before the unfolding of the crisis. The German current account was strongly driven by increasing foreign demand, potentially mirroring the pronounced domestic demand development in the other parts of the EMU. Consequently, the adjustment subsequent to the financial crisis was born partly by a contraction in demand in the economies running deficits, but is also due to adverse supply shocks and lower growth perspectives. Exogenous changes in price competitiveness are found to have played only a minor role for the evolution of current accounts in EMU.

3.5 Conclusion

External indebtedness and macroeconomic imbalances are a defining feature of the European banking and sovereign debt crisis. This paper builds a structural model of EMU current accounts that accommodates potential breaks throughout the sample period while being as parsimonious as possible on the data. The model is used to investigate the validity of the partly competing hypotheses on the drivers of EMU current accounts assessed mainly in reduced form frameworks in the literature. Against this backdrop four structural shocks driving EMU current accounts are identified based on a combination of sign and long-run restrictions — a price competitiveness shock, a domestic supply shock, a domestic demand and a foreign demand shock — in order to investigate the role of these structural drivers for the divergence and subsequent rebalancing of EMU current accounts.

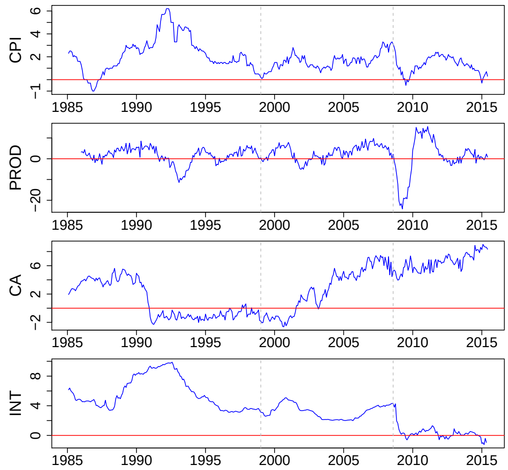
Chow type tests strongly point toward structural breaks for the considered economies at the entry into the monetary union and the onset of the European banking and sovereign debt crisis. A comparison of impulse responses and forecast error variance decompositions across the three regimes (pre-EMU, EMU and crisis) points toward the great recession being an even stronger game changer than the monetary unification.

Impulse responses further exhibit that changes in the shock transmission with the entry into the monetary union have occurred mostly with respect to nominal variables, that is interest rates and prices. Both seem to react less to shocks, as expected given the common monetary policy and the single European market. The impulse responses also reflect the turbulent times of the crisis period, as the impact effects of the structural shocks are more pronounced as compared to the first years of EMU.

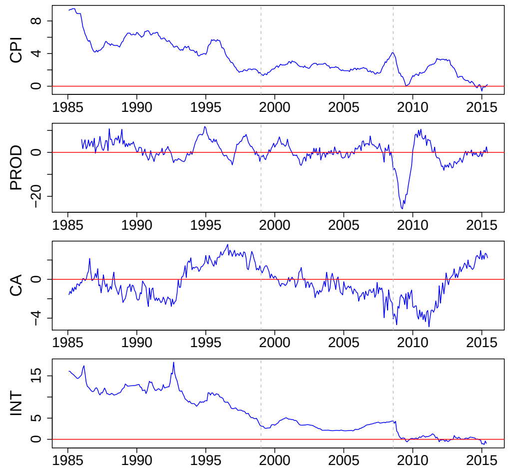
Based on historical decompositions it is found that domestic demand shocks account for a substantial fraction in the current account deficits of EMU periphery countries, while Germany's surplus was driven by foreign demand - the mirror image of the former development. While supply side factors also played a role in explaining current account deficits in Italy, Spain and Portugal in the years before the crisis, shocks to price competitiveness and foreign demand played a minor role for those economies. The adjustment subsequent to the financial crisis was born partly by a contraction in demand in the economies running deficits, but is also due to adverse supply shocks implying lower growth perspectives.

The findings emphasize the role of excessive demand for the current account divergence and make a case for the importance of macro-prudential policies and institutional reforms in order to carefully monitor and manage demand dynamics in the monetary union and to overcome existing as well as prevent future macroeconomic imbalances and crisis-laden adjustment.

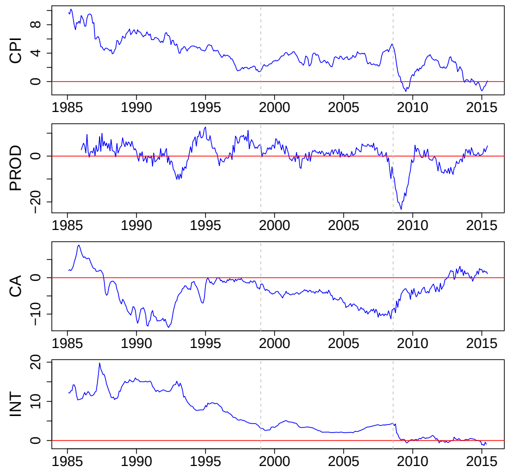
3.A Figures



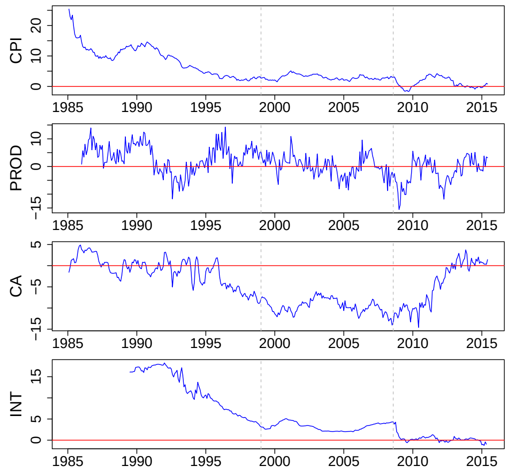
(a) Germany



(b) Italy

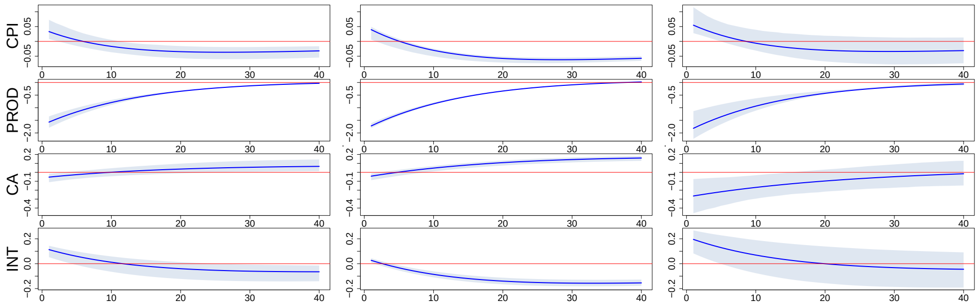


(c) Spain

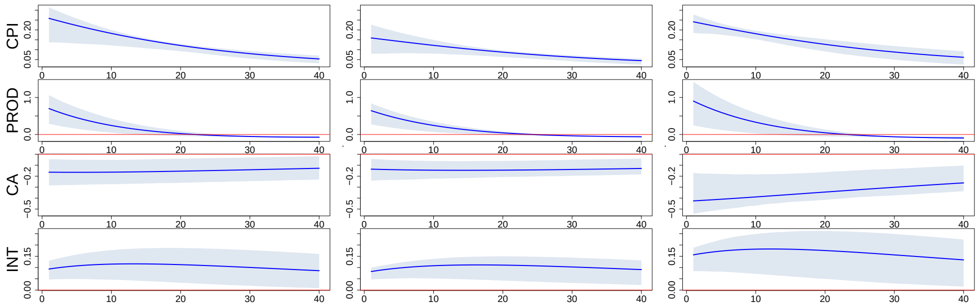


(d) Portugal

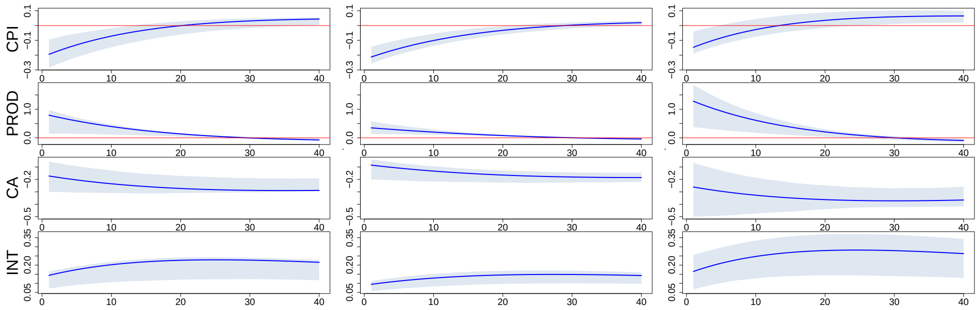
Figure 3.A.4: Data used in the VAR models for Germany, Italy, Spain and Portugal



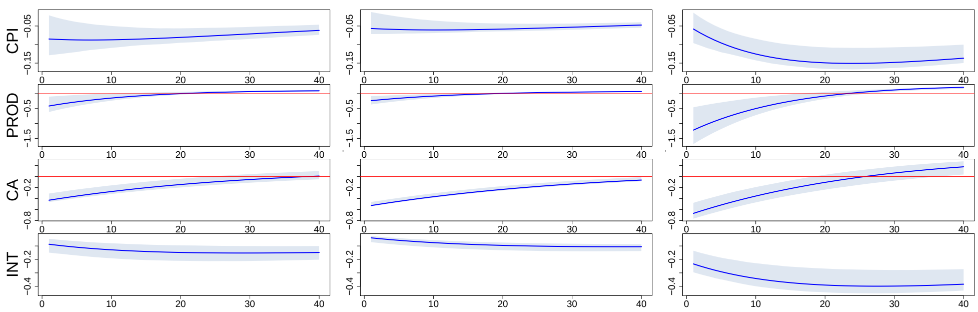
(a) competitiveness shock



(b) domestic demand shock

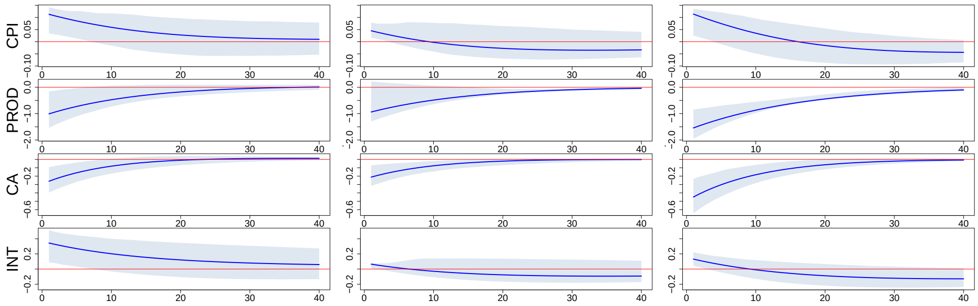


(c) supply shock

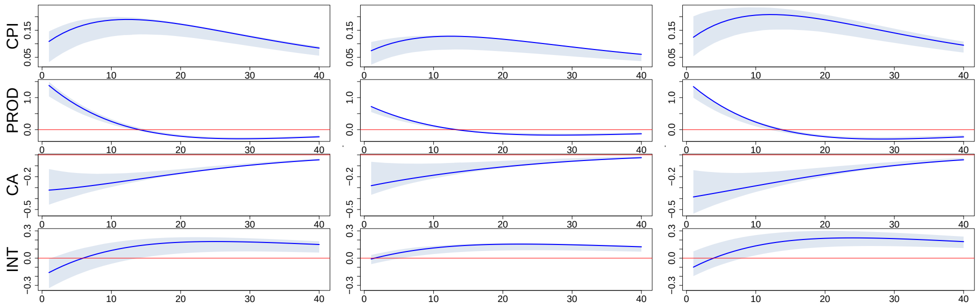


(d) foreign demand shock

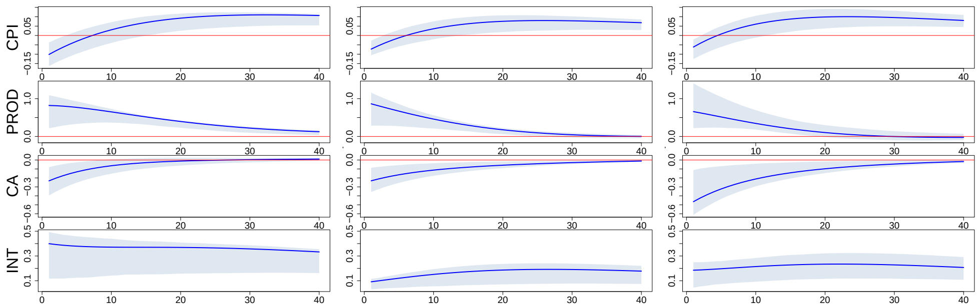
Figure 3.A.5: Impulse responses from German SVAR model: pre-EMU regime (left), EMU regime (middle) and crisis regime (right), 68 percent bootstrapped confidence intervals



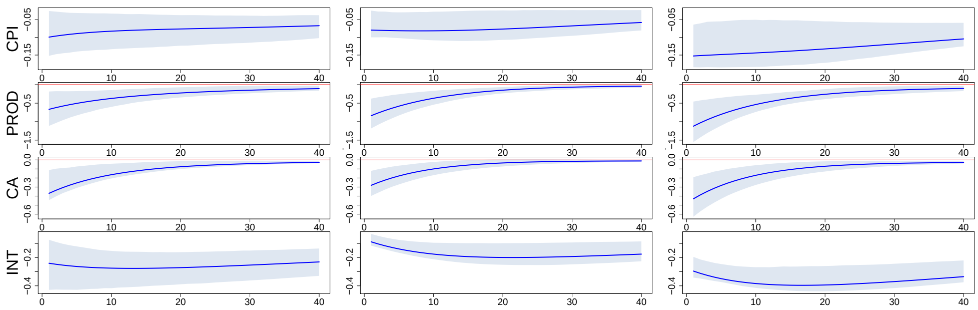
(a) competitiveness shock



(b) domestic demand shock

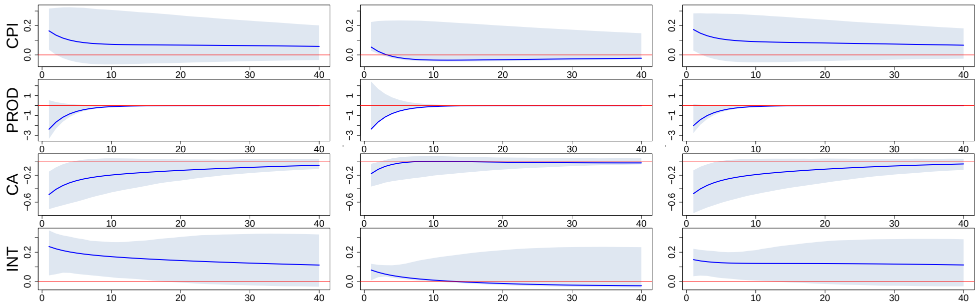


(c) supply shock

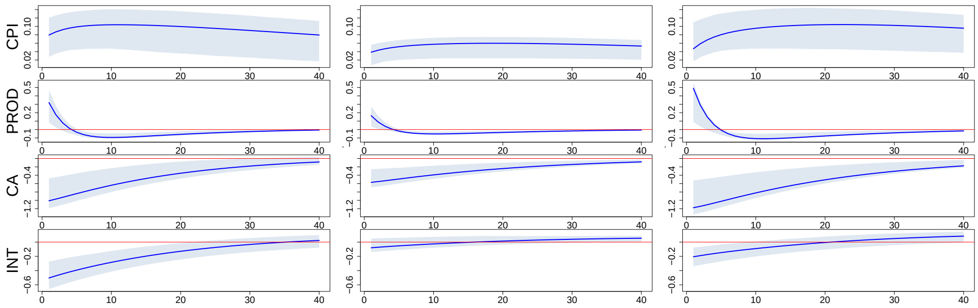


(d) foreign demand shock

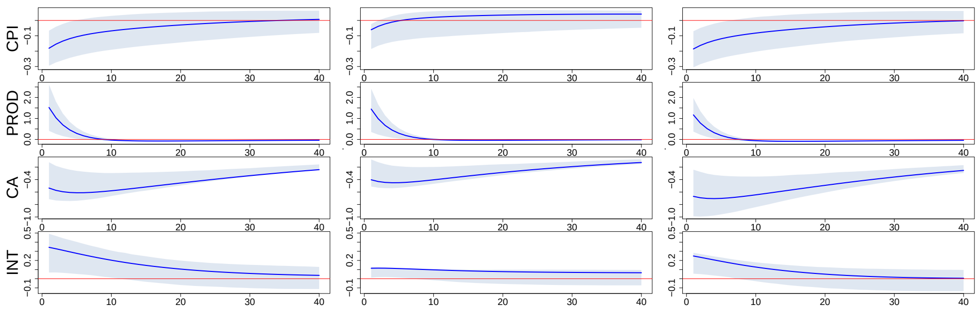
Figure 3.A.6: Impulse responses from Italian SVAR model: pre-EMU regime (left), EMU regime (middle) and crisis regime (right), 68 percent bootstrapped confidence intervals



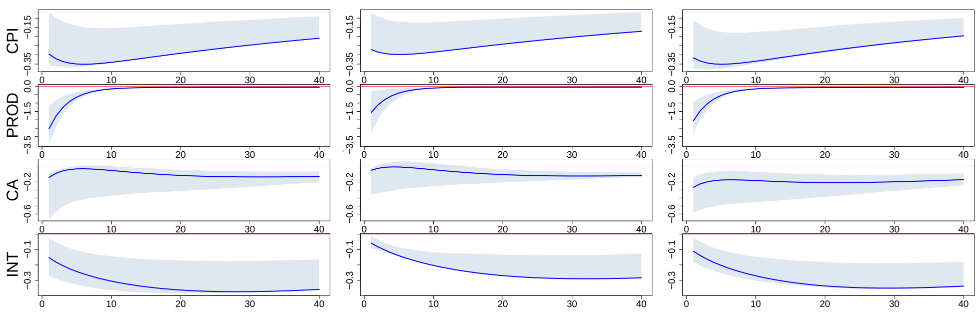
(a) competitiveness shock



(b) domestic demand shock

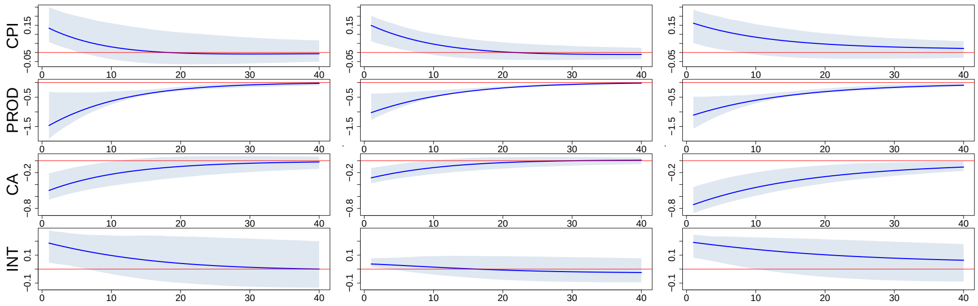


(c) supply shock

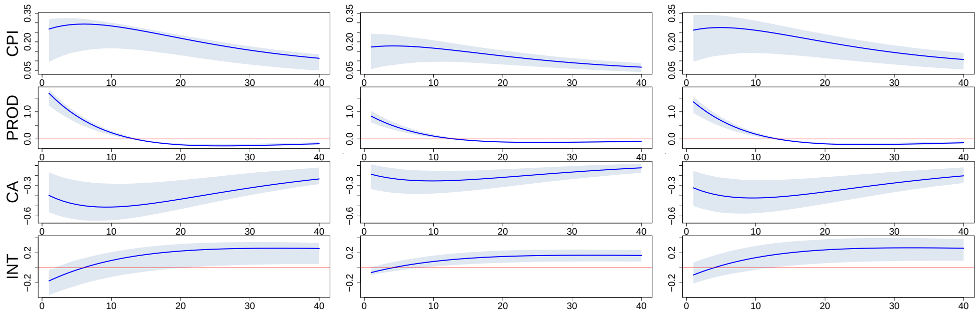


(d) foreign demand shock

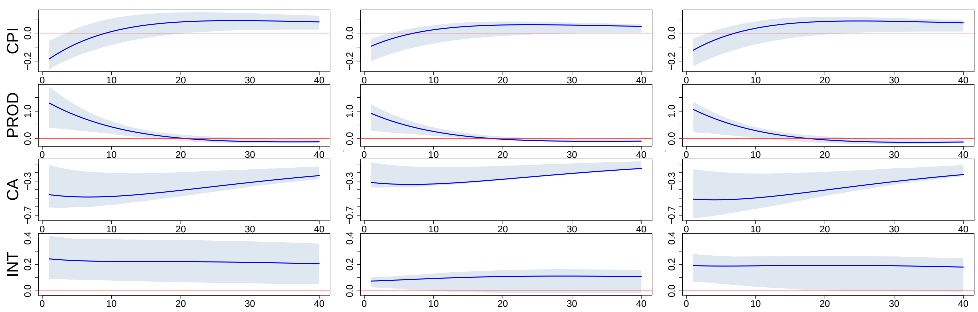
Figure 3.A.7: Impulse responses from Portuguese SVAR model: pre-EMU regime (left), EMU regime (middle) and crisis regime (right), 68 percent bootstrapped confidence intervals



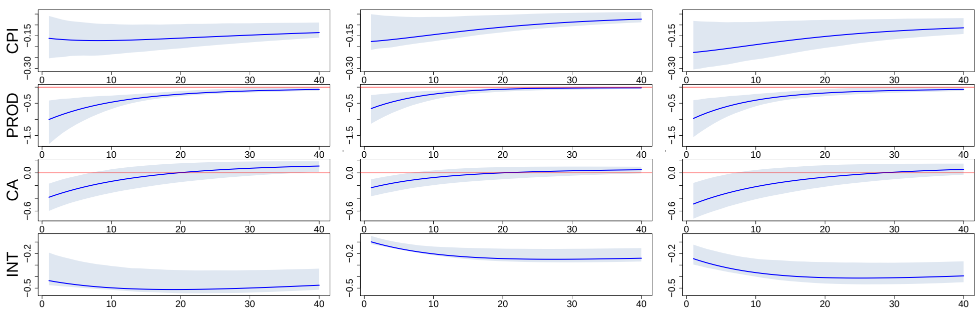
(a) competitiveness shock



(b) domestic demand shock

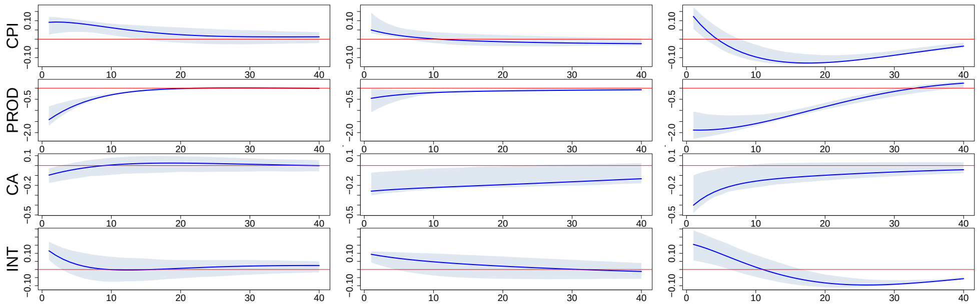


(c) supply shock

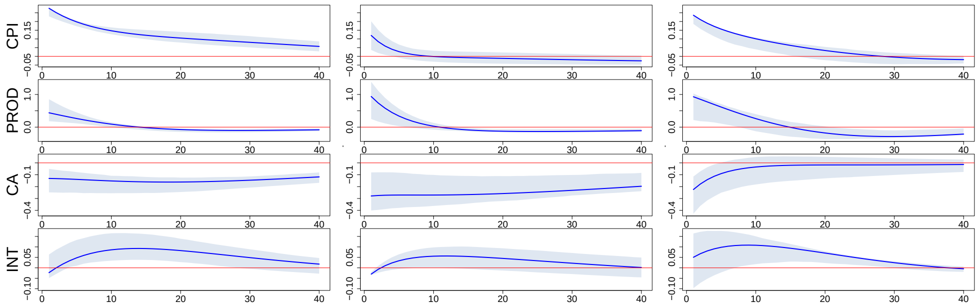


(d) foreign demand shock

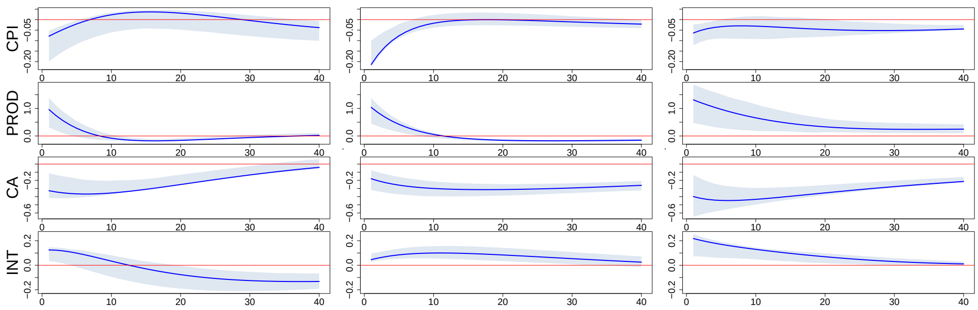
Figure 3.A.8: Impulse responses from Spanish SVAR model: pre-EMU regime (left), EMU regime (middle) and crisis regime (right), 68 percent bootstrapped confidence intervals



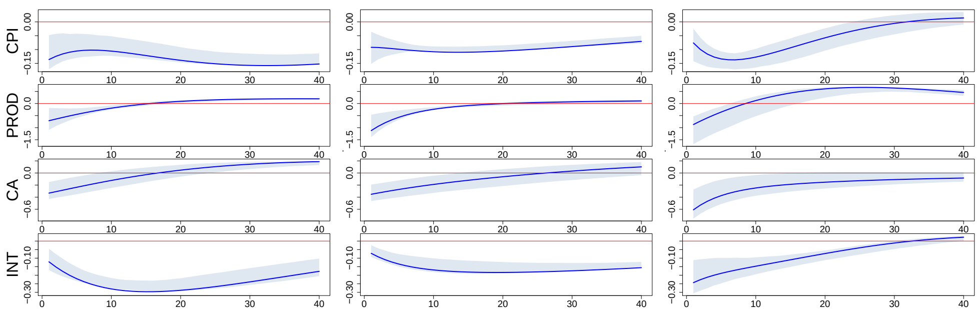
(a) competitiveness shock



(b) domestic demand shock

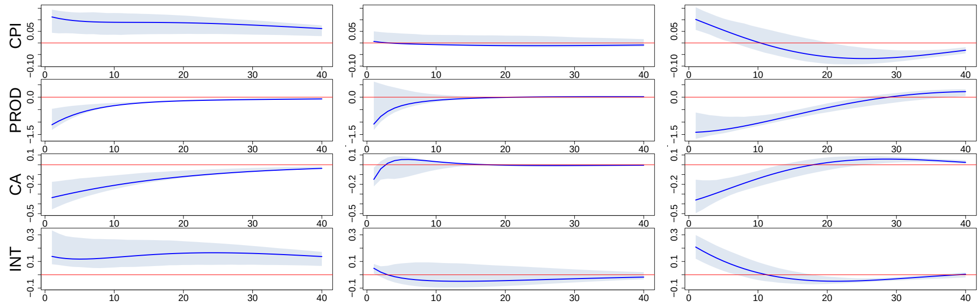


(c) supply shock

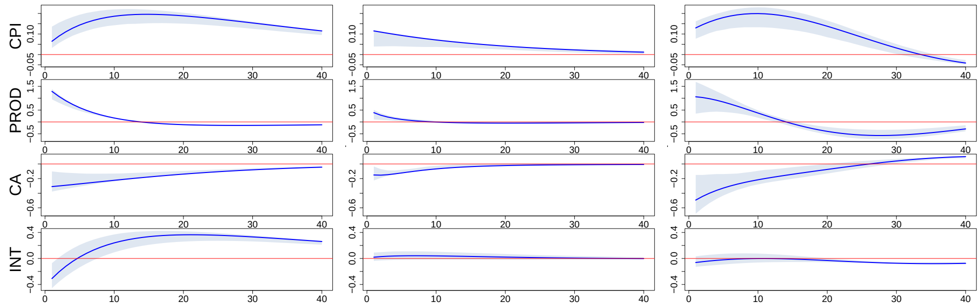


(d) foreign demand shock

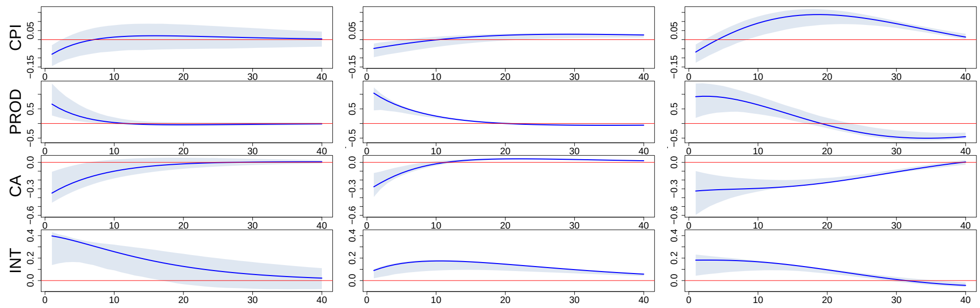
Figure 3.A.9: Impulse responses from German SVAR model with time-varying slope coefficients (Model 6 from Table 3.3.3): pre-EMU regime (left), EMU regime (middle) and crisis regime (right), 68 percent bootstrapped confidence intervals



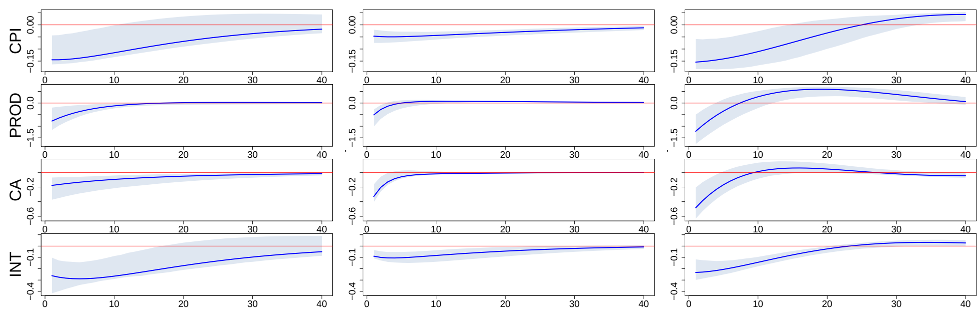
(a) competitiveness shock



(b) domestic demand shock

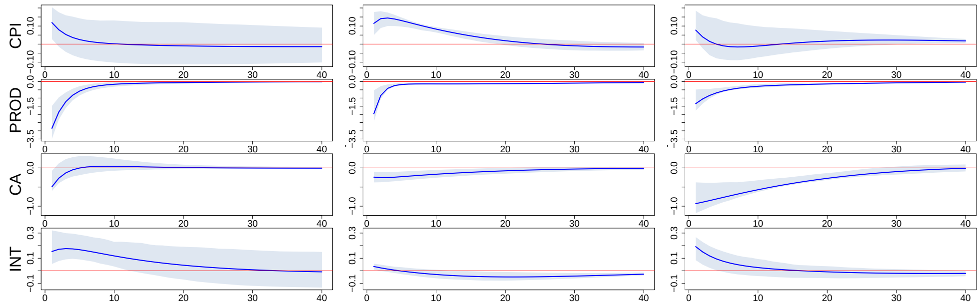


(c) supply shock

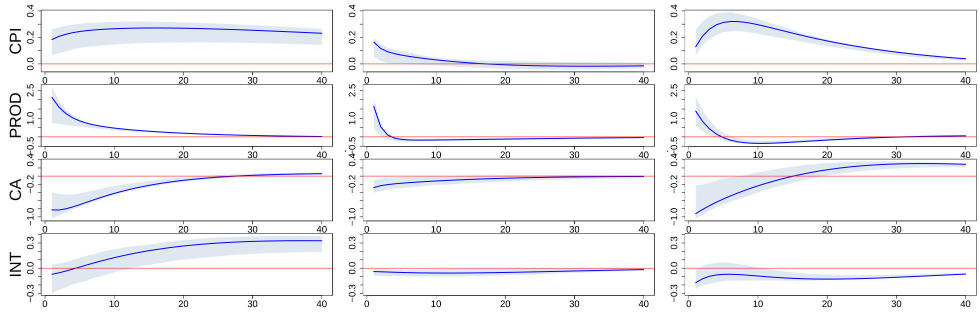


(d) foreign demand shock

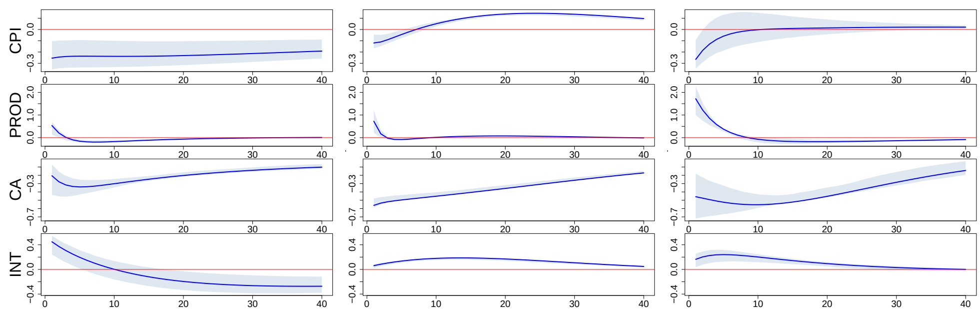
Figure 3.A.10: Impulse responses from Italian SVAR model with time-varying slope coefficients (Model 6 from Table 3.3.3): pre-EMU regime (left), EMU regime (middle) and crisis regime (right), 68 percent bootstrapped confidence intervals



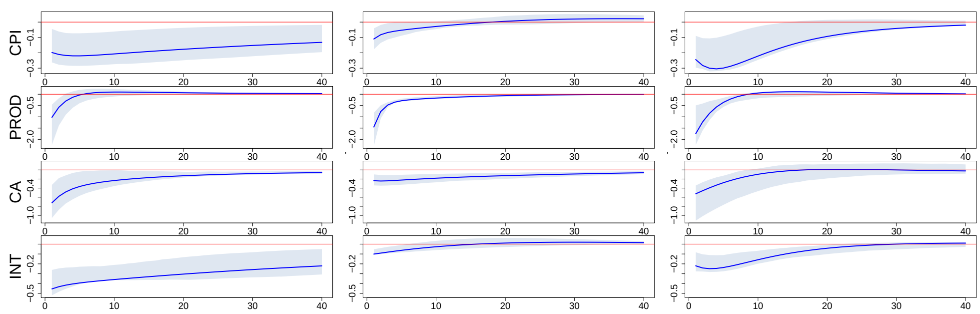
(a) competitiveness shock



(b) domestic demand shock

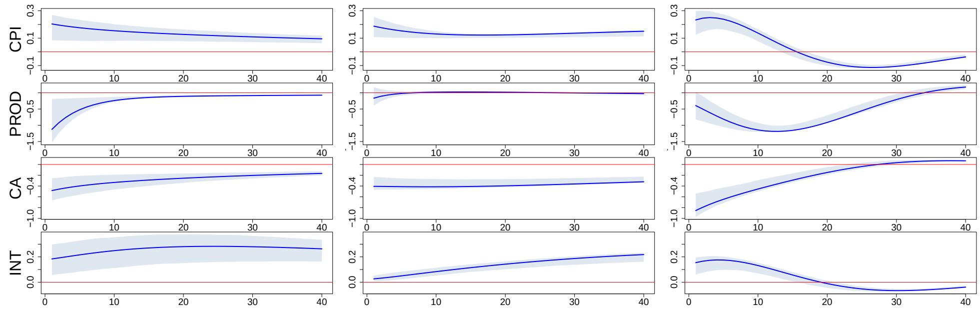


(c) supply shock

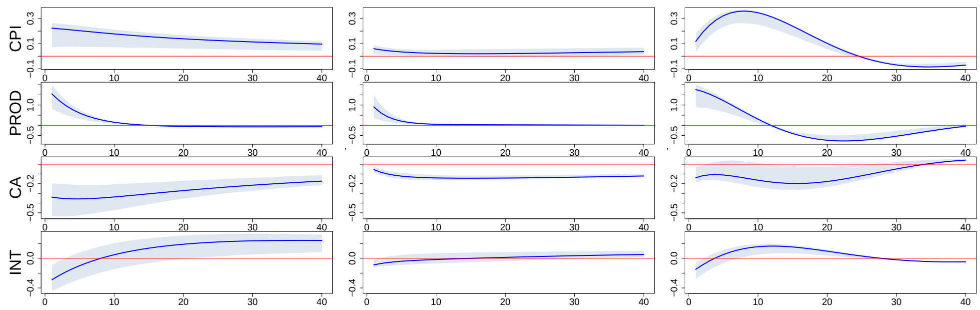


(d) foreign demand shock

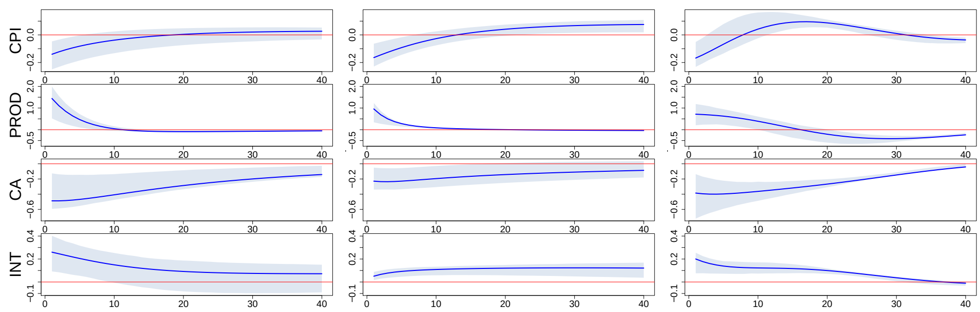
Figure 3.A.11: Impulse responses from Port. SVAR model with time-varying slope coefficients (Model 6 from Table 3.3.3): pre-EMU regime (left), EMU regime (middle) and crisis regime (right), 68 percent bootstrapped confidence intervals



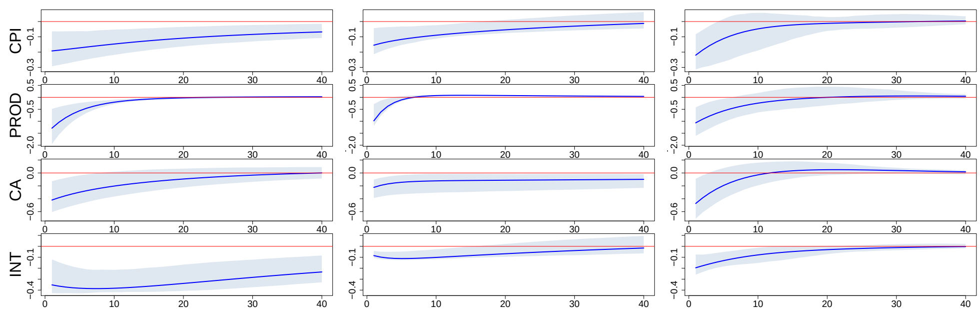
(a) competitiveness shock



(b) domestic demand shock



(c) supply shock



(d) foreign demand shock

Figure 3.A.12: Impulse responses from Spanish SVAR model with time-varying slope coefficients (Model 6 from Table 3.3.3): pre-EMU regime (left), EMU regime (middle) and crisis regime (right), 68 percent bootstrapped confidence intervals

Chapter 4

Identifying Uncertainty Shocks Using the Price of Gold[1]

4.1 Introduction

Economic uncertainty, broadly defined as the difficulty of economic agents to make accurate forecasts (Bloom, 2014; Jurado et al., 2015), is widely believed to have potentially far reaching implications for the economy. Nevertheless, identifying the impact of uncertainty on the economy is challenging, because uncertainty and the economy are determined simultaneously. Since Bloom (2009), this challenge has been addressed in the economic literature by developing strategies to identify uncertainty shocks, and to estimate the impact of such shocks on the economy.

The economic impact of uncertainty shocks has been largely studied using Vector Autoregressive (VAR) models. Their identification largely relies on the use of the recursive approach (see, among others, Bloom, 2009; Baker et al., 2013; Scotti, 2013; Bachmann et al., 2013; Caggiano et al., 2014; Jurado et al., 2015). Nevertheless, the exclusion restrictions implied by the recursive identification have received substantial criticism, because they impose that no other structural shock contemporaneously affects the variables affected contemporaneously by the uncertainty shock (see Stock and Watson, 2012; Baker and Bloom, 2013).

In this paper we propose a new strategy for the identification of uncertainty shocks. We make use of the proxy SVAR methodology developed by Stock and Watson (2012) and Mertens and Ravn (2013) to identify structural VARs using external instruments and propose a new instrument for the identification of uncertainty shocks. In their investigation of the macroeconomic dynamics of the great recession, Stock and Watson (2012) highlight the challenge in isolating exogenous variations in uncertainty. This paper attempts to fill this gap.

[1] This chapter is based on an article that is joint work with Michele Piffer.

The identification strategy proposed in this paper relies on the dynamics of the price of safe haven assets around selected events. It is reasonable to presume that events generating unexpected variations in uncertainty are reflected in the price of assets perceived by market participants as safe havens. For example, an increase in uncertainty due to, say, an event that caused significant geopolitical instability might materialize in a jump in the price of a safe haven asset. This could happen because agents respond to the higher uncertainty by rebalancing their investments toward the safe asset, or because those who hold such an asset are less willing to sell it, or both. Accordingly, the price of safe haven assets can be a useful point of departure to build an identification strategy for uncertainty shocks.

Since the price of a safe asset does not only reflect uncertainty shocks but also many other structural shocks, not all variations in the price of safe assets can be used to isolate uncertainty shocks. For this reason, we exploit the variation in the price of safe assets around specific events. We consider events associated with variations in uncertainty that occurred in an exogenous way relative to the state of the economy. For example, we use the 9/11 terrorist attack to the World Trade Center, the invasion of Kuwait by Iraq, the Chernobyl nuclear disaster and the fall of the Berlin Wall. The use of events to isolate exogenous variations in variables of interest has a long-standing tradition in the literature (see, for instance, Kuttner, 2001; Gurkaynak et al., 2005). Having selected events that exogenously varied uncertainty, we construct an instrument (or proxy) for uncertainty shocks by measuring the variation of the price of safe haven assets around the events. While not measuring the shocks themselves, these variations reflect the response of agents to the underlying uncertainty shocks, and hence are correlated with such shocks, a feature that we exploit to construct an instrument. A battery of tests suggests using the price of gold to construct the proxy, out of a wide range of candidate assets considered. For the price of gold, we use intradaily data from the London Bullion Market, and Bloomberg News to address when the news of each event hit the market.

The identification used in the paper has three main advantages. Firstly, it allows for contemporaneous effects of the uncertainty shock on all variables, while not restricting the uncertainty shock to be the only shock that potentially affects contemporaneously all variables. Secondly, it permits to build the identification approach on high frequency data, instead of relying on monthly data as with identifications pursued within the VAR model itself. Thirdly, it allows to explicitly account for possible measurement errors in the construction of the proxy for uncertainty shocks – a feature that is particularly well-tailored given the approximative nature of uncertainty measures in general.

We compare the effects of an uncertainty shock identified via the proposed proxy SVAR with the effects identified via the popular recursive approach. We find that in the proxy SVAR, the uncertainty shock (1) triggers an instantaneous reaction of the financial market variables, (2) exhibits a larger response of the real economy with a subsequent overshooting as predicted by the model in Bloom (2009), and (3) is followed by a significant and prolonged monetary policy response. In addition, the uncertainty shock identified in the proxy SVAR explains a larger share in the variance of the real variables, while the fraction explained by the recursively identified shock is rather small.

The paper relates to the literature concerned with estimating the effects of uncertainty shocks on real and financial variables. One strand of the literature investigates uncertainty shocks as a potential driver of the business cycle.[2] Another (complementary) strand of the literature focuses on developing and refining measures of economic uncertainty.[3] Others take a Bayesian approach to the interpretation of uncertainty.[4] In this paper we do not aim at constructing a potential measure of uncertainty, but draw inference on the exogenous variations of uncertainty in a proxy SVAR setup.

There are other papers that propose identification approaches differing from the recursive one. Alessandri and Mumtaz (2014) identify uncertainty shocks in a VAR as the exogenous variations to a variable that scales the variance-covariance matrix of the structural shocks. Caldara et al. (2014) identify uncertainty and financial shocks as the ones that have the highest impact on the measure of uncertainty and on the financial variable in the VAR, respectively. Cesa-Bianchi et al. (2014) identify uncertainty shocks as the common stochastic component to the VIX index in several countries. Ludvigson et al. (2015) use projections to isolate an orthogonal component from variables that carry information on the shocks of interest while not

[2] For example Leahy and Whited (1996); Bloom et al. (2007).
[3] For example Dovern et al. (2012); Mankiw et al. (2003); Baker et al. (2013); Scotti (2013); Jurado et al. (2015); Rossi and Sekhposyan (2015); Bachmann et al. (2013).
[4] For example Orlik and Veldkamp (2014).

being part of the VAR system. Based on those orthogonal components they identify macroeconomic and financial uncertainty shocks.

We are aware of two papers closest to our paper. Baker and Bloom (2013) use dummy variables constructed on extreme events as instrument in a single equation model of GDP growth on uncertainty. Using a VAR, we explore, instead, the endogenous dynamic response of the economy. Carriero et al. (2015) also make use of a proxy SVAR setup for the identification of uncertainty shocks. As a proxy they use a dummy variable taking value 1 when the VXO peaks, and then employ a Monte Carlo to study the effect of measurement errors on the estimation of impulse responses. We improve upon these papers by using a proxy variable that is not restricted to a dummy variable. To the best of our knowledge, our paper is the first one to study uncertainty shocks using the dynamics of the price of a safe asset around selected events.

The remainder of the paper is structured as follows. The next section discusses the identification via external instruments in the proxy SVAR setup. Section 4.3 introduces the construction of the proxy for uncertainty shocks used to identify the VAR model. Section 4.4 discusses the model specification and the data. Section 4.5 reports the results and relates them to the literature. Finally, Section 4.6 concludes.

4.2 The proxy SVAR model

Before discussing the construction of the proxy, we introduce the framework for the identification of structural VARs via external instruments and highlight the requirements that the instrument will need to satisfy.

Let the reduced form model be given by

$$\boldsymbol{y}_t = \boldsymbol{\delta} + A(L)\boldsymbol{y}_{t-1} + \boldsymbol{u}_t. \tag{4.1}$$

In equation (4.1), $\boldsymbol{y}_t$ is a $K \times 1$ vector including the endogenous variables, $\boldsymbol{\delta}$ includes constant terms and $A(L)$ is a lag matrix polynomial capturing the autoregressive component of the model. The reduced form shocks captured by the $K \times 1$ vector $\boldsymbol{u}_t$ are assumed to be linearly related to the underlying structural shocks through the equation

$$\boldsymbol{u}_t = B\boldsymbol{\epsilon}_t,$$

where $\boldsymbol{\epsilon}_t$ is an $K \times 1$ vector of structural shocks, whose variance-covariance matrix is normalized to the identity matrix.

We aim to identify the uncertainty shock out of the K structural shocks in $\boldsymbol{\epsilon}_t$. Let the scalar ϵ_t^u be the uncertainty shock and let the vector $\boldsymbol{\epsilon}_t^*$ be the other structural shocks. Under the recursive approach, identifying ϵ_t^u consists of first obtaining the Cholesky decomposition of the variance-covariance matrix of the reduced form shocks, and then selecting the column vector corresponding to the measure of uncertainty in $\boldsymbol{y}_t$. Instead, under the proxy SVAR identification proposed by Stock and Watson (2012) and Mertens and Ravn (2013) and used in this paper, identifying ϵ_t^u consists of estimating the column vector $\boldsymbol{b}^u$ that captures the correlation between the reduced form shocks and the proxy of uncertainty shocks (the position of this vector in the B matrix is irrelevant). To do so, one needs a valid instrument for ϵ_t^u.

Let us start from the statistical requirements that a valid instrument, m_t, needs to satisfy for the estimator to deliver consistent estimates of $\boldsymbol{b}^u$. Formally, given $\boldsymbol{u}_t = \boldsymbol{b}^u \epsilon_t^u + B^* \boldsymbol{\epsilon}_t^*$, the requirements for m_t are

$$E(m_t \epsilon_t^u) \neq 0, \tag{4.2}$$

$$E(m_t \boldsymbol{\epsilon}_t^*) = \mathbf{0}. \tag{4.3}$$

Intuitively the validity of the instruments requires that the instrument is at the same time correlated with the shock of interest, i.e. relevant (equation (4.2)), and uncorrelated with the remaining shocks, i.e. exogenous (equation (4.3)). There is no need for the instrument to capture the uncertainty shock perfectly, it only needs to reflect contemporaneous variations of it and not contemporaneous variations of other structural shocks. In principle, the instrument could still be correlated with other structural shocks in lags and leads, as long as not contemporaneously. In addition, the instrument does not need to be symmetric around zero, cover the entire time length covered by the VAR model nor take non-zero values at every period covered. In Section 4.3, this will imply that the proxy may, and in fact does, cover increases in uncertainty more frequently than decreases, be available for a shorter period relative to the period used for the estimation of the VAR, and take values only for some of the months. It is this ability to deal with several forms of measurement errors that makes the identification of structural VARs with external instruments particularly robust.

The relevance and exogeneity conditions for the proxy are fundamentally non-testable.[5] What can be tested, instead, is the strength of the instrument, and we will use this test as one of the tests to discriminate between candidate instruments. This test requires m_t to be sufficiently correlated with the reduced form shocks $\boldsymbol{u}_t$, in particular, with the reduced form shock of the equation of the VAR which features the measure of uncertainty as dependent variable. Intuitively, the instrument needs to be sufficiently related to the reduced form shocks because it is from these innovations that we aim to learn about the impulse vector $\boldsymbol{b}^u$. Formally, call $\hat{u}_{i,t}$ the estimated reduced form shock in equation i at time t. We test the strength of the instrument from the statistical significance of the parameter β_i in the regressions

$$\hat{u}_{i,t} = \alpha + \beta_i \cdot m_t + \eta_{i,t} \quad , \quad i = 1, 2, ..., K. \tag{4.4}$$

Having discussed the requirements that m_t needs to meet, we now discuss how we compute the proxy for the uncertainty shocks.

4.3 A proxy for uncertainty shocks

The construction of the proxy variable is based upon two steps. Firstly, we collect an array of events that potentially affected economic uncertainty in an unrelated way with respect to other macroeconomic shocks. Secondly, we use variations in the prices of an array of safe haven assets to inform the proxy around the selected events.

4.3.1 Collecting the events

To isolate periods in which uncertainty is likely to have changed exogenously with respect to the economy, we collect a vector of events that potentially generated or reduced uncertainty, that were not anticipated, and that were exogenous with respect to other relevant macroeconomic shocks.

[5] This is in contrast to the standard application of instrumental variable estimation, where the validity of the instruments can be tested as the relationship between the instrument and the endogenous regressor.

In particular, we start from the events already identified by Bloom (2009) through the peaks in the VXO.[6] We then extend the list using natural disaster databases and other publicly available data on armed conflicts, terrorist attacks as well as political elections and judicial decisions. Since the instrument does not need to take values at every period, it is safer to use a small selection of reliable events, rather than a larger array of events that potentially pollutes the information captured in the proxy. We hence exclude from the list all the events that may have been anticipated by economic agents and that are potentially related to other relevant macroeconomic shocks. The baseline specification of the analysis consists of 38 events.[7] Table 4.D.5 in the Appendix 4.D lists all the 38 events[8] In Section 4.5.5 we show that the results are robust to using all events in the construction of the proxy variable.

To assess when the news about the events hit the market, we rely on the news releases from the Bloomberg News agency. We do so because Bloomberg News releases are a main source of information for market participants, and they aggregate information from several sources around the world, hence giving us access to a broad set of information. For the 38 events used in the baseline specification, whenever Bloomberg News could not be used to assess when the news hit the market for a specific event, either because the News agency was not fully operational yet, or because it is not clear which release was the relevant one, other reliable sources were

[6] It may be noted that those peaks do not necessarily indicate an exogenous variation in uncertainty, but potentially an endogenous response to other macroeconomic shocks, or even uncertainty shocks that may have occurred earlier in the sample. Indeed, investigating the timing of the dummies, we found that the peaks of the VXO quite regularly occur with a few months delay after the events used by Bloom (2009) to interpret them. For example, the peak of the VXO in March 1980 is usually interpreted as the effect of the crisis related to the US hostages in Iran and to the Soviet invasion of Afghanistan, events that took place in November and December 1979, respectively; Black Monday occurred in October 1987, while the VXO peaked in November 1987; Iraq invaded Kuwait in August 1990, while the VXO peaked in October 1990; Worldcom bankruptcy happened in July 1990, while the VXO peaked in September 1990. While the peaks of the VXO might be associated to other, contemporaneous exogenous variations in uncertainty, the unclear correspondence of the VXO peaks and the underlying events raises the risk that the proxy based on dummies on the VXO mismatches the timing of the reduced form shocks of the VAR. For this reason, we prefer to inform our dummies using the price of safe haven assets, rather than a dummy variable in correspondence to the peaks of the VXO, as proposed by Carriero et al. (2015). The peaks of the VXO are used only to identify underlying events, whose exact timing is then assessed separately.

[7] The use of 38 events for the identification of the VAR model estimated on about 400 monthly observations is consistent with the number of shocks per observations in the sample of Mertens and Ravn (2013), who use 13 to 16 events for 228 quarterly observations.

[8] The entire database of events is available upon request.

used.[9] Of the 38 events, 19 were based upon Bloomberg News, the remaining 19 using alternative sources.

4.3.2 Comparing candidate safe haven assets

We consider different assets as candidate safe haven assets to construct our proxy. In this preliminary assessment, we use daily data on the price of precious metals (gold, silver, platinum) and government bonds (US treasury bonds with 3 month and 30 year maturity). We also consider the first principal component computed on the price of the precious metals, the daily measure of the VXO, and a dummy variable taking value ± 1 when the event was judged to imply an increase or a decrease in uncertainty, and 0 when the variation in uncertainty could not be *a priori* assessed. This improves upon a dummy variable taking value 1 for all events, which would not distinguish between increases and decreases in uncertainty. The use of daily data in this preliminary analysis ensures a level playing field in the comparison of the candidate assets, as it is the highest frequency available for all candidates.

For each of the candidate safe haven assets, we compute the percentage variation of the corresponding price before and after the occurrence of each of the event. We then aggregate these variations into a monthly time series summing up within a month, as in Romer and Romer (2004). This yields eight candidate proxies for uncertainty shocks. While in principle the identification of structural VARs can be done with several instruments for the same structural shock, it is appropriate to assess which candidate instruments are more suitable for the analysis.

We use two criteria to assess which asset is most suitable for the construction of the proxy. Firstly, the candidate proxy should Granger-cause the majority of measures of uncertainty available from the literature (we use the measures by Jurado et al. (2015), Bachmann et al. (2013), the VIX, the VXO and a measure of realized volatility of the S&P 500). Rejecting the null hypothesis of no Granger-causality suggests that the candidate proxy indeed reflects variations in uncertainty. Secondly,

[9] For example, Bloomberg News agency releases do not cover the period in which the Berlin Wall fell, November 9, 1989. Nevertheless, it is uncontroversial that the trigger of the event was the reply given by the GDR official Günter Schabowski at the press conference in that day, which was broadcast at 7:17 PM, Berlin time, following which East Germans rushed to boarder crossing. As such, the news can be comfortably classified as having occurred before the markets opened the following day.

we require the instrument to be sufficiently strong, i.e. to correlate significantly with the VAR residuals corresponding to the uncertainty measure as dependent variable. In particular, we require that the F statistic for the significance of β in the VAR equation of the measure of uncertainty higher than 10 (Stock and Yogo, 2005). In the baseline specification of the model we use the VXO as a measure of uncertainty.

The results of the tests are shown in Table 4.3.1. Bold values report values supporting the candidate proxy. The Granger-causality tests are displayed in the top part of the table. The results of the tests on the strength of the candidate instruments are shown in the lower part of Table 4.3.1. For the former, we report the p-value on the Granger-causality from the candidate proxy variable to the different measures of uncertainty. For the latter, we report the F statistic on the significance of the candidate proxy, which enters as the regressor in the equation featuring as a dependent variable the residual on the VXO. Overall, the tests strongly support the price of gold as a measure to inform the proxy of uncertainty shock. While also proxies based on other assets such as platinum and the US treasury bills somewhat pass the Granger-causality tests, they do not pass the test on the strength of the instrument. Therefore, the remainder of the analysis proceeds using the proxy informed by the price of gold.[10]

The availability of intradaily data for the price of gold allows us to construct even narrower windows around the events, improving on the identification of the uncertainty shocks. In particular, we use data on physical gold from the London Bullion Market. This market is an over-the-counter market, but it organizes two auctions every day, at 10:30 and at 15:00, and the price of these auctions is publically available. More detail on the gold price data is available in Appendix 4.A. In Section 4.5 we show that the strength of the instrument increases when moving from daily to intradaily data, as the relevant F statistic increases from 11.90 to 19.38.

[10] Baur and McDermott (2010) and Baur and Lucey (2010) find empirical support for the hypothesis that gold is a safe haven asset. Anecdotal evidence from the media also points towards gold as potentially reflecting uncertainty shocks. For example, after the terrorist attack in Paris, November 16, 2015, the Wall Street Journal titled an article "Gold Prices Rise as Paris Attacks Spark Safe-Haven Demand", and the CNBC titled a TV discussion "Safe haven assets gain after Paris attacks". Overall, we found that newspapers tend to comment on the price of gold and other safe haven assets after several events that we use.

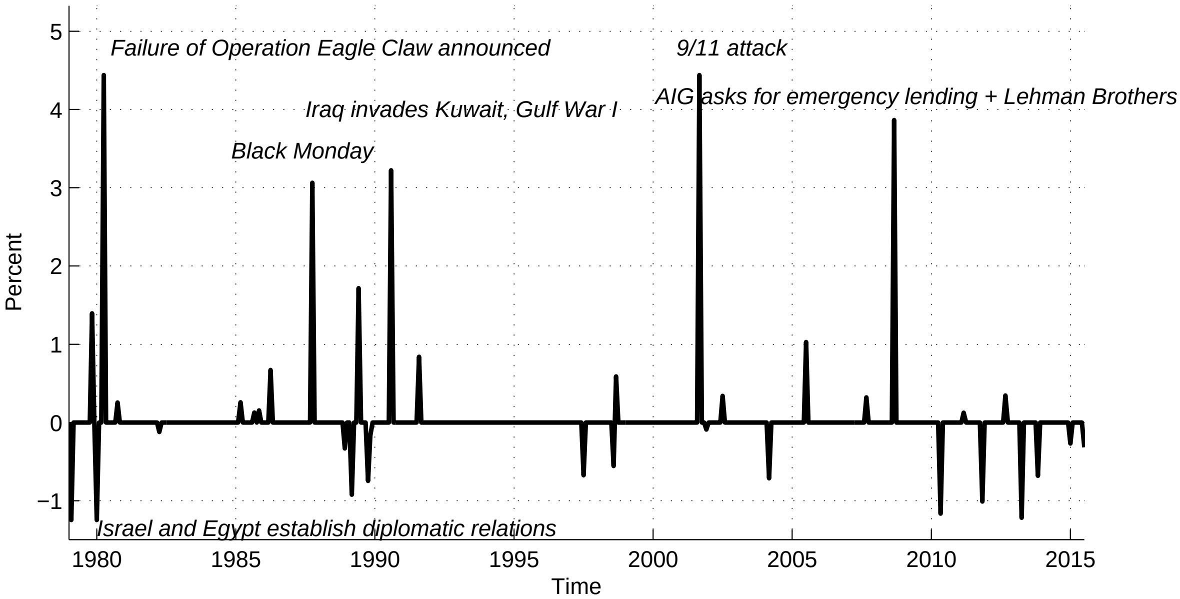
Table 4.3.1: Preliminary tests on candidate assets for the construction of the proxy

	Gold	Silver	Platinum	PC	3mTBILL	30yBond	VXO	Dummy
	Granger-causality from candidate proxy to measure of uncertainty (p-values)							
Jurado et al. (2015)	**0.00**	**0.00**	0.75	0.74	0.21	0.4	0.86	0.75
Bachmann et al. (2013)	0.75	0.94	**0.04**	0.69	0.31	0.82	0.72	**0.09**
VIX	**0.00**	0.61	**0.00**	0.96	**0.00**	**0.02**	**0.01**	0.26
VXO	**0.00**	0.35	**0.00**	0.39	**0.01**	**0.01**	0.19	0.4
Realized Volatility	**0.00**	0.93	**0.00**	0.98	**0.00**	**0.00**	**0.00**	0.91
	Strength of the candidate instrument (F-statistic)							
Residual in VXO eq.	**11.90**	4.50	2.29	0.00	1.90	0.05	4.99	5.28

Notes: Granger-causality tests are run using bivariate VAR models, where the number of lags had been chosen using the Akaike Information Criteria.

4.3.3 The proxy

Figure 4.3.1: Proxy for uncertainty shocks: Variations in the price of gold around events



The final proxy for uncertainty shocks is shown in Figure 4.3.1.[11] The realizations are well distributed among the sample. The peaks of the proxy tend to be predominantly positive and of higher magnitude when positive, a feature consistent with the literature on uncertainty shocks (Bloom, 2014). The peaks are intuitive with respect to the nature of the underlying event, as indicated by the labels in Figure 4.3.1. Figure 4.D.5 in the Appendix 4.D shows the histogram for the variations of the price of gold along the events, while Appendix 4.B discusses a number of illustrative events in greater detail in order to provide further intuition behind the proxy. We refer to a positive uncertainty shock as a shock that exogenously *increases* uncertainty, and which is hence associated with an *increase* in the proxy for the uncertainty shock.

Before using the computed instrument in the identification of the VAR, we further assess the relevance and exogeneity conditions discussed in Section 4.2, equations (4.2) and (4.3) respectively. While these conditions are not directly testable, an indirect assessment can be established using estimates of several structural shocks available in the literature. To do so, we deploy the large set of external instruments used in Stock and Watson (2012) to identify oil, monetary policy, productivity, financial and fiscal policy shocks, as well as two external instruments for uncertainty shocks that they derive. These are the residual of a univariate autoregression with two lags on the VIX, and the common component of the different countries' policy uncertainty indexes from Baker and Bloom (2013). We consider the regression $m_t = \alpha + \beta x_t + \epsilon_t$, where m_t is our proxy for uncertainty shocks and x_t is each of the external instruments listed in Table 4.3.2, one at a time. For each regression, we assess the statistical significance of β based on Huber-White heteroscedasticity-consistent standard errors.

The results of these tests, summarized in Table 4.3.2, confirm that our instrument for uncertainty shocks is not accidentally picking up other structural shocks, although the monetary policy shock taken from Smets and Wouters (2007) and the financial shock from Bassett et al. (2014) are not far from being borderline cases. Reassuringly, the only significant correlation is found with one of the two uncertainty shock instruments, namely the residual from an AR(2) regression on the VIX, while the common component of the policy uncertainty indexes across countries is not

[11] To avoid the results from being driven by outliers, the proxy has been winsorized at the one percent level, although this does not affect the results. Winsorization eliminates outliers in the distribution by replacing values in the tails with those of the respective percentiles.

Table 4.3.2: Relationship between our proxy of uncertainty shocks and the instruments used in Stock and Watson (2012) for several structural shocks

Shock	Source	β	S.E.	P-value	Obs	Sample
Oil	Kilian (2008)	-0.336	0.323	0.3	309	1979M01 to 2004M09
	Ramey and Vine (2010)	0.918	1.355	0.5	397	1979M01 to 2012M01
	Hamilton (2003)	0.106	0.119	0.37	393	1979M01 to 2011M09
Monetary Policy	Romer and Romer (2004)	-3.810	2.822	0.18	216	1979M01 to 1996M12
	Smets and Wouters (2007)	0.232	0.144	0.11	104	1979Q1 to 2004Q4
	Sims and Zha (2006)	-0.052	0.040	0.2	291	1979M01 to 2003M03
Productivity	Basu et al. (2006)[12]	-0.103	0.113	0.36	132	1979Q1 to 2011Q4
	Smets and Wouters (2007)	0.268	0.191	0.16	104	1979Q1 to 2004Q4
Financial	TED spread	0.903	0.628	0.15	394	1979M01 to 2011M10
	Gilchrist and Zakrajšek (2012)	0.583	0.554	0.29	127	1979Q1 to 2010Q3
	Bassett et al. (2014)	0.597	0.392	0.13	76	1992Q1 to 2010Q4
Fiscal Policy	Ramey (2011)	5.638	20.207	0.78	128	1979Q1 to 2010Q4
	Fisher and Peters (2010)	0.400	4.362	0.93	120	1979Q1 to 2008Q4
	Romer and Romer (2010)	0.820	0.604	0.18	116	1979Q1 to 2007Q4
Uncertainty	AR(2) resid. of VIX	0.302	0.165	**0.07**	394	1979M01 to 2011M10
	Baker et al. (2013)	0.016	0.012	0.18	325	1985M01 to 2012M01

Notes: Reported standard errors are white heteroscedasticity-consistent standard errors. If the external instrument, x_t, is only available on quarterly frequency, our uncertainty instrument, m_t, is aggregated by averaging across months.

found to be significantly related to our instrument. Overall, we conclude that the evidence supports our assumptions of relevance and exogeneity of the instrument.

4.4 Data and specification

Following the construction of the proxy for uncertainty shocks, we deploy it for the identification of uncertainty shocks from a VAR model. To facilitate comparison with the recursive identification used in Bloom (2009), we use a specification of the VAR model very similar to his one.

We consider a vector of eight endogenous variables that enter the VAR model in the following order:

$$\boldsymbol{y}_t = \begin{pmatrix} \Delta log(\text{S\&P 500}_t) \\ \text{VXO}_t \\ \text{federal funds rate}_t \\ \Delta log(\text{wages}_t) \\ \Delta log(\text{CPI}_t) \\ \text{hours}_t \\ \Delta log(\text{employment}_t) \\ \Delta log(\text{industrial production}_t) \end{pmatrix}.$$

In the baseline specification, variables either enter in levels or in log differences in order to ensure the stationarity of the system. Based on information criteria we estimate a reduced form VAR with five lags, considering alternative lag lengths in the robustness section. The sample spans from 1962M8 to 2015M6. The data included in the VAR model is plotted in Figure 4.D.6 in the Appendix 4.D.

Our specification of the model deviates from Bloom (2009) in three ways. Firstly, we update the sample up to 2015M6 in order to include more recent uncertainty related events in our database. Secondly, we let the variables enter in log differences rather than in deviations from HP trends (Hodrick and Prescott, 1997), since such a detrending might distort the dynamics in the underlying time series.[13] Thirdly, we use the entire dynamics of the VXO as a measure of uncertainty instead of a dummy series that takes the value of unity in correspondence to the peaks of the series. For robustness, we will also consider specifications in levels and on HP detrended data.

The actual identification of the model, i.e. the estimation of $\boldsymbol{b}^u$ given the instrument and the estimates of the reduced form VAR, is discussed in detail in Appendix 4.C.

4.5 Results

This section discusses the results of the analysis across four dimensions: tests on the strength of the proxy, estimated structural shocks, impulse responses and forecast error variance decompositions. We compare the results of the proxy SVAR with

[13] See King and Rebelo (1993), Harvey and Jaeger (1993), Guay and St-Amant (2005) and Meyer and Winker (2005) for a discussion of potential distortionary effects induced by using of HP filtered data. Indeed, Jurado et al. (2015) find that the overshooting in response to an uncertainty shock documented in Bloom (2009) is an artifact of the transformation of the variables.

the recursively identified SVAR. In short, we find that the proxy strongly relates to VXO, employment and industrial production, and that the proxy SVAR exhibits a stronger effect of uncertainty shocks on the real economy both in terms of impulse responses and of variance decompositions. In addition, monetary policy responds more aggressively to an uncertainty shock.

4.5.1 Tests on the strength of the instrument

Table 4.5.3: Tests on the strength of the instrument

	Reduced form shocks on:							
	S&P 500 (log dif.)	VXO (level)	Fed funds rate (level)	Wage (log dif.)	CPI (log dif.)	Hours (levels)	Employment (log dif.)	Industrial production (log dif.)
β	-0.80^{**}	166.4012^{***}	-5.582	-0.026	0.020	-4.133^{*}	-0.066^{***}	-0.182^{***}
T	438	438	438	438	438	438	438	438
F	4.336	19.380	1.324	1.076	0.779	3.654	9.224	8.035
R^2	0.098	0.042	0.003	0.002	0.002	0.008	0.020	0.018

Notes: The models estimated are of the form $\hat{u}_{i,t} = \alpha + \beta_i m_t + \eta_{i,t}$ with $\hat{u}_{i,t}$ the residual in the equation of the VAR corresponding to the variable indicated in each column of the table and m_t the proxy variable explained in Section 4.3. The null hypothesis refers to $\beta_i = 0$. The statistical significance of $\hat{\beta}_i$ indicated in the table is constructed using the asymptotic distribution of the OLS estimator. The bootstrapped distribution delivered an even stronger statistical significance of the parameters β_i, with the parameter in the first, third and sixth column being significant at a 1% confidence level (unreported).

Starting from equations (4.4), we test the significance of the β parameters ($\beta_i,\ i = 1, 2, ..., K$). The results of the validity tests are reported in Table 4.5.3. They suggest that the instrument contains relevant information for the reduced form residuals and thus for the variables included in the system. The VXO is the only measure positively related to the proxy for uncertainty shocks in a statistically significant way, while four other variables – the stock market index, hours worked, employment and industrial production – are negatively related and in a statistically significant way. The reduced form residuals associated with the federal funds rate, wages and the consumer prices are found to be statistically unrelated to the instrument. The F statistic on the null hypothesis $\beta_i = 0$ is above 10 for the residual on the VXO equation, with an F statistic even higher than the one found using the proxy based on daily data (Section 4.3). The F statistic is close to 10 for the residual on the equations of the employment and of industrial production. Note also that the F statistics are much higher for the residuals in the equation of VXO than in the equation of the stock market index, confirming again that the proxy is picking up uncertainty shocks rather than financial shocks. Given that the majority of the measures respond significantly to the proxy and that the signs of those responses are in line with expectations, we conclude that the proxy is a valid instrument in the chosen setup.

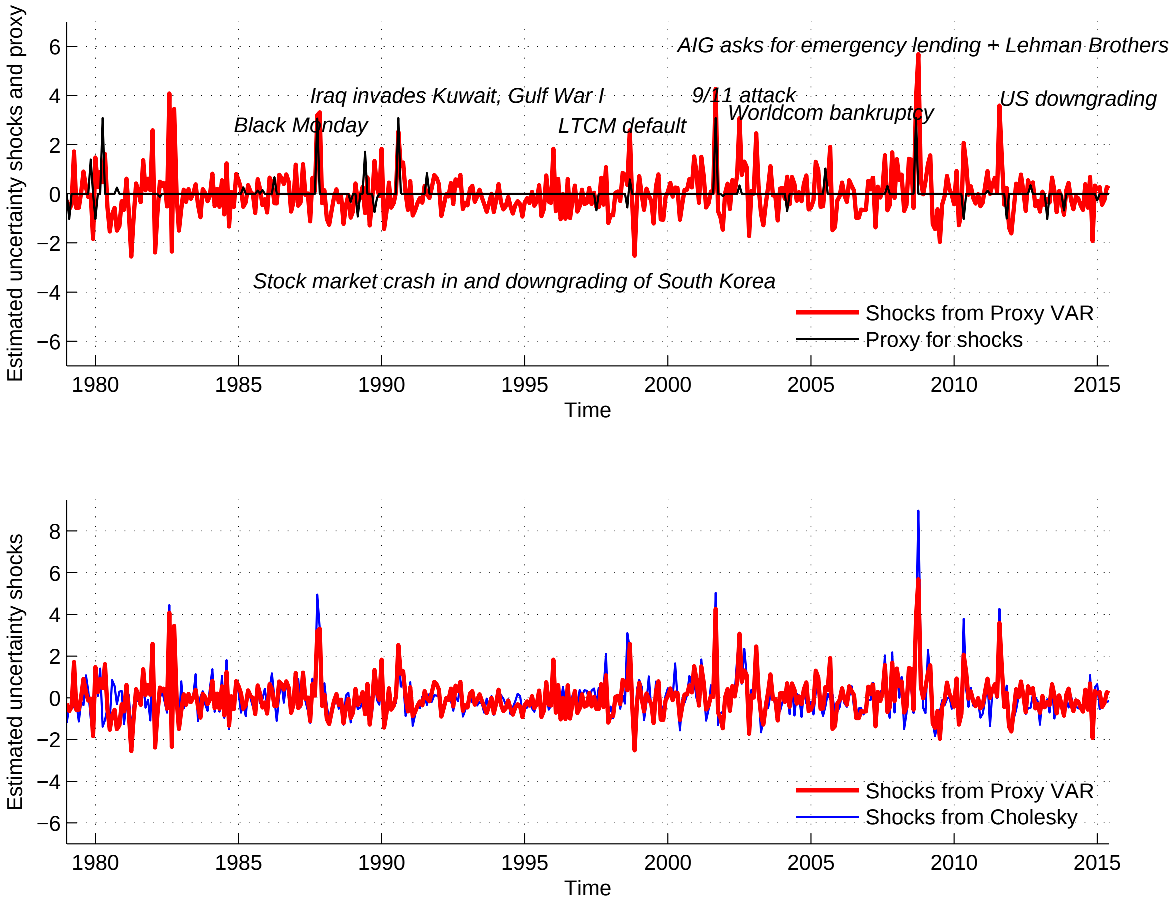
4.5.2 Estimated uncertainty shocks

Figure 4.5.2 reports the estimated shocks from both the recursively identified SVAR and the proxy SVAR.

The top panel plots the proxy variable constructed in Section 4.3 jointly with the uncertainty shock uncovered from the proxy SVAR. The correlation between the proxy for the uncertainty shocks and the uncertainty shocks equals about 25 percent. The two series share several peaks, including most notably, Black Monday, the 9/11 attack and the collapse of Lehman Brothers. The structural shocks obtained from the proxy SVAR also include a number of events that we have not incorporated in the construction of the proxy variable, as for example the US downgrading. We did not include this event in the proxy variable, because within the same window (which goes from Friday to Monday) the European Central Bank reactivated SMP, and we could not control for this monetary event. The estimated uncertainty shocks attribute a strongly positive peak to that period.

The lower panel compares the two structural shock series obtained from the recursively identified SVAR and the proxy SVAR. Both series of structural uncertainty shocks exhibit higher volatility in the aftermath of the early 1980s recession, after the burst of the dotcom bubble in the early 2000s an during the recent financial crisis. Their correlation of about 84 percent indicates that the identifications are not diametrically opposed to each other. However, the shock series from the proxy SVAR seems somewhat smoother and generally exhibits smaller peaks.

Figure 4.5.2: Estimated shocks and proxy of uncertainty shocks

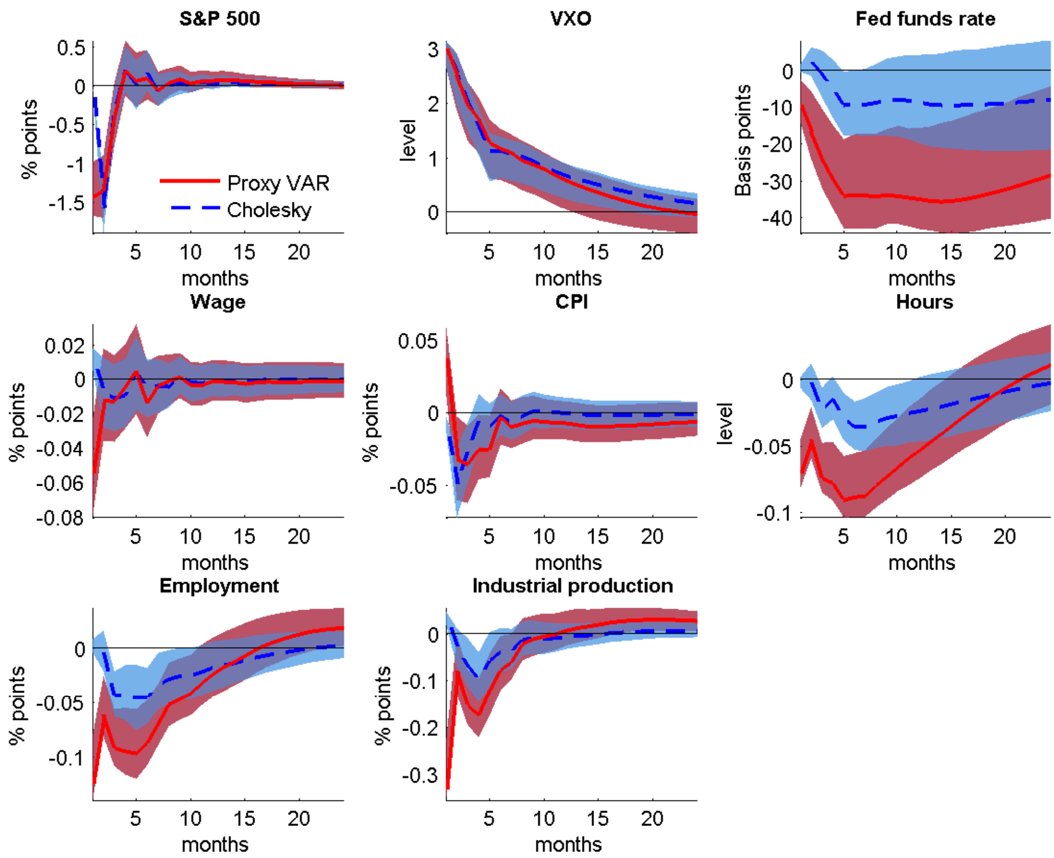


4.5.3 Impulse Responses

In order to facilitate comparison among the impulse responses from two different identification approaches, we first compute the impulse responses in the proxy VAR as the response to a one standard deviation shock. We then give an impulse to the recursively identified model such that the VXO increases on impact by just as much as in the case of the proxy VAR. Figure 4.5.3 plots the responses to an uncertainty shock. We first discuss those responses stemming from the proxy VAR in isolation, before turning to the comparison. Error bands are computed using a Wild bootstrap.[14]

[14] To compute the distribution, we follow Mertens and Ravn (2013) and Gertler and Karadi (2014) in using the wild bootstrap developed by Gonçalves and Kilian (2004). The wild bootstrap resamples the data by changing the sign of the estimated vectors of reduced form shocks at

Figure 4.5.3: Impulse responses to an uncertainty shock



Note: pointwise 90 percent confidence bands reported based on 1000 bootstrap replications.

An uncertainty shock identified within the proxy SVAR approach affects financial markets, monetary policy and the real economy, but has a very limited impact on

randomly-selected periods, and by changing the sign of the instruments in correspondence to the same periods. More precisely, generate a vector $\boldsymbol{c}$, of the same length of the reduced form shocks, which at every period t takes value $+1$ or -1 with equal probability. Then, compute $\boldsymbol{r}_t^{pseudo} = c_t \cdot \boldsymbol{r}_t$, i.e. pseudo reduced form shocks that differ from the original ones not by the order but only by the sign, as specified by the random vector $\boldsymbol{c}$. Use these pseudo reduced form shocks and the estimates of the VAR to recursively generate pseudo data $\boldsymbol{y}_t^{pseudo}$. Estimate the VAR using $\boldsymbol{y}_t^{pseudo}$. Identify the model using instruments $m_t^{pseudo} = c_t \cdot m_t$, i.e. using a pseudo measure of the proxy that differs from the original proxy only for the sign specified by the same vector $\boldsymbol{c}$. Brüggemann et al. (2016) propose using a residual block bootstrap, arguing that the fourth moments are not properly bootstrapped in a wild bootstrapping approach. Given that the distortions for the point wise confidence bands are minor, we follow the literature and deploy a wild bootstrapping to obtain confidence bands.

nominal variables. The stock market index falls on impact, consistent with Caldara et al. (2014), accompanied by a drop in employment, industrial production and hours worked. While the recovery of the financial markets is rather rapid, it takes the real economy two to three quarters to return to pre-shock levels. This recovery is supported by a loose monetary policy coming into play with some lag after the shock. Although wages and prices do not react significantly, the impulse responses seem to reflect pressure on the two variables, generally regarded as downward rigid. Given that wages do not react, additional adjustment on the labor market is borne by hours worked that remain low for about three quarters. Note that the real variables and the stock market index enter in growth rates, and hence their levels still justify a monetary expansion even after their growth rates have reversed, as indeed we find when considering the response of the federal funds rate.

There are three main differences between the responses in the recursively identified VAR and the proxy SVAR. Firstly, in the proxy SVAR the stock market reacts instantaneously to an uncertainty shock, potentially opening up a channel for a stronger transmission of the shock to the real economy. Secondly, employment, industrial production and hours react faster and significantly more negatively when identified based on the proxy SVAR. Thirdly, the proxy SVAR exhibits an overshooting in real variables, as predicted by the theoretical model in Bloom (2009). This does not occur with the recursive uncertainty shock. In addition, it should be noted that prices react negatively in the recursive identification, while monetary policy responds with a stronger decrease in the federal funds rate in the proxy SVAR, as compared to the recursively identified model. The results are consistent with Carriero et al. (2015), including the impact increase in the consumer price index.

While the robustness of the results is addressed in greater detail in Section 4.5.5, two remarks are worth noting here. Firstly, the results are very robust to several alternative specifications, including alternative specifications of the reduced form VAR and alternative computations of the proxy measure. Secondly, the results cannot be generated by simply using an alternative recursive order, placing the measure of uncertainty first. In this latter case, in fact, the response of employment and industrial production would still be estimated to be significantly smaller than in the case of the proxy SVAR.

4.5.4 Forecast error variance decomposition

Table 4.5.4: Forecast error variance decomposition for an uncertainty shock

hor.	S&P 500 (log dif.)	VXO (level)	Fed funds rate (level)	Wage (log dif.)	CPI (log dif.)	Hours (levels)	Employment (log dif.)	Industrial production (log dif.)
				from proxy SVAR				
1	0.20	0.45	0.05	0.00	0.00	0.13	0.31	0.40
6	0.21	0.45	0.25	0.01	0.06	0.41	0.50	0.45
12	0.21	0.42	0.37	0.01	0.06	0.47	0.50	0.43
24	0.21	0.39	0.45	0.01	0.07	0.36	0.48	0.43
				from recursive SVAR				
1	0.00	0.90	0.00	0.00	0.00	0.00	0.00	0.00
6	0.20	0.90	0.01	0.01	0.06	0.04	0.07	0.05
12	0.20	0.87	0.02	0.01	0.06	0.06	0.09	0.05
24	0.20	0.83	0.03	0.01	0.05	0.05	0.09	0.05

The forecast error variance decompositions are reported in Table 4.5.4. While the recursive and the proxy SVAR identifications isolate uncertainty shocks that explain similar fractions of nominal and financial variables, at least at longer horizons, the real variables – employment, industrial production and hours worked – are strongly affected by the proxy SVAR uncertainty shock. In contrast, the fraction explained by the recursively identified shock is very small.

It should also be noted that only a small fraction of the variation in the federal funds rate at short horizons is explained by uncertainty shocks. This fraction grows for larger horizons, potentially reflecting the reaction of the monetary authority to the depressed real economy. We take the small fraction of the short horizon as reassuring, in that we do not pick up a monetary policy shock with the instrumental identification.

A feature of the recursively identified uncertainty shock is that it explains close to all of the variation in the uncertainty measure used in the model. However, the VXO not only contains information about uncertainty but also about the risk aversion of market participants (Bekaert et al., 2013; Ludvigson et al., 2015) and, hence, it should be considered surprising that an uncertainty shock is capable of explaining nearly the entire variation in this measure. As opposed to that, the variation in the VXO explained by the proxy SVAR uncertainty shock fluctuates around 50 percent.

4.5.5 Robustness

We assess the sensitivity of the results along a number of dimensions. Specifically, we vary the lag length of the model, employ levels, HP filter the variables in the VAR as done in Bloom (2009), use the uncertainty measures from Jurado et al. (2015) and from Bachmann et al. (2013) as alternatives for the VXO in the baseline, consider an alternative proxy based on all events in the database (see Section 4.3), aggregate the daily proxy into a monthly time series using the aggregation by Gertler and Karadi (2014)[15] and change the ordering of the variables in the recursive identification. Overall the results are very robust to all these variations to the setup.

Figures 4.D.7 to 4.D.15 in the Appendix 4.D report the set of impulse responses for a range of specifications along the dimensions mentioned above. The main findings from the baseline specifications are insensitive to the changes considered. In response to an uncertainty shock, the stock market index drops instantaneously, the real economy contracts significantly stronger with an overshooting in subsequent periods, while monetary policy reacts more aggressively in the proxy SVAR as compared to the recursive setup.

We also vary the ordering in the recursive model and let the financial variable enter as the first variable (Figure 4.D.14 in the Appendix 4.D). While the reordering renders the response of the financial variable negative on impact, employment and industrial production still decrease significantly less if compared to the proxy SVAR. This may be due to the fact that the recursive approach is identifying an uncertainty shock effectively being a weighted average not only of financial and uncertainty shocks, but also other shocks capable of affecting the entire system contemporaneously. We conclude that reordering variables within a recursive identification still falls short of generating the effects of uncertainty shocks captured by the identification strategy proposed in this paper, although it goes in that direction.

[15] Their aggregation accounts for the timing of the event within the month.

4.6 Conclusion

In this paper we assess the economic impact of uncertainty shocks identified within a proxy SVAR. We propose a new proxy for exogenous uncertainty shocks by exploiting the variations of the price of gold around selected events. For the construction of the proxy we set up a database of events that may have impacted on economic uncertainty. We then inform our proxy variable about the relevance of the event for economic uncertainty via the variations in the price of gold around those events. Our proxy covers the time period from 1979 to 2015.

In comparing the uncertainty shock identified within the proposed proxy SVAR framework to a recursively identified shock prominently featured in the literature, we find that uncertainty shocks (1) trigger an instantaneous reaction of the financial market, (2) exhibit a larger and more rapid response of the real economy with a subsequent overshooting as predicted by the model in Bloom (2009), and (3) are followed by a significant and prolonged monetary policy response that is not present in the recursively identified setup. In addition, the uncertainty shock identified in the proxy SVAR explains a larger share in the variance of the real variables, while the fraction explained by the recursively identified shock is rather small.

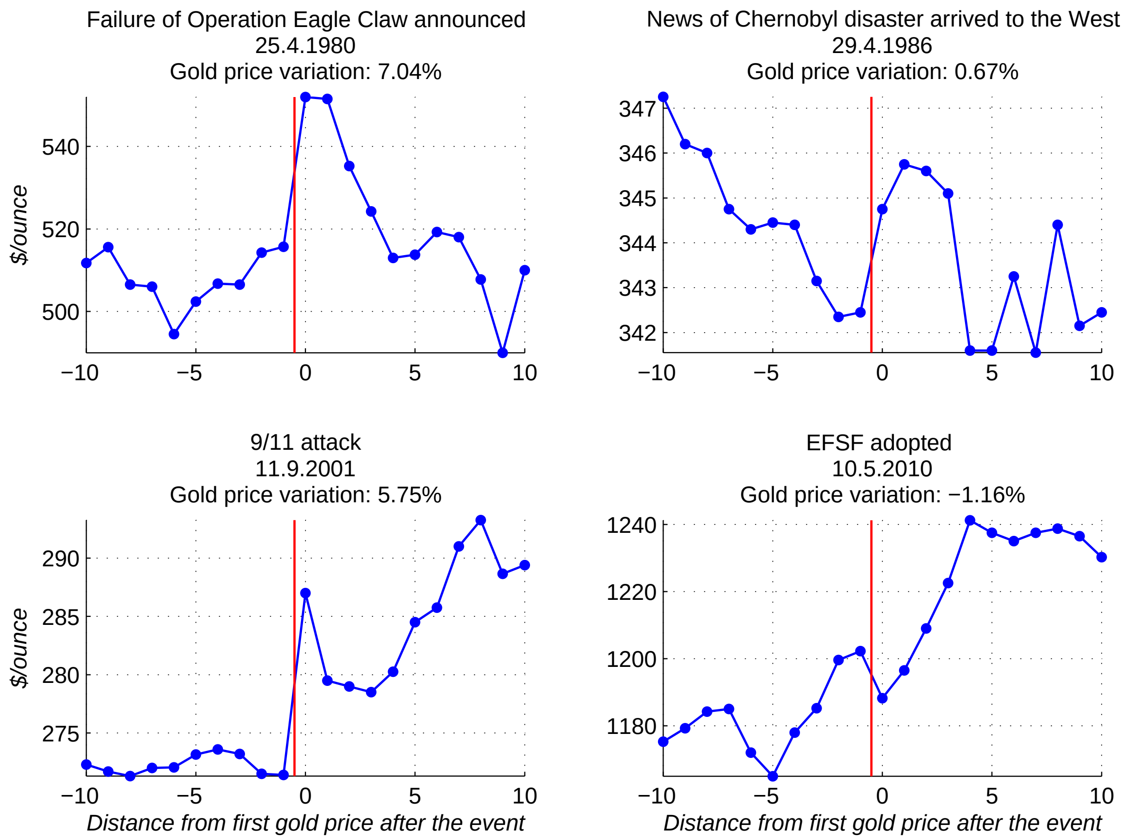
While the literature has put much effort in refining measures of uncertainty as such, less work has been done on improving the identification of uncertainty shocks within SVAR models. Our identification strategy based on the constructed proxy variable improves upon the widely used recursive approach of identifying uncertainty shocks, because it uses outside intradaily information for the identification and allows the entire economy to react instantaneously to an uncertainty shock. Overall, we find that uncertainty shocks may be an even stronger driving force of business cycles, as compared to the recursive identification.

4.A Data on the gold price

We use data from the London market of physical gold, formally known as the London Bullion Market. London is the main hub for the trade of physical gold, and trading occurs through spot transactions over the counter. We use the London price of physical gold rather than the New York price on futures contracts on gold for two reasons. Firstly, Bloomberg provides intradaily data on the futures market for only the last 18 months, while the data on the London market dates back to the 1970s. Secondly, the London market is larger in terms of trade volume.[16] A comparison of the prices on the London spot market and on the New York futures market at daily frequency yields a correlation close to unity.

Since transactions on the London Bullion Market are over-the-counter, market participants are not required to disclose the price of their bilateral agreements. Nevertheless, in order to inform market participants about the tightness of the market, the London Bullion Market Association organizes two auctions per day. The price of such auctions is publicly available. This is the price of gold that we use for the analysis. Auctions take place at 10:30 and 15:00, London time. We refer to these prices as the AM and the PM gold price, respectively. Shortly before 10:30 and 15:00, banks with access to the London Bullion Market vaulting facilities post their orders. It then typically takes 30 seconds to assess if a round of orders can be reconciled with a clearing price, and 3 rounds of orders to find an equilibrium price. Transactions are denominated in US dollars and are settled two days after the transaction.

Figure 4.B.4: Gold price around selected sample events



Notes: The figure shows 10 quotes of the price of gold before and 10 quotes of the price of gold after four different events, whose occurrence is indicated by the vertical line. The figures corresponding to all 117 events collected in the analysis is reported in the on-line appendix. The percentage variations are then windsorized at 0.5% on each side of the tail before aggregating them into the proxy. This explains the lower values in Figure 4.3.1 compared to this figure corresponding to the Failure of Operation Eagle Claw and to the 9/11 attack.

4.B A few examples

Figure 4.B.4 plots the variation in the intradaily gold price (AM and PM prices) around four selected illustrative events: (1) On 24 October 1980 President Carter authorized a secret military operation to free the *hostages in the US embassy* in Tehran. The operation had been kept secret to anyone outside of the inner circle of the President, and its failure was announced by Carter at 1:00 of the day after, Washington time. The announcement triggered an increase in uncertainty due to the heightened tension in the region, and London priced gold in its AM auction 7.04% above the PM price of the day before, likely pricing in the increased uncertainty that was soon to unfold between the US and Iran. (2) In the morning of 25 April 1986, technicians at the *Chernobyl nuclear station* turned off the emergency cooling system and started a test, which was mishandled, resulting in the explosion of the reactor at 01:23 the following morning. The Russian authorities neither informed the neighboring villages nor other countries, the West founding out initially through ordinary tests of radioactivity in Sweden, and then through a US satellite picture of the site. The news of winds coming from East then spread on the day of 29 April, and London priced an increase in the first auction of 30 April, although of only 0.67%. (3) On September 11, 2001, at 08:46 New York time, 13:46 London time, the first plane of the 9/11 terrorist attack hit the *World Trade Center*. The event occurred between the AM and the PM London gold auctions. The news of the event traveled around the world immediately and London priced a 5.75% increase in the price of gold in its PM auction. (4) During the height of the European sovereign debt crisis the European council agreed in an overnight meeting upon the establishment of the *European Financial Stabilization Facility* (EFSF). The press release communicating the positive outcome of the meeting is dated the night of

[16] Following O'Connor et al. (2015), in 2013 the net transactions in London had a daily turnover of 21bn US dollars. This equals 60% and 350% of the daily turnover on the New York Stock Exchange and on the London Stock Exchange, respectively. These figures underestimate the size of the London Bullion Market, as they only include net transactions. Information on gross transactions is not publicly available due to the confidentiality guaranteed by over-the-counter trading. According to a survey conducted in 2011, gross figures might be between 5 and 10 times higher than net figures (`http://www.lbma.org.uk/assets/Loco_London_Liquidity_Surveyrv.pdf`). When considering also gross transactions, London is estimated to account for around 90% of the sum of the global gold spot, futures and options trading volumes. New York, instead, accounts for around 9%. The other markets (Shanghai, Tokyo, Mumbai, Dubai and Istanbul) account for the remaining 1% (Lucey et al., 2013).

May 9, 2010, with Bloomberg reporting the news in the early hours of May 10. The price of gold in the morning auction drops 1.2% as compared to the PM auction the day before.

4.C Identification of the structural VAR

Given the estimates of the reduced form VAR from Section 4.2 and the proxy for the uncertainty shock constructed in Section 4.3, the estimation of the structural VAR proceeds as follows (see Mertens and Ravn, 2013, Stock and Watson, 2012 and Olea et al., 2012 for further details).

To estimate impulse responses, run the following regression for each of the K equations of the VAR model:

$$\hat{u}_{i,t} = \alpha_i + \beta_i m_t + \eta_{i,t}.$$

In this equation, $\hat{u}_{i,t}$ is the estimated VAR residual in equation i and m_t is the proxy. It holds that

$$\hat{\beta}_i = \frac{\hat{Cov}(\hat{u}_{i,t}, m_t)}{\hat{V}(m_t)} = \frac{\hat{E}(\hat{u}_{i,t}m_t) - \hat{E}(\hat{u}_{i,t})\hat{E}(m_t)}{\hat{V}(m_t)} = \frac{\hat{E}(\hat{u}_{i,t}m_t)}{\hat{V}(m_t)} \xrightarrow{p} \frac{E(u_{i,t}m_t)}{V(m_t)},$$

where $\hat{Cov}$, $\hat{V}$ and $\hat{E}$ are the sample covariance, second moment and first moment, respectively, and $\hat{E}(u_{i,t}) = 0$ holds by construction, given the inclusion of a constant in the VAR. Combining the estimates for the vector $\boldsymbol{\beta} = (\beta_1, \beta_2, ..., \beta_8)'$, we get

$$\hat{\boldsymbol{\beta}} \xrightarrow{p} E(\boldsymbol{u}_t m_t)\frac{1}{V(m_t)} = \boldsymbol{b}^u \frac{\phi}{V(m_t)}.$$

The equality follows from the fact that, under relevance and exogeneity of the proxy, $E(m_t \epsilon_t^u) = \phi \neq 0$ and $E(m_t \boldsymbol{\epsilon}_t^*) = \mathbf{0}$, hence

$$E(\boldsymbol{u}_t m_t) = E([\boldsymbol{b}^u \epsilon_t^u + B^* \boldsymbol{\epsilon}_t^*] m_t) = \boldsymbol{b}^u E(\epsilon_t^u m_t) + B^* E(\boldsymbol{\epsilon}_t^* m_t) = \boldsymbol{b}^u E(\epsilon_t^u m_t) = \boldsymbol{b}^u \phi,$$

It follows that $\hat{\boldsymbol{\beta}}$ converges to the true impulse vector $\boldsymbol{b}^u$, up to a scale. Since this scale is constant across equations, the impulse responses are consistently estimated up to a scale that preserves the relative variations across equations. Last, to recover impulse responses to a one standard deviation shock, we need an estimator for $\boldsymbol{b}^u$, not $\boldsymbol{b}^u \frac{\phi}{V(m_t)}$. This can be done by getting an estimate of the scaling factor $\frac{\phi}{V(m_t)}$ by exploiting the informations included in the covariance restrictions $\Sigma = BB'$.

To estimate the structural shocks, use the fact that

$$\begin{aligned}\hat{\Sigma}^{-1}\hat{E}(\hat{\boldsymbol{u}}_t m_t) &= \left(\frac{\sum_{t=1}^{T}\hat{\boldsymbol{u}}_t\hat{\boldsymbol{u}}_t'}{T}\right)^{-1}\frac{\sum_{t=1}^{T}\hat{\boldsymbol{u}}_t m_t}{T}\\ &\xrightarrow{p} \left(BB'\right)^{-1}E(\boldsymbol{u}_t m_t) = B'^{-1}B^{-1}\boldsymbol{b}^{\boldsymbol{u}}\phi = \boldsymbol{a}^{\boldsymbol{u}}\phi,\end{aligned}$$

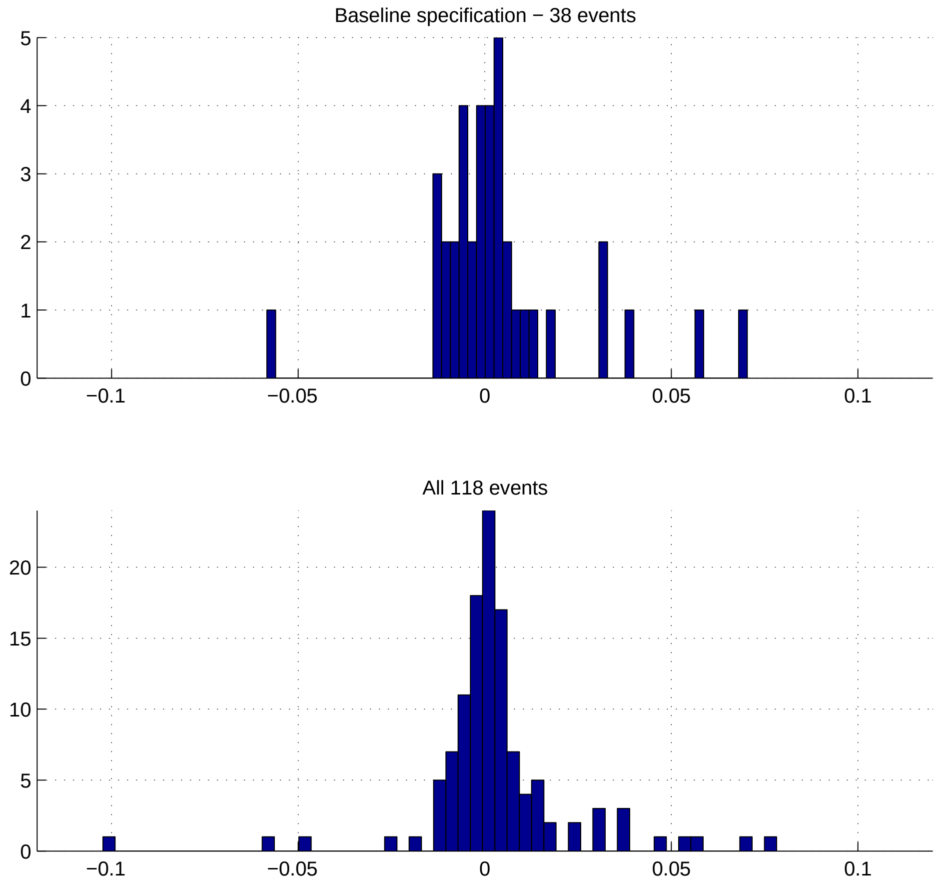
where $V(\boldsymbol{\epsilon}_t)$ is normalized to the identity matrix, and $\boldsymbol{a}^u$ is the row vector (written as column) of the $A = B^{-1}$ matrix corresponding to the vector $\boldsymbol{b}^u$ in B. To estimate $\boldsymbol{a}^u$ and hence the structural uncertainty shocks, obtain an estimate of ϕ from any of the equation in the equality $\hat{E}(\hat{\boldsymbol{u}}_t m_t) = \boldsymbol{b}^u\phi$, given the estimate for $\boldsymbol{b}^u$.

4.D Tables and figures

Table 4.D.5: Events used in the baseline specification, out of the 117 events collected

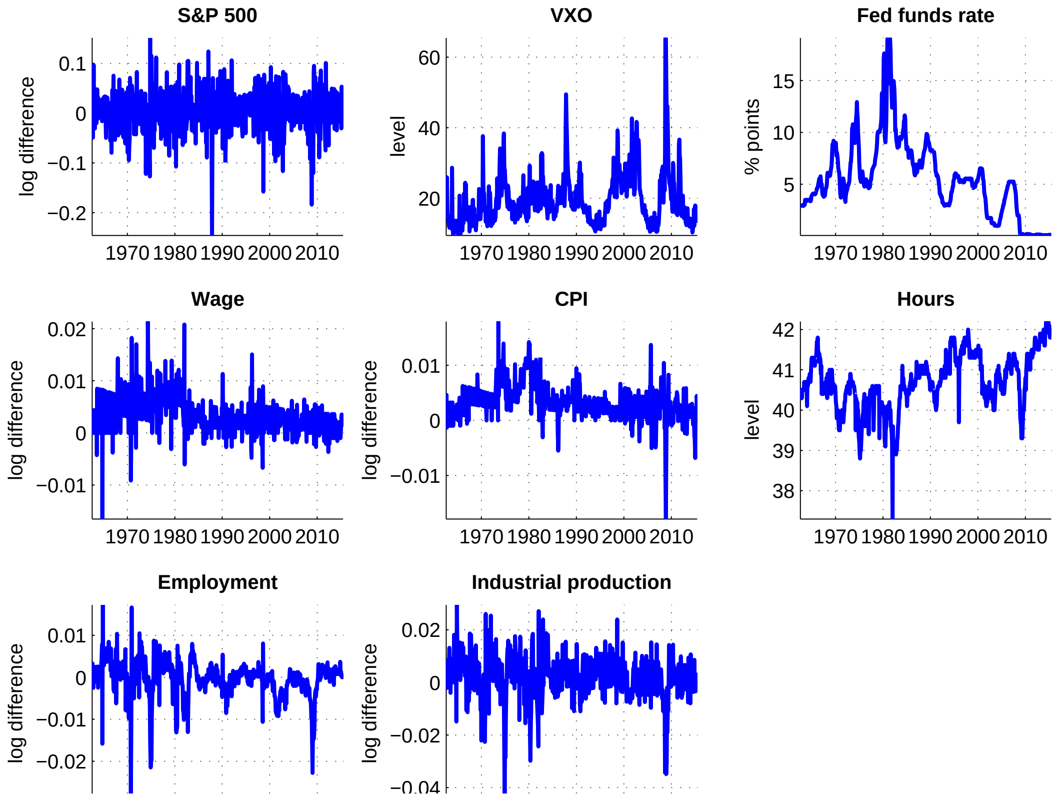
#	Date	Δp_{gold}	Event
1	04/25/1980	+7.04%	Failure of Operation Eagle Claw in the Iranian crisis announced
2	09/11/2001	+5.75%	9/11 attack
3	09/15/2008	+3.87%	AIG asks for lending + Lehman Brothers
4	08/02/1990	+3.22%	Iraq invades Kuwait, Gulf War I
5	10/19/1987	+3.06%	Black Monday
6	06/03/1989	+1.72%	Tienanmen Square
7	11/04/1979	+1.39%	Iran: hostages in US embassy
8	07/07/2005	+1.03%	London bombing
9	08/19/1991	+0.84%	Attempted coup in Moscow
10	04/29/1986	+0.67%	News of Chernobyl disaster arrived to the West
11	09/23/1998	+0.59%	LTCM default
12	09/12/2012	+0.35%	German Court approves ESM
13	07/21/2002	+0.34%	Worldcom bankruptcy
14	09/14/2007	+0.32%	Northern Rock receives liquidity support by BoE
15	03/11/1985	+0.26%	Start of Perestroika, Gorbachev's speech in Leningrad
16	10/10/1980	+0.26%	Earthquake destroys Algeri
17	12/21/1988	+0.23%	Lockerbie bombing, Libyan terrorist down the Pan Am Flight
18	11/13/1985	+0.15%	Volcanic Eruption in Columbia 30.000 dead
19	09/19/1985	+0.13%	Earthquake in Mexico 15.000 dead
20	03/11/2011	+0.12%	Fukushima evacuation order
21	06/10/2014	+0.00%	IS seizes Mosul
22	12/02/2001	-0.09%	Enron bankruptcy
23	04/01/1982	-0.12%	Argentina invades Falkland Islands
24	11/09/1989	-0.17%	Fall of Berlin Wall
25	01/07/2015	-0.27%	Charlie Hebdo attack
26	07/05/2015	-0.32%	Greek referendum supports Tsipras
27	08/07/1998	-0.56%	US embassy bombing, Kenia and Tanzania
28	12/07/1988	-0.56%	Earthquake in Armenia 25.000 dead
29	07/02/1997	-0.67%	Thailand unpegs currency
30	11/21/2013	-0.68%	Ukraine rejects EU association agreement
31	03/11/2004	-0.71%	Madrid train bombings
32	10/17/1989	-0.75%	Loma Prieta earthquake (California)
33	03/24/1989	-0.92%	Exxon-Valdes hits ground and leaks 40.000 tons of oil
34	11/09/2011	-1.01%	Berlusconi resignation announced
35	05/10/2010	-1.16%	EFSF adopted
36	04/15/2013	-1.22%	Boston marathon bombing
37	02/01/1979	-1.31%	Khomeini returns to Tehran
38	01/26/1980	-5.84%	Israel and Egypt establish diplomatic relations

Figure 4.D.5: Distribution of the proxy for uncertainty shocks



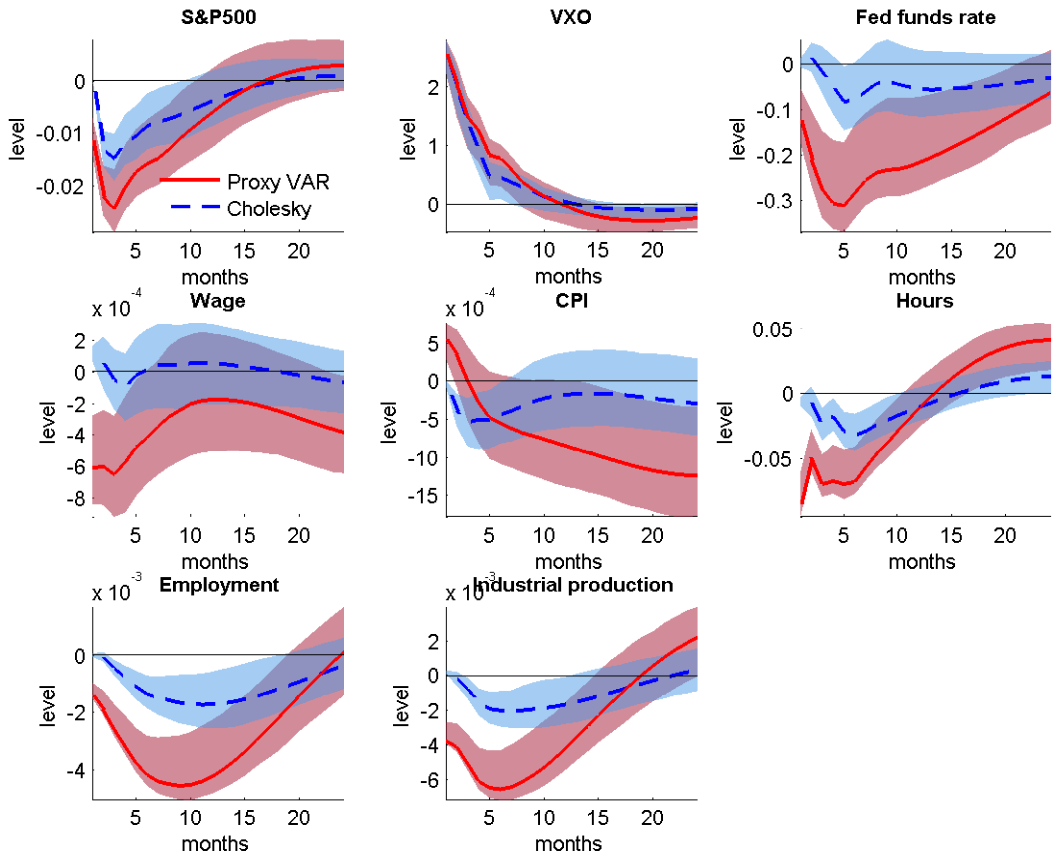
Note: The histogram is computed on the individual events, not on their monthly aggregation.

Figure 4.D.6: Data used in the baseline specification of the VAR model



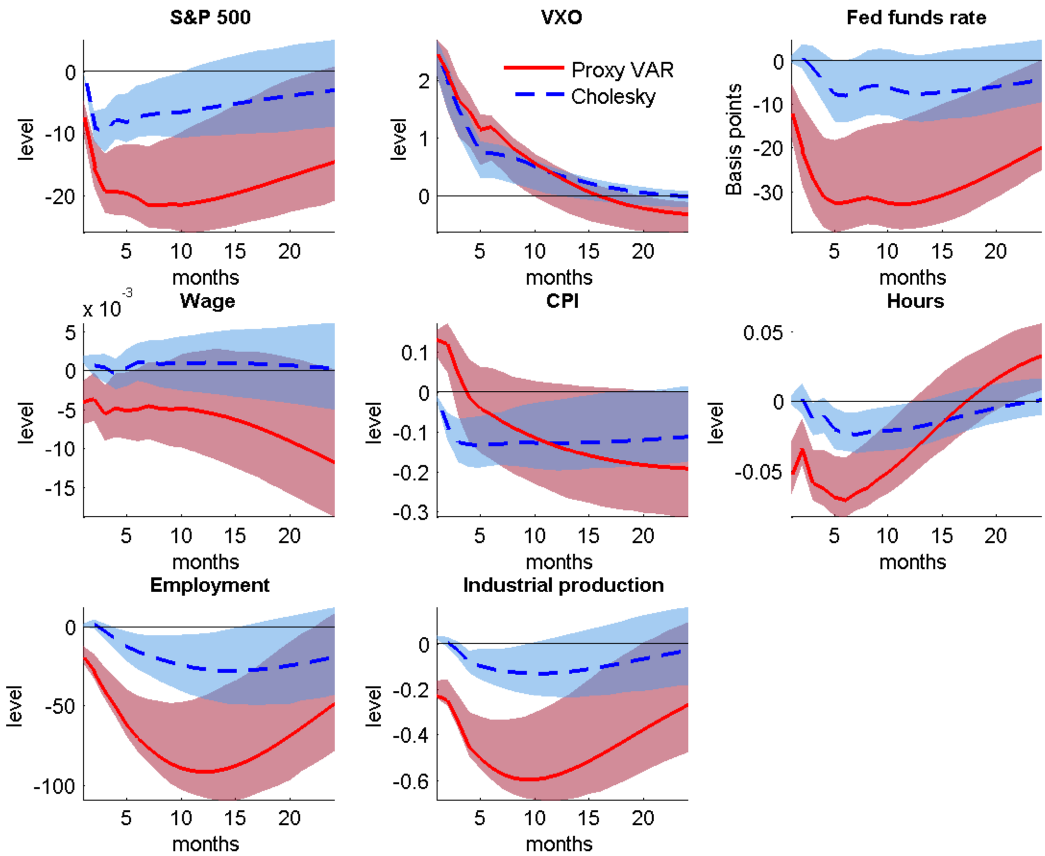
Note: Data plotted as it enters the VAR model: either in levels or in log difference.

Figure 4.D.7: Impulse responses to an uncertainty shock with all variables expressed as deviations from HP trend



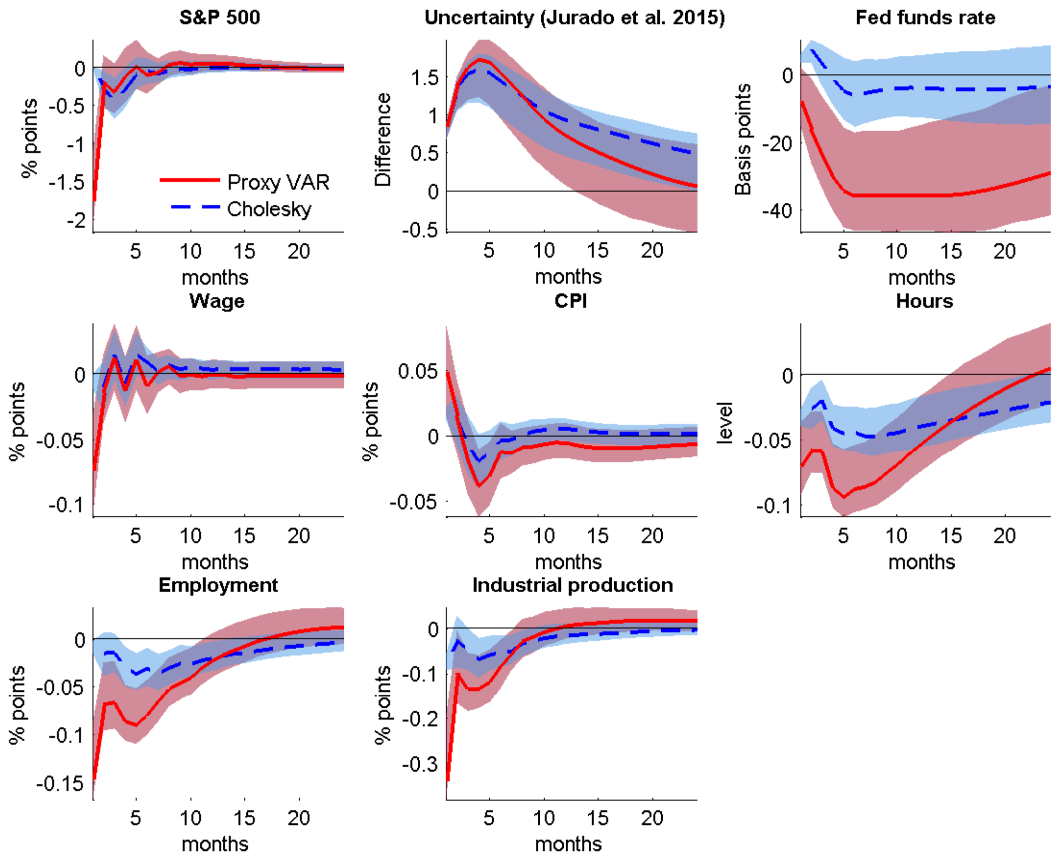
Note: pointwise 90 percent confidence bands reported based on 1000 bootstrap replications.

Figure 4.D.8: Impulse responses to an uncertainty shock with all variables entering in levels



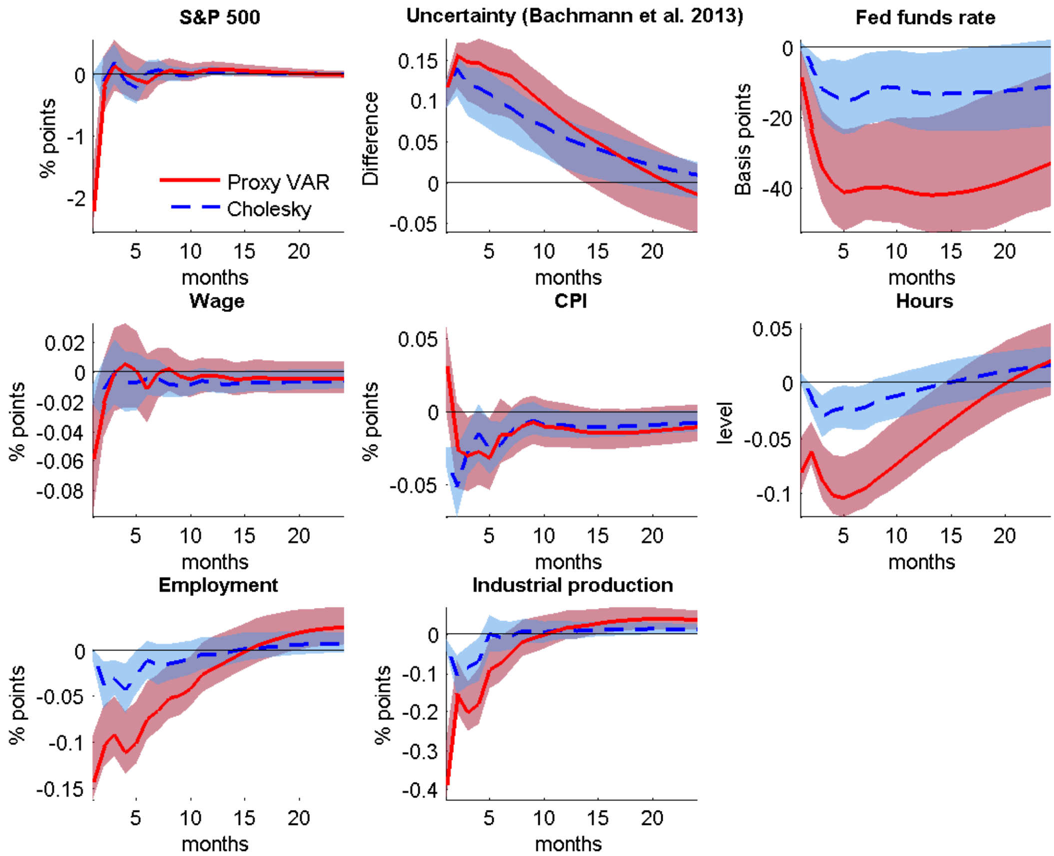
Note: pointwise 90 percent confidence bands reported based on 1000 bootstrap replications.

Figure 4.D.9: Impulse responses to an uncertainty shock with uncertainty measure taken from Jurado et al. (2015)



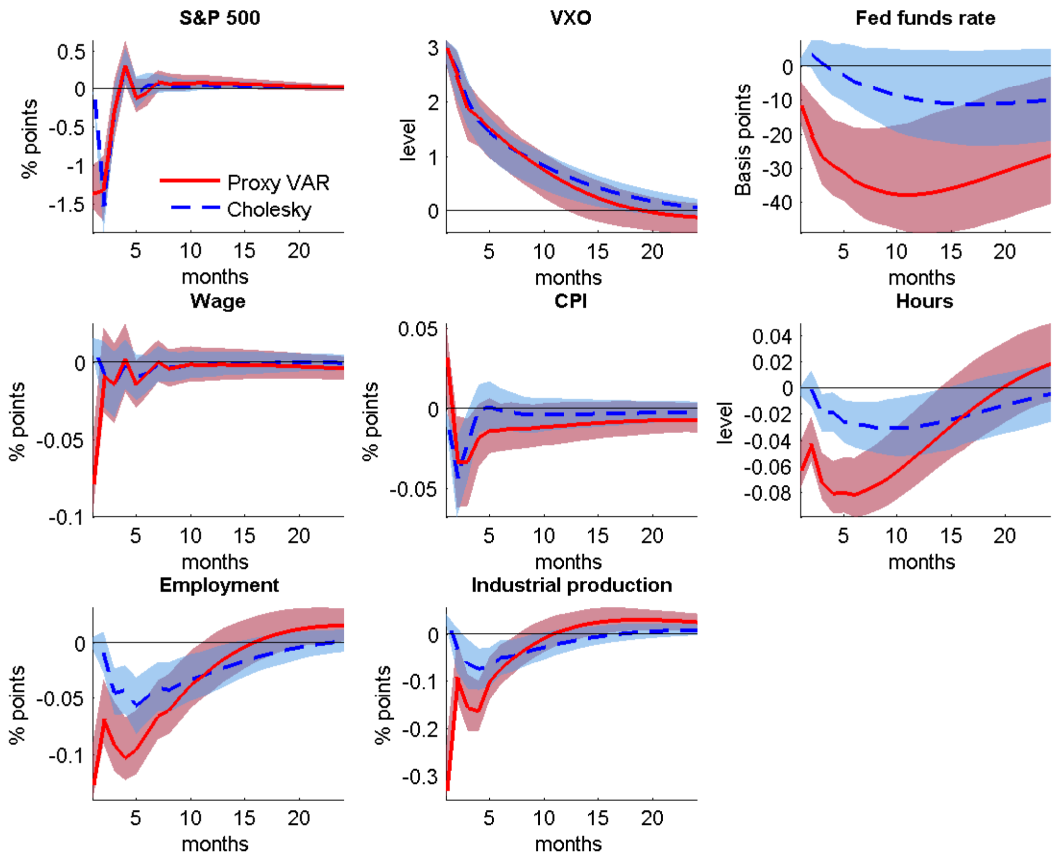
Note: pointwise 90 percent confidence bands reported based on 1000 bootstrap replications.

Figure 4.D.10: Impulse responses to an uncertainty shock with uncertainty measure taken from Bachmann et al. (2013)



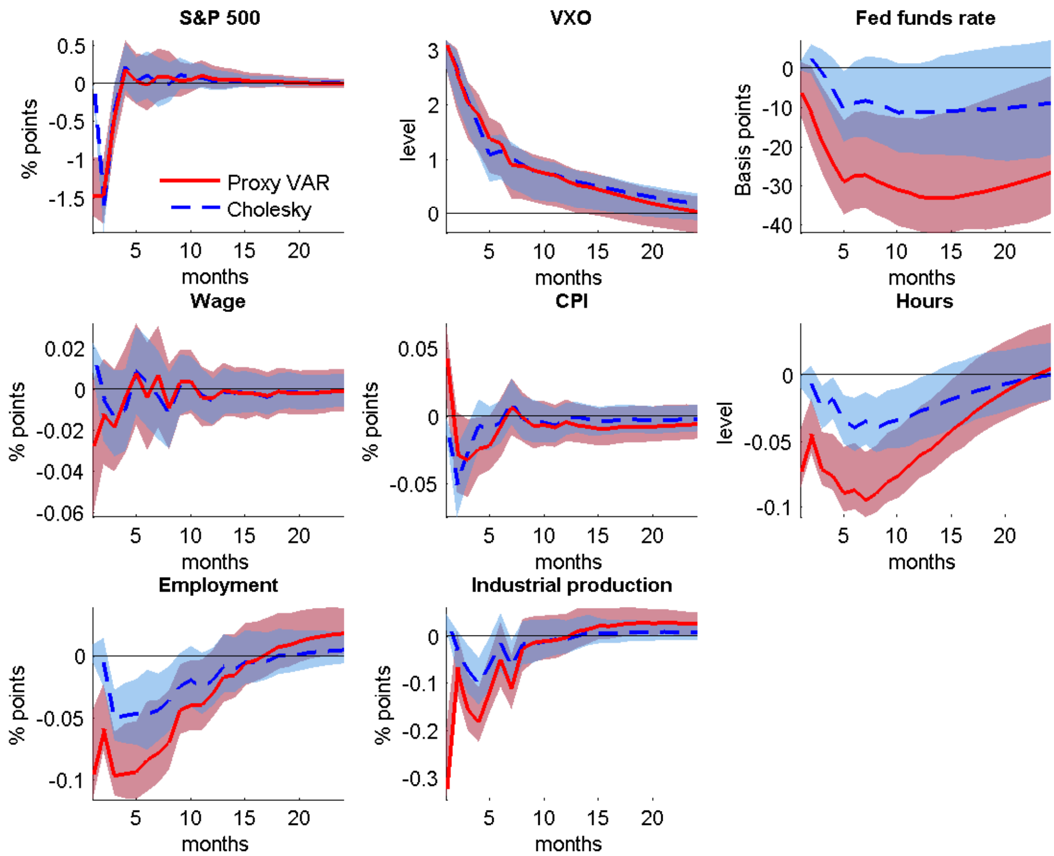
Note: pointwise 90 percent confidence bands reported based on 1000 bootstrap replications.

Figure 4.D.11: Impulse responses to an uncertainty shock based on VAR(3)



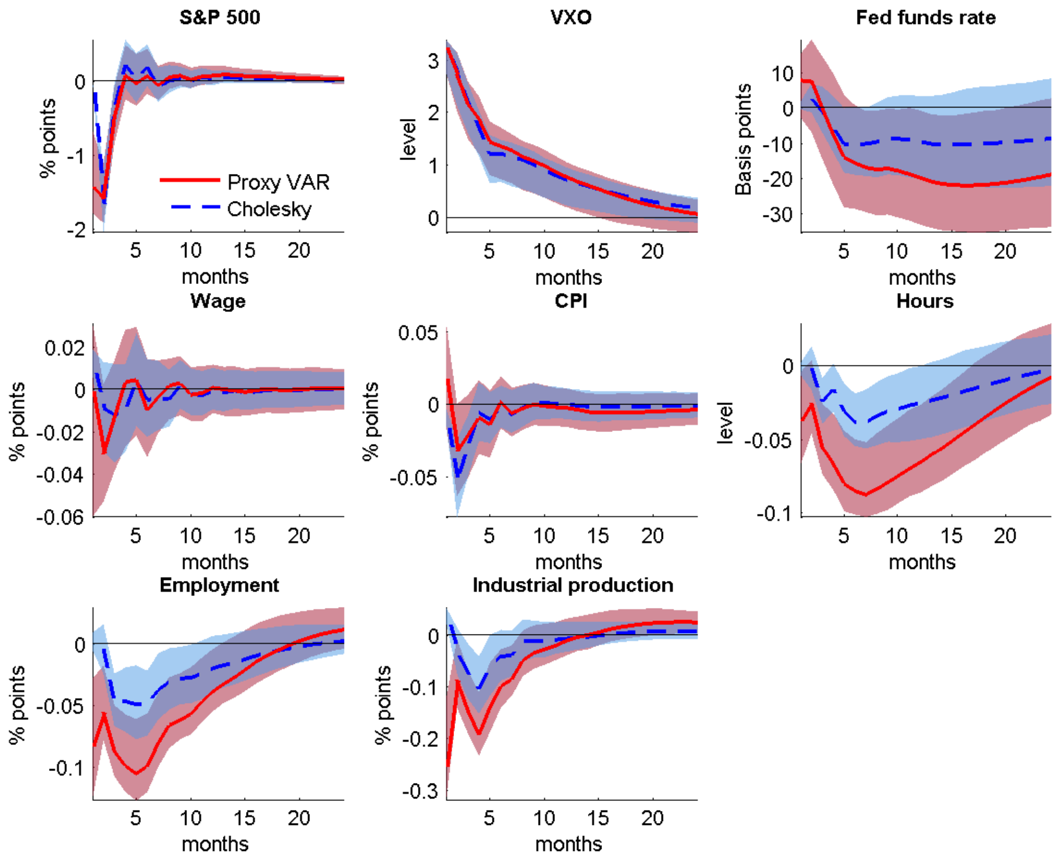
Note: pointwise 90 percent confidence bands reported based on 1000 bootstrap replications.

Figure 4.D.12: Impulse responses to an uncertainty shock based on VAR(7)



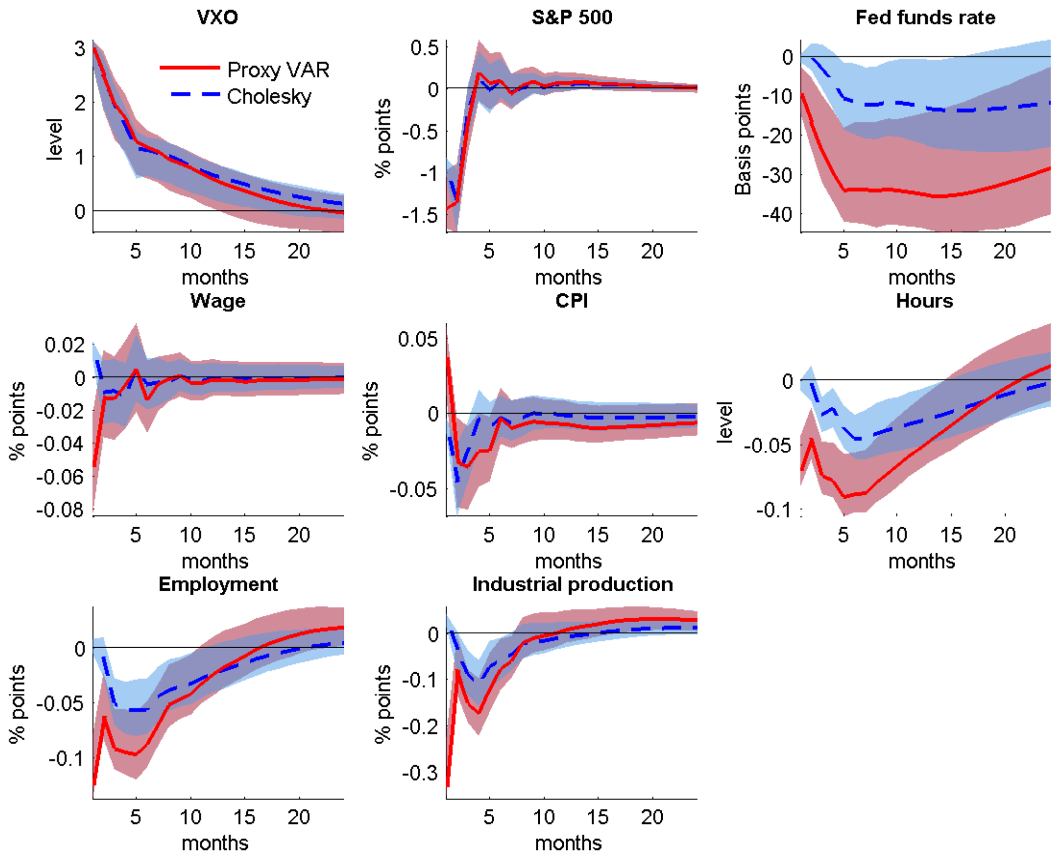
Note: pointwise 90 percent confidence bands reported based on 1000 bootstrap replications.

Figure 4.D.13: Impulse responses to an uncertainty shock based on proxy variable constructed using all 117 events in the database



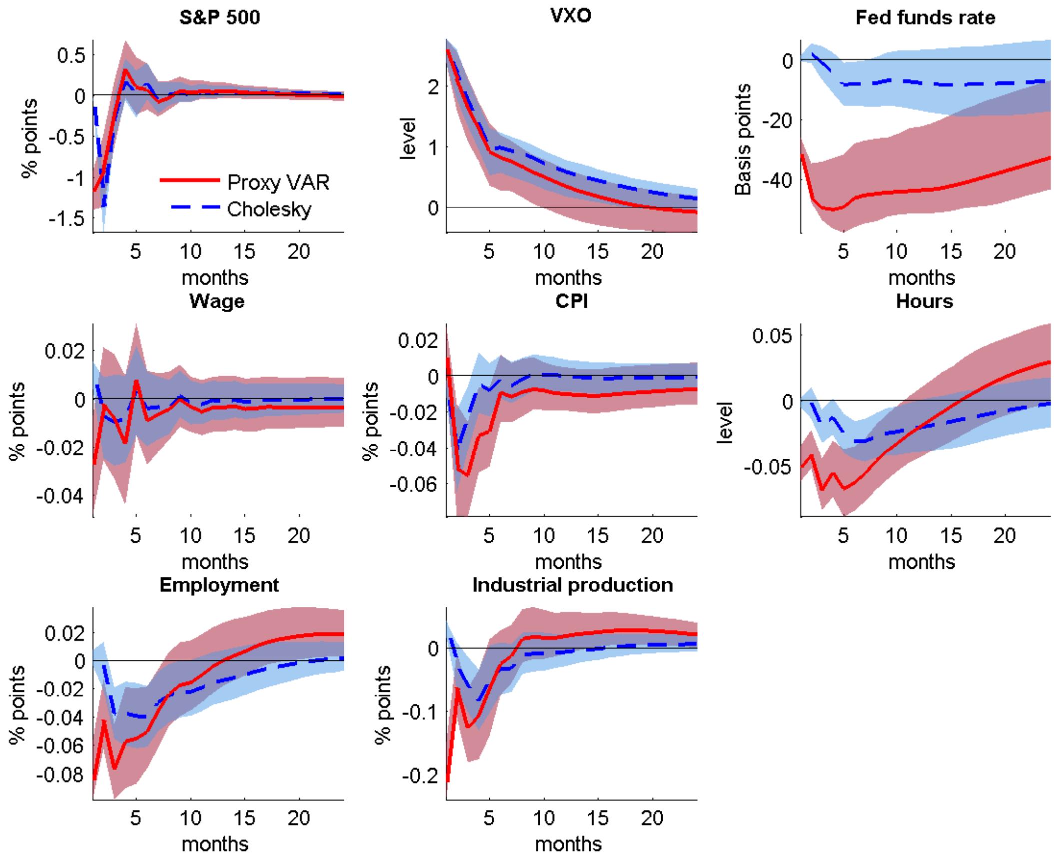
Note: pointwise 90 percent confidence bands reported based on 1000 bootstrap replications.

Figure 4.D.14: Impulse responses to an uncertainty shock with uncertainty measure ordered first in the recursive SVAR model (and baseline proxy SVAR)



Note: pointwise 90 percent confidence bands reported based on 1000 bootstrap replications.

Figure 4.D.15: Impulse responses to an uncertainty shock with monthly aggregation of the proxy for uncertainty computed as in Gertler and Karadi (2014)



Note: pointwise 90 percent confidence bands reported based on 1000 bootstrap replications.

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