Financial stress, Uncertainty, and Economic Activity

Inaugural-Dissertation
zur Erlangung des akademischen Grades eines Doktors
der Wirtschafts- und Sozialwissenschaften
der Wirtschafts- und Sozialwissenschaftlichen Fakultät der
Christian-Albrechts-Universität zu Kiel

vorgelegt von

Diplom-Volkswirt / Statisticien Economiste

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Kiel, 2013

Gedruckt mit Genehmigung

der Wirtschafts- und Sozialwissenschaftlichen Fakultät

der Christian-Albrechts-Universität zu Kiel

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Tag der Abgabe der Arbeit: 19. Juni 2013

Tag der mündlichen Prüfung: 9. September 2013

Acknowledgments

First of all, I would like to express my deep gratitude to my doctoral supervisor Joachim Scheide for supporting me during the past years in my research and my work in the Forecasting Center at the Kiel Institute for the World Economy. Without his invaluable support, his distinct guidance and encouragement, completing this dissertation would not have been thinkable. I especially appreciated the stimulating conversations about economic policy, particularly in the field of monetary economics. This exceedingly helped me to improve my research and its results. Furthermore, I would like to thank Stefan Reitz for becoming my thesis committee member on short notice.

I am deeply indebted to my co-authors Dario Bonciani (chapter 2), Sofiane Aboura (chapter 4), and Jonas Dovern (chapter 5), who contributed to this work. In addition, I would also like to express my deep gratitude to my friends and colleagues from the Forecasting Center of the Kiel Institute for the World Economy. In particular, my thanks go to Alfred Boss, Jens Boysen-Hogrefe, Klaus-Jürgen Gern, Dominik Groll, Nils Jannsen, Stefan Kooths, Martin Plödt, and Tim Schwarzmüller for countless discussions about economic policy. Moreover, I would like to thank Maik Wolters, Henning Weber, Mewael Tesfaselassie, and Christopher Reicher for numerous scientific advices and proposals for improving this dissertation. I would also like to thank Paul Kramer for subsequent corrections and proof-reading.

Last but not least, I would like to thank my family. Thanks to my wife Carolina for her empathy and for her patience during the weekends and evening hours that I spent in the office. Thanks to my parents Doris and Peter van Roye for giving me the opportunity to choose my professional employment career and supporting me in any matter. I am also highly indebted to my dog Filou for always being on my side. I would also like to thank Karin Helms for taking so much care of Filou and covering my back when I was tied up with business.

Abstract

The recent global financial crisis has shown that the importance of financial market developments for business cycle fluctuations had been underestimated substantially. Since financial factors were only peripherally integrated into standard macroeconomic models, these models significantly had underestimated the scope and persistence of the financial crisis.

This dissertation contributes to the literature by providing a comprehensible theoretical and empirical framework for analyzing the propagation of shocks to macroeconomic uncertainty and financial stress on economic activity. To do so, this dissertation employs both theoretical and empirical methods, such as a dynamic stochastic general equilibrium (DSGE) model, dynamic factor models, and vector autoregressive models. The nonlinear nature of uncertainty and financial stress is always taken into account by applying appropriate analytical and numerical methods.

In Chapter 2, we analyze the role of macroeconomic uncertainty for macroeconomic fluctuations in a theoretical model. We set up a medium-sized DSGE model that incorporates heterogeneous agents and a banking sector. The banking sector operates in a not fully competitive environment. We find that frictions in credit supply amplify the effects of uncertainty shocks on economic activity. This amplification channel stems mainly from the stickiness in banking retail interest rates. This stickiness reduces the effectiveness in the transmission mechanism of monetary policy.

In Chapter 3, I derive a financial stress index (FSI) for Germany, using a dynamic approximate factor model that summarizes a stress component of various financial variables. I estimate the model with a combined maximum-likelihood and Expectation Maximization (EM) algorithm, allowing for mixed frequencies and an arbitrary pattern of missing data. Subsequently, I analyze the effects of financial stress on economic activity in a threshold vector autoregressive (TVAR) model. I find that if the index exceeds a certain threshold, an increase in financial stress leads to a decline in economic activity, whereas if the stress level is below this threshold, economic activity is not significantly affected.

In Chapter 4, we develop a FSI for France that can be used as a real-time composite indicator for the state of financial stability. We take 17 financial variables from different market segments and extract a common stress component using a dynamic approximate factor model. In particular, we use the same methodology as in Chapter 3. Subsequently, we use a Markov-Switching Bayesian VAR model (MSBVAR) and show that during episodes of high financial stress economic activity is significantly lower, whereas during episodes of low financial stress economic activity is not significantly affected.

In Chapter 5, we analyze the international transmission of financial stress and its effects on economic activity. We construct country-specific monthly FSIs using dynamic factor models from 1970 until 2012 for 20 countries. We show that there is a strong co-movement of the FSIs during financial crises and that the FSIs of financially open countries are relatively more correlated to FSIs of other countries. Subsequently, we investigate the international transmission of financial stress and its impact on economic activity in a Global VAR (GVAR) model. We show that i) financial stress is quickly transmitted internationally, ii) financial stress has a lagged but persistent negative effect on economic activity, and iii) that economic slowdowns induce only limited financial stress.

Zusammenfassung

Die globale Finanzkrise der Jahre 2008 und 2009 hat gezeigt, dass der Einfluss von Fehlentwicklungen an den Finanzmärkten auf die Konjunktur lange Zeit deutlich unterschätzt wurde. Da Finanzmarktvariablen in den traditionellen makroökonomischen Modellen nur eine untergeordnete Rolle gespielt hatten, wurden sowohl das Ausmaß als auch die Länge der Finanzkrise dramatisch unterschätzt.

Diese Dissertation soll zum einen dazu beitragen, die Finanzstabilität in verschiedenen Ländern anhand einer Vielzahl von Indikatoren in Echtzeit zu messen und eine frühzeitige Erkennung von Fehlentwicklungen an den Finanzmärkten zu ermöglichen. Hierzu werden Finanzmarktstressindikatoren berechnet, die einen möglichst umfangreichen Überblick über die Stabilität des jeweiligen Finanzsystems geben sollen. Zum anderen sollen die konjunkturellen Auswirkungen von Finanzmarktstress und damit zusammenhängenden Unsicherheitsschocks analysiert werden. Hierzu greift die Dissertation methodisch sowohl auf ein theoretisches Modell, in Form eines dynamischen stochastischen Modells des allgemeinen Gleichgewichts (DSGE), als auch auf empirische Methoden, in Form von vektorautoregressiven (VAR) Modellen und dynamischen Faktormodellen, zurück. Dabei wird stets berücksichtigt, dass Nichtlinearitäten bei Finanzmarktschocks von essentieller Bedeutung sind. Vor diesem Hintergrund werden Methoden angewandt, die mit der nichtlinearen Natur von Unsicherheitsschocks und Finanzmarktschocks adäquat umgehen.

In Kapitel 2 wird ein DSGE Modell mit einem stilisierten Bankensektor hergeleitet und die Auswirkungen von makroökonomischen Unsicherheitsschocks auf die Konjunktur untersucht. Es wird gezeigt, dass kreditangebotsseitige Friktionen die konjunkturellen Auswirkungen von Unsicherheitsschocks verstärken. Darüber hinaus wird gezeigt, dass die Geldpolitik unter Friktionen am Kreditmarkt die negativen Effekte von Unsicherheitsschocks nicht vollständig kompensieren kann.

In Kapitel 3 wird ein Finanzmarktstressindikator (FSI) für Deutschland entwickelt, der sich aus Finanzmarktvariablen verschiedener Marktsegmente zusammensetzt. Der Indikator wird mithilfe eines dynamischen Faktormodells über

einen Zeitraum von 1970 bis 2012 konstruiert. Anhand des Indikators wird untersucht, in wie weit sich die Finanzstabilität auf die makroökonomische Stabilität auswirkt. Hierzu wird ein VAR Schwellenwertmodell (Threshold VAR) angewandt, mit dem zwei Regime identifiziert werden: ein Regime mit hohem Finanzmarktstress und ein Regime mit niedrigem Finanzmarktstress. Während sich Veränderungen des Finanzmarktstresses merklich auf die Realwirtschaft auswirken, wenn der FSI oberhalb des Schwellenwerts liegt, hat er keinen Einfluss wenn er sich unterhalb dieses Schwellenwertes befindet.

In Kapitel 4 wird ein Finanzmarktstressindikator für Frankreich entwickelt. Dabei wird die Methode aus Kapitel 3 angewandt. Es wird gezeigt, dass der Indikator wichtige Ereignisse in der jüngeren Geschichte gut abbildet. Darüber hinaus werden anhand eines Bayesianischen Markov-Switching Modells (MSB-VAR) ein Regime mit hohem Finanzmarktstress und ein Regime mit niedrigem Finanzmarktstress identifiziert. Ferner zeigen wir, dass Finanzmarktstress die Konjunktur in Frankreich nur dämpft, wenn sich die Wirtschaft in einem Umfeld mit hohem Finanzmarktstress befindet.

In Kapitel 5 werden der Grad der internationalen Synchronisierung und die internationalen Auswirkungen von Finanzmarktstress untersucht. Hierzu werden Finanzmarktstressindikatoren für 20 Länder berechnet und ihre Korrelation über den Zeitraum von 1970 bis 2012 analysiert. Es wird gezeigt, dass das Ausmaß der Korrelation maßgeblich vom finanziellen Offenheitsgrad der Volkswirtschaften abhängt. Darüber hinaus wird wir anhand eines globalen vektorautoregressiven Modells (GVAR) gezeigt, dass sich Finanzmarktstress über Ländergrenzen hinweg sehr schnell ausbreitet und dass globale Finanzmarktschocks lang anhaltende dämpfende Auswirkungen auf die Konjunktur haben.

Contents

List of Figures

List of Tables

List of Tables

CHAPTER 1

Introduction

The recent global financial crisis has shown that the importance of financial market developments for business cycle fluctuations had been underestimated substantially. Since financial factors were only peripherally integrated into standard macroeconomic models, these models significantly had underestimated the scope and persistence of the financial crisis. In general, the analytical framework that was usually used until the beginning of the financial crisis was unable to systematically incorporate the most relevant elements (Borio (2011a)).

In the meantime, central banks, academic researchers and private financial institutions have increasingly worked on developing new measures for analyzing and predicting extraordinary financial events.[1] Since financial instability is likely to have negative consequences for economic activity, it is crucial for macroeconomic policy to identify financial imbalances and financial stress at an early stage in order to implement appropriate policy measures.

Likewise, macroeconomic uncertainty has proven to be a significant driver during the recent financial crisis (Bloom (2009) and Gilchrist and Zakrajsek (2012)).[2] An increase in macroeconomic uncertainty may lead to precautionary behavior of firms and households such that firms temporarily pause their investment and hiring, and households reduce their consumption spending. While in partial equilibrium output and its components generally co-move after an un-

[1] In practice, the European Central Bank (ECB) has developed indicators that are aimed to "measure the current state of instability, i.e. the current level of frictions, stresses and strains in the financial system" in the euro area (European Central Bank (2011) and Holló et al. (2012)), the IMF has developed financial stress indexes to identify financial turmoils in advanced economies, and Hakkio and Keeton (2009) and Davig and Hakkio (2010) developed financial stress indexes for the Federal Reserve which are frequently used to monitor financial stability.

[2] Macroeconomic uncertainty can be interpreted as a wider distribution of expected future shocks to total factor productivity, for instance.

certainty shock, this may not be the case in a general equilibrium framework (Basu and Bundick (2012) and Christiano et al. (2013)). It is therefore important to further investigate how macroeconomic uncertainty shocks propagate to the economy and which factors are meaningful for the conduct of economic policy.

This dissertation contributes to the literature in several dimensions by proposing theoretical and empirical tools for analyzing the role of macroeconomic uncertainty and financial stress for business cycle fluctuations. First, it provides a comprehensive theoretical DSGE model that incorporates heterogeneous agents, a stylized banking sector, and stochastic volatility to investigate the transmission of macroeconomic uncertainty shocks to real economic activity. The model provides a framework for investigating macroeconomic uncertainty shocks under credit market imperfections. We show that supply side constraints in the financial sector play an important role in amplifying the effects of uncertainty shocks (Chapter 2). Second, this dissertation presents a broad empirical investigation of uncertainty and financial stress. To this end, it provides a number of FSIs for several countries. In particular, it provides a comprehensible FSI as a measure of financial stability for Germany and France and investigates its propagation mechanism on economic activity using nonlinear VAR models (Chapter 3 and 4). Finally, it analyzes the transmission of financial stress in a multi-country framework and its cross-border effects (Chapter 5). In this context, it analyzes the relevance of international synchronization of financial stress and its international impact on economic activity.

1.1 Review of chapter 2[3]

In this chapter (joint work with Dario Bonciani) we investigate the effects of macroeconomic uncertainty shocks on economic activity under credit market imperfections and a frictional banking sector. Since uncertainty shocks mainly occur when the financial system is under strain, we analyze how increasing uncertainty transmits to real macroeconomic aggregates in a model that incorporates a stylized banking sector.

[3] This chapter is based on: Bonciani and van Roye (2013). Uncertainty shocks, banking frictions, and economic activity. Kiel Working Paper No. 1843, The Kiel Institute for the World Economy.

Our contribution to the literature is threefold: first, we set up an empirical analysis for the euro area and show that uncertainty shocks matter for economic activity. Using a Bayesian vector autoregression, we find that an increase in uncertainty leads to a persistent decrease of GDP and investment. Second, we analyze the effects of uncertainty shocks on business cycle fluctuations using a Dynamic Stochastic General Equilibrium (DSGE) model that incorporates nominal rigidities and financial frictions. We build a multi-sector model featuring credit frictions and borrowing constraints for entrepreneurs as in Iacoviello (2005) and price rigidities as in Rotemberg (1982). Moreover, the model is augmented by a stylized banking sector inspired by Gerali et al. (2010). In order to isolate the effects that stem from macroeconomic uncertainty, we apply a nonlinear moving average perturbation technique and approximate the model up to third-order.

The main results of our analysis are as follows. First, we show that frictions in the banking sector considerably amplify the negative effects of uncertainty shocks. Second, we reconcile the stronger effects of uncertainty shocks found in the data by simulating an uncertainty shock while the economy is in a recession. We argue that there could be strong nonlinear effects due to the financial crisis and show that in a recession the impact of uncertainty shocks is potentially much larger.

My own contribution to this chapter is as follows. My co-author Dario Bonciani and I almost exclusively developed the model together. We jointly wrote the code and discussed the results. Finally, we jointly wrote the text and revised it.

1.2 Review of chapter 3[4]

In this chapter I construct a financial stress index (FSI) for Germany and investigate its relevance for business cycle fluctuations. I use 18 financial variables and aggregate them into a single composite index that can be used as a real time index for the state of financial stability. In order to construct the index, I use a dynamic approximate factor model with a broad measure for financial

[4] This chapter is based on: van Roye (2013). Financial Stress and Economic Activity in Germany. *Empirica*, DOI: 10.1007/s10663-013-9224-0, pages 1-27, Springer US.

stress including financial variables for the banking sector, the securities markets, the stock markets, and the foreign exchange market. As Brave and Butters (2011), I allow for the estimation of an unbalanced panel and account for the issue of ragged data edges due to publication lags in order to cope with longer time series and real time data. This is achieved by using a methodology that combines maximum likelihood and EM algorithm estimation techniques. This technique guarantees an efficient estimation for an arbitrary pattern of missing data as proposed by Banbura and Modugno (2012). Subsequently, I investigate the propagation mechanism of financial stress on macroeconomic aggregates by employing a threshold VAR approach. The impulse response analysis is based upon two-regime linear impulse response functions as well as nonlinear impulse responses as in Balke (2000).

Results can be summarized as follows. The FSI appropriately traces important events in German economic history. Moreover, given the results of the VAR analysis, the index can be considered as an additional indicator for the business cycle. While shocks to the index do not have significant effects on economic activity when the level of financial stress is low, they have a major impact when the index exceeds a certain threshold. Against this background, an increase in the index can be considered as an additional early warning indicator for an economic contraction in Germany when the FSI is above the estimated threshold.

1.3 Review of chapter 4[5]

In this chapter (joint work with Sofiane Aboura) we construct a FSI that can be used as a single composite indicator for the state of financial stability and financial fragilities in France. We take 17 financial variables from different market segments and extract a common stress component using a dynamic approximate factor model. We estimate the model with a combined maximum-likelihood and EM algorithm allowing for mixed frequencies and an arbitrary pattern of missing data. We apply a similar methodology as in van Roye (2013), presented in the previous chapter. To gain insights of how financial stress affects economic activity, we employ a Markov-Switching Bayesian VAR (MSBVAR)

[5]This chapter is based on: Aboura and van Roye (2013). Financial stress and economic dynamics: an application to France. Kiel Working Paper No. 1834, The Kiel Institute for the World Economy.

model. We present the smoothed state probabilities and regime dependent impulse responses.

The main results of this chapter are as follows. First, we show that the FSI traces important events in French economic history. Financial stress was extraordinary high after the presidential election of François Mitterand in 1981, when political uncertainty rose sharply due to the government's announcement of nationalizing private companies. Furthermore, we identify peaks during the oil crisis in 1973/1974, the stock market crash 1987, the collapse of the Soviet regime in 1991, and the Asian and Russian crisis in 1997/1998. The most pronounced increase of financial stress in France was during the recent global financial crisis. Second, by using a Markov-Switching model, we identify two regimes; i.e. a high stress and a low stress regime. We show that an increase in financial stress leads to lower economic activity when the economy is in the high-stress regime. Movements in the FSI in a low stress regimes do not lead to significant changes in economic activity.

My own contribution to this chapter is as follows. In general, the paper was joint work. I set up and estimated both the dynamic factor model and the MSBVAR. We wrote and revised the paper jointly. My co-author Sofiane Aboura provided me with the data and data transformations. In particular, he estimated the volatility models.

1.4 Review of chapter 5[6]

In this chapter (joint work with Jonas Dovern) we analyze the international transmission of financial stress and its impact on economic activity. We construct country-specific monthly financial stress indexes (FSI) using dynamic factor models from 1970 until 2012 for 20 countries. We conduct a cross-country correlation analysis and present statistical properties of the FSI. Subsequently, we investigate the international propagation of financial stress in a Global VAR (GVAR) model. We show that financial stress has a persistent negative effect on overall economic activity.

[6]This chapter is based on: Dovern and van Roye (2013). International transmission of financial stress: evidence from a GVAR. Kiel Working Paper No. 1844, The Kiel Institute for the World Economy.

Our contribution to the literature is threefold. First, we construct a comprehensible data set of financial stress indexes for 20 countries. We also provide external (trade-weighted) financial stress indexes for every country. Second, we show that country-specific FSIs co-move especially during financial stress events. The FSIs of countries with a higher degree of financial openness are stronger correlated than the FSIs of countries with a lower degree. Moreover, co-movement of financial stress increases over time reflecting a deepening in financial integration. Third, we find that global shocks in financial stress propagate significantly to industrial production in the analyzed countries. In particular, we find that i) financial stress is quickly transmitted internationally, ii) financial stress has a lagged but persistent negative effect on economic activity, and iii) that economic slowdowns induce only limited financial stress.

My own contribution to this chapter is as follows. In general, the paper was joint work. I collected the data for each country and set up and estimated the dynamic factor model. In addition, I implemented the correlation analysis of financial stress. My co-author Jonas Dovern set up and estimated the GVAR model. We wrote and revised the paper jointly.

CHAPTER 2

Uncertainty shocks, banking frictions, and economic activity[1]

2.1 Introduction

The negative effect of uncertainty on economic activity is a prevalent topic in both economic policy and academic research. Policy makers and economists have repeatedly claimed that high macroeconomic uncertainty among investors hinders the economy to recover. While there has been a vastly growing literature on the macroeconomic effects of uncertainty shocks, led by the seminal paper by Bloom (2009), there has been relatively little research on the effects of uncertainty shocks under financial frictions. In particular, the existing literature has not yet explained the relationship between uncertainty shocks and frictional banking markets. This chapter tries to fill this gap by investigating the effects of uncertainty shocks when banks operate in monopolistic competition and there is an imperfect pass-through of the central bank's policy rate to both the deposit and the loan rate. Both frictions have been shown to be theoretically and empirically important at business-cycle frequency.[2]

Our contribution is threefold: first, we provide an empirical motivation for the study of uncertainty shocks. Therefore we estimate a small Bayesian Vector Autoregressive (BVAR) model and show that higher uncertainty reduces main macroeconomic aggregates in the euro area. Secondly, we analyze the effects of

[1] This chapter is based on: Bonciani and van Roye (2013). Uncertainty shocks, banking frictions, and economic activity. Kiel Working Paper No. 1843, The Kiel Institute for the World Economy.

[2] The importance of monopolistic competition in the banking sector has been extensively documented in the microeconomic literature (see for instance Klein (1971) and Monti (1972)). In addition, there is vast empirical evidence for imperfect pass-through of the monetary policy rate to the retail rates (see for instance Sorensen and Werner (2006) and Gerali et al. (2010)).

uncertainty shocks on business cycle fluctuations using a Dynamic Stochastic General Equilibrium (DSGE) model which incorporates nominal rigidities and financial frictions. We build a multi-sector model featuring credit frictions and borrowing constraints for entrepreneurs as in Iacoviello (2005) and price rigidities as in Rotemberg (1982). Moreover, the model is augmented by a stylized banking sector inspired by Gerali et al. (2010). The main results of our analysis is that frictions in the banking sector considerably amplify the negative effects of uncertainty shocks on economic activity and make uncertainty shocks more persistent than otherwise. Thirdly, we reconcile the stronger effects of uncertainty shocks found in the data, compared with the relatively little ones obtained with our DSGE model. We explain that there could be strong nonlinear effects due to the financial crisis and show that in a recession the impact of uncertainty shocks is potentially much larger.

The relationship between macroeconomic uncertainty shocks and economic activity is widely analyzed in academic research. Economic theory provides a comprehensible framework in which higher uncertainty affects economic activity through irreversible investments, marginal revenues and precautionary savings (Bernanke (1983), Hartman (1976) and Abel (1983), Leland (1968) and Kimball (1990)). While almost all academic research papers find significant negative effects of uncertainty shocks on key economic variables in a partial equilibrium setup, the effects in a general equilibrium are more disputed. While Bachmann and Bayer (2011) claim there are no significant effects of uncertainty shocks in general equilibrium, Basu and Bundick (2012) claim that there are, given that prices are sticky and the central bank is constrained by the zero lower bound. Born and Pfeifer (2011) analyze the contribution of monetary and fiscal policy uncertainty shocks in the United States during the Great Recession. They show that while policy uncertainty can be found in the data, it is unlikely to have played a large role driving business cycle fluctuations. They find even smaller effects of uncertainty shocks to total factor productivity (TFP). Leduc and Liu (2012) study the macroeconomic effects of uncertainty shocks in a DSGE model with labor search frictions and sticky prices. They show that uncertainty shocks act like aggregate demand shocks since they increase unemployment and reduce inflation.

Albeit there is a a vast growing literature on the effects of uncertainty shocks, only few researchers have analyzed their impact of under financial frictions. Gilchrist et al. (2010) show, both empirically and theoretically, how time-varying uncertainty interacts with financial market frictions in dampening economic fluctuations. Using a standard bond-contracting framework, they find that an increase in uncertainty is beneficial to equity holders while it is costly for bond holders, since uncertainty shocks leads to an increase in the cost of capital and ultimately to declining investment. In addition, decreasing credit supply hinders efficient capital reallocation which leads to a further decrease in TFP. Christiano et al. (2013) apply a DSGE model incorporating the financial accelerator mechanism originally proposed by Bernanke et al. (1999) (BGG) and estimate it for the U.S. economy. They find that risk shocks (i.e., changes in the volatility of cross-sectional idiosyncratic uncertainty) play an important role for shaping U.S. business cycles. While Christiano et al. (2013) exclusively analyze idiosyncratic uncertainty shocks, Balke (2000) also investigate the effects of macroeconomic uncertainty shocks under credit frictions. Using a model with agency costs, they show that the financial accelerator amplifies the contractionary effects under price stickiness. In equal measure, Cesa-Bianchi and Fernandez-Corugedo (2013) show that credit frictions amplify the negative impact of uncertainty shocks on output, investment and consumption. They employ a modified version of the financial accelerator model as in Faia and Monacelli (2007). In addition, they find that micro uncertainty shocks seem to be quantitatively more important than a macro uncertainty shocks. This strand of literature using DSGE models based on the financial accelerator mechanism focuses only on frictions that characterize the demand side of the financial sector.

In this chapter, in contrast, we show that supply side constraints in the financial sector also play an important role in amplifying the effects of uncertainty shocks. Accounting for sticky retail interest rates determines an imperfect pass-through of the central bank interest rate to the private sector. The transmission mechanism of the monetary policy is hence weakened and less effective in offsetting the dampening effects of the uncertainty shock. This study is most closely related to Basu and Bundick (2012), Christiano et al. (2013), and Balke (2000). While Basu and Bundick (2012) use a standard New Keynesian model to show the effects of aggregate uncertainty, we assume that entrepreneurs are credit constrained and that lending is implemented through an imperfectly competitive banking sector.

The rest of the chapter is organized as follows. In section 2.2 we present empirical evidence of the effects of uncertainty shocks on economic activity by estimating a small BVAR model for the euro area. In section 2.3 we present short theoretical channels through which uncertainty shocks transmit to economic activity and provide simple economic intuitions. In section 2.4 we present the DSGE model with borrowing constrained entrepreneurs and a banking sector that is monopolistically competitive. In section 2.5 we describe the solution method and simulate the model deriving the main channel through which overall uncertainty transmits via the banking sector to the real economy and drives business cycle fluctuations. Finally, we present concluding remarks in section 2.6.

2.2 Empirical evidence

In order to provide evidence on the relevance of uncertainty shocks on economic fluctuations, we estimate a small BVAR model using euro area data.

2.2.1 Data

As a proxy for aggregate macroeconomic uncertainty we use an index that is derived from the volatility of financial market variables in the euro area. In particular, we use the VSTOXX which provides a measure of market expectations of short-term up to long-term volatility based on the EuroStoxx50 options prices.[3]

In order to investigate the effects of aggregate macroeconomic uncertainty for business cycle fluctuations, we collect further data from the Area Wide model database. We collect data for real GDP, fixed asset investment, the money market rate and the loan rate to non-financial corporations. A detailed description of the data can be found in the appendix.

2.2.2 Evidence from a BVAR model

To investigate the effects of uncertainty on economic dynamics in the euro area we estimate a small BVAR model with orthogonalized shocks to macroeconomic uncertainty. The available data sample for the euro area is relatively short. We estimate the model with quarterly data starting in 2003.[4] Against this background, we choose to estimate the model with Bayesian techniques, since sampling errors in estimating error bands for the impulse responses can occur when using a highly over parametrized model (Sims and Zha (1998)). The BVAR model has the following form:

$$y_t = B_1 Y_{t-1} + \cdots + B_p Y_{t-p} + \epsilon_t, \quad \text{where} \quad \epsilon_t \sim \mathcal{N}(0, \Sigma), \tag{2.1}$$

where $y_t = [VOL_t \ \Delta y_t \ \Delta fai_t \ \Delta c_t \ r_t \ r_t^b]'$ is a vector consisting of the following variables: the implied volatility of EUROSTOXX 50 option prices (VOL_t) as

[3] Basu and Bundick (2012) use a similar implied volatility index for the United States (VIX) in order to identify the uncertainty shock.

[4] The loan rate for non-financial corporations is only available from the beginning of 2003. The other time series are available for a longer time horizon. We also estimated the model with a longer time horizon without the loan rate. The results do not substantially differ from the ones reported here. Results are available upon request.

uncertainty variable, the logarithm of real GDP (y_t) as an indicator for economic activity, the logarithm of fixed asset investment (fai_t), the logarithm of private consumption, the EONIA-money market rate (r_t) as an indicator for the ECB's monetary policy stance and the loan rate r_t^b. $B_1, \ldots, B_p$ are $(q \times q)$ autoregressive matrices and Σ is the $(q \times q)$ variance-covariance matrix. For the prior distribution of the parameters we choose Jeffreys' improper prior to help improve the estimation of error bands for impulse responses. To be precise, the distribution on the parameters B and Σ i given by:

$$p(B, \Sigma) \propto |\Sigma|^{-\frac{ny+1}{2}}. \tag{2.2}$$

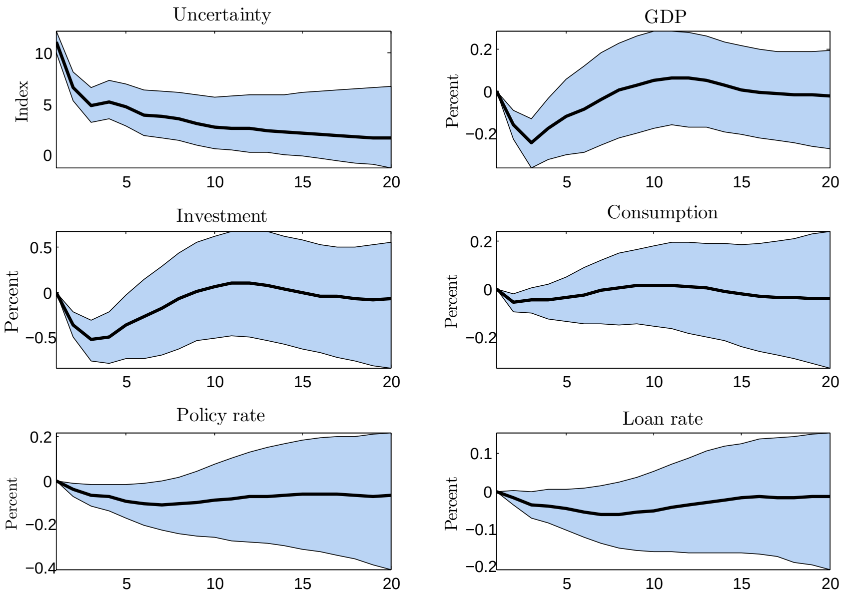
In our baseline model, we choose a lower triangular Choleski identification, ordering the uncertainty index first, such that on impact shocks to the uncertainty index have impact on the real variables. This ordering has been established in a vast majority of the literature (See for example Bloom (2009) and Baker et al. (2012)).[5] Vice versa, we assume that uncertainty is on impact not affected by shocks to the other endogenous variables. The impulse responses are depicted in Figure 2.1. While the black solid lines are median responses of the endogenous variables to one-standard-deviation increase in the innovations to uncertainty, the shaded areas represent 68 percent confidence intervals.

The IRF indicate that an exogenous increase of uncertainty leads to a persistent decline in real GDP and fixed asset investment. The effect on private consumption, the policy rate and the loan rate are very small, however. The strongest effect of a one-standard deviation increase in uncertainty hits after 4 quarters. While the median responses of GDP is a decline of about 0.2 percent, investment drops by about 0.5 percent. The results are in line with other empirical studies about the effects of uncertainty for other countries.[6] Our results indicate that uncertainty has negative business cycle effects in the euro area.

[5] A different ordering of the variables, in particular when the uncertainty index is ordered last, yields qualitatively similar results. Results are available upon request.

[6] Bloom (2009) and Baker et al. (2012) show in a VAR model that uncertainty leads to a persistent decrease in industrial production in the United States. Denis and Kannan (2013) find persistently negative effects of uncertainty on monthly GDP indicators for the United Kingdom and on economic sentiment indicators.

Figure 2.1: *Impulse responses after a macro-uncertainty shock*



NOTES: The volatility of the VSTOXX is ordered first. The black solid lines are median responses of the endogenous variables to one-standard-deviation increase in the innovations to uncertainty. Shaded areas represent 68 percent error bands.

2.3 Uncertainty shocks: Economic theory and intuition

The effects of uncertainty shocks on economic activity have been extensively analyzed in the microeconomic literature over the past decades. In particular it has been highlighted that increases in uncertainty affect the economy mainly via three channels (Born and Pfeifer (2011)):

1. Real options channel;
2. Convex marginal revenue product channel;
3. Precautionary savings channel.

The microeconomic effects of these channels are potentially contrasting and are the result of partial equilibrium analysis. In a general equilibrium framework the aforementioned effects may or may not be completely offset. In this section we briefly describe these channels and put them into a general equilibrium context.

Real options channel

The real option channel refers to the option value associated with irreversible investments. In particular, when an investment is utterly or even partially irreversible (i.e. once constructed, it cannot be undone without facing high costs) and the investor has an imperfect information concerning the future returns on long-term projects, there is an option value associated with avoiding such an investment (Bernanke (1983)). The agent who decides to postpone an investment, giving up short-term returns, will have the option in the next period either to invest or to further postpone the expenditure. As the investor is not endowed with perfect foresight on the returns on his investments, waiting and therefore obtaining new relevant information makes it more likely for her to make a better investment decision.

Investment opportunities, arising for instance from patents or from the ownership of land and natural resources, are similar to a financial call option, while investing in capital which may be sold in the future at a higher price, is effectively equivalent to purchasing a put option. A call (put) option is a contract that gives the right to the buyer to purchase (sell) an underlying asset at a predetermined price. When a firm makes an irreversible investment expenditure, it exercises its option to invest, as it gives up the possibility of waiting for new information to arrive that might affect the desirability or timing of the expenditure. It cannot disinvest in case the market conditions change adversely.

Obviously irreversible investments are particularly sensitive to risk concerning future cash flows, interest rates or the future price of capital. Uncertainty has a negative effect on the payoff of the agent owning the "call option" (the investment opportunity), while it has a positive effect on the payoff of the agents owning the "put option" (who already invested and can resell the capital at a predetermined higher price). As a bottom line, the real options effect may dampen economic activity when including investment and capital in our model. This is particularly the case when firms additionally face investment adjustment costs.

Convex marginal revenue product channel

In models with risk-neutral competitive firms with convex adjustment costs, if the marginal revenue product of capital is a strictly convex function of the price of output, then investment is an increasing function of the variance of price and of TFP. This means that increases in uncertainty about the price of output and TFP determines an increase in investment (Hartman (1976); Abel (1983)). All in all, this channel shows that higher uncertainty may result in accelerating investment and a boost in economic activity, which contrasts with the real options channel described above.

Precautionary savings channel

Under the assumption of additivity of the utility function or of decreasing risk aversion, an increase in uncertainty with respect to the future income stream leads to an increase in savings (Leland (1968)). Faced with higher uncertainty, agents reduce their consumption and supply more labor in order to insure themselves against future negative events. In a closed economy, the increase in savings determines a one-to-one increase in investment. Later on, Carroll and Samwick (1998) show that this behavior also holds empirically and that higher uncertainty about household's future income distribution leads to precautionary savings. As a bottom line, the precautionary savings channel may lead to an increase in investment and a decline in consumption. The overall effect on output cannot be determined a priori.

Effects in General Equilibrium

The effects discussed above are potentially contrasting and are the result of partial equilibrium analysis. While in partial equilibrium output and its components generally co-move after an uncertainty shock, this may not be the case in a general equilibrium framework (Basu and Bundick (2012)). The difficulty of generating business cycle co-movements and sizeable effects of uncertainty on major macroeconomic aggregates stems from the endogeneity of the real interest rate. In a standard Real Business Cycle (RBC) model, in which prices are fully flexible and there is no role for monetary policy, consumption falls and labor increases because of precautionary behavior. Given that capital is predetermined, the increase in labor input leads to an increase in output and savings. In a closed economy this implies a hike in investment. In contrast, in a New Keynesian model (NKM), characterized by sticky prices and time varying markups of prices over marginal costs, this is not necessarily the case. After an uncertainty shock, prices do not adjust immediately to changing marginal costs and markups rise as private households supply more labor. As a consequence of the increase in markups, labor demand falls and in equilibrium, hours worked may decline. In turn, output, consumption and investment fall.

In a NKM, however, the monetary authority can partially offset the negative effects of uncertainty by reducing the nominal interest rate. It is most importantly this reason why many papers do not find strong effects of uncertainty shocks on economic activity. A central bank that is aggressively counteracting uncertainty shocks offsets the negative effects on output similarly to other exogenous shocks (Born and Pfeifer (2011)). Also Bachmann and Bayer (2011) show that the endogenous feedback of nominal interest rates and nominal wages mitigate the negative effects on output. When the monetary authority is constrained by the zero lower bound, the effects of uncertainty become much more significant, as the central bank cannot perfectly respond to the shock. Similarly, accounting for frictions in the banking sector affects the transmission mechanism of monetary policy. When changes in the central bank's policy rate are not perfectly passed through to the private sector (by imposing monopolistic competition in the retail banking sector and assuming sticky loan and deposit rates), the offsetting power of the monetary authority is notably undermined. The zero lower bound is a more extreme constraint on the monetary policy than the imperfect pass-through. Nevertheless, it is important to point out that the zero lower bound is constraining under the circumstance of the policy interest rate actually being close to zero. The amplification channel in this chapter occurs also in "normal" times when the interest rate is far from the zero lower bound.

2.4 The model

We derive a medium-sized DSGE model based on Iacoviello (2005) and Gerali et al. (2010) featuring a frictional banking sector. The economy is populated by two types of agents: households and entrepreneurs. These are heterogeneous in their time preferences, such that in equilibrium, households are net lenders and entrepreneurs are net borrowers. Households maximize their discounted lifetime utility by choosing consumption and labor. They deposit their savings at commercial banks, which remunerate them with an interest rate r^d. In addition, we assume that households own shares of the commercial banks and of the final-good firms (i.e. retail firms).

Entrepreneurs own competitive firms that produce a homogeneous intermediate good by mixing labor services, supplied by the households, and capital that they purchase from capital producers. They sell the intermediate good to retailers, who use it to produce the final consumption good. Entrepreneurs get loans from the banks at a loan interest rate r^b. Their ability to borrow is constrained by the value of their stock of physical capital that is used as collateral. Entrepreneurs are furthermore assumed to own the capital producing firms.

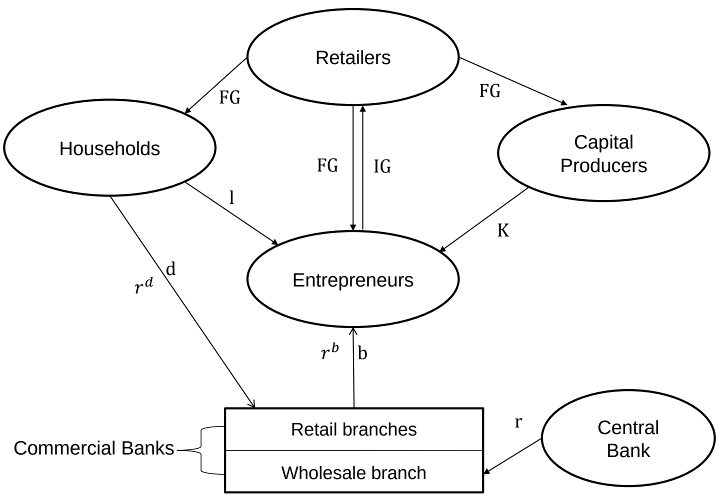
Capital-producing firms combine old undepreciated capital, acquired from the entrepreneurs, and final goods, purchased from the retailers in order to fabricate new capital. Transforming final goods into capital involves adjustment costs. Capital-producing firms sell the new capital back to the entrepreneurs.

Similarly as in Bernanke et al. (1999), price stickiness is introduced at the final-good firms level, with price adjustment costs á la Rotemberg (1982). These firms operate in monopolistic competition. They acquire intermediate goods from the entrepreneurs and produce differentiate final-consumption goods. These differentiation is only marginal, e.g. different brands or different colors.

The model economy features a frictional banking sector. Commercial banks conduct the financial intermediation activities. Each bank consists of two branches: a competitive wholesale branch that manages the capital of the bank and chooses the wholesale amount of deposits and loans; a retail branch that lends resources to entrepreneurs and collects deposits of the households. The retail branch operates in a monopolistically competitive environment and has therefore a certain degree of market power. It can therefore assert a relatively high loan interest rate to the entrepreneurs and a low deposit interest rate to the households with respect to the central bank interest rate, such that $r^d \leq r \leq r^b$. A very important characteristic of the model is the assumption that banks pay adjustment costs when changing the retail interest rates. The stickiness in the retail interest rates determines an imperfect pass-through of the monetary policy rate.

The model accounts for two exogenous shocks: a TFP "level" shock, i.e. a standard first-moment shock to technology, that enters the entrepreneur's production function; a TFP uncertainty shock, i.e. a second-moment shock to technology that enters indirectly the solution of the model. In figure 2.2 we depict the model economy.

Figure 2.2: *The model economy*



Notes: FG denotes the final good and IG the intermediate good.

2.4.1 Non-financial sector

We assume two different types of non-financial agents, i.e. households and entrepreneurs. Households are more patient than entrepreneurs and are therefore characterized by a higher intertemporal discount factor (i.e. $\beta_h > \beta_e$). This determines that in equilibrium households will be net lenders and entrepreneurs net borrowers.

Households

Each household i chooses consumption $c_t^h(i)$, labor $l_t(i)$ and savings to be deposited at the bank $d_t(i)$ in order to maximize its expected discounted lifetime utility:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta_h^t \left[log(c_t^h(i)) - \frac{l_t(i)^{1+\phi}}{1+\phi} \right], \tag{2.3}$$

where ϕ is the inverse of the Frisch labor supply elasticity. Each representative household maximizes its utility subject to its budget constraint:

$$c_t^h(i) + d_t(i) = w_t l_t(i) + \frac{1 + r_{t-1}^d}{(1+\pi_t)} d_{t-1}(i) + J_t^R(i) + (1-\varphi) J_t^B(i). \tag{2.4}$$

The expenditures of the current period consist of consumption and deposit contracts. The income stream of the households is composed of wage income ($w_t l_t(i)$), real interest payments resulting from last period's deposits made at the bank, deflated by the consumer price inflation ($(1 + r_{t-1}^d)/(1 + \pi_t)$), profits of the monopolistically competitive retail sector (J_t^R) and a share $(1 - \varphi)$ of profits J_t^B from the monopolistically competitive banking sector which is paid out as dividend.

Entrepreneurs

Entrepreneurs own firms that produce a homogeneous intermediate good. Each entrepreneur j maximizes her lifetime utility choosing consumption $c_t^e(j)$, borrowing $b_t(j)$ and the stock of physical capital $k_t(j)$

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta_e^t \left[\log(c_t^e(j)) \right], \tag{2.5}$$

subject to:

$$c_t^e(j) + w_t l_t(j) + \frac{1 + r_{t-1}^b}{(1+\pi_t)} b_{t-1}(j) + q_t^k k_t(j) = \frac{y_t^e(j)}{x_t} + b_t(j) + (1-\delta) q_t^k k_{t-1}(j),$$

where r^b represents the loan rate, δ is the capital depreciation rate, and q_t^k the real price of capital. Ultimately, $1/x_t = P_t^W/P_t$ is the relative price of the intermediate good, such that x_t can be interpreted as the gross markup of the final good over the intermediate good. The firm uses a Cobb-Douglas production function given by:

$$y_t^e(j) = z_t[k_{t-1}(j)]^\alpha l_t(j)^{1-\alpha}, \tag{2.6}$$

where z_t represents TFP and α is the share of capital employed in the production process.

As previously mentioned, entrepreneurs are allowed to borrow an amount of resources that is commensurate with the value of physical capital the entrepreneurs own. Hence, they face a borrowing constraint á la Kiyotaki and Moore (1997) that is given by:

$$(1 + r_t^b)b_t(j) \leq m\mathbb{E}_t[q_{t+1}^k(1 + \pi_{t+1})(1 - \delta)k_t(j)], \tag{2.7}$$

where the left-hand side is the amount to be repaid by the entrepreneur and the right-hand side represents the value of the collateral. In particular m represents the loan-to-value (LTV) ratio.

Capital producers

Capital producing firms are introduced in order to obtain a price for capital that is necessary to determine the value of the entrepreneur's collateral. These firms act in a perfectly competitive market and are owned by the entrepreneurs. They purchase last period's undepreciated capital $(1-\delta)k_{t-1}$ from the entrepreneurs at a price Q_t^k and i_t units of final goods from retail firms and combine them to produce new capital. In order to transform final goods into capital, these firms face quadratic adjustment costs. The new capital is then sold back to the entrepreneurs at the same price Q_t^k. The real price of capital is defined as $q_t^k \equiv \frac{Q_t^k}{P_t}$. Capital producers maximize then their expected discounted profits:

$$\underset{\{k_t,i_t\}}{max}\mathbb{E}_0\sum_{t=0}^{\infty}\Lambda_{0,t}^e\left(q_t^k\Delta k_t - i_t\right), \tag{2.8}$$

subject to:

$$k_t = k_{t-1} + \left[1 - \frac{\kappa_i}{2}\left(\frac{i_t}{i_{t-1}} - 1\right)^2\right] i_t, \tag{2.9}$$

As stated above, entrepreneurs own the capital producing firms. These take as given the entrepreneurs' stochastic discount factor (i.e the intertemporal marginal rate of susbtitution) $\Lambda^e_{0,t} \equiv \frac{\beta_e c^e_0}{c^e_t}$. κ_i governs the magnitude of the adjustment costs associated with the transformation of the final good into capital.

2.4.2 Retailers

The retailing firms are modeled similarly as in Bernanke (1983). These firms are owned by the households, they act in monopolistic competition and their prices are sticky. They purchase the intermediate-good from entrepreneurs in a competitive market, then slightly differentiate it, e.g. by adding a brand name, at no additional cost. Let $y_t(\nu)$ be the quantity of output sold by the retailer ν, and $P_t(\nu)$ the associated price. The total amount of final good produced in the economy:

$$y_t = \left[\int_0^1 y_t(\nu)^{(\epsilon^y-1)/\epsilon^y} \mathrm{d}\nu\right]^{\epsilon^y/(\epsilon^y-1)}, \tag{2.10}$$

with the associated price index:

$$P_t = \left[\int_0^1 P_t(\nu)^{(1-\epsilon^y)} \mathrm{d}\nu\right]^{1/(1-\epsilon^y)}. \tag{2.11}$$

In (2.10) and (2.11), ϵ^y represents the elasticity of substitution between differentiated final goods. Given (2.10), the demand that each retailer faces is equal to:

$$y_t(\nu) = \left(\frac{P_t(\nu)}{P_t}\right)^{-\epsilon^y} y_t. \tag{2.12}$$

Each firm ν chooses its price to maximize the expected discounted value of profits subject to the demand for consumption goods (2.12):

$$\underset{\{P_t(\nu)\}}{max}\, \mathbb{E}_0 \sum_{t=0}^{\infty} \Lambda^h_{0,t} \left[\left(P_t(\nu) - P^W_t\right) y_t(\nu) - \frac{k_P}{2}\left(\frac{P_t(\nu)}{P_{t-1}(\nu)} - (1+\pi)\right)^2 P_t y_t\right], \tag{2.13}$$

It is assumed that firms take the households' (that own the firms) stochastic discount factor , $\Lambda^h_{0,t} \equiv \frac{\beta_h c^h_0}{c^h_t}$, as given. Prices are assumed to be indexed to steady state inflation. The last term of the objective function represents quadratic adjustment costs the retailer j faces whenever she wants to adjust her prices beyond indexation (Rotemberg (1982)). As we have already mentioned P^W_t represents the price of intermediate goods that the retailers take as given.

2.4.3 Financial sector

The financial sector consists of commercial banks modeled similarly as in Gerali et al. (2010). Households are the shareholders of these banks. These operate on a wholesale level and on a retail level. The wholesale branch acts in a perfectly competitive market, manages the total capital of the bank and is characterized by the following balance sheet identity:

$$b_t = d_t + k_t^b, \tag{2.14}$$

which can be graphically represented by:

Banks Balance Sheet

Assets	***Liabilities***
b_t	k_t^b
	d_t

All bank assets consist of loans to firms b_t, whereas liabilities consist of bank capital (net worth) k_t^b, and wholesale deposits d_t.
The retail branch of the bank operates in a monopolistically competitive market and is composed by two divisions:

1. A loan-retail division, which is responsible for lending resources to the entrepreneurs;

2. A deposit-retail division, which collects the deposits of the saving households.

The market power in this market is modeled in a Dixit-Stiglitz fashion. Every loan (deposit) retail branch marginally differentiates the loan (deposit) contract. All these contract are then assembled in a CES basket that is taken as given by entrepreneurs and households. The demand for loans at bank n can be derived by minimizing the total debt repayment of entrepreneur j:

$$\min_{b_t(j,n)} \int_0^1 r_t^b(n) b_t(j,n) \mathrm{d}n, \tag{2.15}$$

subject to

$$\bar{b}_t(j) \leq \left[\int_0^1 b_t(j,n)^{(\epsilon^b - 1)/\epsilon^b} \mathrm{d}n \right]^{\epsilon^b/(\epsilon^b - 1)}, \tag{2.16}$$

where $\bar{b}_t$ is the amount of real loans sought by entrepreneur j and ϵ^b is the elasticity of substitution of loan contracts. The aggregate demand for loans at bank n is then given by:

$$b_t(n) = \left(\frac{r_t^b(n)}{r_t^b}\right)^{-\epsilon^b} b_t. \tag{2.17}$$

The demand function $b_t(n)$ depends negatively (as ϵ^b is assumed to be larger than 1) on the loan interest rate $r_t^b(n)$ that is set at the retail-division level, and positively on the total amount of loans b_t. The demand for deposits at bank n can be derived similarly by maximizing the total revenue of savings accruing to household i:

$$\max_{d_t(i,n)} \int_0^1 r_t^d(n) d_t(i,n) \mathrm{d}n \tag{2.18}$$

subject to

$$\bar{d}_t(i) \geq \left[\int_0^1 d_t(i,n)^{(\epsilon^d-1)/\epsilon^d} \mathrm{d}n\right]^{\epsilon^d/(\epsilon^d-1)}, \tag{2.19}$$

where $\bar{d}_t(i)$ is the amount of real deposits sought by household i and ϵ^d is the elasticity of substitution of deposit contracts. The aggregate demand for loans at bank n is equal to:

$$d_t(n) = \left(\frac{r_t^d(j)}{r_t^d}\right)^{-\epsilon^d} d_t. \tag{2.20}$$

The demand function $d_t(n)$ depends positively both on the deposit rate r_t^d that is set by the deposit retail-division, (since ϵ^d is assumed to be smaller than 1) and on the total volume of resources deposited in the bank d_t.

Wholesale branch

As mentioned above, the wholesale banking market is perfectly competitive. The wholesale branch of each bank maximizes the discounted sum of cash flows by choosing wholesale loans and deposits, b_t and d_t, taking into account the stochastic discount factor of the households $\Lambda_{0,t}^h$:

$$\underset{\{b_t,d_t\}}{max}\mathbb{E}_0\sum_{t=0}^{\infty}\Lambda_{0,t}^{h}\Big[(1+R_t^b)b_t-(1+\pi_{t+1})b_{t+1}+d_{t+1}-(1+R_t^d)d_t+(K_{t+1}^b(1+\pi_{t+1})-k_t^b)\Big], \tag{2.21}$$

subject to the budget constraint:

$$b_t = d_t + k_t^b, \tag{2.22}$$

and given the following law of motion for bank capital:

$$(1+\pi_t)k_t^b = (1-\delta^b)k_{t-1}^b + \varphi J_{t-1}^b. \tag{2.23}$$

It is moreover assumed that banks can obtain unlimited funding from the central bank at the policy rate r_t. The no-arbitrage condition hence implies that the wholesale deposit and loan rates coincide with r_t:

$$R_t^b = R_t^d = r_t. \tag{2.24}$$

Retail branch

Retail banks, in both loan and deposit activities, operate in monopolistic competition and are therefore profit maximizers. Loan-retail divisions maximize their expected discounted profits by choosing the interest rate on loans and facing quadratic adjustment costs. These banks borrow liquidity from the wholesale branch at rate R_t^b (which as we previously showed is equal to the policy rate) and lend it to the entrepreneurs at rate $r_t^b(n)$. The optimization problem of the loan-retail division of bank n is given by:

$$\mathbb{E}_0\sum_{t=0}^{\infty}\Lambda_{0,t}^{h}\left[\left(r_t^b(n)-r_t\right)b_t(n)-\frac{\kappa_b}{2}\left(\frac{r_t^b(n)}{r_{t-1}^b(n)}-1\right)^2 r_t^b b_t\right], \tag{2.25}$$

subject to the demand for loans (2.17).

Deposit-retail divisions maximize their profits by choosing the interest rate r_t^d which they pay on households' deposits. Their activity consists in collecting the households' deposits and lend those resources to the wholesale bank that pays an interest rate R_t^d (equal to r_t) on them. The optimization problem of the deposit division of bank n is:

$$\mathbb{E}_0\sum_{t=0}^{\infty}\Lambda_{0,t}^{h}\left[\left(r_t-r_t^d(n)\right)d_t(n)-\frac{\kappa_d}{2}\left(\frac{r_t^d(n)}{r_{t-1}^d(n)}-1\right)^2 r_t^d d_t\right], \tag{2.26}$$

where $d_t(n)$ are the wholesale deposits of bank n. The optimization problem is constrained by the demand for deposits of the households (2.20).

2.4.4 Monetary Authority

The central bank sets the nominal interest rate following a conventional Taylor type rule:

$$\frac{1+r_t}{1+r} = \left(\frac{1+r_{t-1}}{1+r}\right)^{\phi_r} \left[\left(\frac{1+\pi_t}{1+\pi}\right)^{\phi_\pi} \left(\frac{y_t}{y_{t-1}}\right)^{\phi_y}\right]^{(1-\phi_r)}, \tag{2.27}$$

where ϕ_r is a smoothing parameter that captures the gradual movements in the interest rate as in Clarida et al. (1999), r and π are respectively the steady state values of the policy rate and of inflation. ϕ_π and ϕ_y represent the weights the central bank gives to deviations of inflation from its steady state level and to output growth.

2.4.5 Market clearing

Ultimately the model is closed by combining the first order conditions of all agents to the clearing condition of the goods market:

$$y_t = c_t + [k_t - (1-\delta)k_{t-1}] + \delta^b \frac{k^b_{t-1}}{(1+\pi_t)} + ADJ_t, \tag{2.28}$$

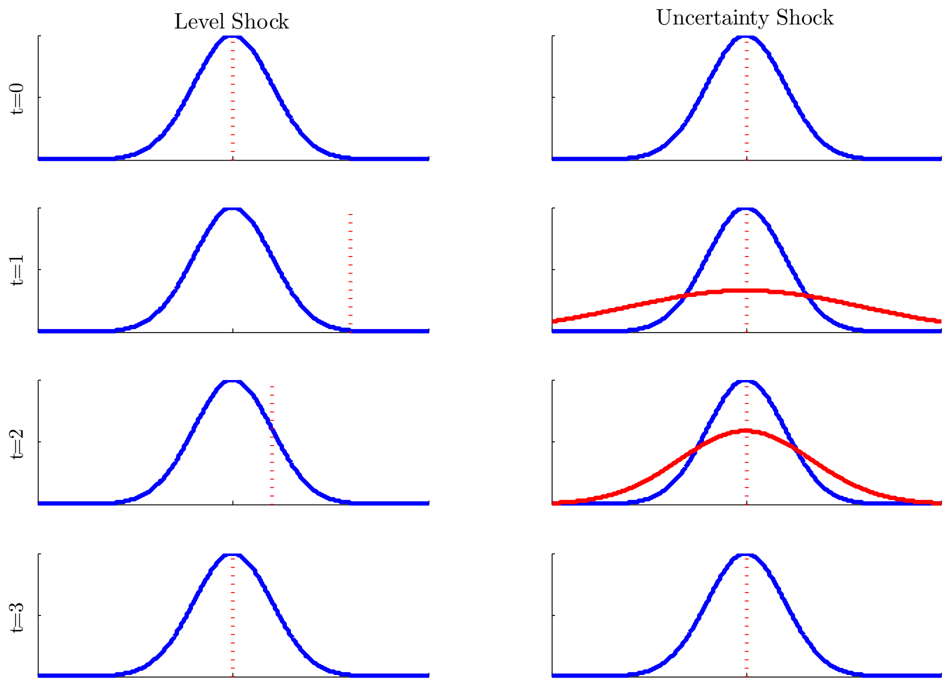
where $c_t \equiv c^h_t + c^e_t$ is aggregate consumption, k_t is aggregate physical capital and k^b_t, as mentioned before, represents aggregate bank capital. Ultimately ADJ_t includes all real adjustment costs for prices and interest rates:

$$ADJ_t \equiv \frac{\kappa_p}{2}(\pi_t)^2 y_t + \frac{\kappa_d}{2}\left(\frac{r^d_{t-1}}{r^d_{t-2}} - 1\right)^2 r^d_{t-1} d_{t-1} + \frac{\kappa_b}{2}\left(\frac{r^b_{t-1}}{r^b_{t-2}} - 1\right)^2 r^b_{t-1} b_{t-1}. \tag{2.29}$$

2.4.6 Shock processes

In order to model uncertainty shocks, we use the stochastic volatility approach as proposed by Fernandez-Villaverde et al. (2011), assuming time varying volatility of the innovation to TFP. An uncertainty shock is a second-moment shock that affects the shape of the distribution by widening the tails of the level shock and keeping its mean unchanged. A level shock is a first-moment shock that varies the level of TFP, keeping its distribution unchanged. A graphical comparison between the two types of shocks is shown in figure 2.3.

Figure 2.3: *Level and uncertainty shock*



NOTES: The left column represents a level shock to TFP. The right column represents a second moment shock. We assume the shock to die out in period $t = 3$.

The red dotted line represents the level of TFP that increases after a positive TFP level shock and returns to its initial level only after three periods. With a positive uncertainty shock, instead, the level of TFP remains constant, while its distribution becomes wider as the variance of the TFP shock increases. As the effect of the shock dissipates, the distribution returns to its initial shape.

The stochastic volatility approach ensures that the dispersion of the level shocks varies over time, such that there are sometimes large shocks and other times less intensive ones. We consider an exogenous shock to the volatility of TFP, that can also be interpreted as supply-side uncertainty. TFP follows an AR(1) process with time-varying volatility of the innovations:

$$z_t = (1 - \rho_z)z + \rho_z z_{t-1} + \sigma_t^z e_t^z. \tag{2.30}$$

The coefficient $\rho_z \in (-1, 1)$ determines the persistence of the TFP level shock. The innovation to the TFP shock, e_t^z, follows an *i.i.d.* standard normal process.

Furthermore the time-varying standard deviation of the innovations, σ_t^z, follows the stationary process:

$$\sigma_t^z = (1-\rho_{\sigma^z})\sigma^z + \rho_{\sigma^z}\sigma_{t-1}^z + \eta_z e_t^{\sigma_z}, \quad \text{where } e_t^{\sigma_z} \sim \mathcal{N}(0,1) \tag{2.31}$$

in which ρ_{σ^z} determines the persistence of the uncertainty shock, σ^z is the steady state value of σ_t^z and η_z is the (constant) standard deviation of the TFP uncertainty shock, $e_t^{\sigma_z}$.

2.5 Macroeconomic effects of uncertainty

2.5.1 Solution and simulation method

The model is solved with the algorithm and software developed by Lan and Meyer-Gohde (2011). Their solution method consists of a nonlinear moving average perturbation technique that maps our nonlinear DSGE model:

$$\mathbb{E}_t f(x_{t+1}, x_t, x_{t-1}, e_t) = 0, \tag{2.32}$$

into a system of equations, known as policy function:

$$x_t = h(\sigma, e_t, e_{t-1}, e_{t-2}, \dots). \tag{2.33}$$

In (2.32) and (2.33), x_t and e_t represent the vectors of endogenous (control and state) variables and exogenous shocks. $\sigma \in [0,1]$ denotes a scaling parameter for the distribution of the stochastic shocks e_t, such that $\sigma = 1$ corresponds to the original stochastic model (2.32), and $\sigma = 0$ to the non-stochastic case. The basic idea behind this solution method is to approximate the policy function with Volterra series expansion around the deterministic steady state:

$$x_t = \sum_{j=0}^{J} \frac{1}{j!} \prod_{l=1}^{j} \sum_{i_l=0}^{\infty} \left(\sum_{n=0}^{J-j} \frac{1}{n!} x_{\sigma^n i_1 i_2 \dots i_j} \sigma^n \right) (e_{t-i_1} \otimes e_{t-i_2} \otimes e_{t-i_3} \dots). \tag{2.34}$$

This Volterra series directly maps the exogenous innovations to the endogenous variables. As noted by Schmitt-Grohe and Uribe (2004), with a first order approximation, shocks only enter with their first moments. The first moments of future shocks in turn drop out when taking expectations of the linearized equations. This determines the property of certainty equivalence, i.e. agents completely disregard of the uncertainty associated with $\mathbb{E}_t[e_{t+1}]$. This property makes the first order approximation not suitable for the analysis of second moment shocks. In a second order approximation there are effects of volatility shocks that enter as cross-products with the other state variables (Fernandez-Villaverde et al. (2011)). This order of approximation is therefore not sufficient to isolate the effects of uncertainty from those of the level shock. As we are interested in analyzing the effects of uncertainty shocks, keeping the the first moment shocks shut off, it is necessary to approximate (2.33) up to a third order:

$$x_t = \bar{x} + \frac{1}{2}y_{\sigma^2} + \frac{1}{2}\sum_{i=0}^{\infty}(x_i + x_{\sigma^2,i})e_{t-i} + \frac{1}{2}\sum_{j=0}^{\infty}\sum_{i=0}^{\infty}x_{j,i}(e_{t-j}\otimes e_{t-i})$$
$$+ \frac{1}{6}\sum_{k=0}^{\infty}\sum_{j=0}^{\infty}\sum_{i=0}^{\infty}x_{k,j,i}(e_{t-k}\otimes e_{t-j}\otimes e_{t-i}). \tag{2.35}$$

A common problem when simulating time series with higher-order approximated solutions is that it often leads to explosive paths for x_t. A common solution, suggested by Kim et al. (2008), is that of "pruning" out the unstable higher-order terms. Nevertheless with the algorithm we have adopted (Lan and Meyer-Gohde (2013)) the stability from the first order solution is passed on to all higher order recursions, and no pruning is hence required.

2.5.2 Calibration

We calibrate the benchmark model on a quarterly basis for the euro area and set the parameter values according to stylized facts and to previous findings in the literature. The calibrated structural parameters of the model are illustrated in table (2.1). The discount factor for households is set to 0.9943 which results into a steady state interest rate on deposits of approximately 2 percent, while we set the loan rate for entrepreneurs to 0.975 as in Iacoviello and Neri (2010). The inverse of the Frisch labor supply elasticity is set to 1.0, in line with Christiano et al. (2013). We set the depreciation rate of capital δ to 0.025 and the share of capital in the production process α to 0.25. In the goods market we assume a markup of 20 percent and set ϵ^y to 6, a value frequently used in the literature. According to the posterior estimates of Gerali et al. (2010), we calibrate the paramater for the investment adjustment costs κ_i to 10.2 and the one for the price adjustment costs κ_p to 30.

Regarding the parameters for the banking sector, we base our calibration on Gerali et al. (2010). We set the loan-to-value ratio for entrepreneurs m to 0.35, the elasticities of substitution of the deposit (loan) rate to -1.46 (3.12) which implies a markdown (markup) on the deposit (loan) rate of about 1.6 (2.0) percentage points, values that are in line with statistical evidence of interest rate spreads in the euro area. In addition, bank management costs δ^b are set to 0.0105. Banks retain half of their profits in order to cover bank management costs. For this reason we set φ equal to 0.5. Furthermore, we set the loan rate adjustment costs κ_b to 9.5 and the deposit rate adjustment costs κ_d to 3.5, consistent with the estimation results of Gerali et al. (2010).

We assume the central bank to react aggressively to inflation by setting the parameter ϕ_π to 2.0, while it responds only marginally to changes in output growth ($\phi_y = 0.3$). Additionally, we include interest rate smoothing with a smoothing parameter ρ_r equal to 0.75.

The uncertainty shock to TFP is calibrated according to the empirical evidence in the euro area. We set the volatility of the second moment TFP shock η_z to 15 percent, which is in line with the implied volatility index VSTOXX. The other parameters related to the shock processes are calibrated similarly to Basu and Bundick (2012). The persistence parameters of the first moment TFP shock ρ_z is equal to 0.9. The persistence parameter of the second moment shock ρ_{σ^z} is equal to 0.83.

Table 2.1: *Deep parameters of the benchmark model*

Parameter	Value	Description
Non-financial sector		
β_h	0.9943	Discount factor private households (savers)
β_e	0.975	Discount factor entrepreneurs (borrowers)
ϕ	1	Inverse of Frisch labor supply elasticity
δ	0.025	Depreciation rate of physical capital
α	0.25	Weight of capital in aggregate production function
ϵ^y	6	Elasticity of substitution in the goods market
κ_i	10.2	Investment adjustment costs
κ_p	30	Price adjustment costs (Rotemberg)
m	0.35	Loan-to-value (LTV) ratio for the entrepreneurs
Financial sector		
ϵ^d	-1.46	Elasticity of substitution for deposits
ϵ^b	3.12	Elasticity of substitution for loans
φ	0.5	Share of banks' retained earnings
δ^b	0.1	Bank management costs
κ_b	9.5	Loan rate adjustment costs
κ_d	3.5	Deposit rate adjustment costs
Monetary Policy		
ϕ^y	0.30	Weight on output in Taylor rule
ϕ^π	2.0	Weight on inflation in Taylor rule
ρ^r	0.75	Interest rate smoothing parameter
Shocks		
z	1	Steady state of TFP
σ^z	0.01	Steady state volatility of TFP first moment shock
ρ_z	0.9	Persistence parameter of TFP first moment shock
ρ_{σ^z}	0.83	Persistence parameter of TFP second moment shock
η_z	0.0015	Volatility of TFP second moment shock

2.5.3 Results

In the following we analyze the effects of an uncertainty shock to TFP on main macroeconomic aggregates using impulse response functions. The aim is to assess the importance of financial frictions and financial intermediation in response to increases in uncertainty. Therefore, we compare three different specifications of our model. Starting with our benchmark model which we derived in section 2.4, we successively switch off the frictions in the banking sector and reduce the model finally to one that closely resembles a standard New Keynesian model.

The benchmark model (henceforth BM) includes a variety of financial frictions, such as borrowing constraints on entrepreneurs, monopolistic competition in the banking sector, and sticky loan and deposit rates. Starting from the BM, we switch off the stickiness of loan and deposit rates, such that the retail rates immediately respond to changes in the policy rate. However, we keep monopolistic competition in the banking sector such that there still is a markdown to the deposit rate and a markup to the loan rate. We denote this model as the flexible rate model (FRM). Finally, we switch off the entire banking sector and the borrowing constraints of the entrepreneurs. This model specification comes closest to a standard New Keynesian model which does not include any financial frictions. We refer to this model as Quasi New Keynesian model.[7]

TFP uncertainty

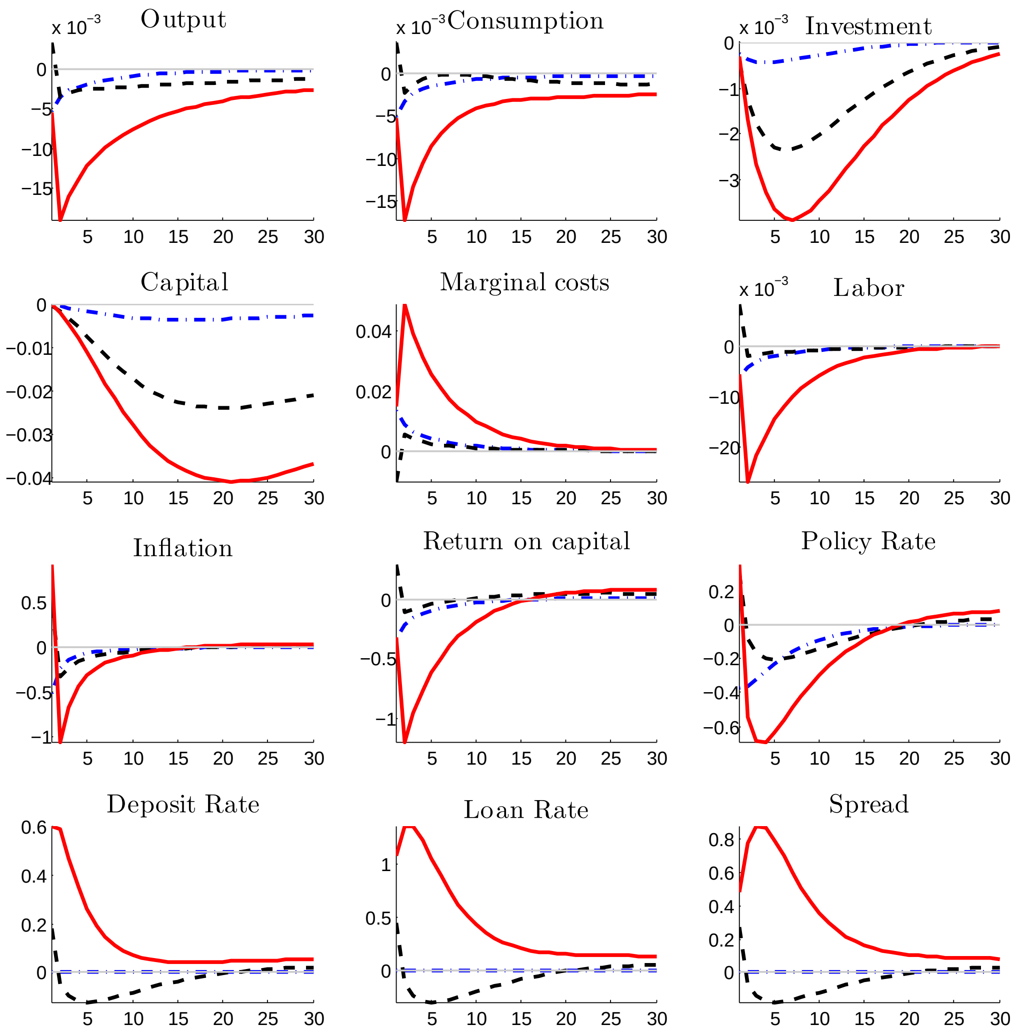
Figure 2.4 plots the impulse response functions of a one-standard deviation shock to TFP uncertainty for all three models. We consider the Quasi New Keynesian model (blue dashed-dotted line); the Flexible Rate model (black dashed line); and the benchmark model featuring all financial frictions (red solid line). Consistently with the literature, we find that a one-standard deviation increase in TFP uncertainty has dampening effects on macroeconomic aggregates. As in Basu and Bundick (2012) we find that output, consumption and investment co-move negatively under sticky prices, while this is generally not the case under flexible prices.[8] When prices do not immediately adjust to

[7] We call the model Quasi New Keynesian since it has the main characteristics of a NKM but additionally incorporates heterogenous agents.

[8] Under flexible prices, agents reduce consumption due to precautionary motives while they increase their labor supply which boosts output; in a closed economy this leads to an increase in investment.

changing marginal costs, the increase in markups of the final good firms leads to a fall in the demand for the intermediate good. This in turn determines the intermediate good firm to reduce their labor input. Hence, aggregate output falls and so does investment. This effect can be seen in the impulse responses of the QNKM.

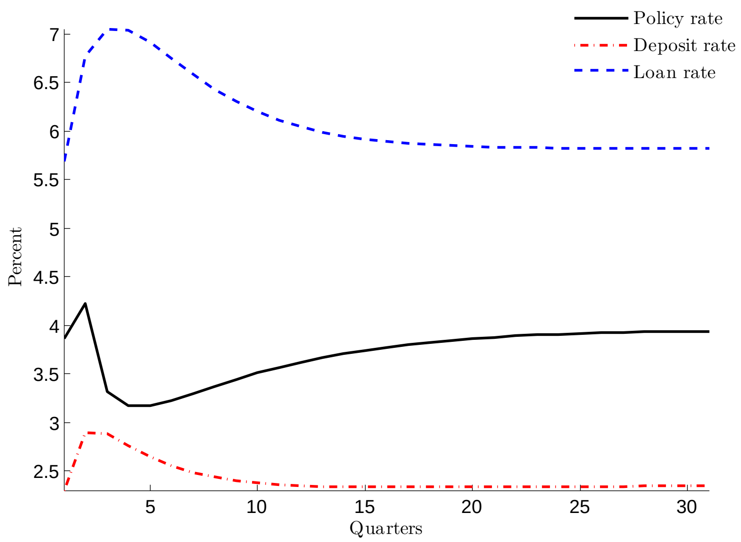
Figure 2.4: *Impulse responses to a shock in TFP uncertainty*



Notes: Red solid line: Benchmark model (BM); Black dashed line: Model with flexible rates (FRM); Blue dashed-dotted line: Quasi New Keynesian model (QNKM). All variables are expressed in percentage deviations from steady state, except interest rates which are expressed in annualized absolute deviations from steady state in basis points and the inflation rate which is expressed as the annualized absolute deviation from steady state in percentage points.

The negative shock is partly offset by the central bank by reducing the nominal interest rate. This becomes more evident when we compare the QNKM and the FRM to the BM. Including a frictional banking sector with sticky retail rates reduces the effectiveness of the transmission mechanism of monetary policy. Due to an increase in TFP uncertainty, which can be interpreted as a higher dispersion future costs for the intermediate firm, marginal costs increase on impact and so does inflation. The central bank responds initially with an increase in the policy rate which leads the loan and deposit to rise. As the effect on marginal costs gets weaker after one quarter, inflation drops and the central bank lowers the interest rate. However, the loan and deposit rate, which are directly relevant for the non-financial sector in the BM, do not immediately follow the change in the policy rate, but slowly adjust to it as they are assumed to be sticky (Figure 2.5).

Figure 2.5: *Response of policy and retail interest rates to an uncertainty shock*



Notes: The illustrated scenario is a response to a 150 percent shock in TFP uncertainty.

In the FRM retail rates immediately respond to the change in the policy rate and for this reason the uncertainty shock is not amplified compared to the QNKM.

The result of including a frictional financial sector is that macroeconomic aggregates react stronger to the TFP uncertainty shock. Output and consumption fall about three times as strong as in the QNKM and investment about four times. However, the overall effects of TFP uncertainty are small. This result is consistent with previous studies, such as Born and Pfeifer (2011), Bachmann and Bayer (2011), and Basu and Bundick (2012). This is basically because of two effects. First, the parameter of the Frisch labor supply elasticity is set to a value that is relatively low such that household immediately react to shock and adjust their labor supply. Second, the aggressive and quick response of the central bank to offset the negative shock mitigates the potential effects of uncertainty. The small effects become even more evident when comparing the effects of the uncertainty shock to a shock in the level of TFP. While output only declines 0.02 percent after a standard deviation TFP uncertainty shock it declines by about 1 percent after a negative standard deviation TFP level shock (see Figure A1 in the appendix).

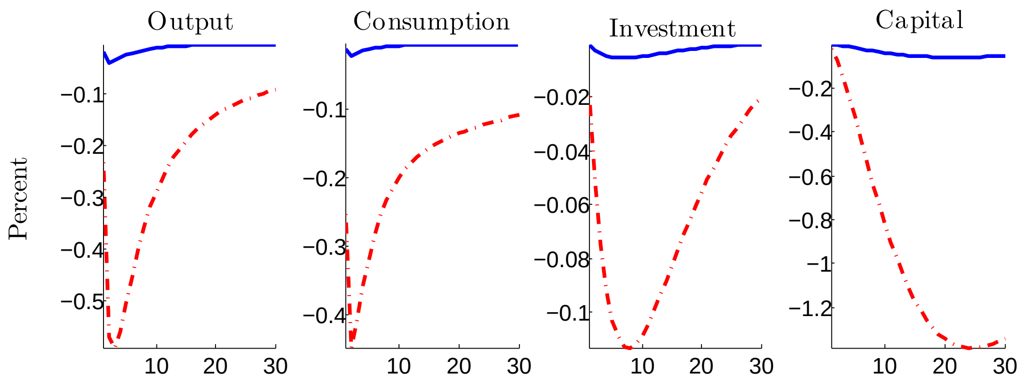
The outcomes of our model are qualitatively in line with the empirical findings in section 2.2.2. However, the magnitude of the responses of macroeconomic aggregate in the data indicates that uncertainty shocks have a stronger effect in the euro area than predicted by our model.

2.5.4 Reconciling the model with the data

One possible explanation for the strong effects of uncertainty from the BVAR is that the global financial crisis is included in our data sample. During 2007-2009 uncertainty increased sharply and macroeconomic aggregates plummeted strongly. Empirical analysis from other studies indicate that non-linearities are an important driver to explain the strong amplification of financial markets shocks on the economy. While there tend to be small effects of uncertainty and financial shocks in a "normal" macroeconomic environment, the effects of uncertainty are high in a distressed regime (van Roye (2011), Aboura and van Roye (2013) and Hubrich and Tetlow (2012)). In this subsection we show that in periods of recession, the impact of uncertainty of shocks on economic fluctuations is considerably higher and closer to the empirical findings.

To simulate a distressed scenario, we simultaneously hit the economy with a negative two standard deviations TFP level shock and one standard deviation uncertainty shock. Afterward, we subtract the effect of the TFP shock from that of the combined shock. The outcome is the isolated effect of the uncertainty shock. Figure 2.6 shows the different impact of the uncertainty shock on main macroeconomic aggregates under two scenarios: the baseline case, as in figure 2.4, and in times of strong economic downturn, as described above.

Figure 2.6: *Impulse responses to an uncertainty shock in a normal regime and in a distressed regime.*



NOTES: The blue solid line represents the IRF to an uncertainty shock in the baseline case; the red dashed-dotted line represents the IRF to an uncertainty shock during a strong economic downturn.

The effects of the uncertainty shocks are significantly stronger in the distressed scenario. This exercise emphasizes the importance of non-linearities and potential regime dependencies, when analyzing uncertainty shocks.

2.6 Conclusion

In this chapter we present a framework to analyze the impact of uncertainty shocks on macroeconomic aggregates under financial frictions. In particular, we include a banking sector that operates in a monopolistically competitive environment and sticky retail rates in a DSGE model with heterogenous agents. We depart from the strand of literature that analyzes uncertainty shocks under financial frictions on the credit demand side by focusing on frictions on the credit supply side. This seems to be a very important channel through which uncertainty shocks transmit to the real economy. In fact, we show that these features amplify significantly the effects of uncertainty shocks. This finding is mainly due to a reduction in the effectiveness in the transmission mechanism of monetary policy. A possible extension of our analysis could be to include uncertainty in the financial sector. Moreover, a regime-switching DSGE model could be an appropriate extension to shed light on non-linear effects of uncertainty shocks. We leave both to future research.

A Appendix

A.1 Complete model equations

First order conditions of the households

Households' Euler equation

$$\frac{1}{c_t^h} = \beta \mathbb{E}_t \left[\frac{1}{c_{t+1}^h} \frac{(1 + r_t^d)}{(1 + \pi_{t+1})} \right], \tag{2.36}$$

Labor supply equation

$$l_t^{\phi} = w_t \frac{1}{c_t^h}, \tag{2.37}$$

Households' budget constraint

$$c_t^h + d_t = w_t l_t + (1 + r_{t-1}^d) \frac{d_{t-1}}{(1 + \pi_t)} + J_t^R, \tag{2.38}$$

First order conditions entrepreneurs

$$s_t \bar{m} \mathbb{E}_t (1 + \pi_{t+1})(1 - \delta^k) + \beta^e \mathbb{E}_t \left[\left(\frac{1}{c_{t+1}^e} \right) \left((1 - \delta^k) + r_{t+1}^k \right) \right] = \frac{1}{c_t^e}, \tag{2.39}$$

Wage equation

$$w_t = (1 - \alpha) \frac{y_t^e}{l_t x_t}, \tag{2.40}$$

Euler equation entrepreneurs

$$\frac{1}{c_t^e} - s_t (1 + r_t^b) = \beta^e \mathbb{E}_t \left[\frac{1}{c_{t+1}^e} \frac{(1 + r_t^b)}{(1 + \pi_{t+1})} \right], \tag{2.41}$$

Budget constraint entrepreneurs

$$c_t^e + \left(\frac{(1 + r_{t-1}^b) b_{t-1}}{1 + \pi_t} \right) + w_t l_t + q_t^k k_t = \frac{y_t^e}{x_t} + b_t + q_t^k (1 - \delta) k_{t-1}, \tag{2.42}$$

Production function

$$y_t^e = z_t (k_{t-1})^{\alpha} l_t^{1-\alpha}, \tag{2.43}$$

Borrowing constraint

$$(1+r_t^b)b_t = m\mathbb{E}_t\Big[q_{t+1}^k(1+\pi_{t+1})k_t(1-\delta)\Big], \tag{2.44}$$

Capital producers

Return on capital

$$r_t^k = \frac{\alpha a_t\left(k_{t-1}\right)^{\alpha-1} l_t^{1-\alpha}}{x_t}, \tag{2.45}$$

Capital equation

$$k_t = (1-\delta)k_{t-1} + \left[1-\frac{\kappa_i}{2}\left(\frac{i_t}{i_{t-1}}-1\right)^2\right]i_t, \tag{2.46}$$

Banks

$$R_t^b = R_t^d = r_t, \tag{2.47}$$

$$k_t^b(1+\pi_t) = (1-\delta^b)k_{t-1}^b + \varphi J_{t-1}^b, \tag{2.48}$$

$$b_t = d_t + k_t^b, \tag{2.49}$$

Markup and markdown equations

Markdown on deposits

$$\begin{aligned} &-1+\frac{\epsilon_t^d}{(\epsilon_t^d-1)}-\frac{\epsilon_t^d}{(\epsilon_t^d-1)}\frac{r_t}{r_t^d}-\kappa_d\left(\frac{r_t^d}{r_{t-1}^d}-1\right)\frac{r_t^d}{r_{t-1}^d} \\ &+\beta_h\mathbb{E}_t\left[\frac{c_t^h}{c_{t+1}^h}\kappa_d\left(\frac{r_{t+1}^d}{r_t^d}-1\right)\left(\frac{r_{t+1}^d}{r_t^d}\right)^2\frac{d_{t+1}}{d_t}\right]=0, \end{aligned} \tag{2.50}$$

Markup on loans

$$1-\frac{\epsilon^b}{(\epsilon^b-1)}+\frac{\epsilon^b}{(\epsilon^b-1)}\frac{R_t^b}{r_t^b}-\kappa_b\left(\frac{r_t^b}{r_{t-1}^b}-1\right)\frac{r_t^b}{r_{t-1}^b}$$
$$+\beta_h\mathbb{E}_t\left[\frac{c_t^h}{c_{t+1}^h}\kappa_b\left(\frac{r_{t+1}^b}{r_t^b}-1\right)\left(\frac{r_{t+1}^b}{r_t^b}\right)^2\frac{b_{t+1}^E}{b_t}\right]=0, \tag{2.51}$$

Bank profits

$$J_t^b=r_t^bb_t-r_t^dd_t-\frac{\kappa_d}{2}\left(\frac{r_t^d}{r_{t-1}^d}-1\right)^2r_t^dd_t$$
$$-\frac{\kappa_b}{2}\left(\frac{r_t^b}{r_{t-1}^b}-1\right)^2r_t^bb_t, \tag{2.52}$$

Retailers

$$J_t^R=y_t\left(1-\frac{1}{x_t}-\frac{\kappa_p}{2}\pi_t^2\right), \tag{2.53}$$

Nonlinear Phillips curve

$$1-\epsilon_t^y+\frac{\epsilon_t^y}{x_t}-\kappa_p\pi_t(1+\pi_t)$$
$$+\beta_h\mathbb{E}_t\left[\frac{c_t^h}{c_{t+1}^h}\kappa_p\pi_{t+1}(1+\pi_{t+1})\frac{y_{t+1}}{y_t}\right]=0, \tag{2.54}$$

Aggregation and Equilibrium

$$c_t=c_t^h+c_t^e, \tag{2.55}$$

$$y_t=c_t+[k_t-(1-\delta)k_{t-1}]+\delta^b\frac{k_{t-1}^b}{\pi_t}+ADJ_t, \tag{2.56}$$

Taylor Rule and Profits CB

$$\frac{1+r_t}{1+r}=\left(\frac{1+r_{t-1}}{1+r}\right)^{\phi_r}\left[\left(\frac{1+\pi_t}{1+\pi}\right)^{\phi_\pi}\left(\frac{y_t}{y_{t-1}}\right)^{\phi_y}\right]^{(1-\phi_r)}, \tag{2.57}$$

Exogenous Processes

TFP level shock

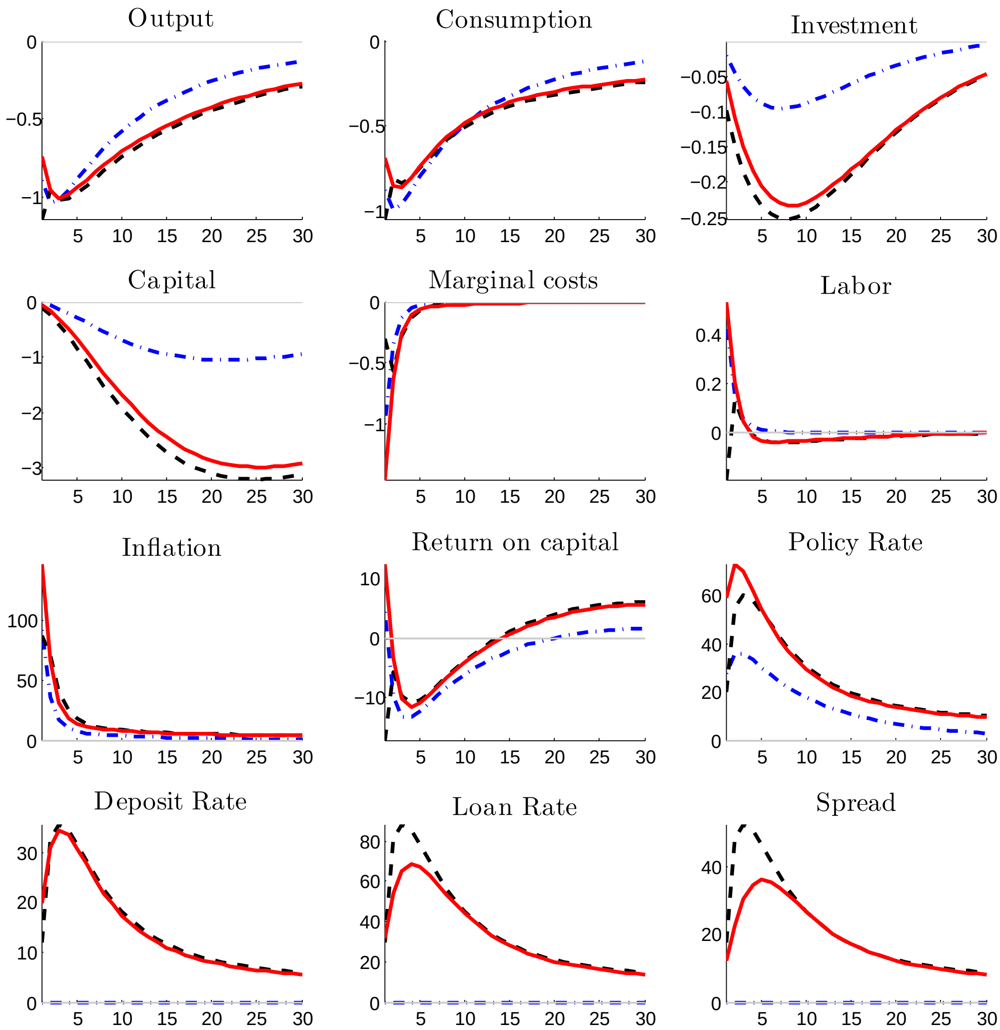
$$z_t = (1 - \rho_z)z + \rho_z z_{t-1} + \sigma_t^z e_t^z, \tag{2.58}$$

TFP uncertainty shock

$$\sigma_t^z = (1 - \rho_{\sigma^z})\sigma^z + \rho_{\sigma^z}\sigma_{t-1}^z + \eta_z e_t^{\sigma_z}, \quad \text{where } e_t^{\sigma_z} \sim \mathcal{N}(0, 1) \tag{2.59}$$

A.2 Impulse responses to level shocks

Figure A1: *Impulse response functions to a shock in the level of TFP*



Notes: Red solid line: Benchmark model (BM); Black dashed line: Model with flexible rates (FRM); Blue dashed-dotted line: Quasi New Keynesian model (QNKM). All variables are expressed in percentage deviations from steady state, except interest rates which are expressed in annualized absolute deviations from steady state in basis points and the inflation rate which is expressed as the annualized absolute deviation from steady state in percentage points.

A.3 Details on data used in estimation

Below we describe the data we use in the empirical exercise in section 2.3.

Uncertainty index We use both the implied volatility index VSTOXX provided by Thomson Financial Datastream and the the Eurostoxx50 which we use to approximate a historical volatility index prior to 1999. For this proxy we use a standard GARCH(1,1) model using monthly data and build 3-month averages over this index. Source: Thomson Financial Datastream.

Real GDP We use the time series YER provided by the AWM database originally provided by Fagan et al. (2001) and take log-differences of this index. For data after 2011Q4 we use the log-differences of the real GDP index provided by Eurostat. Source: AWM database and Eurostat.

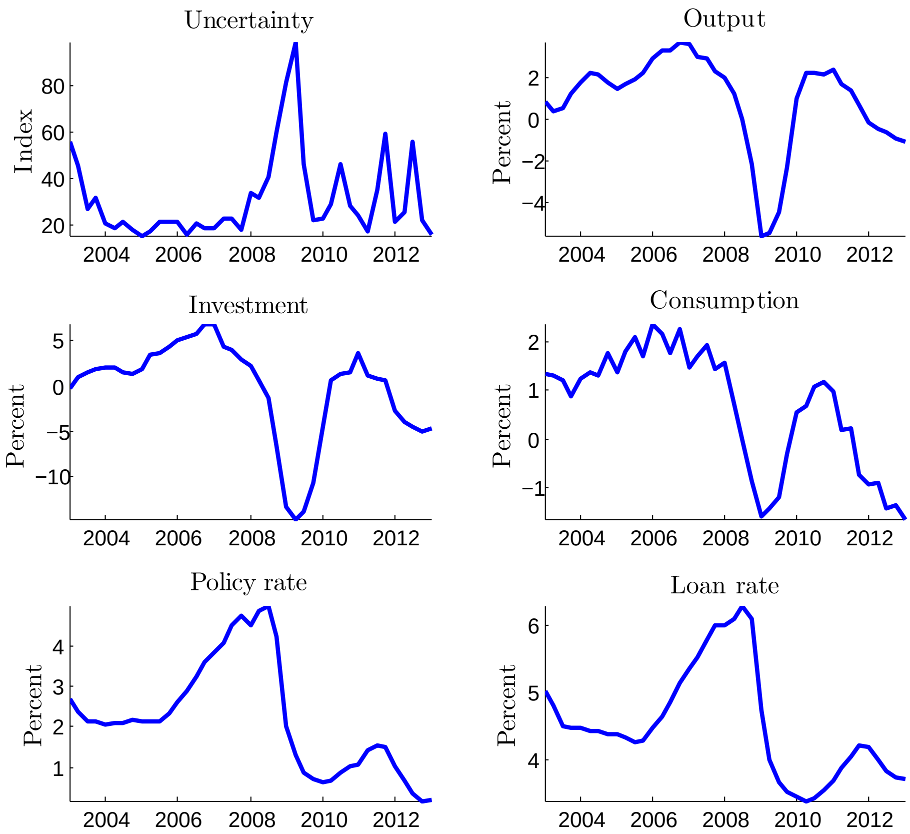
Investment We use the time series ITR provided by the AWM database originally provided by Fagan et al. (2001) and take log-differences of this index. For data after 2011Q4 we use the log-differences of the real GDP index provided by Eurostat. Source: AWM database and Eurostat.

Consumption We use the time series PCR provided by the AWM database originally provided by Fagan et al. (2001) and take log-differences of this index. For data after 2011Q4 we use the log-differences of the real GDP index provided by Eurostat. Source: AWM database and Eurostat.

Loan rate Interest rate charged by monetary financial institutions (excluding Eurosystem) for loans to non-financial corporations (outstanding amounts, all maturities), in percent (ECB). Source: ECB and Thomson financial datastream (Code: EMBANKLPB).

Interest rate We use the 3-month average of the unsecured Euro interbank offered rate (Euribor). Source: Thomson Financial Datastream (Code: EMINTER3)

Figure A2: *Variables used in estimation*



Notes: The uncertainty variable is the VSTOXX. All variables are expressed in log-differences, except the policy rate and the loan rate which are expressed in levels. estimated median impulse responses.

CHAPTER 3

Financial stress and economic activity in Germany[1]

3.1 Introduction

The financial crisis of 2008-2009 showed that strongly increasing financial stress may have dramatic effects on the economy. The collapse of Lehman Brothers led to a full-blown systemic crisis triggering the sharpest and severest downturn in economic activity in industrialized countries since the Great Depression. In the euro area, this crisis was exacerbated by a sovereign debt crisis, which was accompanied by a systemic crisis in the euro area banking system. Beside these very recent events, there is further empirical and theoretical evidence that financial stress may cause severe financial crises and recessions in general (Borio and Lowe (2002), Borio and Drehmann (2009), and Bloom (2009)). Against this background, it is a crucial challenge to monitor and to detect potential signs of financial stress for the conduct of economic policy.

Until the outbreak of the financial crisis, monetary and financial factors were only peripherally integrated into standard macroeconomic models. In particular, these models did not include financial market variables, such as stock market volatility, capital market spreads, and variables indicating imbalances on interbank markets. As a consequence, these models significantly underestimated the scope and persistence of the financial crisis. One major challenge is to include these financial market variables as real-time indicators into these models to better assess the macro-financial interdependence. These indicators may allow an early identification of a financial turmoil and may be able to guide decision mak-

[1]This chapter is based on the paper van Roye (2013). Financial stress and economic activity in Germany. *Empirica*, DOI: 10.1007/s10663-013-9224-0, Springer, US.

ers to tighten or loosen monetary or macroprudential policies even if inflation remains subdued (Borio (2011a), Borio (2011b), and Goodhart (2011)).

Monitoring the state of financial stability has also become an increasingly important task for central banks and international organisations. In practice, the European Central Bank (ECB) has developed indicators that are aimed to "measure the current state of instability, i.e. the current level of frictions, stresses and strains in the financial system" (European Central Bank (2011)). The Federal Reserve Bank of Kansas City and the Federal Reserve Bank of St. Louis established the so-called *KCFSI* and *STLFSI* Indexes (Hakkio and Keeton (2009) and Kliesen and Smith (2010) in order to establish a single and comprehensive index measuring financial stress for conducting future monetary policy. International institutions, such as the International Monetary Fund (IMF), the Organisation of Economic Co-operation and Development (OECD), and the Bank for International Settlements (BIS) have also developed indexes as an early warning tool for increases in financial stress.

Illing and Liu (2006) were among the first to use a principal components analysis calculating a financial stress index. They use a static factor model for Canada and show that their index provides an ordinal measures for stress in the financial system. Hakkio and Keeton (2009) and Kliesen and Smith (2010) use a similar approach to calculate the so-called *KCFSI* and *STLFSI* indexes for the U.S. economy, which are used by the Federal Reserve Bank of Kansas City and the Federal Reserve Bank of St. Louis. In a subsequent article, Davig and Hakkio (2010) analyze the effects of financial stress on economic activity using the *KCFSI*. They find that the U.S. economy fluctuates between a normal regime, in which financial stress is low and economic activity is high, and a distressed regime, in which financial stress is high and economic activity is low. Hatzius et al. (2010) calculate an alternative financial stress index using 45 variables to explore the link between financial conditions and economic activity in the United States and show that during most of the past two decades, including the five years leading up to the crisis, the index can explain the path of future economic activity better than other existing indexes. Their major innovation is that they estimate an unbalanced panel, which makes it possible to calculate the index back to 1970. Ng (2011) examines the predictive power of the indexes developed by Hatzius et al. (2010), and two indexes developed by the Basel Committee on Banking Supervision. He comes to the conclusion that using financial stress indexes as additional predictors improves forecasting accuracy of United States GDP growth at horizons from 2 to 4 quarters. Bloom (2009) takes a somewhat different approach to exploring the link between financial stress and economic activity in the United States by analyzing the impact of uncertainty shocks, measured by the volatility index (VIX) of the S&P500, on industrial production. He uses a vector autoregressive model (VAR) and finds the stock market volatility affects industrial production significantly and persistently.[2]

Holló et al. (2012) develop a composite indicator of systemic stress (*CISS*) which is thought to measure the current state of financial stability in the euro area. They employ a threshold bivariate VAR model including the *CISS* and industrial production. They show that the effects of financial stress depends on the regime, i.e. while the impact of financial stress on economic activity in a low-stress regime is insignificant, the impact in a high stress regimes noticeably dampens economic activity after the shock. Mallick and Sousa (2011) use a financial stress index in a Bayesian VAR and a sign-restriction VAR model to examine the real effects of financial stress. They find that unexpected variation in financial stress leads to significant variations in output. Grimaldi (2010) derives a financial stress index for the euro area and studies its ability to detect periods of financial stress. She finds that the index is able to extract information from an otherwise noisy signal and that it can provide richer information than simple measures of volatility. Finally, Afonso et al. (2011) analyze the impact of financial stress and fiscal developments in a threshold VAR model for several countries. Using the FSI developed by the IMF, they find that high financial stress significantly reduces output.

There are also several articles in the recent literature that deal with various comparable financial stress indexes that can be used across countries. These indexes have been used recently by the IMF to improve the assessment of economic activity in the World Economic Outlook (International Monetary Fund (2011)). Matheson (2011), for example, developed the indexes for the United States and the euro area and Unsal et al. (2011) developed indexes for several

[2] In fact, Bloom (2009) does not use a financial stress index, but instead uses the S&P stock market volatility, which he interprets as a measure of market uncertainty.

Asian countries and Australia. Cardarelli et al. (2011) use an augmented index including more variables from the banking sector and examine why some financial stress periods lead to a downswing in economic activity in 17 advanced economies over the past 30 years. They find that financial stress often but not always precedes a recession.

This chapter contributes to the recent literature in several ways. First, I estimate a financial stress index (FSI) for Germany using a dynamic approximate factor model. I use a broad measure of financial stress considering financial variables from the banking sector that proved to be relevant when explaining the sharp downturn during the financial crisis, financial variables from the capital market, and a financial variable from the foreign exchange market. As Brave and Butters (2011), I estimate an unbalanced panel in order to apply a long data sample and to account for the issue of ragged data edges due to publication lags. Against this background, I allow for an estimation of an arbitrary pattern of missing data as in Banbura and Modugno (2012). Subsequently, I estimate a small threshold VAR model in order to analyze the effects of financial stress on economic activity. I show that nonlinear effects play a crucial role in explaining the sharp downturn during the recent financial crisis.

This chapter is organized as follows. In section 3.2, I estimate the FSI for Germany, applying a dynamic approximate factor model. Using the FSI, events of high and low financial stress in German history are identified. In addition, the FSI is compared to alternative indexes for the United States and Germany. After having presented the TVAR model and threshold tests in Section 3.3, I show the results of an impulse response analysis for a one-regime linear VAR, a two-regime linear VAR and nonlinear impulse responses. In section 3.4 I briefly present conclusions.

3.2 The Financial Stress Index (FSI)

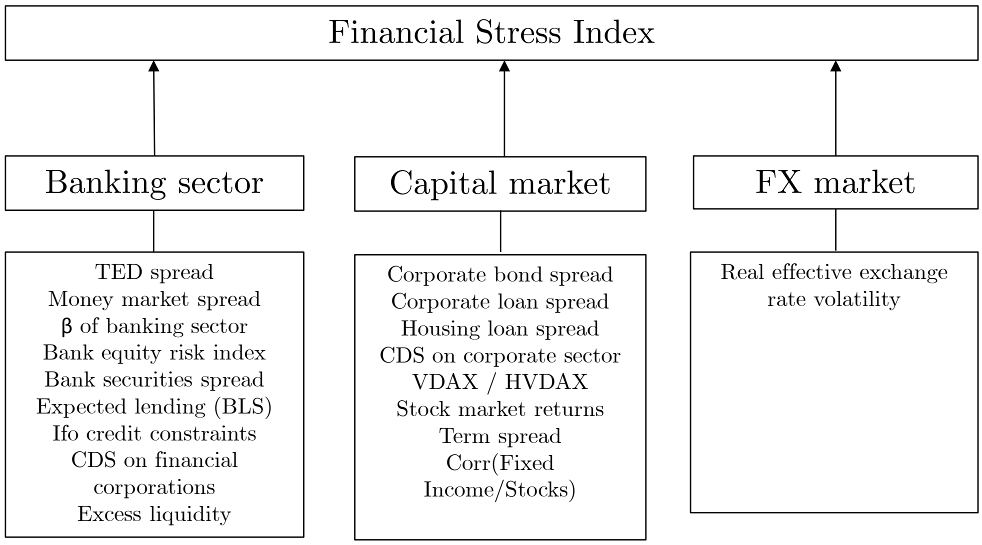
3.2.1 Methodology

In general, financial stress is unobservable and it is not straightforward to measure it. One possible approach to proxy financial stress is to construct one single index that serves as a proxy for the financial systems ability to intermediate. Alternatively, this single index can be interpreted as the state of financial stability and therefore as a thermometer of the financial system. Since financial stress is presumably reflected in various financial market variables, I use a multitude of financial market variables. The index consists of variables that are included with both first and second moments. Variables that enter the index in first moments (e.g. spreads) reflect the state of investors risk perception. Higher risk perception leads to increasing spreads and therefore exacerbates funding conditions for certain market participants. Financial variables that enter the index with its second moments (e.g. volatility measures) reflect the state of uncertainty on financial markets. High uncertainty may lead to a downturn in economic activity due to precautionary savings, real option effects or Hartman-Abel effects (Bernanke (1983), Abel (1983) and Hartman (1972)). In order to identify which market segment is primarily under strain, I build three subgroups that independently contribute to the financial stress index. In the following, I distinguish between the banking sector as a financial intermediary, the capital market as a funding source and the foreign exchange market as stress which is related to the currency (Figure 3.1).

I follow a similar methodology as Doz et al. (2011), Brave and Butters (2011), and Banbura and Modugno (2012) and use a dynamic approximate factor model combined with the Expectations Maximization (EM) algorithm. This methodology has the advantage that it allows for treating ragged data edges due to publication lags.[3] In addition, this methodology allows for estimating unbalanced panel data and mixed frequencies. This is particularly important in the construction of a financial stress index, since many financial variables are not available until very recently and the data frequency of financial data is usually not homogeneous.

[3]Therefore, this methodology is quite prominent in the forecasting literature (see Stock and Watson (2002), Giannone et al. (2008) and Doz et al. (2011)).

Figure 3.1: *Conceptual construction of the FSI*



Dynamic Approximate Factor Model

The model can be written in state space form. The measurement equation relates the observed data to the state vector of the latent factor f_t.[4]

$$y_t = \Lambda f_t + \varepsilon_t, \qquad \text{where } \varepsilon_t \sim iid\, \mathcal{N}(0, C) \tag{3.1}$$

where y_t is a vector of stationary and standardized endogenous financial variables, f_t is a a single common latent factor, and Λ is a $n \times 1$ vector of the time series' factor loadings. The values in the factor loading vector represent the extent to which each financial variable time series is affected by the common factor. The financial stress index is then given by $FSI_t = f_t$. The $n \times 1$ vector ε_t represents the idiosyncratic component which is allowed to be slightly correlated both serially at all leads and lags and cross-sectionally. This ensures that the idiosyncratic component is not too restrictive in the case of large cross-sections (Stock and Watson (2002)). The dynamics of the latent factor f_t are described in the transition equation, i.e.:

$$f_t = A f_{t-1} + \xi_t, \qquad \text{where } \xi_t \sim iid\, \mathcal{N}(0, D) \tag{3.2}$$

where A is the matrix of autoregressive coefficients, capturing the development of the latent factor f_t in an autoregressive model over time.

[4] I assume that a single factor reflects "financial stress". Including more factors does not significantly change the outcome. Results are available upon request.

Estimation

In order to estimate the unbalanced panel, I use the EM algorithm, originally proposed by Dempster et al. (1977). This iterative procedure allows for an efficient estimation to compute the maximum likelihood when data is missing or hidden. In general, the EM algorithm consists of two steps: in the estimation step, missing data are estimated using observed data by means of current parameter estimates and the conditional expectation. Subsequently, under the assumption that the data are known, the likelihood is maximized in the maximization step. The EM algorithm ensures convergence since at each iteration the likelihood is increasing. In particular, in the Expectation step the expectation of the log-likelihood conditional on the data is compute using estimates from the prior iteration $\theta(i)$, i.e.

$$L(\theta, \theta(i)) = E_{\theta(i)}[l(Y, F; \theta)|\Omega_T]$$

The parameters are subsequently re-estimated through a log-likelihood-maximization with respect to θ:

$$\theta(i+1) = \arg E_{\theta(i)}[l(Y, F; \theta)|\Omega_T] \tag{3.3}$$

In the following, I base the estimation methodology on Banbura and Modugno (2012). The parameter set consists of $\theta = \{\Lambda, A, C, D\}$. Maximization of equation (3.3) leads to the iteration processes of the factor loading matrix Λ and the matrix A of autoregressive coefficient in the dynamic factor equation (3.2):

$$\Lambda(i+1) = \left[\sum_{t=1}^{T} E_{\theta(i)}[y_t f_t'|\Omega_T]\right]\left[\sum_{t=1}^{T} E_{\theta(i)}[f_t f_t'|\Omega_T]\right]^{-1} \tag{3.4}$$

and

$$A(i+1) = \left[\sum_{t=1}^{T} E_{\theta(i)}[f_t f_t'|\Omega_T]\right]\left[\sum_{t=1}^{T} E_{\theta(i)}[f_{t-1} f_{t-1}'|\Omega_T]\right]^{-1} \tag{3.5}$$

which is similar to an ordinary least squares estimation of the log-likelihood for complete data sets with the difference that for missing data, expectation terms are introduced. The iteration processes for the covariance matrices are computed as follows:

$$C(i+1) = diag\left[\frac{1}{T}\left(\sum_{t=1}^{T} E_{\theta(i)}[y_t y_t'|\Omega_T] - \Lambda(i+1)\sum_{t=1}^{T} E_{\theta(i)}[f_t y_t'|\Omega_T]\right)\right] \tag{3.6}$$

and

$$D(i+1) = \frac{1}{T}\left[\sum_{t=1}^{T} E_{\theta(i)}[f_t f_t'|\Omega_T] - A(i+1)\sum_{t=1}^{T} E_{\theta(i)}[f_{t-1} f_t'|\Omega_T]\right] \tag{3.7}$$

To calculate the moments of the unobservable factors, the data is passed through the Kalman smoother.
Given that the data sample is incomplete, a diagonal selection matrix W has to be used, in order to further develop the factor loading matrix from equation (3.4):

$$vec(\Lambda(i+1)) = \left[\sum_{t=1}^{T} E_{\theta(i)}[f_t f_t'|\Omega_T] \otimes W_t\right]^{-1} vec\left[\sum_{t=1}^{T} W_t y_t E_{\theta(i)}[f_t'|\Omega_T]\right] \tag{3.8}$$

Similarly, equation (3.6) evolves as follows:

$$\begin{aligned} C(i+1) = diag\Bigg[\frac{1}{T}\sum_{t=1}^{T}\Big(& W_t y_t y_t' W_t' - W_t y_t E_{\theta(i)}[f_t'|\Omega_T]\Lambda(i+1)' W_t \\ & - W_t \Lambda(i+1) E_{\theta(i)}[f_t|\Omega_T] y_t' W_t + W_t \Lambda(i+1) E_{\theta(i)}[f_t f_t'|\Omega_T]\Lambda(i+1)' W_t \\ & + (I - W_t) C(i+1)(I - W_t)\Big)\Bigg] \end{aligned} \tag{3.9}$$

I estimate the model using monthly data over a sample period from February 1970 until December 2012. I transform the quarterly data series to monthly data by imposing restrictions on the factor loadings.[5] For daily series, I use monthly averages. Many time series are not available over the whole sample

[5]The only quarterly variable in the data sample is expected bank lending from the Bank Lending Survey. For this variable, I construct a partially observed monthly counterpart as in Mariano and Murasawa (2003) and Banbura and Modugno (2012).

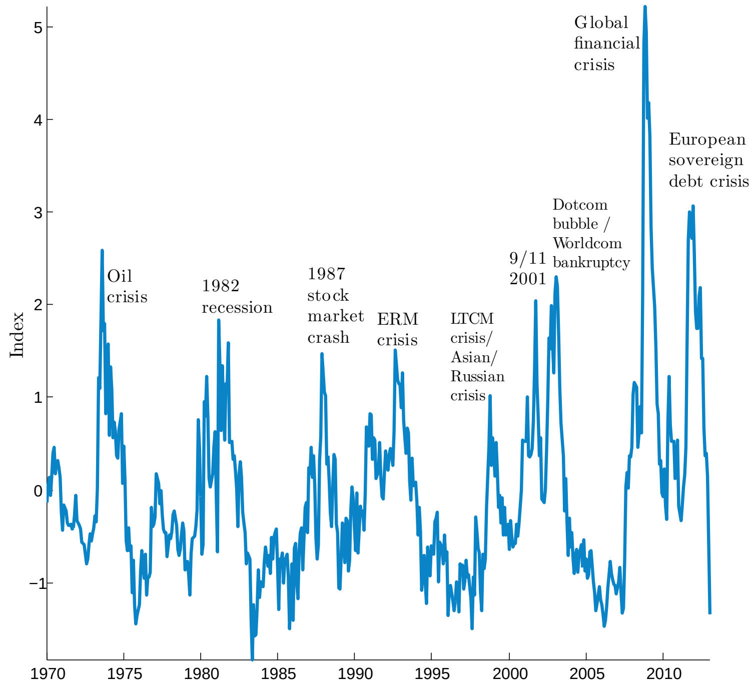
period. Yet, according to the methodology, the FSI can be estimated when some data are still missing because of publication lags and missing past values.

3.2.2 Data and the FSI

I have collected data from various sources. As mentioned above, the financial variables for the estimation can be summarized into three different subgroups, i.e. the banking sector, the capital market and the foreign exchange market. The first group contains variables related to the banking sector. These include the TED spread, the money market spread (Euribor over Eurepo), the β of the banking sector (a measure of bank return volatility relative to overall volatility calculated with the standard capital-asset pricing model), an indicator for a risk premium on bank equity, the spread on bank securities, lending conditions expected by German banks surveyed by the ECB's Bank Lending Survey, the availability of credit to firms as surveyed by the ifo Institute, credit default swaps on financial corporations, and an indicator of excess liquidity that is based on Germany's contribution to the ECB's deposit facility. The second group contains variables related to the capital market. These include a corporate bond and a corporate loan spread, credit default swaps on DAX30 non-financial corporations, annual stock market returns, implied and historical volatility of the DAX (VDAX/HVDAX), the term spread, the correlation of the fixed income market and the stock market (REX and DAX), and a housing loan spread. Finally, the third group contains a variable related to the foreign exchange market. In this case, I use a GARCH(1,1) model as a proxy for real effective exchange rate volatility. More details on data sources and data construction can be found in the appendix of this chapter.

The evolution of the FSI is shown in Figure 3.2. Several major events in German economic history can be identified when analyzing the time pattern of index. The first significant increase of financial stress occurred during the oil crisis in 1973/1974. In particular, high inflation rates due to increasing commodity prices led to high volatilities on the foreign exchange market. After about a decade of a calm financial environment, financial stress peaked during the 1982 recession when commodity prices had been strongly increasing once again. From 1982 until 1987 stock markets rallied all over the world and the financial environment in Germany seemed to be extremely favorable and calm. However, in 1987 the global stock market crash hit also the German

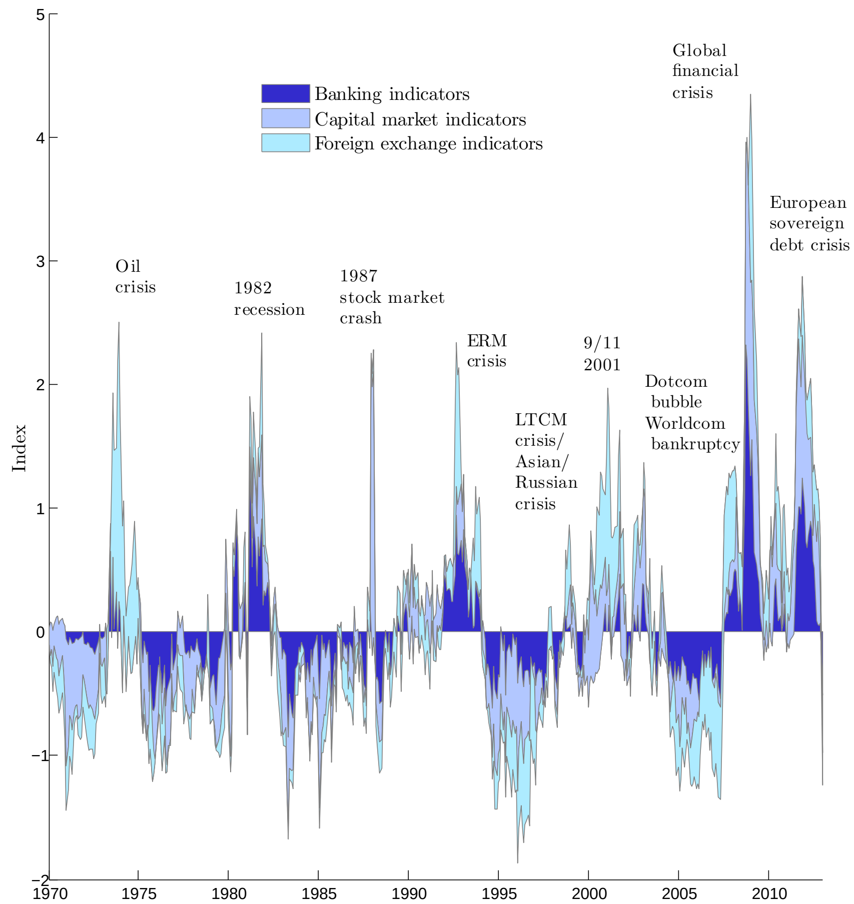
Figure 3.2: *Financial stress index for Germany*



Notes: The index is calculated on a basis of 18 financial market variables using a dynamic approximate factor model.

stock market like a shock wave. On October 19, 1987, also referred to as Black Monday, the DAX 30 dropped by 9.4 percent. Also other market segments were strongly affected by this event such that financial stress increased significantly. While financial stress only rose slightly during German reunification at the beginning of the 1990's, it peaked again during the 1992/1993 Exchange Rate Mechanism (ERM) crisis, when many currencies in the European Monetary System came under pressure and several countries finally had to abandon their currency peg to the Deutschmark. After the ERM crisis had been abated, financial stress persistently declined and returns on stock markets in Germany sharply increased. This stock market rally suddenly stopped with the insolvency of the hedge fund Long Term Capital Management (LTCM) during the Asian and the Russian currency crisis. As a consequence, financial stress rose appreciable, but remained at lower levels than it was in the crises before. After a very calm financial environment during the establishment of the European Monetary Union, the terror attacks in the United States in September 2011 led to widespread financial stress in Germany. Stress stayed persistently high during the following years since financial markets were still coping with the legacy of the dotcom bubble. Financial stress peaked again with the insolvency of WorldCom in 2002. The period after the burst of the dotcom bubble was characterized by a very profitable environment for financial corporations. Financial conditions were extremely favorable and financial innovations led to high returns on bank equities. This period of very calm financial stress was dramatically interrupted with the outbreak of the financial crisis in 2008. The collapse of Lehman Brothers triggered the strongest increase of financial stress over the observation period. Almost all financial variables indicating financial stress soared dramatically in all market segments. After a short drop in financial stress, it sharply rose again with the financial market turmoil associated with the sovereign debt crisis in the euro area. The announcement of the ECB to buy government bonds of selected European countries if necessary, led to a strong decrease in financial stress in the second half of 2012.

Figure 3.3: *Contribution of indicator groups*



Notes: Contributions are calculated with the respective factor loading of the financial variables and its belonging to the subgroup.

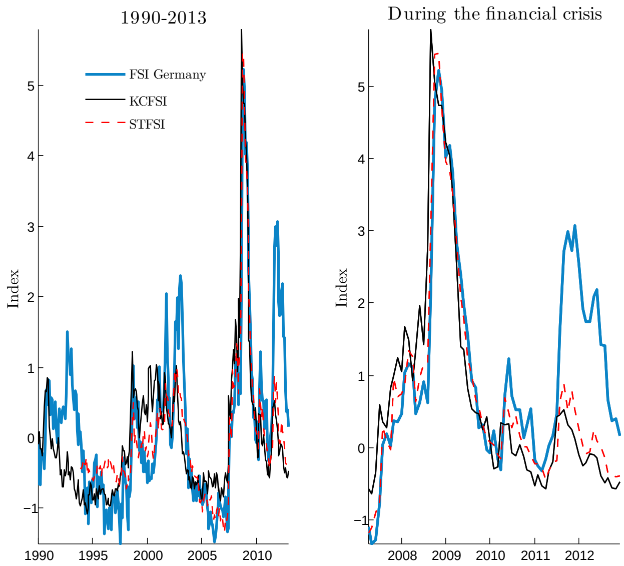
Decomposing the FSI in its three subgroups allows for tracking the source of financial stress in different periods (Figure 3.3). First, high real exchange rate volatility was the primary source of financial stress during the oil crisis (particularly because of high inflation volatility) and the ERM crisis. In contrast, very stable exchange rates contributed appreciably to the low stress environment from 1995 until the Russian currency crisis and the period in the run up to the financial crisis. Second, high financial stress was mainly driven by capital market variables during the 1987 stock market crash (in particular stock market volatility and sharply decreasing stock returns), and the recent financial crisis and the European sovereign debt crisis. Third, the German banking sector was a source of financial stress particularly during the recent financial crisis, the European sovereign debt crisis but also to a smaller extent during the 1982 recession.

3.2.3 Comparison with other indexes

Over the past years, several financial stress and financial conditions indexes have been developed. Especially for the United States economists have derived varios indexes for financial stress. The most prominent indexes that are frequently used to observe the state of financial stability are the *KCFSI* and the *STFSI*. Comparing these indexes to the FSI for Germany shows that financial stress co-moved significantly over time (Figure 3.4). However, there are a significant discrepancies during some major historic events. First, the ERM crisis did not affect financial markets in the United States as it affected financial markets in Germany. Second, the FSI in the United States increased earlier before the financial crisis, indicating that financial markets in the United States were affected earlier than in Germany. Third, while the European sovereign debt crisis had a significant effect on financial stress in Germany, the effects on financial markets in the United States seem to have been very limited.

Comparing the FSI with an alternative FSI for Germany calculated by the IMF shows that the indexes behave relatively similar (Figure 3.5). The most striking difference between the FSI developed in this chapter and the index calculated by the IMF is during German reunification. While the IMF index strongly increases during the year 1991, the FSI developed in this chapter remains at very low levels. Regarding the recent financial crisis both indicators

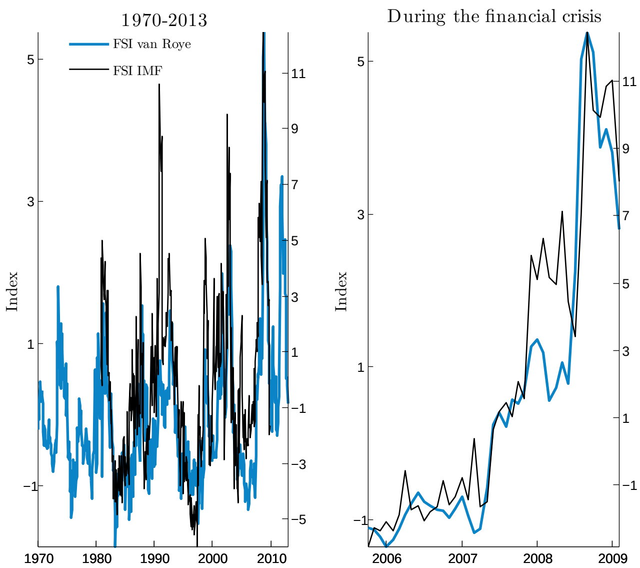
Figure 3.4: *Financial stress indexes for Germany and the United States*



NOTES: The data for the KCFSI and the STFSI are provided by Thomson Financial Datastream.

already increase in the run up to the collapse of Lehman Brothers during the years 2007 and 2008 and finally peak in October 2008.

Figure 3.5: *Financial stress indexes for Germany*



NOTES: The data for the FSI IMF is taken from the online appendix of the paper from Balakrishnan et al. (2009). The index is calculated using the methodology in Cardarelli et al. (2011). Data were only available until the end of 2009.

3.3 The impact of financial stress on economic activity

In order to obtain insights into the effects of financial stress on economic activity, I estimate a simple threshold VAR (TVAR) model, containing the FSI, the 12-month growth rate of industrial production, the inflation rate and the short-term interest rate. The advantage of the TVAR model is that it allows accounting for nonlinear effects. Particularly, asymmetric behavior of certain variables in response to shocks and a framework of multiple equilibria can be captured using this model framework. Linear VAR models underlay the assumption that there is local instability, that the effects of financial stress are symmetric and that the variables revert to their deterministic steady-state. Additionally, one major weakness of linear VAR models to analyze the effects of financial stress on economic activity is that responses are independent of the economy's state. Therefore, I will use a framework that subsequently allows for capturing asymmetric responses to shocks and the economy's state-dependencies. One straightforward possibility is to implement regime changes is a Markov-switching model as proposed by Hamilton (1989). Since the states are unobservable and do not provide an intuitive economic interpretation, I abstract from this modeling approach.[6]

In the following, I will derive a TVAR model to analyze the impact of financial stress on economic activity. A priori, I assume that financial stress becomes a major concern for the real economy when it exceeds a certain threshold and the financial system is under strain. First, I test for threshold effects and present linear impulse response functions. Particularly, I compare a one-regime linear VAR with a regime dependent linear VAR. Second, I estimate a non-linear VAR and present nonlinear impulse responses..

A TVAR model is a simple extension of a threshold autoregressive model, originally introduced by Tong (1978). I set up a model consisting of the FSI, the growth rate of industrial production (ΔIP_t), the inflation rate (π_t), and the short-term interest rate i_t. The TVAR model has the following form:

$$Y_t = \Lambda_1 Y_{t-1} + \Lambda_2 Y_{t-1} I[z_{t-d} \geq z^*] + \eta_t, \tag{3.10}$$

[6] Results for a Markov-Switching model using the indicator are available upon request.

where $Y_t = [FSI_t \;\; \Delta IP_t \;\; \pi_t \;\; i_t]'$ is a 4×1 vector of endogenous variables at time t, z_t is a scalar regime indicator and z^* the estimated threshold value and Λ_1 and Λ_2 are time-invariant 4×4 matrices. The function $I[\cdot]$ is an indicator function which takes the value 1 if the threshold variable z_{t-d} is above the estimated threshold value z^*. η_t is an $(n \times 1)$ vector of i.i.d. error terms fulfilling $\mathbb{E}(\eta_t) = 0$ and $\mathbb{E}(\eta_t \eta_t') = \Sigma$. The data are taken from Thomson Financial Datastream. I use monthly data covering a sample period from April 1970 to December 2012.

In order to identify independent standard normal shocks based on the estimated reduced form shocks, I apply a standard Cholesky decomposition of the variance-covariance matrix. The FSI is contemporaneously independent of all shocks excluding its own. This ordering approach has become standard in the literature. It is for example also employed by Bloom (2009), Matheson (2011), Cardarelli et al. (2011) and Holló et al. (2012).[7] First, the structural shock identification can be justified by considering information availability. Data on industrial production is published with a significant time lag. The data information is thus not available for financial market participants in real time. Therefore, it is unlikely to be reflected in contemporaneous asset prices and other financial market variables.[8] Second, it can be justified from a theoretical perspective. Increasing financial stress reflects uncertainty and high risk perception which can lead to "wait and see effects" (Bloom (2009) and Basu and Bundick (2012)).

I assume that the threshold model is determined by a single regime indicator z_t. In general, this indicator is specified as a moving average of one variable in the VAR model. The lag-length of the TVAR is determined jointly with the delay of the threshold variables. In this case, the regime indicator is the first lag of the FSI. In the subsection below, I report the critical values of the threshold tests.

3.3.1 Threshold Tests

In order to estimate the TVAR model, it is essential to initially test for potential thresholds. This can be formally tested using the two-step conditional least

[7]An alternative ordering, where industrial production is independent and the FSI is contemporaneously dependent of all other shocks, yields qualitatively similar results, which are available upon request.

[8]See Holló et al. (2012).

squares procedure proposed by Tsay (1998) and alternatively by a Wald test developed by Hansen (1999).[9] In both tests the null hypothesis of a linear VAR can be tested against the alternative hypothesis of a non-linear VAR.

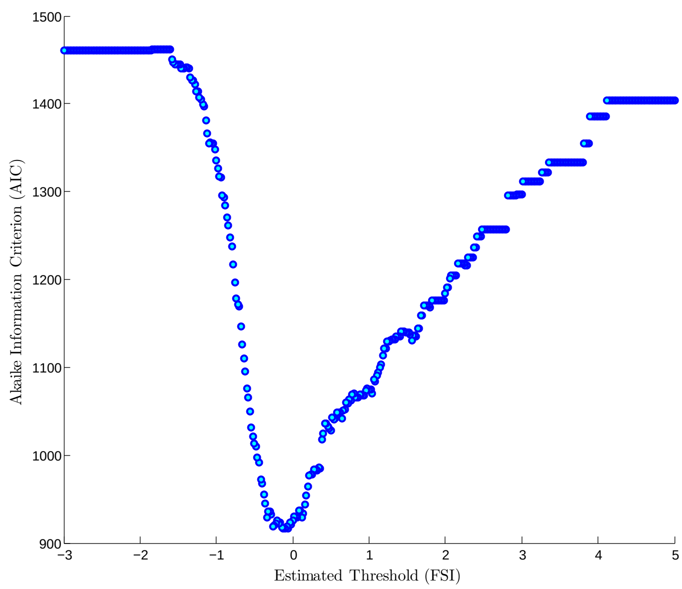
Table 3.1: *Threshold Tests*

	Tsay-test		Hansen-test
d	Test Statistic	Estimated threshold value	Estimated threshold value
1	35.44 (0.00001)	-0.0154	-0.0514 (0.031)
2	34.87 (0.00006)	-0.0284	-0.0522 (0.035)

Notes: H_0: linear VAR, H_1: threshold VAR; The p-values are reported in brackets.

One problem that arises is that the threshold value z^* is not identified under the null-hypothesis. Therefore the tests consist of running a grid search of the threshold variables z_t. Tsay (1998) developed a test simultaneously determining the delay of the threshold variable and the threshold value z^*. In both cases, with a threshold delay of d=1 and d=2, the test rejects the null hypothesis of a linear VAR (Table 3.1).

Figure 3.6: *Threshold test*



Notes: Scatterplot of threshold estimation based on AIC for TVAR(4) against VAR(4).

[9]The p-values for the Hansen test is computed by bootstrapping techniques with 1000 replications. Detailed results of the Hansen test statistic are available upon request.

The results of this test shows that the threshold value are in both cases close to zero. The Hansen test supports this finding. Figure 3.6 shows the Akaike Information Criteria (AIC) with respect to various potential threshold values for the FSI with two lags (TVAR(4)) under the Tsay-test. The optimal specification is a TVAR(4) model with the first lag of the FSI (z_{t-1}) as a threshold variable.

3.3.2 Impulse Response Analysis

In order to analyze the propagation mechanism of financial stress on economic activity I conduct an impulse response analysis. First, I compute impulse response functions (IRF) of a linear one-regime VAR as a benchmark model. Second, I compare these results with the TVAR model described above. In particular, I calculate regime-dependent linear IRF. Within this specification, it is assumed that the economy permanently stays in the regime for the rest of the time period. Finally, similarly to Balke (2000), I apply the methodology of Koop et al. (1996) and calculate nonlinear impulse response functions (NIRF), which allows for conditional dynamics due to the endogenous nature of the threshold variable. In all three analysis, financial stress has a significant effect on economic activity.

Linear Impulse Responses

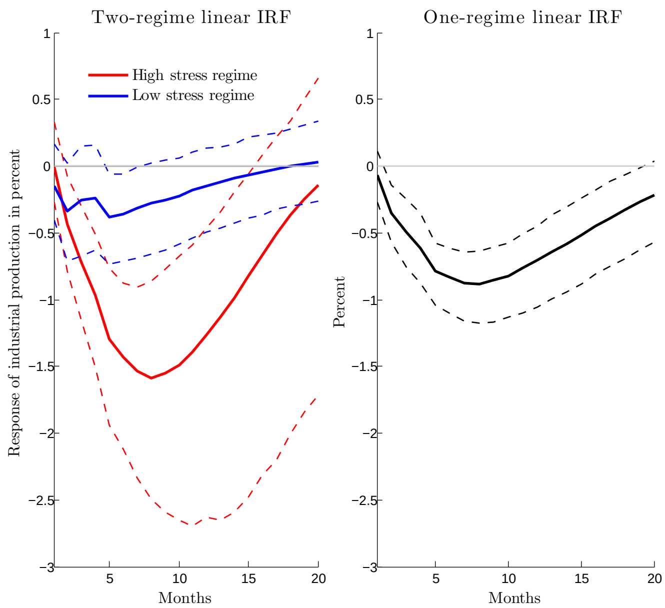
The impulse responses of a linear VAR can be written in the following form:

$$IRF_{t+h|t}(e_t) = E[Y_{t+h}|Y_{t-1}, e_t] - E[Y_{t+h}|Y_{t-1}], \tag{3.11}$$

where the realization of the expected path of responses depends on the state realized in $t-1$, and e_t is a vector of random disturbances. For the one-regime linear VAR, the IRF are directly computed by taking the estimated coefficients over the entire sample period. For the TVAR model described above, I assume two regimes a priori: a high stress regime and a low stress regime. In the regime-dependent linear IRF, I split the samples with respect to their regime state and estimate independently two different linear IRF. At time t the economy is either in the low stress or in the high stress regime. This methodology assumes that the FSI remains in the same state infinitely and does not change regimes. Given that the economy is in a certain regime the impulse responses may differ after a standard deviation shock to financial stress. For the linear IRF and the regime dependent IRF, I assume a similar identification scheme for all regimes, i.e. a standard Cholesky decomposition with a lower triangular matrix.

The results from the impulse response analysis are threefold. First, the IRF show that increases in financial stress have significant effects on economic activity in general (Figure 3.7).

Figure 3.7: *Linear IRF of industrial production growth to shocks in the FSI*



Notes: Error bands are based on 1.000 Monte Carlo draws with a significance level of 95 percent.

Second, while financial stress shocks in the high stress regime dampen industrial production significantly, its effects in the low stress regime are negligible. In the high stress regime, one positive standard deviation increase of the FSI causes industrial production to drop by about 1.5 percent after 8 months. The effects on the inflation rate are more modest, reducing headline inflation by only about 0.2 percentage points after 5-8 months (see appendix for details). The short-term interest rate falls slightly but persistently in response to a shock in financial stress. After 12 months, the interest rate is about 0.4 percentage points lower. At a longer horizon, the endogenous variables converge back to their deterministic steady-state level. Third, the effects of financial stress on economic activity are noticeably underestimated when the model is estimated in a one-regime linear VAR model. While a one standard deviation financial stress shock leads to a reduction in output of about 1.5 percent in the high stress regime, the one-regime linear VAR indicates a drop by about 0.8 percent. These findings emphasize the importance of a nonlinear estimation methodology for the analysis of financial shocks.

Nonlinear Impulse Responses

Alternatively to regime-dependent linear impulse responses, under which the impulse responses are symmetric and independent of the shocks' algebraic sign, I compute nonlinear IRF, originally proposed by Koop et al. (1996). Technically, the nonlinear IRF can be expressed as follows:

$$NIRF_h = E[Y_{t+h}|\Omega_{t-1}, e_t] - E[Y_{t+h}|\Omega_{t-1}], \tag{3.12}$$

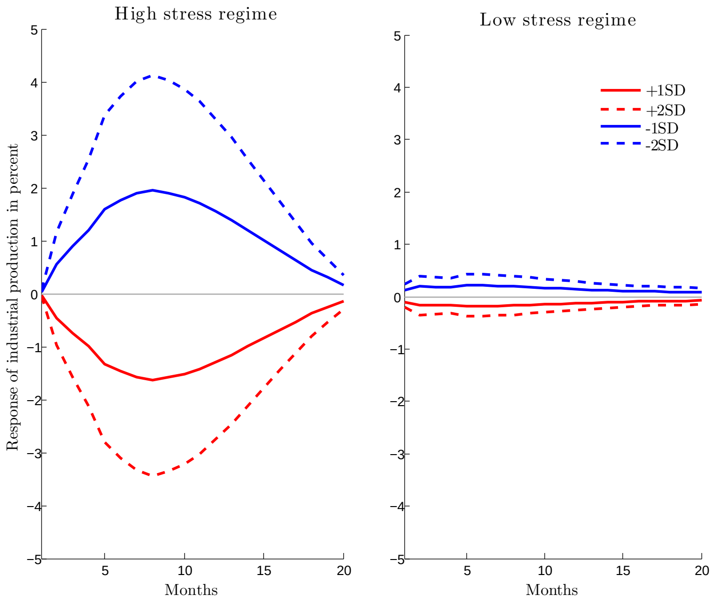
where Ω_{t-1} is an information set available in $t-1$ and e_t is a particular realization of shocks.

I closely follow the methodology of Balke (2000), who estimates the effects of credit growth on economic using a TVAR model. This methodology requires to calculate the conditional expectation expressions of the endogenous variables with the shock ($\mathbb{E}[Y_{t+k}|\Omega_{t-1}, e_t]$) and without the shock ($\mathbb{E}[Y_{t+k}|\Omega_{t-1}]$) in order to account for different size and the algebraic sign of the IRF. Accordingly, the simulation is implemented by drawing vectors of shocks e_{t+j}, where $j = 1, \ldots, n$. The simulation is implemented with 500 draws. The model has to be simulated with negative shocks analogously in order to ensure that possible asymmetry is excluded (Balke (2000)). Similarly to the findings using linear regime-dependent IRF, the nonlinear IRF indicate that an increase in financial stress leads to a strong downturn of economic activity (Figure 3.8).

The reaction to a shock in financial stress is quite symmetric with respect to the sign, i.e. negative shocks induce a similar dynamic adjustment pattern of the endogenous variables as positive shocks. Notably, industrial production decreases significantly stronger after a shock to the FSI in the high stress regime than in the low stress regime. In addition, responses in inflation and the interest rate also are more pronounced in the high stress regime.

To sum up, the results from the impulse response analysis, both linear and nonlinear IRF indicate that shocks in the FSI lead to a downturn in economic activity when the FSI exceeds a certain threshold. Additionally, financial stress also also exhibits stronger effects on inflation and the nominal interest rate,

Figure 3.8: *Nonlinear impulse responses*



Notes: +2SD reflects the response of a positive two standard deviation shocks of the FSI; +1SD reflects the response of a positive one standard deviation shocks of the FSI; -2SD reflects the response of a negative two standard deviation shocks of the FSI; -1SD reflects the response of a negative one standard deviation shocks of the FSI; vectors of shocks are drawn 500 times.

when the level of the FSI is above the threshold. These results are also robust with respect to other specifications.

3.4 Conclusion

The disruptive events on financial markets during the past years showed that financial factors were too peripheral in standards macroeconomic models. Monitoring the state of financial stability has become a major concern for policy makers in the wake financial and the European sovereign debt crisis. In this chapter, I have developed a financial stress index for Germany that is applicable as an index for the state of financial stability. The index is calculated with a dynamic approximate factor model using 18 financial market variables from 1970 until 2012. The methodology I apply allows for an arbitrary pattern of missing data, which is useful to consider the index in real time.

To evaluate the effects of financial stress on economic activity, I estimated a set of impulse response functions. As the threshold tests support the presence of two different regimes financial stress, I set up a threshold VAR model with standard macroeconomic variables and the financial stress index. While a one-regime linear VAR strongly underestimates the impact of financial stress during financial market turmoils, a two-regime linear VAR model captures the nonlinearities in the model. Subsequently, I also calculate nonlinear impulse response functions to evaluate the proportionality of different financial stress shock sizes. The nonlinear impulse response functions are calculated as differences between the simulated paths of the model variables with and without the shock of financial stress. The results emphasize the importance of nonlinearities when analyzing financial shocks

The main findings of this chapter are that high financial stress has significant effects on output. I show that if the index exceeds a certain threshold, an increase in the index can be considered as an additional early warning variable for a decline of industrial production in Germany. This finding is in line with other related papers such as Bloom (2009), Holló et al. (2012) and Brave and Butters (2011).

B Appendix

B.1 Data

All data series included in the index, including the native frequency, the first observation, the data category and the original source are presented in table B1.

Variables related to the banking sector (figure B1)

TED spread The TED spread is calculated as the difference between the one-month and twelve-month money market rate (Fibor/Euribor). The TED spread is an important money market indicator, indicating liquidity and confidence in the banking sector. A shortage of liquidity causes a decrease in supply in the money market, which causes an increase in the TED spread and contributes positively to the FSI.

Money market spread The money market spread is the difference between the 3-month Euro Interbank Offered Rate (Euribor, which is the average interest rate at which European banks lend unsecured funds to other market participants) and the Eurepo (the benchmark for secured money market operations). An increase in the spread reflects an increase in uncertainty in the money market and can be interpreted as a risk premium.

β **of the banking sector** The beta of the banking sector is determined as the covariance of stock market and banking returns divided by the standard deviation of stock market returns. It follows from the standard capital asset pricing model (CAPM). A beta larger than one indicates that banking stocks shift more than proportionally than the overall stock market and that the banking sector is thus riskier (see also Balakrishnan et al. (2009)).

Banking equity risk index The banking equity index is a capital weighted total return index calculated by Thomson Financial Datastream. It consists of eight German Banks that have been included in the index continuously since 1973 and further 10 banks that were gradually included over the course of the sample period. I calculate the risk premium as in Behr and Steffen (2006), where it is constructed as a fraction bank stock returns over a risk-free interest rate. I determine the yield of the banking equity index by using daily log-differences of the time series and then subtract it from a risk-free interest rate. In this case, I use the one-month secured money market rate (1m Eurepo).

Bank securities spread This indicator is measured by the difference between bank securities with the maturity of 2 years and AAA-rated (German) government bonds with the same maturity. An increase in the spread reflects that investors perceive the risk in the banking sector to be on the rise. The time series for bank securities is taken from the banking statistics from the Bundesbank.

Expected bank lending (BLS) This indicator comes from the ECB's Bank Lending Survey. In this survey, banks are asked to report their assessment of how credit lending standards will evolve within the next three months. The Bundesbank reports the national results for the survey. The survey is conducted on a quarterly basis. Increasing values indicate an expected tightening in lending standards which contributes positively to the FSI.

ifo credit constraint indicator This indicator comes from a survey conducted by the ifo Institute. In this survey, firms are asked to report their assessment of how credit lending standards are currently evolving. Increasing values of the indicator reflect a tightening of credit conditions, which contributes positively to the FSI. The ifo credit conditions indicator is reported on a monthly basis.

CDS on financial corporations This index is an average of 5-year credit default swaps on the most important (largest ten) financial corporations, i.e. commercial banks. Increasing values of the index reflects that investors perceive the risk in the financial sector to be on the rise.

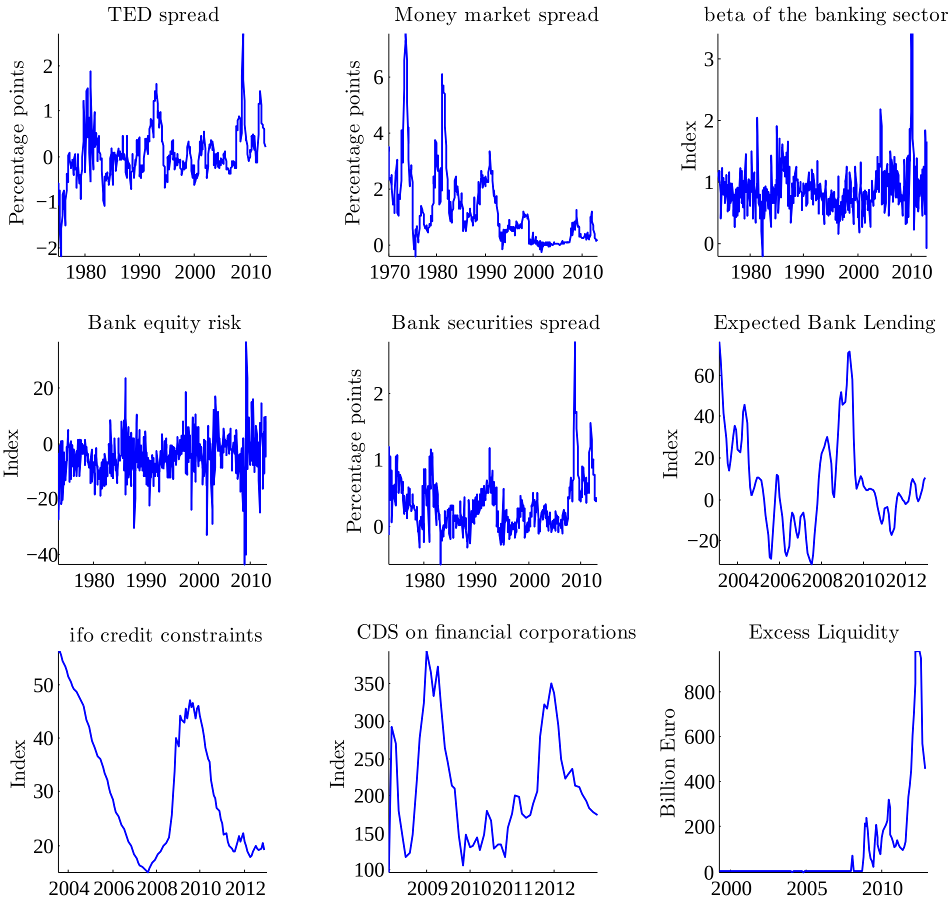
Excess liquidity Value of bank deposits at the ECB that exceed the minimum reserve requirements. High use of the ECB deposit facility reflects uncertainty in the interbank market. Banks prefer to hold their excess reserves with the ECB rather than to lend it to the non-financial sector or to other banks via the interbank market.

Table B1: *Data description*

Indicators	Native frequency	First observation	Category	Raw data source
Banking sector				
TED spread	monthly	$1975M02$	Spreads	Deutsche Bundesbank
Money market spread	monthly	$1970M01$	Spreads	Deutsche Bundesbank, ECB
β of banking sector	daily	$1974M01$	Spreads	Deutsche Bundesbank
Banking equity risk index	daily	$1973M02$	Spreads	Thomson Financial
Bank securities spread	monthly	$1973M04$	Spreads	Deutsche Bundesbank
Expected bank lending (BLS)	quarterly	$2003M01$	Index	Deutsche Bundesbank
ifo credit constraint indicator	monthly	$2004M05$	Index	ifo Institute
CDS on financial corporations	daily	$2007M01$	Index	Thomson Financial
Excess liquidity	monthly	$1999M01$	Value Euro	Deutsche Bundesbank
Capital market				
Corporate bond spread	monthly	$1970M01$	Spreads	Deutsche Bundesbank
Corporate loan spread	monthly	$1996M11$	Spreads	Deutsche Bundesbank
Housing loan spread	monthly	$1975M02$	Spreads	European Central Bank
CDS on corporate sector	monthly	$2008M01$	Spreads	Thomson Financial
VDAX/HVDAX	monthly	$1974M01$	Volatilities	Deutsche Bundesbank
Stock market returns	daily	$1970M01$	Prices	Thomson Financial
Term spread	monthly	$1972M09$	Spreads	Deutsche Bundesbank
$Corr(REX, DAX)$	daily	$1971M01$	Correlations	Deutsche Bundesbank
Foreign exchange market				
REERV (GARCH(1,1))	monthly	$1970M02$	Volatilities	Deutsche Bundesbank

Sources: European Central Bank, Deutsche Bundesbank, ifo institute, Thomson Financial Datastream, own calculations.

Figure B1: *Variables related to the banking sector*



Sources: Thomson Financial Datastream, European Central Bank, ifo institute, Deutsche Bundesbank, own calculations.

Variables related to the capital market (figure B2)

Corporate bond spread The corporate bond spread is the difference between the yield on BBB-rated corporate bonds with a maturity of 5 years and the yield on AAA-rated (German) government bonds with the same maturity. The spread increases with higher perceived risk in the corporate bond market. This spreads contains credit, liquidity, and market risk premia.

Corporate loan spread The corporate credit spread measures the difference between the yield on one-to-two year loans to non-financial corporations and the rate for secured money market transactions (Eurepo).

Housing loan spread The housing spread measures the difference between the interest rate on all housing loans to private households and the interest rate for secured money market transactions (3m Eurepo).

CDS on corporate sector This index is an average of 5-year credit default swaps on the DAX 30 non-financial corporations' outstanding debt. For the euro area, it is a simple average of non-financial firms, using data for different sectors from Thomson Financial Datastream. Increasing values of this index indicate that investors perceive the risk that non-financial corporate will default on their debt to be on the rise.

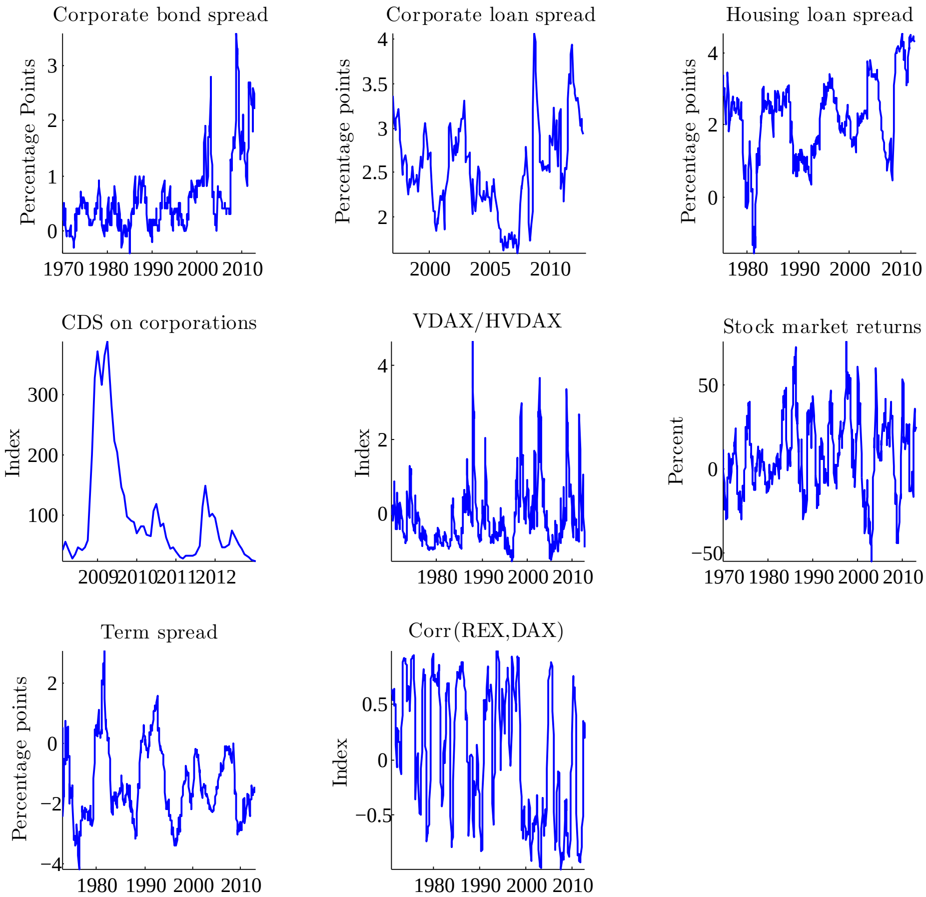
VDAX/HVDAX The VDAX measures implied stock volatility. Usually, an increase in stock market volatility reflects a higher degree of uncertainty and risk perception. This time series is available from 1996M1. Before 1996 I use the historical volatility of the DAX (HVDAX), estimated with a GARCH(1,1) model of the realized stock return volatility of the DAX30. The correlation of this time series between 1996 and 2011 is over 90 percent.

Stock market returns This variable measures the inverted monthly year-on-year yield of the DAX. Increasing values contribute positively to the FSI.

Term spread The term spread reflects bank profitability. I determine this indicator by taking the difference between the short- and long-term yields on government bonds. It can be seen as a measurement for the possible degree of maturity transformation. Usually, banks generate profits by intermediating from short-term liabilities (deposits) to long-term assets (loans). A negative slope of the yield curve, i.e. a negative term spread, therefore indicates a decrease in bank profitability.[10]

$Corr(REX, DAX)$ The REX is a fixed-income performance index. Increasing interest rates imply a decreasing REX index. Hence, a negative correlation between REX and DAX indicates a positive correlation between DAX and the general level of interest rates.

Figure B2: *Variables related to the capital market*



Source: Thomson Financial Datastream, Deutsche Bundesbank, European Central Bank, own calculations.

[10]See Cardarelli et al. (2011).

Variables related to the foreign exchange market (figure B3)

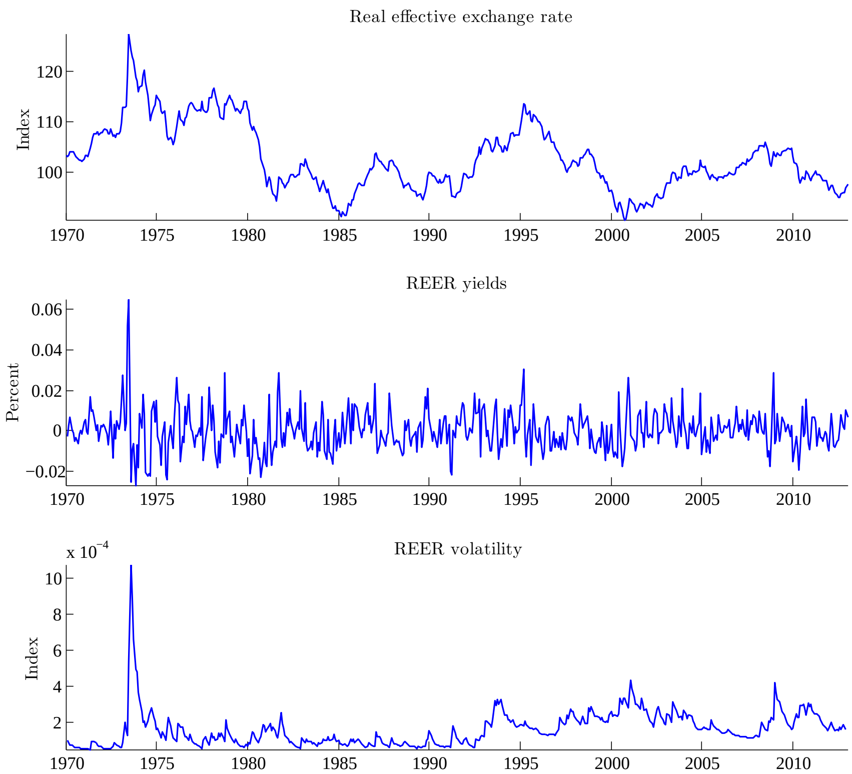
REERV (GARCH(1,1)) This index measures the volatility of the real effective exchange rate (REER). The REER is deflated by the consumer price index with respect to 20 trading partners. An ARCH-test rejected the null hypothesis of the lack of GARCH effects at a significance level of 95 percent. Hence, in order to determine real exchange rate volatility, I use a GARCH(1,1) model. The results are displayed below.

Table B2: *Estimation Results of the GARCH(1,1) model*

Parameter	Value	Standard Error	t-Statistic
C	0.00	0.00	-0.39
K	0.00	0.00	1.23
GARCH(1)	0.61	0.25	2.64
ARCH(1)	0.08	0.06	1.35

Notes: The conditional probability distribution was chosen to be Gaussian.

Figure B3: *Real effective exchange rate*

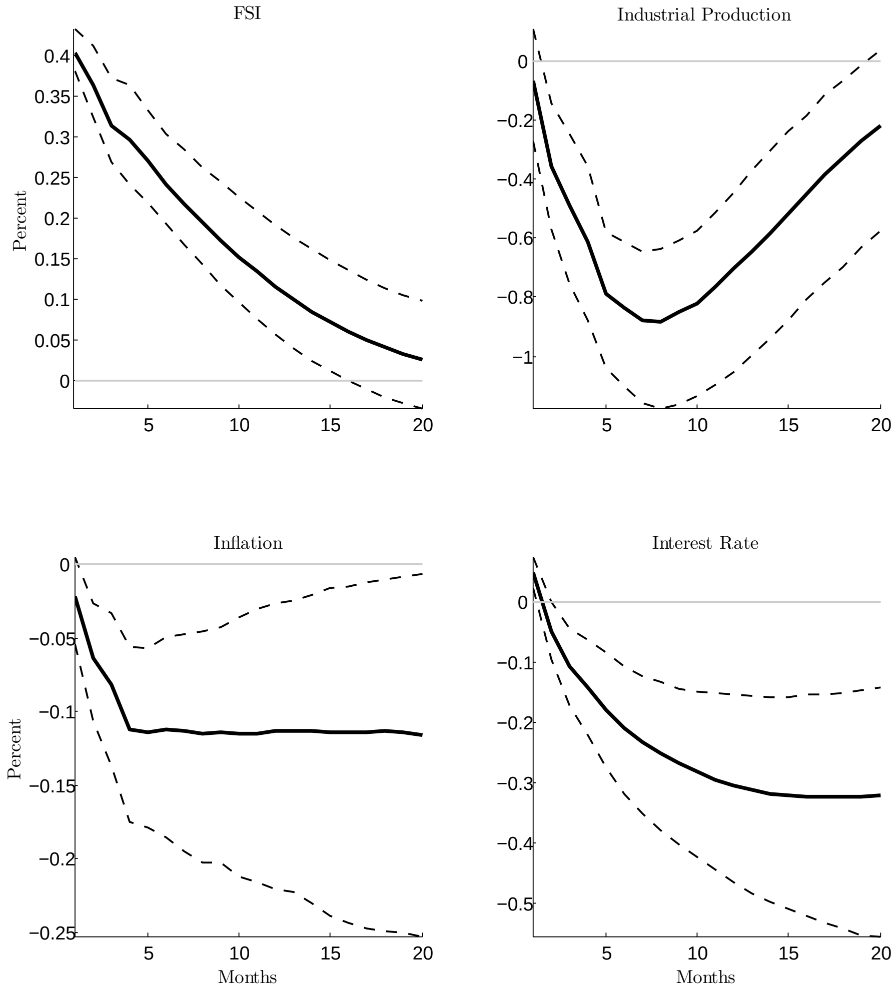


Sources: Thomson Financial Datastream, own calculations.

B.2 Linear impulse response functions

Linear VAR

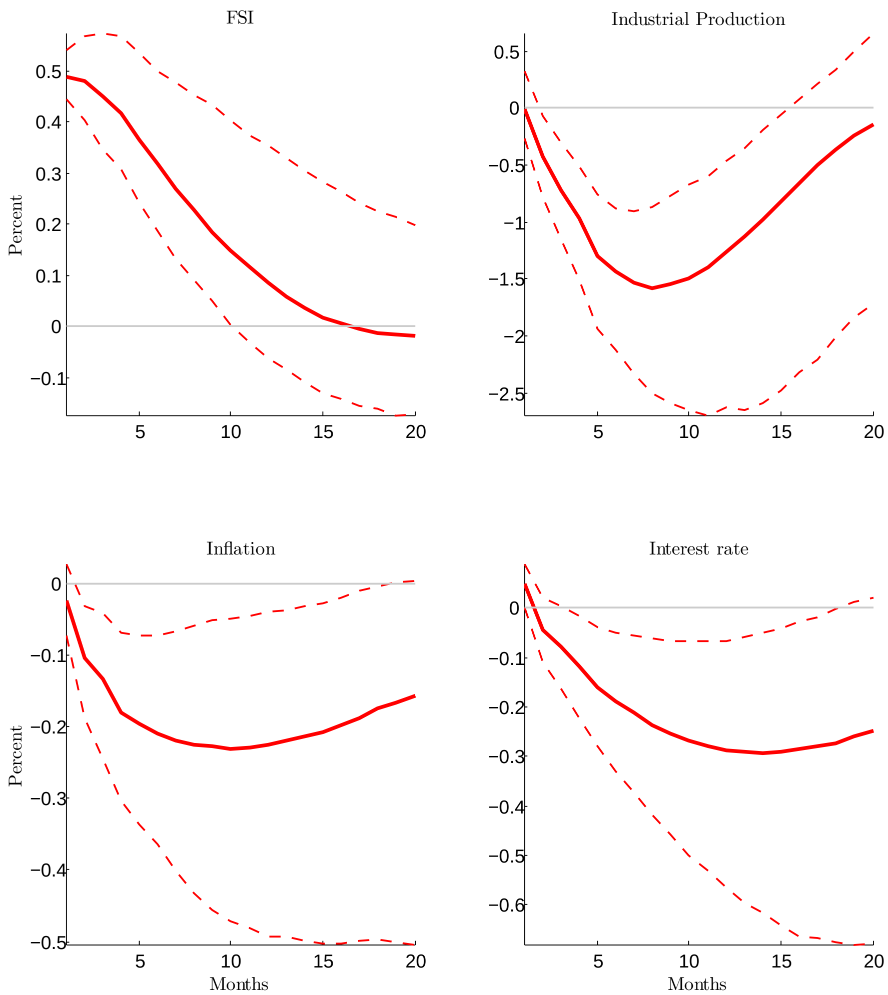
Figure B4: *Impulse response function of the linear VAR to a shock in financial stress*



Notes: Error bands are based on 1.000 Monte Carlo draws with a significance level of 95 percent.

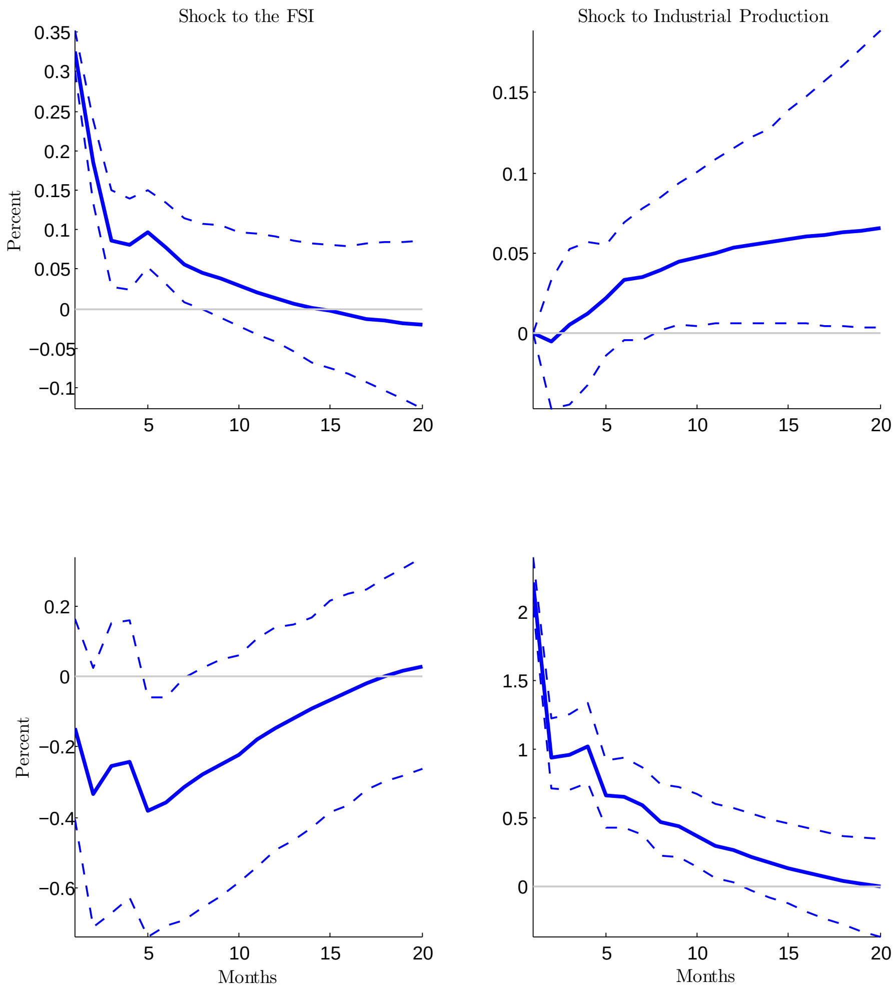
Regime dependent linear impulse response functions

Figure B5: *Impulse response functions: high-stress regime*



Notes: Error bands are based on 1.000 Monte Carlo draws with a significance level of 95 percent.

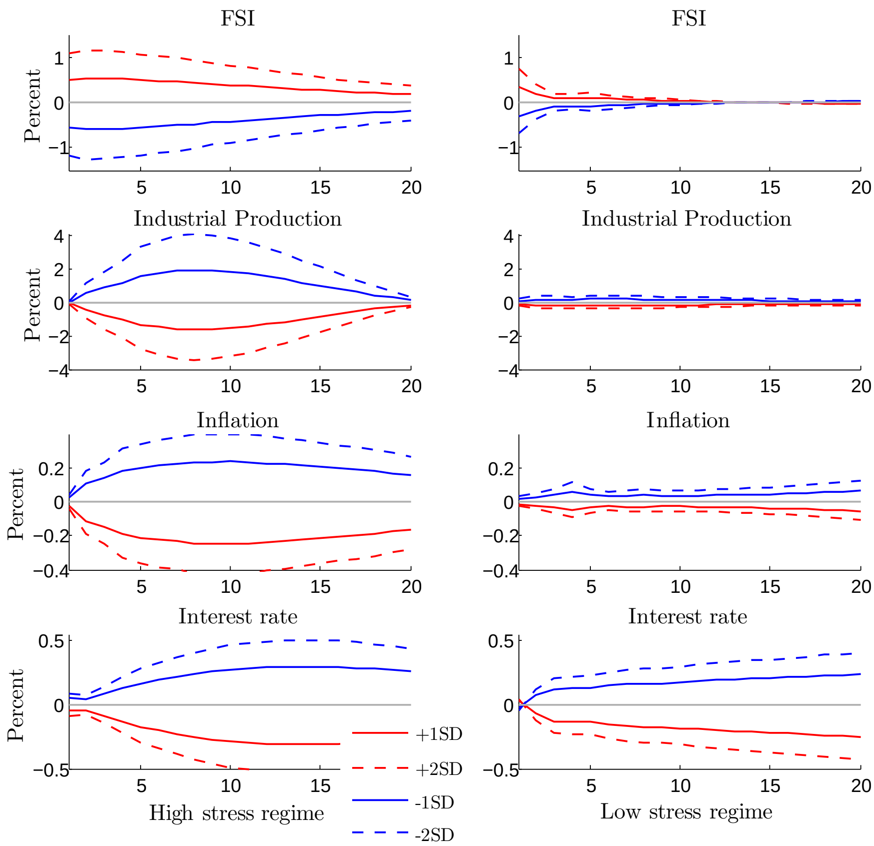
Figure B6: *Impulse response functions: low-stress regime*



Notes: Error bands are based on 1.000 Monte Carlo draws with a significance level of 95 percent.

B.3 Nonlinear impulse response functions

Figure B7: *Nonlinear impulse response functions*



Notes: +2SD reflects the response of a positive two standard deviation shocks of the FSI; +1SD reflects the response of a positive one standard deviation shocks of the FSI; -2SD reflects the response of a negative two standard deviation shocks of the FSI; -1SD reflects the response of a negative one standard deviation shocks of the FSI; vectors of shocks are drawn 500 times.

CHAPTER 4

Financial stress and economic dynamics: An application to France[1]

4.1 Introduction

The financial crisis following the collapse of Lehman Brothers in 2008 led to severe recessions in industrialized countries. In the euro area, the crisis was exacerbated by strongly increasing government debt positions of several member states and systemic banking crises due to a high exposure of commercial banks. The potential impact of financial shocks had been dramatically underestimated before the financial crisis, as central banks had mainly focused on price stability and banking regulations had been further relaxed over the past decade.

Before the financial crisis, developments on financial markets had only a marginal role in most macroeconomic models (Borio (2011b)). Therefore, the vast majority of these models did not take into account imbalances in financial accounts and financial stress.[2] However, for policy makers, it is crucially important to enhance theoretical and empirical methods for detecting potential misalignment on financial markets at an early stage. In particular, major challenges are to (1) improve the monitoring of financial stability, (2) identify and foresee potential sources and causes of financial stress and (3) elaborate and communicate the effects of financial stress on the economy.

[1] This chapter is based on: Aboura and van Roye (2013). Financial stress and economic dynamics: an application to France. Kiel Working Paper No. 1834, The Kiel Institute for the World Economy.

[2] Some structural models already included financial variables, such as the financial accelerator model of Bernanke et al. (1999) and Iacoviello (2005), who modeled asset prices in an otherwise standard structural macroeconomic model.

Against this background, monitoring and supervising the soundness of the financial system is eminent for both the monetary and fiscal authority. Particularly, a detailed analysis of financial stress is one major tool in a broader micro- and macro-prudential policy framework. To this end, the recent events have led to a re-orientation of financial stability for central banks, regulation authorities and policy makers in the meantime. Many institutions have begun intensifying its monitoring of financial variables such as stock market indicators, volatility measures and credit aggregates. In addition to monitoring single indicators independently, many institutions have begun to capture a general development of whole financial markets in composite indicators.[3] The European Central Bank (ECB), the Federal Reserve, the International Monetary Fund (IMF), the Organization for Economic Co-operation and Development (OECD) and the Bank for International Settlement (BIS) have developed financial stress indexes for different countries to assess and monitor their current states of financial stability.[4]

In addition to monitoring and supervising the financial system, a financial stress analysis is important for understanding the effects of financial shocks on the economy. From both a theoretical and empirical perspective, the effects of financial stress may be considerable. Economic theory suggests that increases in financial stress lead to changing behavior of private sector investment and consumption. While effects through the investment channel are driven by long-term interest rates and the user costs of capital, the effects through the consumption channel are mainly driven by wealth and income effects. Higher risk perception of market participants and increasing uncertainty may lead to a downturn in the business cycle. Paries et al. (2011) show that increases in money market spreads decrease bank lending, which directly reduces economic activity. In addition, Bloom (2009), Baker et al. (2012), Basu and Bundick (2012), Christiano et al. (2013), and Bonciani and van Roye (2013) show that increasing uncertainty directly leads to economic contractions.

Empirical evidence suggests that financial stress leads to economic contractions (Cardarelli et al. (2011), Davig and Hakkio (2010), Hakkio and Keeton

[3]For a detailed description of the necessity of building financial stress indexes for policy makers, see Gadanecz and Jayaram (2009) and Borio (2011a).

[4]See Holló et al. (2012), Hakkio and Keeton (2009), Cardarelli et al. (2011), Guichard et al. (2009) and Ng (2011).

(2009), and Cevik et al. (2012)). Holló et al. (2012) show that increases in the Composite Index of Systemic Stress (CISS), that is constructed by the ECB for its macroprudential analysis, lead to persistent declines industrial production in the euro area if the CISS exceeds a certain threshold. Similarly, van Roye (2013) shows contractionary business cycle effects for Germany. Finally, Hubrich and Tetlow (2012) investigate the impact of the financial stress index developed by the St. Louis Federal Reserve on economic activity in the U.S. using a five-variable Markov-Switching Bayesian Vector Autoregressive Model (MSBVAR). They also find evidence that economic dynamics are regime dependent, conditional on a high- or low-stress regime.

The definitions of financial stress vary across the literature. In general, financial stress is synonymous to the state of financial instability. Financial instability itself has quite different definitions and different dimensions. While measuring price stability is fairly straightforward, financial instability is not directly observable and it is difficult to measure. Therefore, several approaches have been introduced to capture financial instability. In this chapter, we define financial stress as a mixture of uncertainty and risk perception. In fact, Gilchrist and Zakrajsek (2012) show that periods of high uncertainty are also associated with higher risk perception, i.e. rising credit spreads. We exploit this co-movement of uncertainty and risk perception by using a dynamic factor model that identifies a common underlying component of these two measures. While uncertainty is mostly reflected in the second moments of the variables, risk perception is captured in the first moments. High levels of uncertainty and high risk premia create a situation in which the financial system is strained and its intermediation function is impaired. We closely follow the econometric methodology of van Roye (2013), who constructs a financial stress index for Germany.

This chapter proceeds as follows. Section 4.2 explains the modeling methodology and the estimation technique. Section 4.3 presents the indicator and evaluates its ability to capture the main systemic events that have occurred in France. Subsequently, in section 4.4, we analyze the effects of financial stress on economic dynamics using a Markov-Switching VAR model. Section 4.5 summarizes the main results and concludes.

4.2 Methodology

The literature proposes many different approaches to aggregate data into a single indicators. Researchers typically face two trade-offs when being confronted with data collection and aggregation methods. These trade-offs also apply to to construction of financial stress indexes.[5] The first trade-off is the data selection with respect to the time span. In general, a large sample with a long history is desirable to test the indicator's predictive properties and statistical characteristics over the business cycle. However, many financial variables that are particularly reflective for financial stress, e.g. credit default swap premia and money market spreads, are only available over very recent time periods. In this case, a shorter data sample might be preferable because these variables might better reflect financial stress than other measures that are available for a longer time horizon. The second trade-off is the frequency at which the financial variables enter the financial stress index. This trade-off depends on the type of data used, which can be available in daily, weekly, monthly or quarterly frequencies. For instance, stock market indexes and credit default swap premia are available on a daily basis, whereas some survey indicators, such as bank lending credit standards, are only reported once in a quarter. The advantage of having higher frequency data is that the potential stress signals on financial markets can be identified at an early stage. The disadvantage is that it is significantly more volatile and usually delivers more false signals.

We address these trade-offs by using a methodology that addresses both the data frequency trade-off and the time span trade-off. First, using a dynamic factor model in combination with the Expectation Maximization algorithm allows to include time series that are available over a long time period as well as those that have a short data history. The approach also allows for treating mixed frequency data. We can include native daily, monthly and quarterly frequencies into the estimation of the financial stress index, which will ultimately be calculated on a monthly basis. In the following subsection, we will present the underlying econometric methodology of the model and provide details on the construction and transformation of the data.

[5] For a detailed description of these trade-offs and how this issue is addressed in the literature, see Kliesen and Smith (2010).

4.2.1 Dynamic Approximate Factor Model

In this chapter, we follow the methodology of Banbura and Modugno (2012) and van Roye (2013), estimating a dynamic approximate factor model (DFM) that allows for an arbitrary pattern of missing data and a mixed frequency estimation including daily, monthly and quarterly data in the indicator. The factor model allows us to capture the co-movement of all considered financial variables and extract the underlying latent factor that can be interpreted as financial stress. In particular, the model takes the following form:

$$y_t = \Lambda f_t + \varepsilon_t, \qquad \text{where } \varepsilon_t \sim iid\,\mathcal{N}(0, C), \tag{4.1}$$

where y_t is a matrix of financial variables, f_t is the $1 \times T$ common latent factor containing the time-varying co-movement in the $N \times T$ matrix (the common volatility factor), and Λ is a $N \times 1$ vector of the time series' factor loadings. The values in the factor loading vector represent the extent to which each financial variable time series is affected by the common factor. The $N \times 1$ vector ε_t represents the idiosyncratic component, which is allowed to be slightly correlated at all leads and lags. The dynamics of the latent factor f_t are described in the transition equation:

$$f_t = Af_{t-1} + \xi_t, \qquad \text{where } \xi_t \sim iid\,\mathcal{N}(0, D), \tag{4.2}$$

Before estimation, the time series are de-meaned and standardized. Regarding the estimation technique of the model, we closely follow Banbura and Modugno (2012) and apply a maximum-likelihood approach combined with the Expectation Maximization algorithm originally proposed by Dempster et al. (1977). This model allows for an efficient treatment of ragged edges, mixed data frequencies and an arbitrary pattern of missing data.[6]

4.2.2 Data

The financial variables that we include for calculating the financial stress index are in a way subjectively chosen. We select the financial variables that we believe are mostly relevant to describe the stability of the financial system. All of the data rely on economic fundamentals such as interest spreads, credit spreads,

[6] For a detailed description of the estimation technique, see Banbura and Modugno (2012), and for an application to a financial stress index, see van Roye (2013).

liquidity premia, stock market indicators and volatility measures of financial markets. First, we collect data that are directly linked to the banking sector. Beside profit expectations, risk spreads, and credit default swaps, we compute a banking sector volatility index given by a ARMA(1,1)-TGARCH(1,1) model. In addition, using a CAPM model we calculate the implicit cost of equity for commercial banks. Second, we collect general capital market data, such as bond yields, the stock returns of important French corporations, and derivatives such as CDS spreads. Third, we collect data from the foreign exchange market and calculate a nominal exchange rate volatility index. A detailed description about data sources and data transformation is provided in the following subsection.

Variables related to the banking sector (figure 4.1)

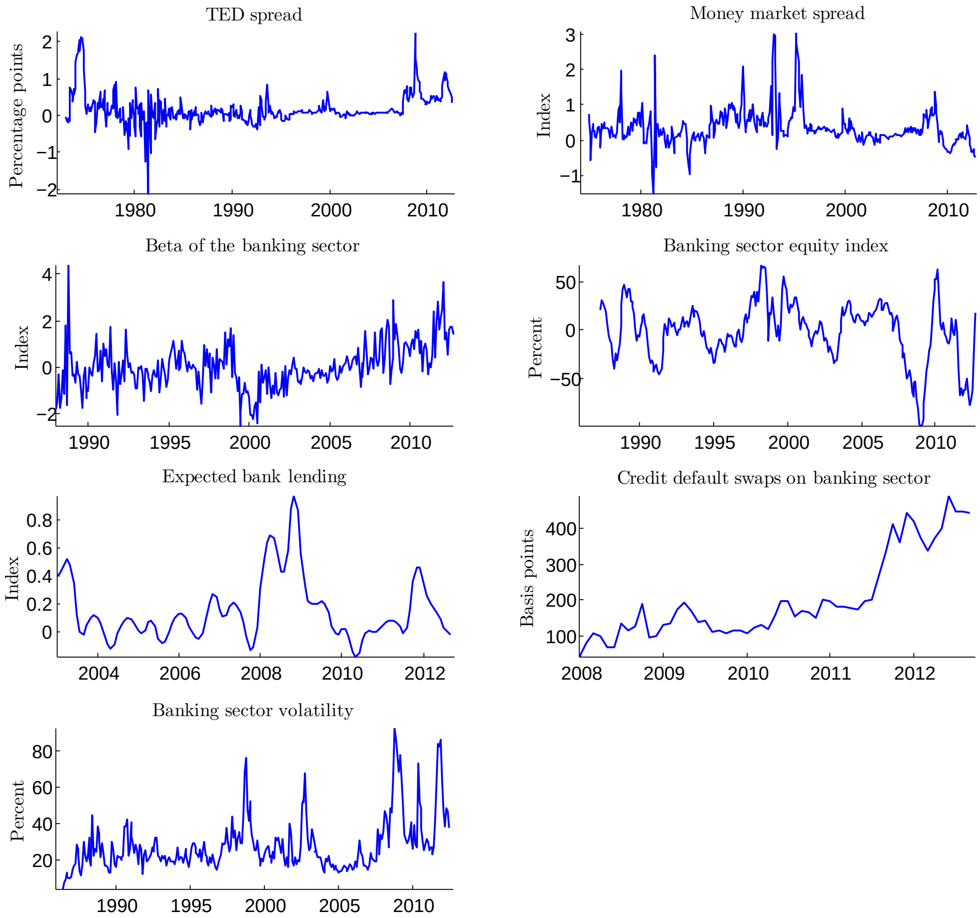
The first group we consider are financial variables related to the banking sector. In particular, we calculate indicators that in some way reflect the state of financial stability in the sector of monetary financial institutions. For the banking sector, we use 7 financial variables.

TED spread The TED spread is calculated as the difference between the 3-month PIBOR/Euribor as reported by the OECD and French government treasury bills with a maturity of 13 weeks as reported by the Banque de France. The TED spread is an important indicator for interbank lending conditions. While increasing liquidity in the money market leads to a reduction, decreasing money market liquidity leads to an increase in this spread. An increasing TED spread therefore contributes positively to financial stress.

Money market spread We calculate the indicator by taking the difference of the 3-month unsecured money market rate (3-month Euribor) and the secured money market rate (3-month Eurepo). An increasing spread between these two interest rates induces a rising risk perception in the money market. Similar to the TED spread, an increasing money market spread contributes positively to financial stress.

β of the banking sector The β of the banking sector is derived from the standard CAPM model and represents the sensitivity of bank stocks to general market risk. It is calculated as the covariance of bank stocks and the French stock market index SBF 250 divided by the variance of the SBF 250. Increases

Figure 4.1: *Variables related to the banking sector*



in β can be interpreted as a proxy for rising equity costs for commercial banks. The β of the banking sector contributes positively to financial stress.

Banking sector equity index The database consists of 6.782 daily closing prices that span the period of June, 25^{th} 1986 to June, 21^{st} 2012. This period includes both calm and extreme sub-periods. The prices are computed by Datastream as a French banking sector index. The sector includes 4 banks: BNP Paribas, Crédit Agricole, Sociéte Générale, Natixis. We calculate the first differences of this index as a measure of the state of a banking profit situation. A decreasing equity index reflects negative profit expectations, which may put pressure on the financial sector's balance sheet. Decreasing bank equity leads to an increase in financial stress.

Expected bank lending The expected bank lending is directly taken from the ECB Bank Lending Survey. Selected country-specific results are available at certain national central banks. In our case, the Banque de France provides data for France for expected bank lending in the next 3 months. The data are only available on a quarterly basis. Increases in this indicator reflect a tightening in credit standards for private sector credit, as reported by important financial institutions in France. Increases in this indicator contribute positively to financial stress.

Credit default swaps on financial corporations The credit default swap (CDS) index is the weighted average of the 10 year maturity CDS of important French financial institutions. In particular, we include the following banks: BNP Paribas, Crédit Agricole, Dexia, Crédit Local and Société Générale. Weights are computed according to market capitalization. Because these credit default swaps indicate the default risk of financial institutions, increasing values contribute positively to financial stress.

Banking sector volatility The volatility of the French banking sector is computed from the banking sector equity index with the following methodology. First, we examine all the possible specifications within five lags to choose the appropriate volatility model. We test 25 specifications of ARMA(p,q) models with $p = 1, ..., 5$ and $q = 1, ..., 5$ in addition to 25 specifications with ARMA(p,q) + GARCH(1,1). Second, we select the more parsimonious model. Four criteria are used for comparison: the log-likelihood value, the Akaike criterion, the autocorrelogram of residuals and squared residuals and the ARCH effect test. We take into consideration the trade-off between parsimony and maximizing criteria and find that the ARMA(1,1) + GARCH(1,1) model produces the best fit. Third, we test an alternative model that allows for leverage effects by considering the contribution of the negative residuals in the ARCH effect. The ARMA(1,1) + TGARCH(1,1) model offers improvements for the considered criteria. We define the banking sector log returns as $\{B_t\}_{t=1,...,T}$ with T = 6.782 daily observations. The ARMA(1,1) +TGARCH (1,1) specification is then provided as follows:

$$\log B_t = \mu_1 + \phi_1 \log B_{t-1} + \theta_1 \epsilon_{B,t-1} + \epsilon_{B,t} \tag{4.3}$$

with the innovations $\epsilon_{B,t}$ being functions of $Z_{B,t}$ and $\sigma_{B,t}$

$$\epsilon_{B,t} = Z_{B,t}\sigma_{B,t} \tag{4.4}$$

where the standardized returns $Z_{B,t}$ are independent and identically distributed, such as:

$$Z_t \hookrightarrow F_{B,Z}(0,1) \tag{4.5}$$

where $F_{B,Z}$ is an unknown distribution of Z. The time-varying volatility model $\sigma_{B,t}$ is given by:

$$\sigma^2_{B,t} = \omega + \alpha\left(Z_{B,t-1}\sigma_{B,t-1}\right)^2 + \gamma\left(Z_{B,t-1}\sigma_{B,t-1}\right)^2 I_{Z_{B,t-1}\sigma_{B,t-1}<0} + \beta\sigma^2_{B,t-1} \tag{4.6}$$

The banking sector volatility index is a proxy for uncertainty in the financial sector. Since higher uncertainty on the banking sector's outlook may concur in more restrictive lending to the non-financial sector, this index contributes to positively to the financial stress index.

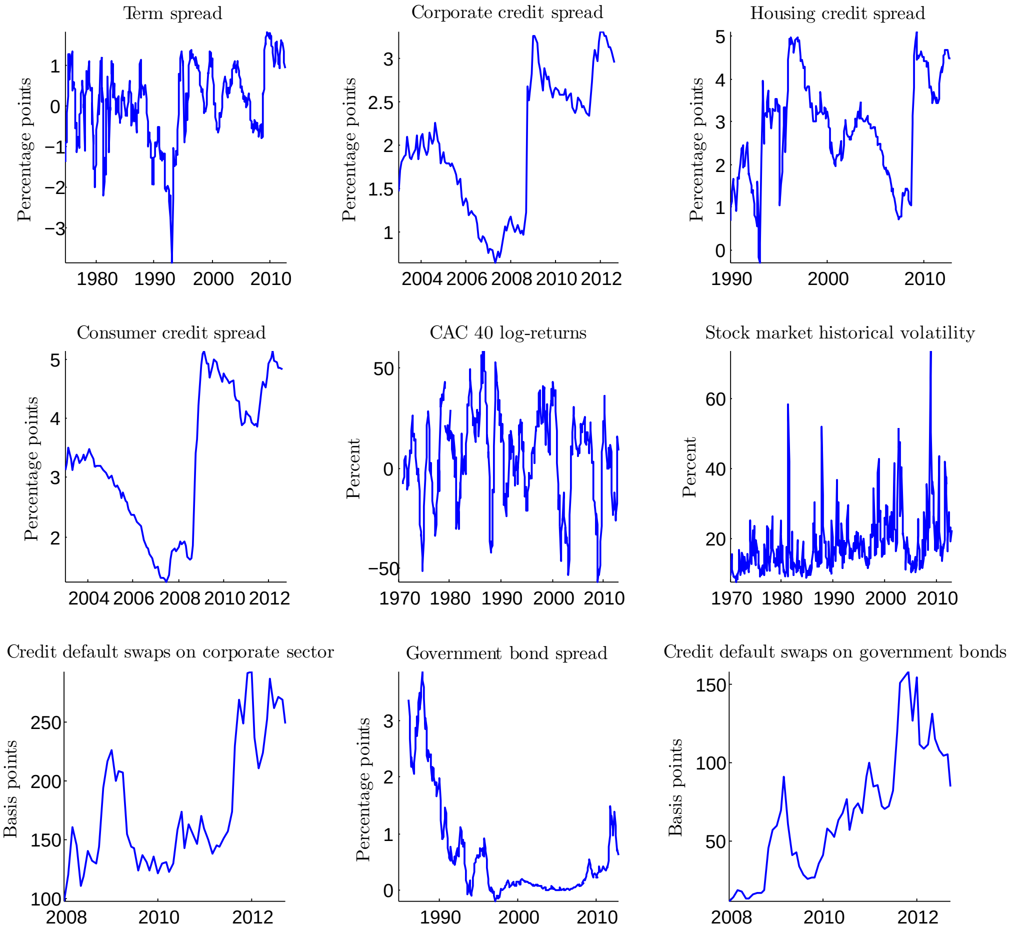
Variables related to the capital market (figure 4.2)

The second group of financial variables we consider are variables related to the capital market. In particular, we consider credit spreads, bond spreads, yield indexes and credit default swaps. For the capital market variables, we choose 9 indicators.

Term spread The term spread – the difference between short-term and long-term interest rates – is an indicator for predicting changes in economic activity. Usually, the term spread is positive; i.e., the yield curve slopes upward. However, many recessions are preceded by decreasing term spreads and sometimes even exhibit an inverted yield curve.[7] A decreasing term spread results in higher values of the financial stress index.

[7]For a survey on the ability to forecast output growth in industrialized countries, see Wheelock and Wohar (2009).

Figure 4.2: *Variables related to the capital market*



Corporate credit spread The credit spread measures the difference between the yield on one to two year loans to non-financial corporations and the rate for secured money market transactions (Eurepo) with the same maturity. An increase in this spread reflects higher capital costs for non-financial corporations which contributes positively to financial stress.

Housing credit spread The housing spread is calculate by taking the difference between interest rates for mortgages with an average maturity of 5 years and the yield of French government bonds with the same maturity. Rising spreads reflect increasing risk perception by banks with respect to their mortgage lending. Therefore, this indicator contributes positively to the financial stress index.

Consumer credit spread The consumer credit spread is calculated by taking the difference between the interest rates for consumer credit with an average maturity of 5 years and the yield of French government bonds with the same maturity. Rising spreads reflect increasing risk perception by banks with to consumer loans. Therefore, this indicator is contributes positively to the financial stress index.

Stock market log-returns (CAC 40) The French stock market series of log returns is a special series combining the "Indice General" stock index (January, 2^{nd} 1970 to December, 30^{th} 1987) and the CAC 40 stock index, which has been computed since December, 31^{st} 1987. The Indice General, which is the ancestor of the CAC 40, is not publicly available. For simplicity, this long series representing the French stock market is called CAC 40 log returns. This database consists of 10.671 daily closing prices. Falling stock prices contribute positively to the financial stress index.

Stock market historical volatility We construct the historical volatility series from the CAC 40 log return series. Therefore, this database consists of 10.671 daily volatilities that span from January, 2^{nd} 1970 to July, 31^{st} 2012. We follow the same methodology used for the banking sector index volatility construction. We find that the ARMA(2,4)+TGARCH(1,1) model improves the fit in all considered criteria. We define the market log-returns as $\{R_t\}_{t=1,\dots,T}$ with T= 10.671 daily observations. The ARMA(2,4) + TGARCH (1,1) specification is as follows:

$$R_t = \mu + \sum_{i=1}^{2} \phi_i R_{t-i} + \sum_{i=1}^{4} \theta_i \epsilon_{R,t-i} + \epsilon_{R,t} \tag{4.7}$$

with the innovations $\epsilon_{R,t}$ being functions of $Z_{R,t}$ and $\sigma_{R,t}$:

$$\epsilon_{R,t} = Z_{R,t}\sigma_{R,t} \tag{4.8}$$

where the standardized returns $Z_{R,t}$ are independent and identically distributed:

$$Z_{R,t} \hookrightarrow F_{R,Z}(0,1) \tag{4.9}$$

where $F_{R,Z}$ is an unknown distribution of Z. The time-varying volatility model $\sigma_{R,t}$ is given by the following:

$$\sigma^2_{R,t} = \omega + \alpha \left(Z_{R,t-1} \sigma_{R,t-1} \right)^2 + \gamma \left(Z_{R,t-1} \sigma_{R,t-1} \right)^2 I_{Z_{R,t-1}\sigma_{R,t-1}<0} + \beta \sigma^2_{R,t-1} \quad (4.10)$$

Stock market volatility can be interpreted as aggregate uncertainty on financial markets on future economic activity (Bloom (2009)). Higher uncertainty increases potential strains on financial markets. Against this background, this index contributes positively to the financial stress index.

Credit default swaps on corporate sector The credit default swap index is the weighted average of the 10 year maturity CDS of important French corporations. In particular, we include the following firms: Accor, Alcan France, Alcatel, Allianz France, Arcelor Mittal France, Assurance Générale de France, Axa, Bouygues Télécom, Carrefour, Casino, Cie de Saint-Gobain, Danone, EDF, France Télécom, GDF Suez, Gecina, Havas and Air Liquide. Weights are computed according to market capitalization.

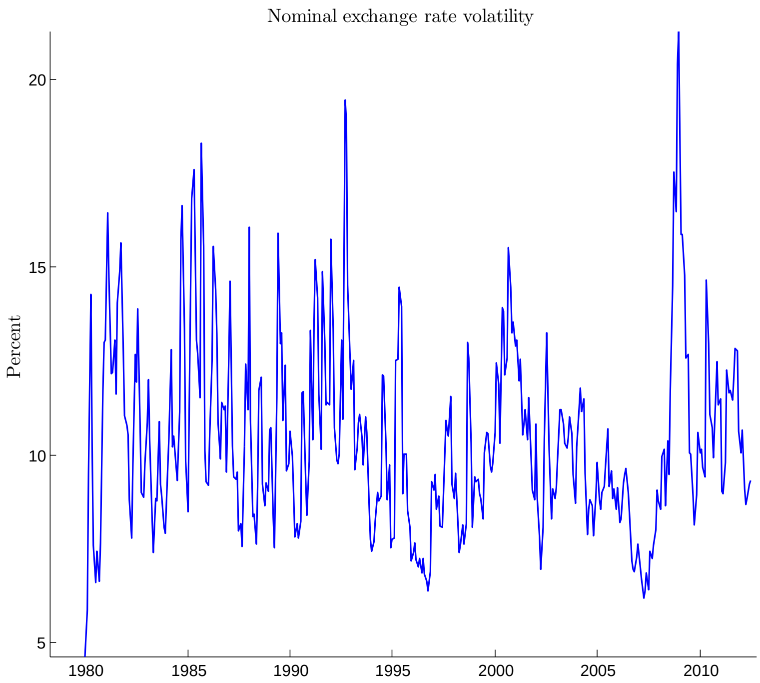
Government bond spread The government bond spread is calculated by using the average yield of French government bonds with a maturity of 10 years and subtract it from the corresponding German government bonds. An increase in this spread reflects the market's higher risk perception with respect to French government bonds and contributes positively to financial stress.

Credit default swap on 1Y Government Bonds The premium for government credit default swaps reflects a default probability of outstanding sovereign debt. If the default probability rises, tensions on banks' balance sheets and the whole financial system increase. Therefore, the government CDS affects financial stress positively.

Variable related to the foreign exchange market (figure 4.3)

The third group consists of an indicator that indicates stress on the foreign exchange market. More precisely, we calculate a nominal synthetic exchange rate volatility.

Figure 4.3: *Variable related to foreign exchange market*



Nominal synthetic exchange rate volatility This historical volatility series is constructed from the nominal synthetic exchange rate. This special series is the synthetic dollar-euro nominal exchange rate and is based on trade weights given by the share of external trade of each euro area member state in the total euro area trade. It is computed by the ECB. The database consists of 8.499 daily exchange rates that span from January, 7^{th} 1980 to July, $31, 2012$. We follow the same methodology used for the banking sector index volatility construction. We find that the ARMA(2,4)+TGARCH(1,1) model improves the fit in all considered criteria. We define the exchange rate log-returns as $\{E_t\}_{t=1,...,T}$ with T= 8.499 daily observations. The ARMA(2,2) + TGARCH (1,1) specification is then provided as follows:

$$E_t = \mu + \sum_{i=1}^{2} \phi_i E_{t-i} + \sum_{i=1}^{2} \theta_i \epsilon_{E,t-i} + \epsilon_{E,t} \tag{4.11}$$

with the innovations $\epsilon_{E,t}$ being functions of $Z_{E,t}$ and $\sigma_{E,t}$:

$$\epsilon_{E,t} = Z_{E,t}\sigma_{E,t} \tag{4.12}$$

where the standardized returns $Z_{E,t}$ are independent and identically distributed:

$$Z_t \hookrightarrow F_{E,Z}(0,1) \tag{4.13}$$

where $F_{E,Z}$ is an unknown distribution of Z. The time-varying volatility model $\sigma_{E,t}$ is given by the following:

$$\sigma^2_{E,t} = \omega + \alpha \left(Z_{E,t-1}\sigma_{E,t-1}\right)^2 + \gamma \left(Z_{E,t-1}\sigma_{E,t-1}\right)^2 I_{Z_{E,t-1}\sigma_{E,t-1}<0} + \beta\sigma^2_{E,t-1} \tag{4.14}$$

After the estimation, we present the factor loadings of the considered financial variables (table 4.1). The financial variables that contribute most strongly to the financial stress index are the historical volatility of the CAC 40, the CAC 40 log returns and the banking sector volatility. The term spread and the government bond spread do not have a significant impact on financial stress in France.

Table 4.1: *Factor loadings of the DFM*

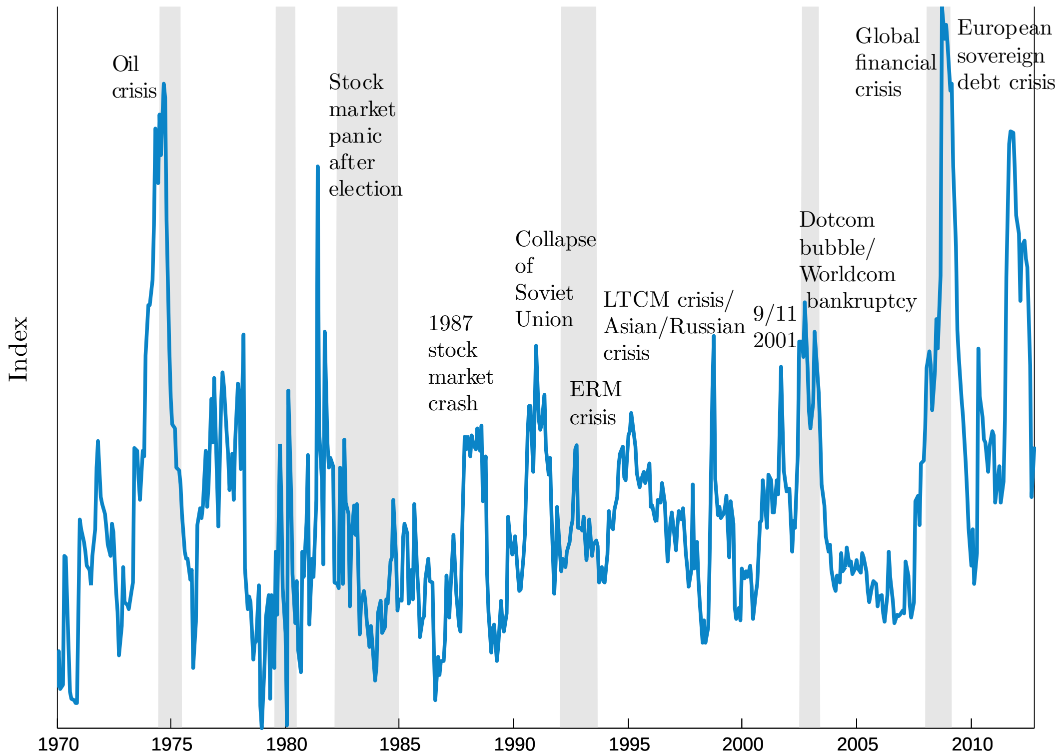
Financial variable	λ_i
Banking sector volatility	0.8572
TED spread	0.6966
Historical volatility of the CAC	0.6101
β of the banking sector	0.4726
Expected bank lending	0.4389
Corporate credit spread	0.4308
Exchange rate volatility	0.3851
Consumer credit spread	0.3782
Housing credit spread	0.2851
Credit default swaps on corporate sector	0.2102
Credit default swaps on banking sector	0.1135
Credit default swaps on government bonds	0.1093
Money market spread	0.0989
Term spread	0.0582
Government bond spread	-0.0652
CAC 40 log-returns	-0.7945
Banking sector equity index	-0.9079

Notes: The values are extracted from the loading matrix Λ of the DFM.

4.3 A financial stress index for France

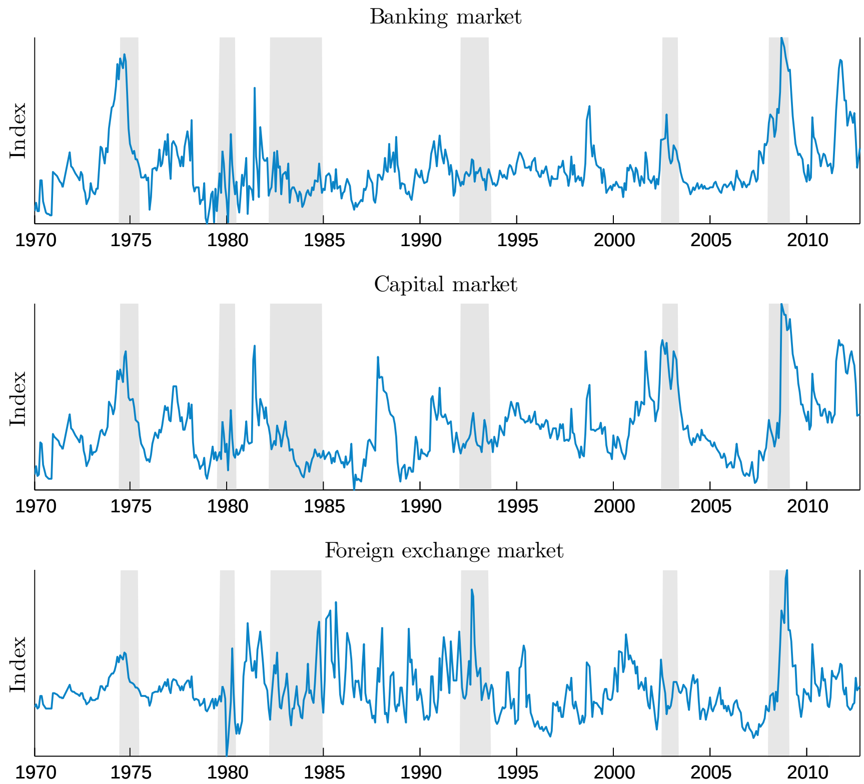
After estimating the model, we obtain a single composite financial stress index for France (Figure 4.4). The first incident to which the FSI strongly reacts is the OPEC oil embargo from October 1973 to March 1974, when France entered into a recession. Even if France was relatively little exposed to the embargo due to its specific foreign policy, it was significantly hit by an increase in oil prices and rising commodity prices. Soaring import prices led to sharply increasing production costs for the French industry. Splitting up the index into the three subgroups indicates that mainly the indicators from the banking sector and from the capital market contributed to the stress on financial markets (Figure 4.5). Nominal exchange rate volatility slightly increased.

Figure 4.4: *Financial stress index for France*



Notes: The index is calculated on the basis of 17 financial market variables using a dynamic approximate factor model. Shaded areas indicate recessions using calculations by the Economic Cycles Research Institute.

Figure 4.5: *Contributions of subgroups to the FSI*



Notes: Shaded areas refer to recession dates provided by the Economic Cycle Research Institute.

The next peak of the FSI depicts the largest drop in stock market returns since the Second World War. It occurred after the presidential election of François Mitterrand on May 10, 1981. On May 13, 1981, when the left wing released the list of the companies to be nationalized, it induced a panic on the French stock market with a one-day decline of -15.1%. The day after, the volatility reached its highest level of 94.3%. The FSI fairly reproduces this stress on stock markets and peaks only slightly below the level reached during the oil embargo. Figure 4.5 confirms that the large part of the FSI increase came from capital markets (especially stock returns and stock market volatility) and the banking sector (money market spread), while exchange rate volatility remained rather subdued.

On October 19, 1987, the French stock market collapsed once again, reacting to the events happening on stock markets in the United States on "Black Monday". The stock market index successively declined until it reached its lowest level in January 1988. At that time, the stock market index lost approximately 40% of its capitalization. Three years later, on August 19, 1991, the Soviet coup d'état attempt against President Mikhail Gorbachov led to high political uncertainty in France given the post-Cold War context.

On July, 22 1992, the European exchange rate mechanism was under attack; indeed, the exchange rate bands widened so much that central banks had to intervene to stop devaluation in countries like France and support the French franc. On October, 2 1992, the Bank of France spent 80 billion franc to support its currency. The FSI also strongly reacts to this event. Figure 4.5 fairly depicts that the increases in the FSI were mainly driven by higher exchange rate volatility while the sub-indexes of the banking sector and the capital market do not rise significantly, since other market segments were not strongly affected. This is the reason that the effect of the ERM crisis did not have a large effect on the FSI: it peaks far below the other events in French history.

The next significant increase in the FSI depicts the events associated to the Asian and Russian crisis as well as the default of the large hedge fund Long Term Capital Management (LTCM) in 1998. The French banking sector was significantly affected by this financial market turmoil. The bank volatility index was the main driver of increases in financial stress, reaching the highest value since its first registered value in 1986.

From 1998 until 2001, financial stress dropped to very low levels. Investors perceived the introduction of the euro as a positive sign for France such that stock markets dynamically increased and government bond spreads decreased further. The stock market rally was interrupted with the attacks on the world trade center on September 11, 2001. Afterward, stock markets recovered quickly before the worldwide stock market downturn of 2002.[8]

The highest peak of the FSI occurred before the financial crisis 2008/2009, after the collapse of the investment bank Lehman Brothers in September 2008. All three subgroups of the FSI indicate large increases in financial stress. The second largest drop in French stock market returns in history occurred on October 6, 2008, when a panic effect related to the stability of the financial sector

[8]Stock markets across the United States, the United Kingdom, Canada, Asia and all over Europe slid persistently reaching troughs last recorded in 1997 and 1998.

spread throughout Europe, inducing a dramatic one-day decline of -9.5% of the CAC. When the US stock market plunged on October 15, 2008, French volatility hit its second highest level at 92.5% the following day. In this context, after accumulating bad news, the FSI reached its highest level in November 2008. As a comparison, the highest level of historical (implied) volatility of the French stock market since 1982 occurred on October, 16 2008 at 92.7%. In addition, the highest exchange rate volatility level since 1982 occurred on December 22, 2008 at 29%.

As an economic response to the financial crisis, the French government announced a 26 billion Euro stimulus plan on December 2008 to stabilize the economy, anticipating the drastic fall in aggregate demand which in the end resulted in the worst recession since 1945. At the end of 2010, this stimulus package was increased to 38.8 billion Euro. On the one hand, this policy may have contributed in a decline of the stress index at the beginning of April 2009, the month that corresponds approximately to the end of the recession in France. On the other hand, it rapidly increased the government's debt-to-GDP ratio putting at stake fiscal solvency. As a result, rating agencies began downgrading various countries, pushing their sovereign yields up. In May 2010, the FSI peaked locally, when money markets almost dried out and the European financial system was under strain. In reaction to this, the ECB intervened on capital markets through bond purchases to reduce the interest rate levels of sovereign borrowers. Subsequently, the perception of the crisis gravity diminished temporarily. In particular, the French economy has been relatively resilient to investors uncertainty and did not suffer from a large confidence loss like other peripheral countries such as Spain and Italy.

From August 2011 to January 2012 when market concerns of contagion effects on other countries in the euro area came up, the FSI increased sharply. In particular, investors attributed higher default risks to Spain's and Italy's debts, which partly contaminated the credit spread of French corporations and the government. In addition, investors became uncertain about the future design of the European monetary union (due to delays in the implementation of the European Stability Mechanism, general policy uncertainty, and the possible exit of Greece). This spillover effect to the French economy was quite pronounced for two reasons. France contributes about 20% to the European Financial Stability

Facility with a maximum guarantee of 110 billion Euros, which means that it bears a fifth of a potential bail out. Second, French banks are the most exposed to peripheral countries; indeed, US money-market funds have cut their lending to French banks because they may experiment problems of contagion from the peripheral countries. Consequently, the banking sector index declined from 1026 points on January 2007 to 235 points in January 2012. The volatility of the French banking sector peaked at 121% in November, 2 2011. With the announcement of ECB's Long Term Refinancing Operations to loan 489 billion Euros to European banks for three years, the FSI has begun to shift downward since early 2012. The FSI has decreased further with the launch of the Outright Monetary Transactions (OMT) by the ECB on August, 2 2012.

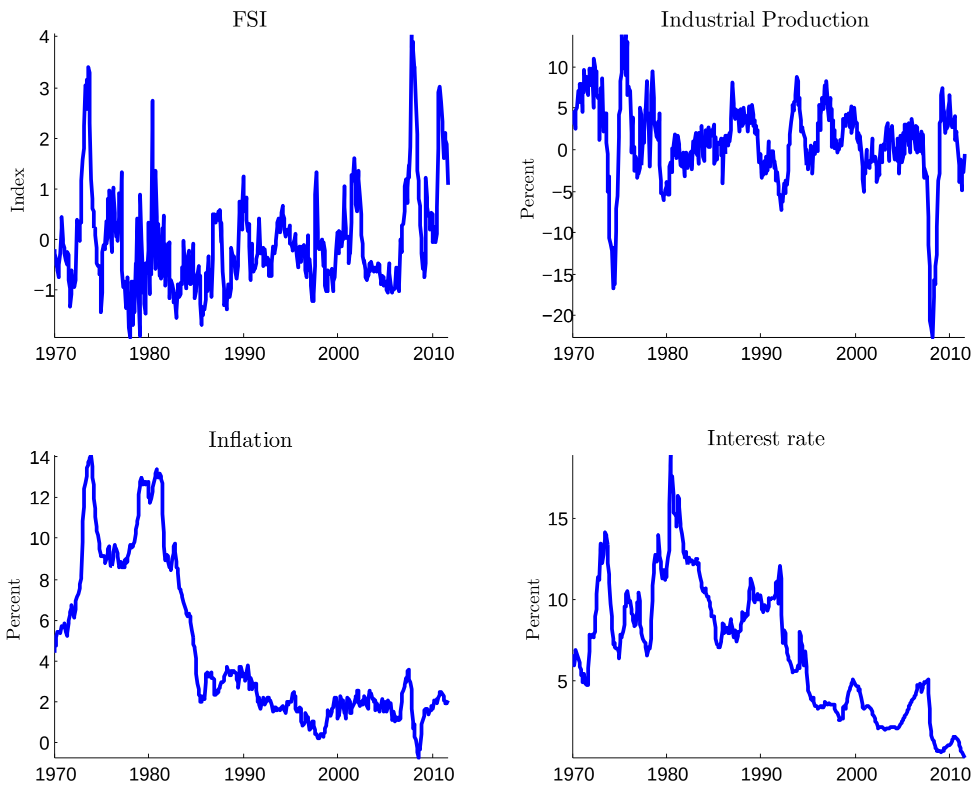
4.4 The FSI and economic activity

Typically, periods of high financial stress lead to a reduction in economic activity. This has been shown both theoretically and empirically for different countries. From the theoretical perspective, there are three different channels through which financial stress has effects on macroeconomic activity. First, in episodes of high financial stress, firms hesitate to invest or are reluctant to hire new workers. This effect is sometimes called the "wait-and-see effect" (Bloom (2009)). Second, banks are more cautious to lend because they increase credit standards (Bonciani and van Roye (2013)). This channel can be summarized as a loan supply effect. Third, high financial stress leads to higher funding costs of the private sector due to higher interest rate spreads and rising liquidity premia (Gilchrist and Zakrajsek (2012)). The negative impact of high financial stress episodes has also been shown empirically for different countries (see Bloom (2009), Baker et al. (2012), Hakkio and Keeton (2009), Holló et al. (2012), and van Roye (2013), among others, and Kliesen and Smith (2010) for a survey). Beside its purpose for financial stability monitoring, the usefulness of the French FSI crucially depends on its ability to relate financial market developments to economic activity. Therefore, we will test the FSI on its statistical properties and its relationship to economic activity in France.

A Markov-Switching Bayesian Vector Autoregressive Model

First, we will identify periods of high financial stress and those of low financial stress. To do so, we have to assume that the properties of FSI are state dependent. Because financial instability can be considered a tail event, we assume two regimes a priori. In particular, we assume that financial stress occurs suddenly and stochastically with a certain persistence within either regime. We apply a Markov-Switching Bayesian Vector Autoregressive model (MSBVAR) model to identify the regimes, i.e., low-stress and high-stress regimes. The Markov-Switching setup is particularly useful in a nonlinear environment because it can identify sudden behavioral changes of financial variables. In particular, we use the MSBVAR model developed by Sims et al. (2008). Therefore, our analysis is comparable to that of Hubrich and Tetlow (2012), who analyze the impact of financial stress on the US economy. We set up the model with four endogenous variables: the financial stress index, the inflation rate, industrial production growth and the short-term interest rate, i.e., the 3-month PIBOR/EURIBOR (Figure 4.6).

Figure 4.6: *Variables included in the MSBVAR*



The endogenous vector of the model is given by $y_t = [FSI_t \quad \Delta IP_t \quad \pi_t \quad i_t]$. We follow Sims et al. (2008) and set up a MSBVAR as follows:

$$y_t' A_0(s_t) = \sum_{i=1}^{\rho} y_{t-i}' A_i(s_t) + z_t' C(s_t) + \varepsilon_t' \Theta^{-1}(s_t), \; t = 1, \ldots, T, \tag{4.15}$$

where y_t is the 4-dimensional column vector of endogenous variables, A_0 is a non-singular 4×4 matrix and $A_i(k)$ is a 4×4 matrix for $1 \leq k \leq h$, s_t are unobserved states at time t, and ρ is the lag length. and $\varepsilon_t \sim \mathcal{N}(0, \sigma^2)$ is an n-dimensional shock process. In our case, we assume two states $s_t = 1, 2$. Furthermore, z_t is an indicator matrix taking the value 1, representing a column vector of constants. $C(s_t)$ is an $m \times n$ intercept matrix for $1 \leq k \leq h$, and Θ is an $m \times n$ diagonal matrix of factor loadings scaling the stochastic volatility factors on the vector of unobserved shocks ε_t. The structural shocks ε_t are normal with mean and variance equal to the following:

$$\mathbb{E}[\varepsilon_t | Y_1, ..., Y_{t-1}, z_1, \ldots, z_{t-1}] = 0, \tag{4.16}$$

$$\mathbb{E}[\varepsilon_t \varepsilon(t)' | y_1, \ldots, y_{t-1}, z_1, , \ldots, z_{t-1}] = I_n, \tag{4.17}$$

Defining the initial conditions $x_t = [y_{t-1}, \ldots, y_{t-\rho}, z_t]'$ and $F(s_t) = [A_1(s_t)', \ldots, A_\rho(s_t)', C(s_t)]'$, the model can be written in compact form:

$$y_t' A(s_t) = x_t' F(s_t) + \varepsilon_t' \Theta^{-1}(s_t), \forall\ 1 \leq t \leq T, \tag{4.18}$$

Finally, assuming conditionally normal structural disturbances: $\varepsilon_t' | Y^{t-1} \sim \mathcal{N}(0, I_n)$, where $Y^t = \{y_0, \ldots, y_t\}$ we can write the model in reduced form:

$$y_t' = x_t' B(s_t) + u'(s_t), \tag{4.19}$$

where

$$B(s_t) = F(s_t) A^{-1}(s_t), \tag{4.20}$$

and

$$u(s_t) = A^{'-1}(s_t) \epsilon_t' \Theta(s_t), \tag{4.21}$$

The regime change is determined by a first-order Markov process. The Markov chain has the following probability rule: $\mathcal{P}(S_t = j | s_{t-1} = i) = p_{ij}$, where $p_{11} + p_{12} = 1$ and $p_{21} + p_{22} = 1$. This implies that the current regime s_t only depends on the regime one period before. The model's parameters $\hat{\theta} = (\hat{\phi}_1, \hat{\phi}_2)$ depend on the unobservable regimes in a nonlinear manner. Like Sims et al. (2008), we apply Bayesian techniques to estimate the model's parameters.

Prior selection As in all Bayesian models, the priors have to be chosen carefully because the results crucially depend on them. Along with the priors we have to select for the parameters in the reduced-form BVAR, we also have to impose priors on the transition matrix. We choose priors very similar to those chosen by Sims et al. (2008) and Hubrich and Tetlow (2012) that are appropriate for a monthly model. We set the overall tightness for the matrices A and F to 0.6. The relative tightness of the matrix F is set to 0.15, whereas the relative tightness of the constant term is chosen to be 0.1. The Dirichlet priors are set to 5.6 for both the variances and coefficients. All parameters are presented in the table below.

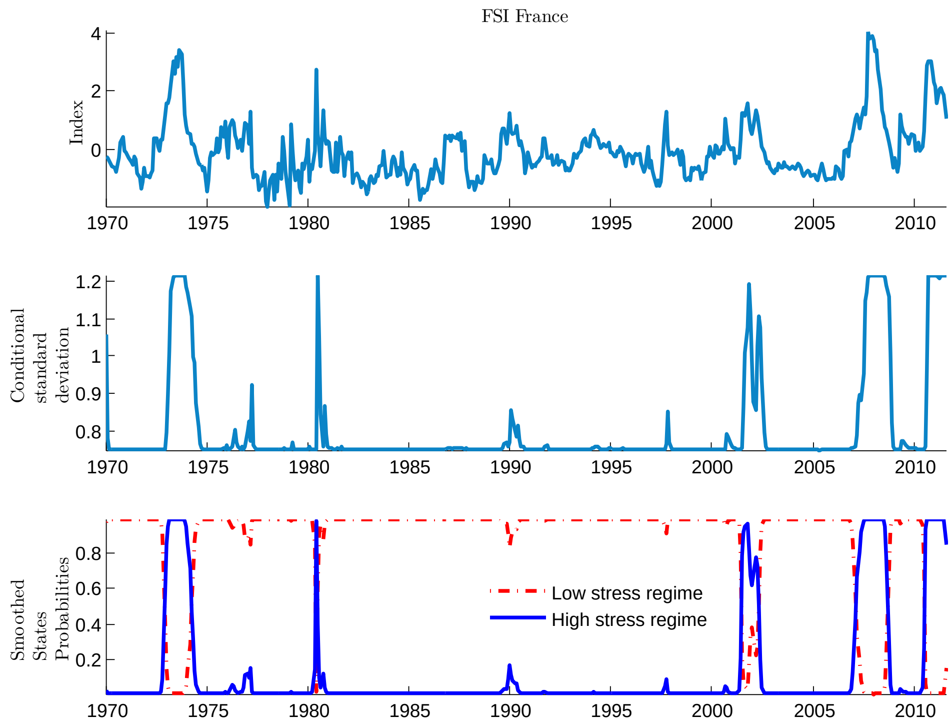
Table 4.2: *Prior selection for hyperparameters*

Type of prior	Value
Overall tightness for A and F	0.57
Relative tightness for F	0.13
Relative tightness for the constant term	0.1
Tightness on lag decay	1.2
Weight on nvars sums of coefficients dummy observations	10
Weight on single dummy initial observation including constant	10

Notes: Priors are selected based on Sims et al. (2008) and Hubrich and Tetlow (2012).

We use monthly data that range from 1971M1 to 2012M8, which leaves us 488 data points for each time series. To identify the BVAR model, we apply a lower triangle Choleski-decomposition of $A(s_t)$. In figure 4.7, the FSI, its conditional standard deviation and the smoothed state probabilities are depicted over time. The model indicates that the probability is very high that the French economy was in a high-stress regime during the oil crisis, the 1982 recession, the burst of the dotcom bubble, the recent global financial crisis and the European sovereign debt crisis.

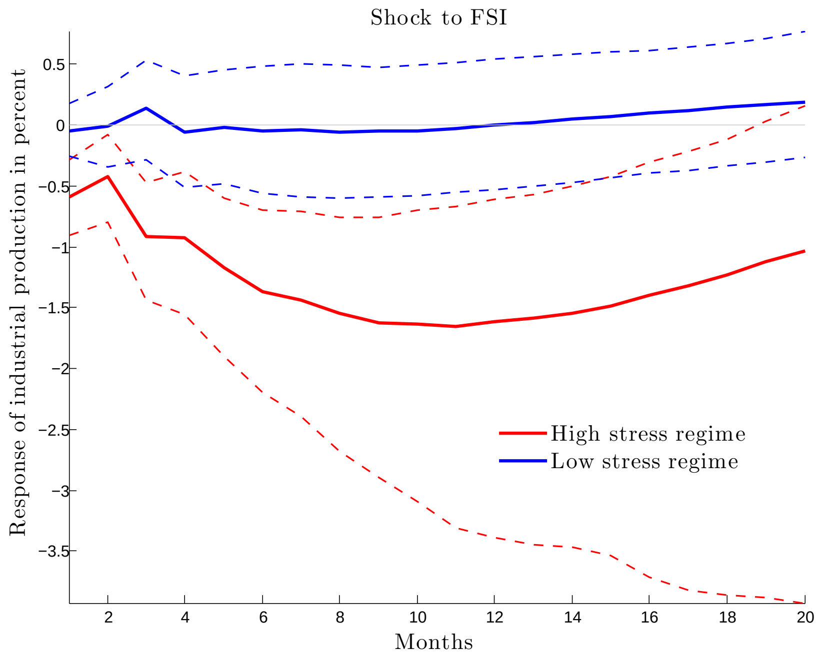
Figure 4.7: *Markov-Switching model FSI France*



Notes: The regime probabilities are illustrated in the lower panel.

In figure 4.8, we present the impulse response functions for the change in industrial production to a shock in the financial stress index. The feedback of financial stress differs considerably between regimes. While there is no significant change in industrial production in response to a financial stress shock in a low-stress regime, the shock in financial stress has great and persistent negative effects on industrial production in a high-stress regime. This finding is in line with studies for other countries and highlights the importance of nonlinearities in a crisis situation.

Figure 4.8: *Impulse response functions: BVAR model*



Notes: Error bands are 10% on each side generated by Monte-Carlo with 500 replications.

4.5 Conclusion

In recent years, several papers have found a negative relationship between financial stress and economic activity. This study complements these papers by offering a useful financial stress index that is available in real time and is constructed using a sophisticated modeling approach. More precisely, in this chapter, we construct a financial stress index (FSI) for France that can be used in real time to evaluate financial stability in the French financial system. We construct the index using 17 financial variables. From these variables, we extract a common stress component using a dynamic approximate factor model. The model is estimated with a combined maximum-likelihood and Expectation Maximization algorithm, allowing for mixed frequencies and an arbitrary pattern of missing data. Subsequently, we test how the index relates to economic activity. Against this background, we set up a Markov-Switching Bayesian Vector Autoregressive Model (MSBVAR). In particular, we impose two regimes on the model, one low-stress and one high-stress regime, and analyze whether the transmission of financial stress on economic activity depends on the respective state.

The financial stress index fairly indicates important events in French history. It soars when liquidity premia, risk spreads and uncertainty measures increase sharply. Therefore, the index can capture systemic events when a batch of indicators shows signs of financial market tensions.

We find evidence that one regime is not sufficient to model economic activity within this model setup. A two-regime model delivers results that are significantly more appropriate and are able to capture the nonlinearities in the model. Furthermore, the estimation results indicate that financial stress transmits very strongly to economic activity when the economy is in a high-stress regime, whereas economic activity remains nearly unaltered in a low-stress regime. These findings are robust across different identification schemes within the BVAR model.

C Appendix

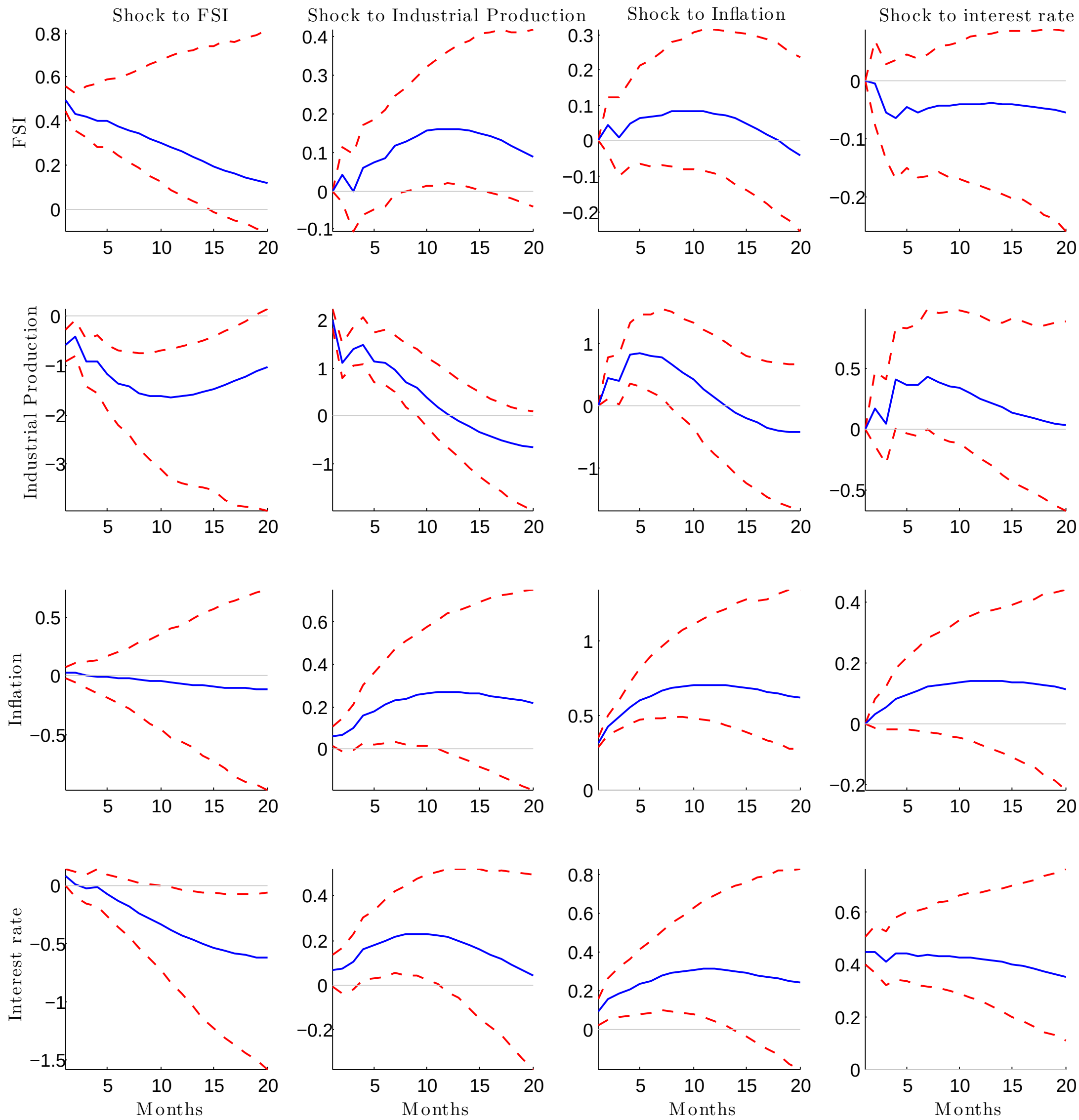
C.1 Table and Figures

Table C1: *Data description*

Indicators	Native frequency	First observation
Banking indicators		
TED-spread	monthly	1973M01
Money market spread	daily	1999M01
β of banking sector	daily	1980M03
Banking sector equity index	daily	1986M06
Expected Lending	quarterly	2003M01
CDS on banking sector	monthly	2007M01
Banking sector volatility	daily	1986M06
Capital market indicators		
Term spread	monthly	1976M01
Corporate credit spread	monthly	2003M01
Housing credit spread	monthly	1990M01
Consumer credit spread	monthly	2003M01
CAC 40 log-returns	daily	1970M01
Stock market historical volatility	daily	1970M01
Government bonds spread	daily	1987M12
CDS on corporate sector	monthly	2008M01
CDS on 10Y government bonds	daily	2007M12
Foreign exchange indicators		
Nominal synthetic exchange rate volatility	daily	1980M01

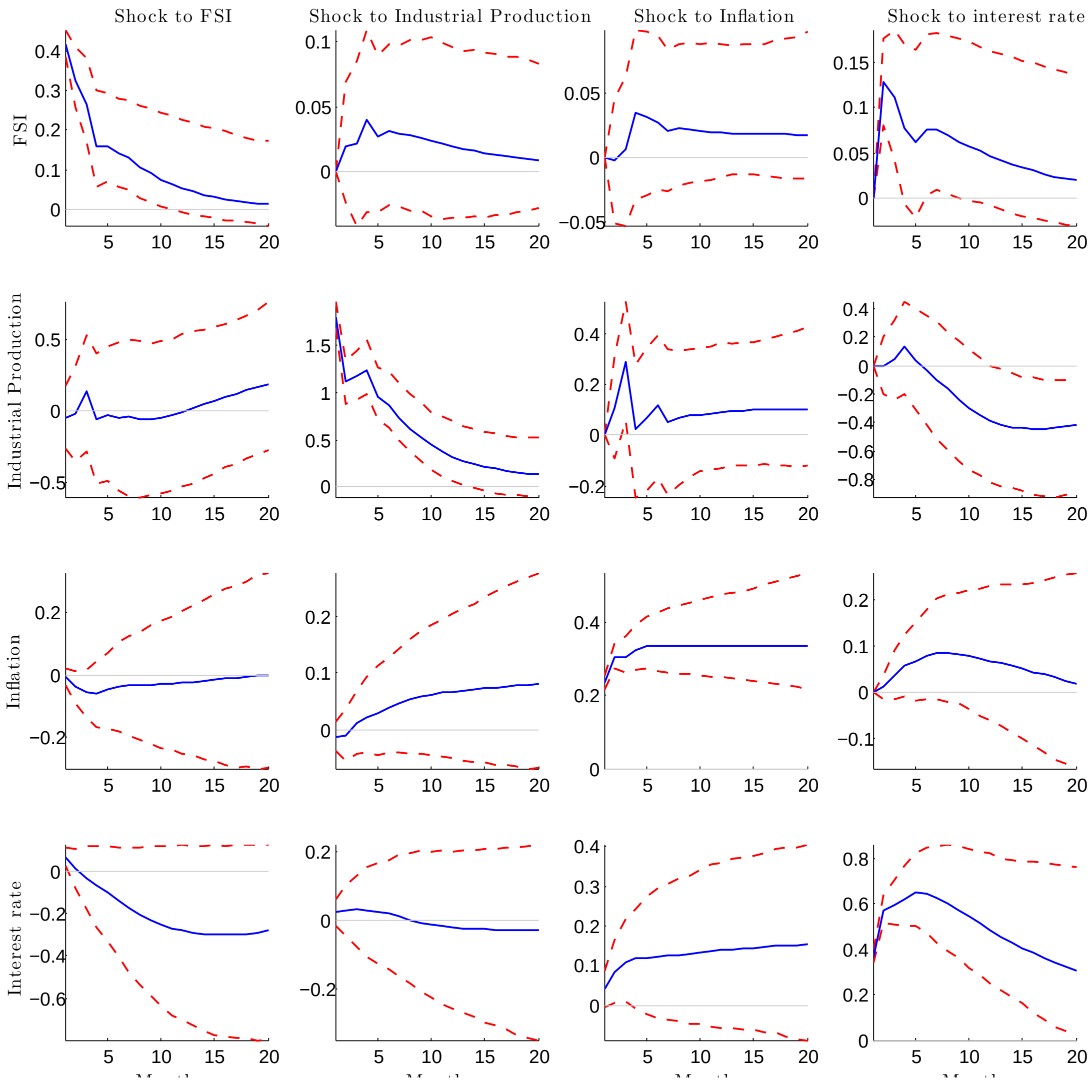
Source: European Central Bank, Banque de France, Thomson Financial Datastream, own calculations.

Figure C1: *Impulse response functions: high-stress regime*



Notes: Error bands are 66% bands generated by Monte-Carlo with 500 replications.

Figure C2: *Impulse response functions: low-stress regime*



Notes: Error bands are 66% bands generated by Monte-Carlo with 500 replications.

CHAPTER 5

International transmission of financial stress: evidence from a GVAR[1]

5.1 Introduction

The financial and economic crisis of 2008-2009 had a widespread impact on countries all over the world. While advanced economies were directly exposed to the events in the wake of the default of Lehman Brothers, also financial markets in the emerging economies were negatively affected. In nearly all countries, stock markets plummeted, bank stocks came under pressure due to systemic risk, and volatilities on stock markets and foreign exchange markets increased significantly.

While there is a vast growing literature of analyzing the role of financial conditions and financial stress during these events, relatively little research has been undertaken to investigate the global perspective of financial stress. This chapter tries to contribute closing this gap, by taking a global perspective of financial stress and its spillover effects between countries. We investigate the international transmission channels of financial stress by analyzing how financial stress events propagate to the economy in various countries. In order to shed light on these international macro-financial linkages, we construct financial stress indexes (FSIs) for 20 countries and investigate the relationship to main macroeconomic variables. Using the FSIs, we employ a Global VAR model, originally developed by Pesaran et al. (2004), and investigate the propagation of financial stress shocks. We find that financial stress quickly spreads internationally and has a lagged but persistent negative effect on industrial produc-

[1] This chapter is based on: Dovern and van Roye (2013). International transmission of financial stress: evidence from a GVAR. Kiel Working Paper No. 1844, The Kiel Institute for the World Economy.

tion. Likewise, a shock to financial stress that is solely originated in the United States transmits quickly to financial markets in other countries and also incurs a lagged but persistent economic contraction. These findings are in line with other studies that investigate the impact of international housing shocks and find persistent effects on real economic activity after housing and financial crises (Jannsen (2010), Cesa-Bianchi (2012) and Claessens et al. (2012)).

Measuring financial stress has become more and more prominent in recent years. Central banks and international organizations, private banks and economic research institutes have constructed financial stress indexes to assess the state of financial stability and to identify potential systemic risk at an early stage. Among the first, Illing and Liu (2006) constructed a FSI for Canada for providing a "snapshot" of the current degree of stress in the financial system. Hakkio and Keeton (2009) and Kliesen and Smith (2010) constructed financial stress indexes for the United States, which are regularly referred to by the Federal Reserve.[2] The European Central Bank periodically publishes a Composite Indicator for Systemic Stress (CISS) as a tool for its macroprudential monitoring.[3] The CISS consists of variables from the money, equity, bond, and foreign exchange market and summarizes the market specific sub-indexes in one composite index for the euro area. Also for other countries financial stress indexes were established as a thermometer of the financial system.[4]

In addition to a simple measure of financial stability, also the role of financial stress for economic dynamics has gained center stage in recent years. Several studies find that financial stress reduces economic activity significantly. Most of these studies investigate the effects of financial stress on economic activity in the United States. While Hakkio and Keeton (2009) show that increases in financial stress lead to persistent business cycle downturns when the financial system is under stress, Hubrich and Tetlow (2012) support their results, employing a Markov-Switching Bayesian Vector Autoregressive (MSBVAR) model. They show that financial stress events leads to a strong economic contraction and

[2] The indexes can be downloaded on the Federal Reserve's webpages: KCFSI and STLFSI.

[3] The CISS was constructed by Holló et al. (2012) and is published on the website of the European Central Bank as a macroprudential risk indicator of the European Stability and Risk Board: CISS.

[4] Cardarelli et al. (2011) develop FSIs for a variety of countries which were also used for analysis of the IMF World Economic Outlook. van Roye (2013) and Aboura and van Roye (2013) constructed a FSI for Germany and for France using a very broad selection of financial variables over a long time horizon.

that conventional monetary policy is only little effective in this regime. Mittnik and Semmler (2013) employ a multi-regime vector autoregression (MRVAR) approach, to capture the regime-dependency and size-dependency of financial stress shock. By employing the financial stress index constructed by the IMF, they find that large negative shocks to financial stress have sizable positive effects on real activity and support the idea of unconventional monetary policy measures in cases of extreme financial stress.

Beyond the studies for the United States, the relationship between financial stress and economic activity has been investigated also for other countries. Aboura and van Roye (2013) develop a financial stress index for France, consisting of 17 financial variables, and analyze the impact of financial stress on economic activity. They find evidence for a two-regime economy; i.e. a high stress regime when financial stress has a negative effect on economic activity and a low stress regime when financial stress does not incur any significant effect on the business cycle. An alternative approach to model these regime dependencies, is developed by van Roye (2013). Using a threshold VAR model, he estimates a threshold above which financial stress significantly affects economic activity in Germany. Cevik et al. (2012) analyze the relationship between financial stress on economic activity in transition countries. They use a linear bivariate VAR to show that financial stress dampens industrial production in these countries.

While there is a there is a vast literature on country-specific analysis, the international transmission of financial stress has been only analyzed scarcely. Balakrishnan et al. (2009) were the first who analyzed the transmission of financial stress between countries. They use a common time-varying component in the FSIs for emerging markets and its relationship to the FSIs in advanced economies and other global factors. Furthermore, they employ a two stage econometric analysis of monthly financial stress co-movement using a country-by-country approach and an annual panel data analysis of determinants of financial stress. They find that financial stress spreads quickly from advanced economies to emerging markets with a high pass-through.

This chapter contributes to the literature in several dimensions. First, we construct a comprehensive measure of financial stress for 20 countries that is available in real time. Second, we show that the correlation of financial stress across countries is particularly high during financial crises. Third, we show that countries that are financially open exhibit stronger correlation of financial stress to other countries than do countries that have relatively higher restrictions on financial openness. Finally, we show how financial stress propagates internationally and how it impacts the business cycles of the sample countries.

The chapter is organized as follows. Section 5.2 characterizes the conceptual methodology that is used to construct the financial stress indexes, shortly describes the data and the estimation technique, and finally presents the financial stress indexes for all countries. We identify important country-specific and global financial stress events and analyze how financial stress is correlated between countries. Section 5.3 describes the GVAR model and investigates how financial stress is transmitted internationally and how it dampens economic activity. Section 5.4 briefly concludes.

5.2 Measuring financial stress: Constructing financial stress indexes

Financial stress is unobservable but presumably reflected in many financial variables. As Illing and Liu (2006) point out, financial stress may be defined as the force exerted on economic agents by uncertainty and changing expectations of a loss in financial markets and its institutions behind. Given this definition, we primarily focus on measures of uncertainty on financial markets. In particular, we include a measures for aggregate stock market volatility as an indicator for aggregate market uncertainty, the volatility of bank equities as an indicator of uncertainty in the banking sector (a proxy of systemic risk), and foreign exchange rate volatility that indicates pressures on foreign exchange markets. To capture all these features, we construct single composite indexes containing a broad measure of potential misalignments on these markets. In particular, we use a dynamic approximate factor model and interpret the single factor as the measure of financial stress.

5.2.1 Methodology

To extract a common stress component of the financial variables, we apply a dynamic approximate factor model. The methodology is similar to that in Banbura and Modugno (2012) and van Roye (2013). In particular, we set up a model that has the following form:

$$y_t = \Lambda f_t + \varepsilon_t, \qquad \text{where } \varepsilon_t \sim iid\, \mathcal{N}(0, C), \tag{5.1}$$

where y_t is a vector of stationary and standardized endogenous financial variables, f_t is a single common latent factor, and Λ is a $n \times 1$ vector of the time series' factor loadings. The values in the factor loading vector represent the extent to which each financial variable time series is affected by the common factor. The financial stress index is then given by $FSI_t = f_t$. The $n \times 1$ vector ε_t represents the idiosyncratic component which is allowed to be slightly correlated both serially at all leads and lags and cross-sectionally.[5] The idiosyncratic errors are assumed to be normally distributed with zero mean and the diagonal variance-covariance matrix C. The advantage of the dynamic approximate

[5]The weak correlation of the idiosyncratic component (all eigenvalues of $\mathbb{E}(\varepsilon_t \varepsilon_t') = \Sigma$ are bounded) makes the factor model "approximate"; see Breitung and Eickmeier (2006).

factor model is that it ensures that the idiosyncratic component is not too restrictive in the case of large cross-sections (Stock and Watson (2002)). The dynamics of the latent factor f_t are described in the transition equation, i.e.:

$$f_t = Af_{t-1} + \xi_t, \qquad \text{where } \xi_t \sim iid\, \mathcal{N}(0, D), \tag{5.2}$$

where A is the matrix of autoregressive coefficients, capturing the development of the latent factor f_t. Since we aim to estimate the model over a longer time horizon and for many countries the data availability is limited, we choose an estimation methodology that can appropriately deal with missing data. In particular, we estimate the model using a combined maximum likelihood and Expectation Maximization (EM) algorithm approach. Originally proposed by Dempster et al. (1977) this method serves as a general solution for models where the likelihood is hardly tractable because of incomplete or hidden data. Compared to non-parametric methods based on principal components, the methodology we use has the advantage that we can deal with an arbitrary pattern of missing data and it is more efficient for small samples (Banbura and Modugno (2012)).

5.2.2 Data

In order to compute the FSI, we use 5 indicators for each country. These indicators can individually be interpreted as a measure for financial stress in a specific sector and are well established in the literature when analyzing financial stress (Illing and Liu (2006), Holló et al. (2012), Cardarelli et al. (2011), Misina and Tkacz (2009), and Duca and Peltonen (2011). In particular, we focus on financial stress in the banking sector, on bond markets, and on foreign exchange markets. We illustrate a brief overview of the employed indicators and the contsruction method in table 5.1.

To develop a measure for stress in the banking sector, we construct a volatility index of bank equity. We take the equity index of the countries' most important financial institutions provided by Thomson Reuters Professional Datastream. Using the bank equity monthly returns, we construct a historical volatility measure by estimating a GARCH(1,1) model. For aggregate financial market uncertainty, we use a GARCH(1,1) model of the countries' main stock market returns. In addition, we take the inverse of the three month moving-average stock market returns as an indicator for financial market losses. To express financial stress on government bond markets, we construct a volatility measure using a GARCH(1,1) model of a government bond index returns that are provided by Thomson Reuters Professional Datastream.[6] Finally, we calculate a monthly volatility index for the real effective exchange rate to map financial stress on foreign exchange markets. To do this, we use a GARCH(1,1) model of the real effective exchange rate returns.

Table 5.1: *Indicators, construction method and market segment*

Indicator	Construction method	Market segment
Stock market volatility	GARCH(1,1) model of month-to-month stock market returns	Stock market
Exchange rate volatility	GARCH(1,1) model of month-to-month real effective exchange rate returns	Foreign exchange market
Stock market returns	Negative values of the 3-month moving-average stock market returns	Stock market
Government bond volatility	GARCH(1,1) model of month-to-month government bond yields	Bond market
Banking sector volatility	GARCH(1,1) model of month-to-month returns on bank equity	Stock market

[6] An alternative measure to express stress on government bond markets would be to take government bond spreads vis-à-vis a risk-free benchmark bond. However, since government bond yields are not directly comparable between countries and it is difficult to identify a risk-free government bond currently, we rather chose this volatility index.

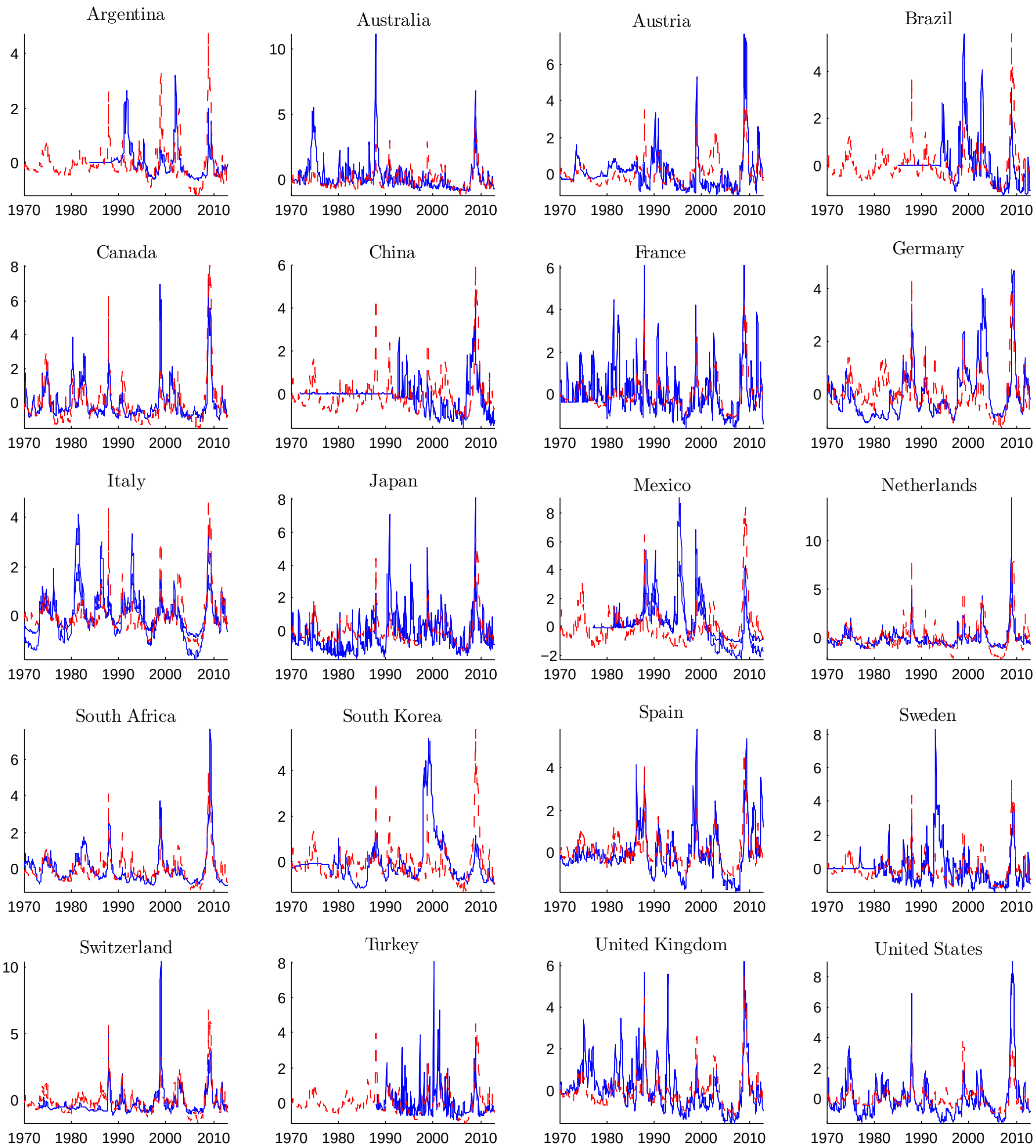
5.2.3 The financial stress indexes

In figure 5.1 the financial stress indexes for all considered countries are illustrated. In addition, we report an external financial stress index that is calculated by taking a trade-weighted average of financial stress in all other countries. Some episodes, during which the financial system was under strain, become immediately evident when considering the FSI for each country. Depending on the country, the amplitude during these events significantly differ. The first episode of high financial stress in our data sample occurs during the oil crisis in 1973-1974. During this crisis financial stress increased especially in the advanced economies, which were primarily dependent on oil. The second period of high financial stress occurred during the increasingly restrictive monetary policy of the Federal Reserve during the years 1980-1982. This financial stress event was primarily triggered by a restrictive monetary stance in the United States, accompanied by steep cuts in government spending under the Reagan administration. Although many countries dropped into a recession, the magnitude of financial stress remained rather limited, especially in the United States.

The next remarkable peak of financial stress was due to the stock market crash in 1987. On Monday, 19 October 1987 stock markets all over the world plummeted. The Dow Jones dropped by about 23 percent in one day. Until the end of October, the stock market index of Canada decreased by more than 20 percent, of Australia by more than 40 percent, and of Hong Kong by even more than 45 percent.

Compared to these large amplitudes during the 1987 stock market crash, the collapse of the Soviet Union had a very tiny impact on financial stress. Similarly, the crisis of the European exchange rate mechanism (ERM) in 1992-1993 had only a very regional effect. In particular, only European countries, such as the United Kingdom, Italy, France and Spain were directly exposed to the sharp corrections of their currencies with respect to the Deutschmark. On a global scale, the ERM crisis had almost no effect on financial markets. This becomes evident when considering the FSI for the United States, Canada, Australia or China. The Tequila crisis in Mexico 1995 and the Argentinian crisis in 2002 are good examples for domestic crises, which had a large impact on Mexico and Argentina but had no major repercussions on other countries.

Figure 5.1: *Financial stress indexes*



Notes: Blue solid line: Domestic financial stress index; red dashed-dotted line: external (trade-weighted) financial stress index; the FSI consist of respectively 5 different variables that represent financial stress. The FSI are constructed using a dynamic approximate factor model.

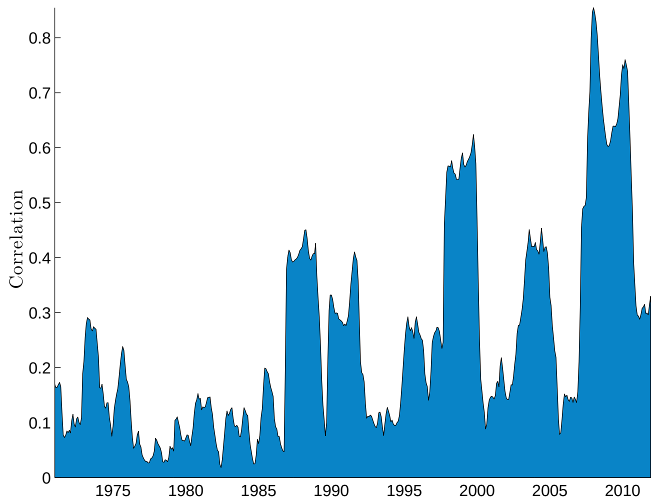
The next global financial stress event was the outbreak of the Asian and Russian crisis and the associated default of the large hedge fund Long Term Capital Management (LTCM)in 1997-1998. For the Asian economies, the Asian crisis is the largest peak of financial stress in our analysis. Especially in South Korea financial stress rose to very high levels. The Brazilian crisis, which immediately connected to the events in Russia and Asia, led to widespread strains in the financial system in Latin American countries. In particular, it was the beginning of the persistent turmoil in Argentina, which culminated in a sharp financial crisis in 2002.

The legacy with the burst of the dotcom bubble was another event when financial stress was present in many countries all over the world. Most notably financial markets in Germany and in Italy were affected significantly by sharp corrections in stock markets. The most significant peak over the sample period was clearly the recent financial crisis. Nearly all indicators from all market segments point to a sharp increase in financial stress in almost all countries. While the amplitude in several emerging market economies is not exceptionally high, mainly the advanced economies were exposed to extraordinary high levels of financial stress. The European sovereign debt crisis led mainly to financial stress increases in European countries, such as Spain and Italy, while it remained subdued in the rest of the world. This emphasizes that the crisis in the euro area still remains a crisis within the euro area and, up to now, has not substantially affected the currency area as a whole.

5.2.4 Correlation of financial stress

To gain insights of how financial stress co-moves across countries, we carry out a correlation analysis. First, we compute an average cross-correlation among all countries over the sample period. Second, we examine how financial openness is a factor that contributes to an exposure of financial stress. Third, we report country-specific bivariate correlation statistics to analyze between which countries the financial cycle is mostly synchronized. For the average cross-country correlation we compute pair-wise contemporaneous cross-correlations of the FSI over the sample period. Particularly, we compute a 24-month moving average of the contemporaneous correlations between 1970 and 2012. The correlations are calculated as follows: $\rho_t = \frac{1}{N-1}\sum_{i=i}^{N} Corr(FSI_{i,[t-12,t+12]}, FSI_{j,[t-12,t+12]})$, where $N = 20$ represents the number of countries. The results from the correlation analysis are graphically illustrated in Figure 5.2.

Figure 5.2: *Average cross-correlations of financial stress*



Notes: The cross-correlation is computed by taking a 24-month moving average of the contemporaneous bivariate pairwise FSIs. In particular, the computation is: $\rho_t = \frac{1}{N-1}\sum_{N}^{i=1} Corr(FSI_{i,[t-12,t+12]}, FSI_{j,[t-12,t+12]})$

The results of the cross-country correlation analysis are twofold. First, the increasing trend in the cross-country correlation financial stress emphasizes the vigorous growth in international financial integration. In general, financial cycles tend to co-move more among countries over time. Second, the synchronization of financial stress among countries varies significantly over time. There tends to be a strong co-movement in financial stress in selected stress episodes that reflect global financial stress events, such as the 1973-1974 oil crisis, the

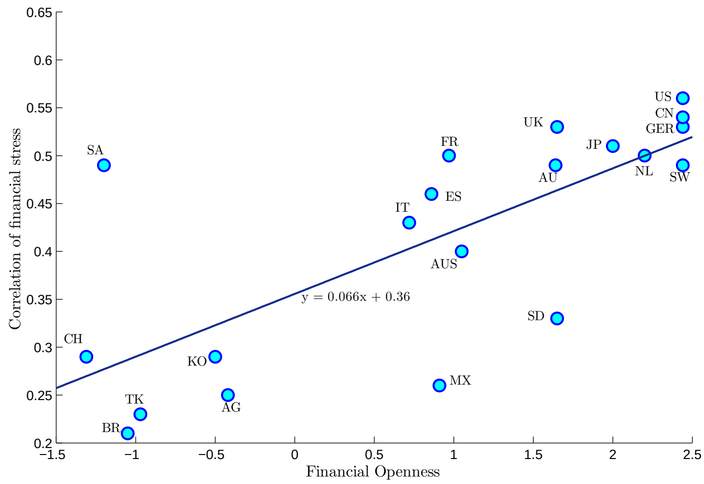
1987 stock market crash, the Asian and Russian crisis 1997-1998, the legacy of the dotcom bubble burst and most prominently the recent financial crisis.

When considering the relationship between financial openness and the correlation of financial stress to other countries, the results indicate that financial openness is an important factor to explain differences in the co-movement of financial stress across countries (Figure 5.3).[7] We find a significant positive relationship (p-value of the slope: 0.0001) between the degree of financial openness and the correlation of financial stress among countries. While there is only little correlation of financial stress in countries that have a low degree of financial openness, the financially high integrated countries exhibit strong correlation of financial stress. It stands out that correlation of financial stress in emerging markets is relatively low and over the sample period these countries were financially closed. In particular, Brazil, Turkey, Argentina, China and Korea stand out with a low correlation of financial stress and low values in financial openness. In contrast, countries with high financial openness, such as the United States, Canada, Switzerland, Germany, and the Netherlands exhibit a strong correlation with the financial stress indexes of the other countries. A single outlier in the sample is South Africa, which has a low degree of financial openness over the sample period, but exhibits a strong correlation of financial stress with the other countries.

The lower exposure of emerging markets to global financial stress events also becomes evident when analyzing the country-specific cross-correlations of financial stress (Table 5.2). The financial cycle in emerging markets exhibits a different pattern than the financial cycle in the advanced economies. For instance, the degree of correlation of financial stress in Argentina, Mexico and Korea with other countries is on average by far lower than the correlation of Germany, the United Kingdom or the United States. While there is also a clear regional dependency of financial stress correlation, such as the high correlation of financial stress between Argentina and Brazil, Korea and China, Spain and France, the

[7] As an indicator for financial openness we use the Chinn-Ito index, a de jure measure of financial openness, which measures a country's degree of capital account openness. The index was originally introduced in Chinn and Ito (2006). Given that the degree of financial openness does not change very often over time, we use an average degree of financial integration from 1970 until 2011. For emerging markets, where financial markets developed substantially over the past decade, this measure might leave out the recent change in financial integration of these countries.

Figure 5.3: *Correlation of financial stress and financial openness*



Notes: The correlation of financial stress is expressed as country-specific correlations of the domestic FSI with all other FSIs ($\frac{1}{N-1}\sum_{j=1}^{N} Corr(FSI_{i,[t-12,t+12]}, FSI_{j,[t-12,t+12]})$); AG: Argentina; AUS: Australia; AU: Austria; BR: Brazil; CN: Canada; CH: China; FR: France; GER: Germany; IT: Italy; JP: Japan; MX: Mexico; NL: Netherlands; SA: South Africa; KO: South Korea; ES: Spain; SD: Sweden; SW: Switzerland; TK: Turkey; UK: United Kingdom; US: United States.

correlation of financial stress in the United States with all other countries is in general very high. This supports the presumption that the United States are the most important propagator of financial shocks in the world economy.

Table 5.2: *Cross-country correlations of financial stress*

	AG	AUS	AU	BR	CN	CH	FR	GER	IT	JP	MX	NL	SA	KO	ES	SD	SW	TK	UK	US
AG	1	0.13	0.29	0.32	0.23	0.14	0.27	0.26	0.47	0.34	0.24	0.25	0.23	0.14	0.16	0.25	0.14	0.17	0.29	0.31
AUS		1	0.28	0.12	0.47	0.34	0.61	0.31	0.40	0.34	0.31	0.52	0.48	0.07	0.38	0.21	0.39	0.20	0.63	0.60
AU			1	0.31	0.71	0.37	0.48	0.42	0.52	0.43	0.26	0.59	0.67	0.15	0.53	0.40	0.55	0.18	0.61	0.71
BR				1	0.20	0.13	0.40	0.50	0.38	0.35	0.42	0.46	0.36	0.60	0.39	0.26	0.56	0.23	0.33	0.28
CN					1	0.29	0.66	0.59	0.49	0.52	0.33	0.72	0.62	0.44	0.59	0.31	0.75	0.34	0.62	0.79
CH						1	0.32	0.01	0.32	0.26	0.31	0.39	0.30	0.65	0.04	0.30	0.51	0.12	0.39	0.34
FR							1	0.35	0.55	0.39	0.31	0.63	0.50	0.15	0.47	0.24	0.55	0.29	0.58	0.63
GER								1	0.25	0.36	0.41	0.56	0.52	0.41	0.63	0.18	0.51	0.18	0.54	0.58
IT									1	0.27	0.24	0.43	0.42	0.19	0.46	0.48	0.27	0.28	0.57	0.52
JP										1	0.33	0.49	0.26	0.25	0.32	0.22	0.42	0.33	0.25	0.45
MX											1	0.12	0.31	0.30	0.16	0.21	0.27	0.15	0.26	0.22
NL												1	0.52	0.19	0.46	0.21	0.52	0.30	0.54	0.77
SA													1	0.33	0.54	0.31	0.62	0.15	0.61	0.76
KO														1	0.36	0.11	0.50	0.16	0.09	0.16
ES															1	0.37	0.66	0.14	0.52	0.54
SD																1	0.26	0.14	0.50	0.67
SW																	1	0.11	0.39	0.53
TK																		1	0.56	0.51
UK																			1	0.67
US																				1

Notes: AG: Argentina; AUS: Australia; AU: Austria; BR: Brazil; CN: Canada; CH: China; FR: France; GER: Germany; IT: Italy; JP: Japan; MX: Mexico; NL: Netherlands; SA: South Africa; KO: South Korea; ES: Spain; SD: Sweden; SW: Switzerland; TK: Turkey; UK: United Kingdom; US: United States.

5.3 Financial stress and economic activity: Evidence from a GVAR model

In order to investigate the international transmission channels of financial stress, we use a GVAR model framework. Originally established by Pesaran et al. (2004), it was, amongst others, further developed by Dées et al. (2009) and Dées et al. (2010). GVAR models can be used to analyze international interdependencies among countries and the transmission channels of international shocks.

This type of model has been used to analyze for example the international transmission of oil price shocks (Cashin et al. (2012)), housing price shocks (Cesa-Bianchi (2012)), credit supply shocks (Eickmeier and Ng (2011)), cost-push shocks (Galesi and Lombardi (2009)), and liquidity shocks during the Great Recession of 2007-2009 (Chudik and Fratzscher (2011)).

5.3.1 The GVAR framework

In what follows, we present a very brief sketch of the GVAR model. For a detailed description of the methodology we refer to Smith and Galesi (2011). The GVAR model basically consists of a number of VAR models for each individual country that are linked to each other via a weighting matrix, which is based on trade weights in our model. For each country $i = 1, \ldots, N$ the VAR(p_i, q_i) model links a $k_i \times 1$ vector of domestic variables x_{it} to a $k_i^* \times 1$ vector of foreign variables x_{it}^*; these foreign variables are assumed to be weakly exogenous in the country VAR model. In addition, we allow for a constant and a deterministic trend in the VAR models:

$$x_{it} = a_{0i} + a_{1i}t + \Psi_{1i}x_{i,t-1} + \ldots + \Psi_{p_i i}x_{i,t-p_i} + \Lambda_{1i}x_{i,t-1}^* + \ldots + \Lambda_{q_i i}x_{i,t-q_i}^* + u_{i,t}, \quad (5.3)$$

where the $\Psi_{i,n}$ and $\Lambda_{i,n}$ are $k_i \times k_i$ and $k_i \times k_i^*$ coefficient matrices connected to the domestic and foreign variables respectively, a_{0i} is a $k_i \times 1$ vector of constant terms, a_{1i} is a $k_i \times 1$ vector of slope coefficients, and u_t is a $k_i \times 1$ vector of country-specific shocks that are assumed to be serially uncorrelated with mean zero and a constant covariance matrix Σ_i.

The country-specific variables are constructed as trade weighted averages across the domestic variables of all countries, i. e. $x^*_{it} = \sum_{i=1}^{N} w_{ij} x_{jt}$, with $w_{ii} = 0$ and sum over all $w = 1$. In our empirical implementation we use fixed trade weights that are computed as an average of the weights over the sample period. These country-specific VAR models can be transformed into error correction form and separately estimated on a case-by-case basis taking potential cointegration between x_{it} and x^*_{it} into account.[8]

In a second step, they are grouped together and the GVAR is solved globally, i. e. jointly for all countries, since from a global perspective all variables are endogenous to the GVAR as a whole. To this end, all country-specific vectors with endogenous variables are stacked into $x_t = [x'_{1t}, x'_{2t}, \ldots, x'_{Nt}]'$, which is of dimension $k^* = \sum_{i=1}^{N} k_i$. It can be shown that using the appropriate weight matrices and stacking the equations of all country-specific VAR models yields

$$G_0 x_t = a_0 + a_1 t + G_1 x_{t-1} + \ldots + G_r x_{t-r} + u_t, \tag{5.4}$$

where $r = max\{\{p_i\}, \{q_i\}\}$ and the parameters of the G_n are functions of the weight matrices and the parameters estimated for each of the country-specific VAR models.[9] Since G_0 is known, one can premultiply equation (5.4) by G_0^{-1} to obtain the GVAR model as

$$x_t = b_0 + b_1 t + F_1 x_{t-1} + \ldots + F_r x_{t-r} + \epsilon_t, \tag{5.5}$$

with $b_0 = G_0^{-1} a_0, b_1 = G_0^{-1} a_1, F_1 = G_0^{-1} G_1, \ldots, F_r = G_0^{-1} G_r$, and $\epsilon = G_0^{-1} u_t$. There are no a-priory restrictions placed on the covariance matrix of the vector of shocks $\mathbb{E}_t(\epsilon_t \epsilon'_t)$ and the GVAR can basically be treated like an ordinary VAR model for most purposes.

5.3.2 Computing GIRFs for the GVAR model

In this chapter, we use generalized impulse response functions (GIRF; Pesaran and Shin (1998)) to analyze the dynamics of the international transmission of financial stress. Though intellectually not satisfying we constrain our analysis to the use of GIRFs as opposed to the identification of true structural shocks,

[8] See Smith and Galesi (2011) for a detailed description of the estimation procedure and a battery of diagnostic tests for the VAR models.

[9] For details, see Smith and Galesi (2011), p.98.

because for a GVAR with usually dozens of endogenous variables there is no good way to place enough meaningful restrictions to identify what could be called a structural GVAR.[10] If u_t is assumed to have a multivariate normal distribution the GIRFs for a standardized shock of one standard deviation at time t_0 to the l^{th} equation of the GVAR corresponding to the j^{th} variable of the GVAR at time t_{0+n} is given by the j^{th} element of

$$GIRF(x_t; u_{lt}, n) = \frac{e' A_n G_0^{-1} \sum_u e_l}{\sqrt{e_l' \sum_u e_l}}, \; n = 0, 1, 2, \ldots, l; \; j = 1, 2, \ldots, k, \tag{5.6}$$

where e_l is a vector of dimension k^* with a 1 as the l^{th} element and zeros otherwise if one wants to simulate the responses to a country-specific shock. In case of a global shock to a specific type of variable (e. g. financial stress as analyzed below) e_l has PPP GDP weights that sum to one at the positions of the specific variables in the GVAR and zero elements otherwise. A_n can be computed recursively by using

$$A_s = F_1 A_{s-1} + F_2 A_{s-2} + \cdots + F_p A_{s-r}, s = 1, 2, \ldots \tag{5.7}$$
$$\text{with} \quad A_0 = I_m, \; A_s = 0, \; \text{for } s < 0.$$

These GIRFs are invariant to the ordering of the variables (and countries) in the GVAR but they are not interpretable in a structural sense, since the error terms are not orthogonalized.

5.3.3 Empirical GVAR specification

We implement the GVAR that we use to analyze the international transmission of financial stress on the basis of monthly data about (log) industrial production, the (log) price level (CPI), the short-term policy rate[11], and the measure of financial stress that was presented in section 5.2. We use a balanced sample covering the time between February 1991 and December 2012. The lag orders of the country-specific VAR models are restricted to a maximum of $p_i = 2$

[10] In some settings it has been argued that sign-restrictions (Uhlig (2005)) can be an appropriate method to identify structural shocks in GVAR models (see e. g. Cashin et al. (2012)).

[11] The policy rate is transformed as $0.25 \times \ln(1 + R_t/100)$ to deal with the very high interest rate levels in some of the emerging economies of our sample during the early period of our sample.

and $q_i = 2$ for all countries to ensure stability of the GVAR.[12] The number of cointegration vectors for each country model is determined using the maximum eigenvalue statistic with an upper limit of 2. The model was estimated using *RATS 8.2*.

To shed light on the international transmission of financial stress, and on the dynamics of financial stress that is caused in the different countries by major shocks to the world economy, we simulate GIRFs for the following shocks:

- a global shock to financial stress (using PPP GDP weights as discussed in the previous section);
- a US shock to financial stress
- a (negative) shock to industrial production in the US.

The GIRFs are computed for 36 months and median responses as well as confidence bands are based on bootstrap simulations with 250 replications.

[12] For a cointegrated GVAR the roots of the determinantal equation of the companion matrix of the model should lie inside or on the unit circle. Apparently, it is a common feature that GVAR models with a richer lag structure show an explosive behavior and are not well suited for dynamical analysis.

5.3.4 Results

A global financial stress shock

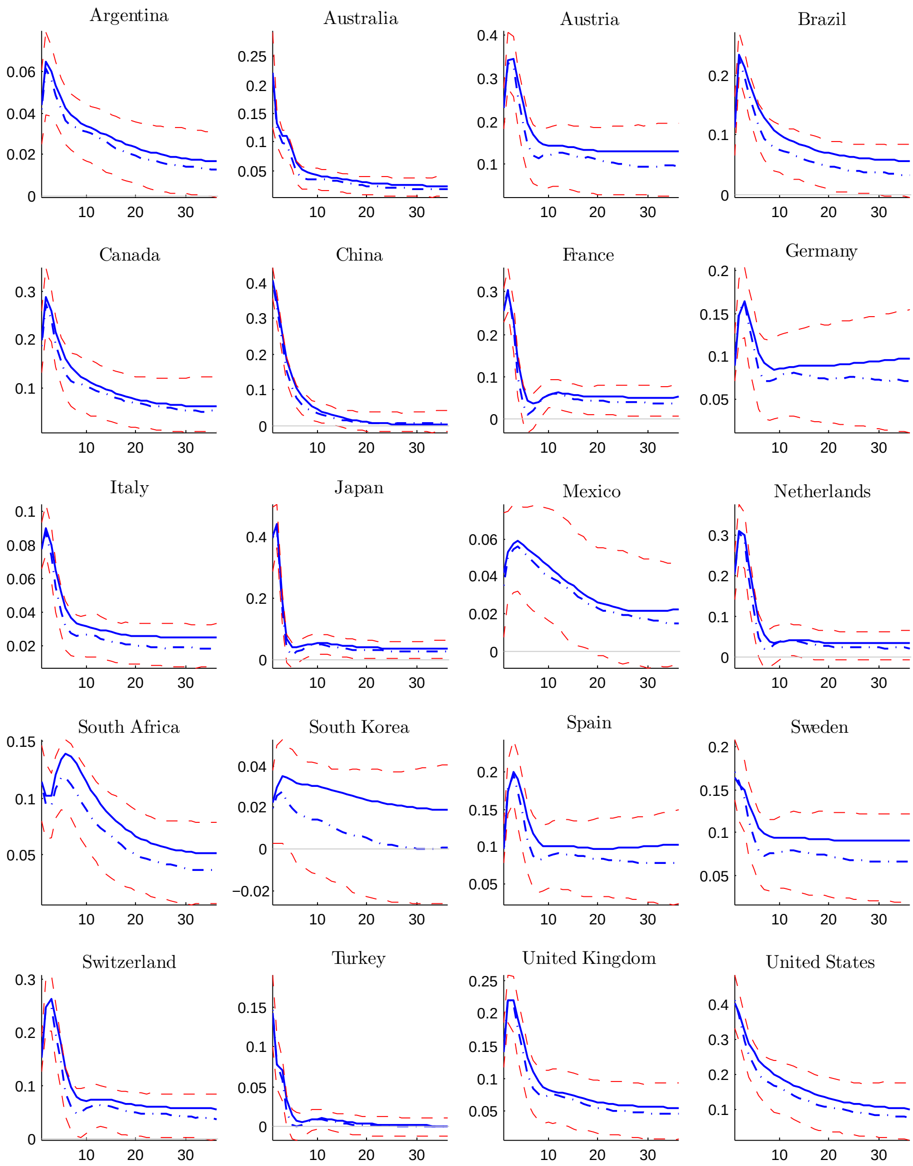
Figures 5.4.a and 5.4.b show the dynamic responses of the level of financial stress and industrial production respectively to a standardized global shock to financial stress. Financial stress significantly increases on impact in all countries and – with the exception of a few countries such as China, France, Japan, or the Netherlands – remains high quite persistently.

Industrial production is negatively affected in all countries – though not significantly in all of them. In most cases the maximum impact is reached with a lag of approximately one year. The countries that are least affected in terms of production losses are Australia, China, and surprisingly the United Kingdom. The strongest effects can be expected in Germany, Turkey, and the United States. In these cases, the economic contraction is very persistent and the production level remains significantly below its initial level after 3 years. In South Korea, global financial stress seems to have only a transitory effect. After a sharp contraction on impact (almost 0.7 percent), the economy recovers quickly after the shock and industrial production reaches its initial level after 10 months.

To demonstrate how devastating financial stress can be for economic activity, we re-scale the size of the shock to financial stress in such a way that it matches the experience of the most recent financial crises. To this end, we pick the US as the reference country. During the crisis our measure of financial stress increased by about 8 points in the US which is about 20 times larger than the initial reaction in response to the standardized global shock. Based on our simulation results this would translate to a fall in industrial production of about 8 percent.[13]

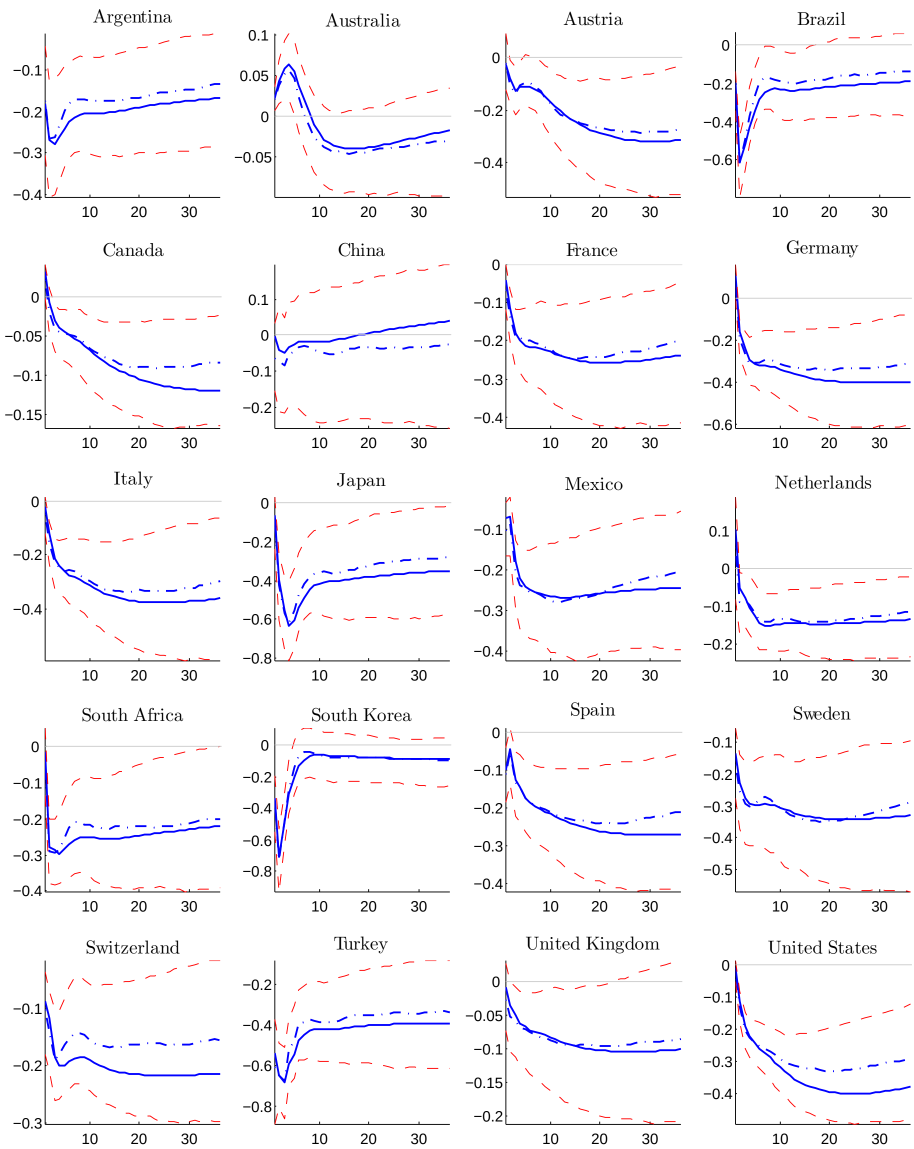
[13] In reality, industrial production fell by about 17 percent between Dec. 2007 and Jun. 2009. Thus, the relatively parsimoniously specified GVAR accounts for about 50 percent of the decline.

Figure 5.4.a: *Generalized impulse responses for financial stress to a global financial stress shock*



Notes: The solid blue line represents the mean impulse response, the dashed-dotted blue line the median impulse response, and the dashed red lines represent the 66 percent bias-corrected bootstrap error bands.

Figure 5.4.b: *Generalized impulse responses for industrial production to a global financial stress shock*



Notes: The solid blue line represents the mean impulse response, the dashed-dotted blue line the median impulse response, and the dashed red lines represent the 66 percent bias-corrected bootstrap error bands.

A US financial stress shock

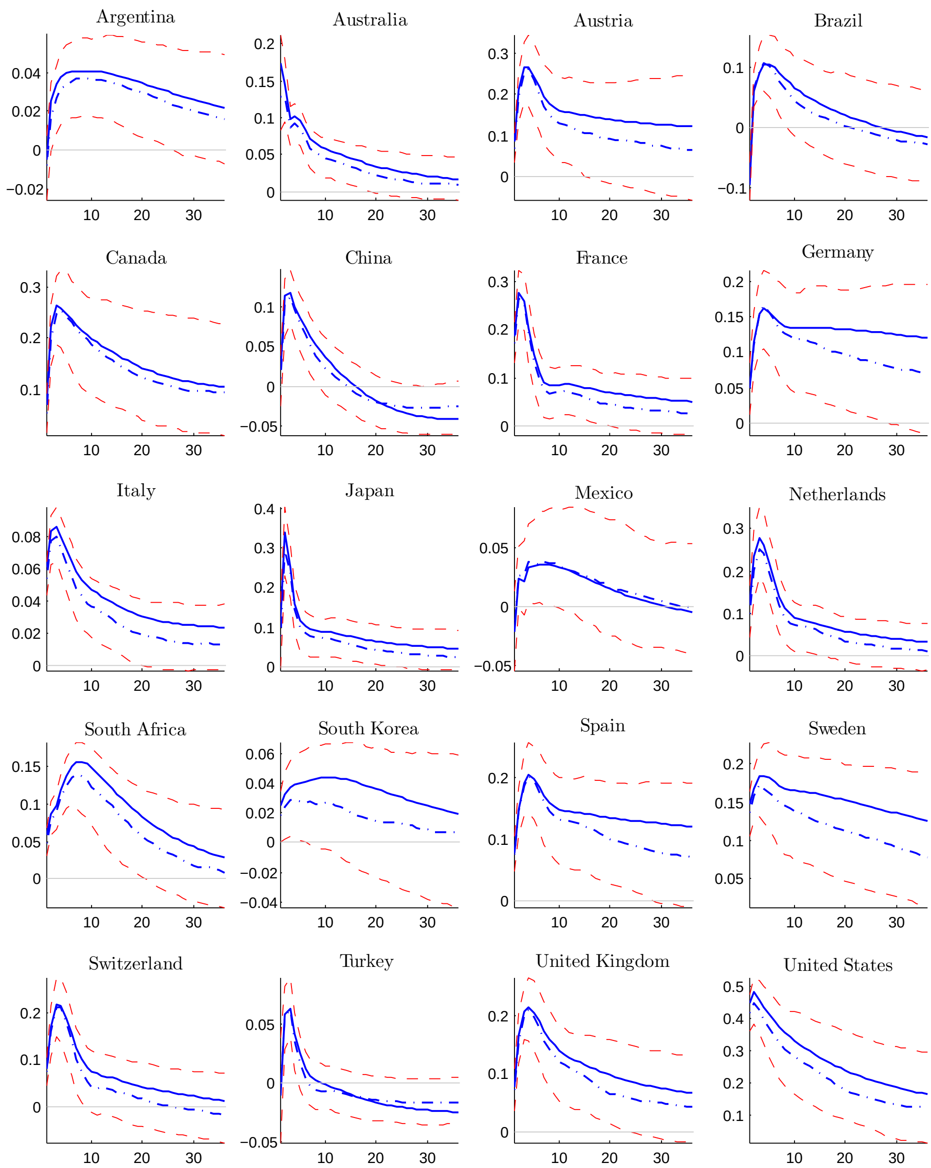
To investigate how financial stress is transmitted internationally when the original shock is limited to a single country, we plot GIRFs of financial stress and industrial production corresponding to a standardized shock to financial stress in the US in Figures 5.5.a and 5.5.b. [14]

The transmission of financial stress in the United States to the financial system in other countries is in most cases unambiguous. An increase of the FSI in the United States leads to a persistent increase of financial stress in the other countries – though not significantly so in some cases, such as Mexico or South Korea. The increase of financial stress outside the US is, however, much smaller than the initial shock inside the US. On average, the maximum increase is less than half the size of the standardized shock to financial stress in the US. On average, the GIRFs show a hump-shaped responses indicating that the transmission takes some time; on average the largest impact of financial stress in the other countries is reached after 3 to 4 months. There are some countries, however, that are most heavily affected almost at impact. Examples are Australia, Canada and Japan which presumably have very close financial ties with the US.

The propagation of financial stress in the United States to economic activity in other countries is quite strong. Industrial production declines persistently in almost all countries. Surprisingly the output losses are as high as those in the US in many cases although the effect on financial stress in other countries is more limited. This indicates that a considerable part of the adverse effect on economic activity is not transmitted via financial markets directly but rather indirectly via a fall in foreign demand from the US. Similarly to the transmission of financial stress, industrial production reacts with a considerable time lag in many countries. This indicates that financial stress in the United States does not have an immediate effect on production in other countries but that transmission takes time.

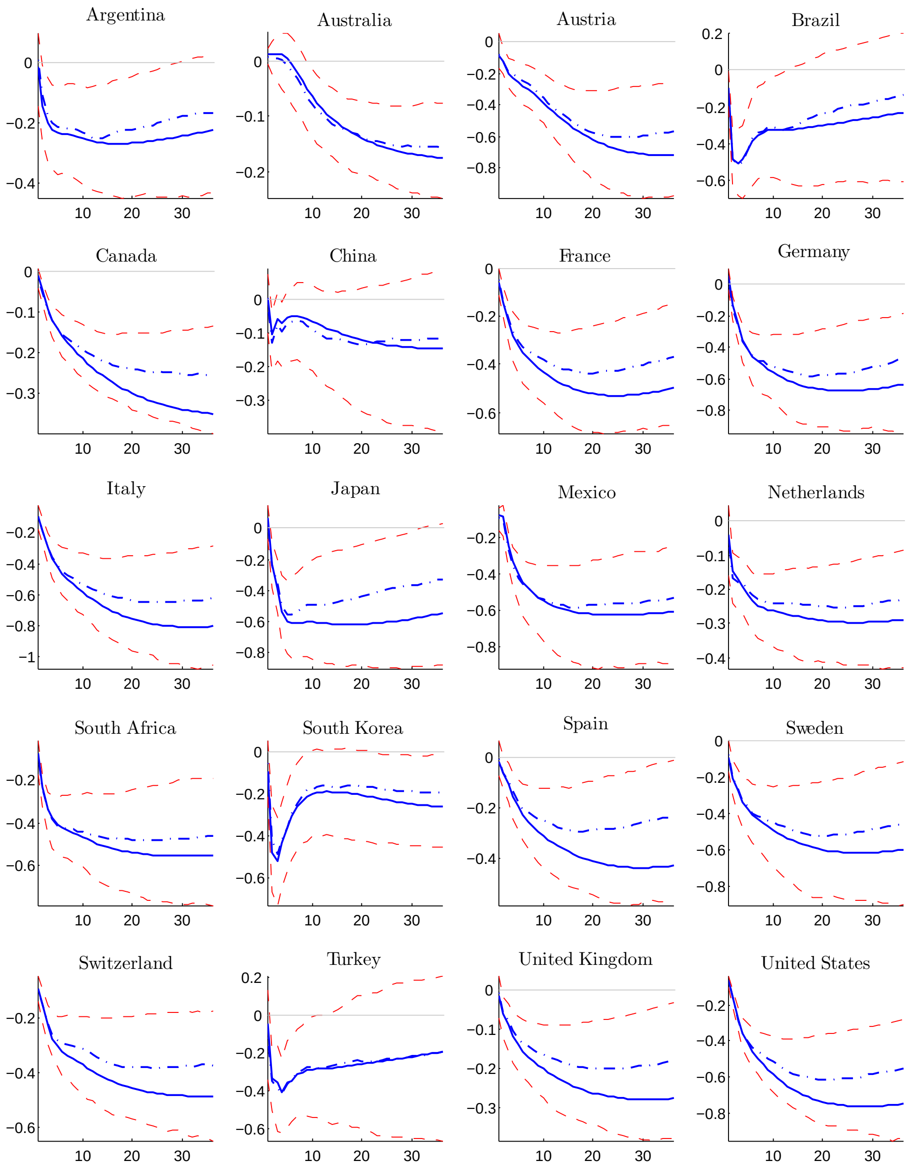
[14] This has been arguably been the plot of the financial crisis of 2008-2009 which had its origins in the turmoils on the financial markets in the US following the burst of the US housing bubble.

Figure 5.5.a: *Generalized impulse responses for financial stress to a US financial stress shock*



Notes: The solid blue line represents the mean impulse response, the dashed-dotted blue line the median impulse response, and the dashed red lines represent the 66 percent bias-corrected bootstrap error bands.

Figure 5.5.b: *Generalized impulse responses for industrial production to a negative shock in industrial production in the US*



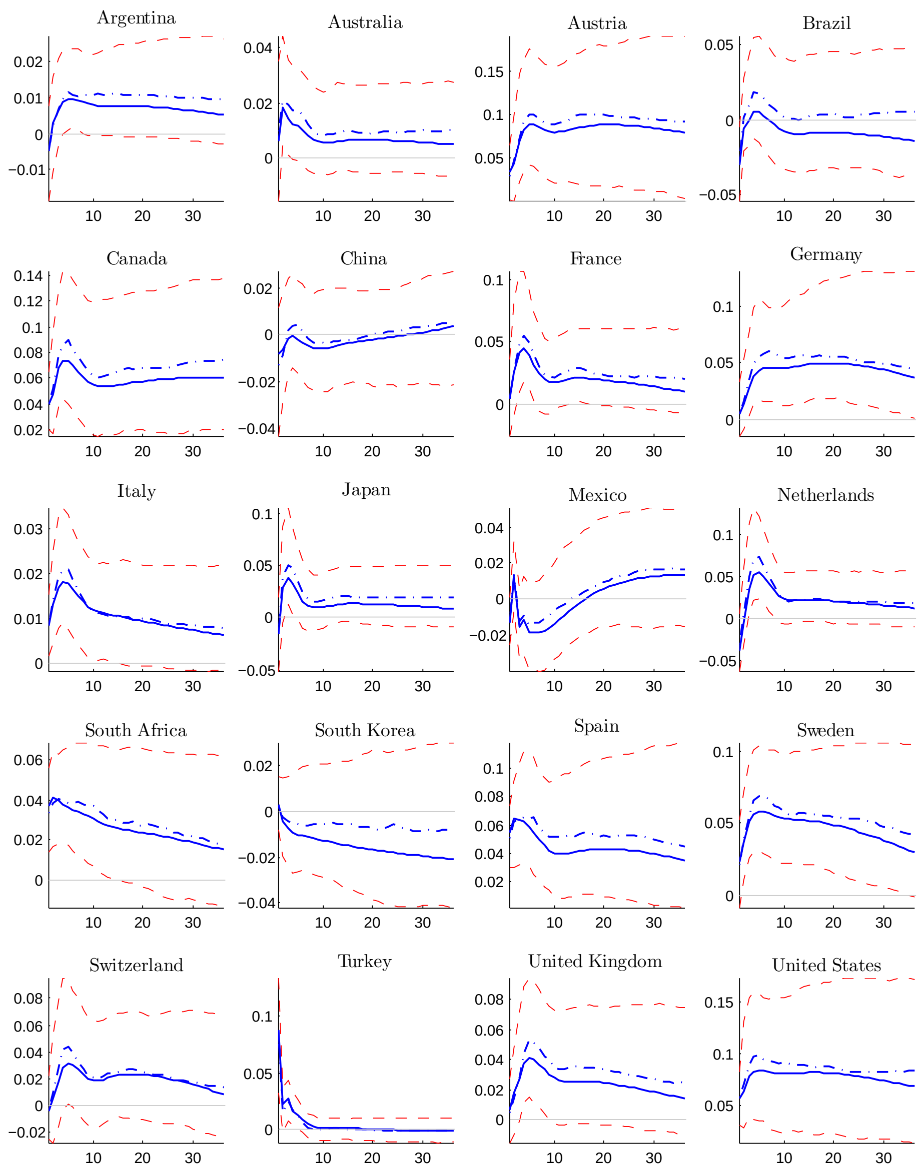
Notes: The solid blue line represents the mean impulse response, the dashed-dotted blue line the median impulse response, and the dashed red lines represent the 66 percent bias-corrected bootstrap error bands.

A shock to US industrial production

Figures 5.6.a and 5.6.b show how industrial production and financial stress behave in response to a shock to industrial production in the US. In the United States a fair amount of financial stress is triggered by the slowdown in economic activity which fades only slowly. The rise of financial stress in other countries is much smaller – with the exception of the direct neighbor Canada where the level of financial stress is also strongly affected. Surprisingly, the stress level in neither Mexico nor China – two major trading partners of the United States – are significantly affected following the shock to economic activity in the United States. In most other countries the response of economic activity is lagged and the highest negative effect is often reached not until after six to twenty months.

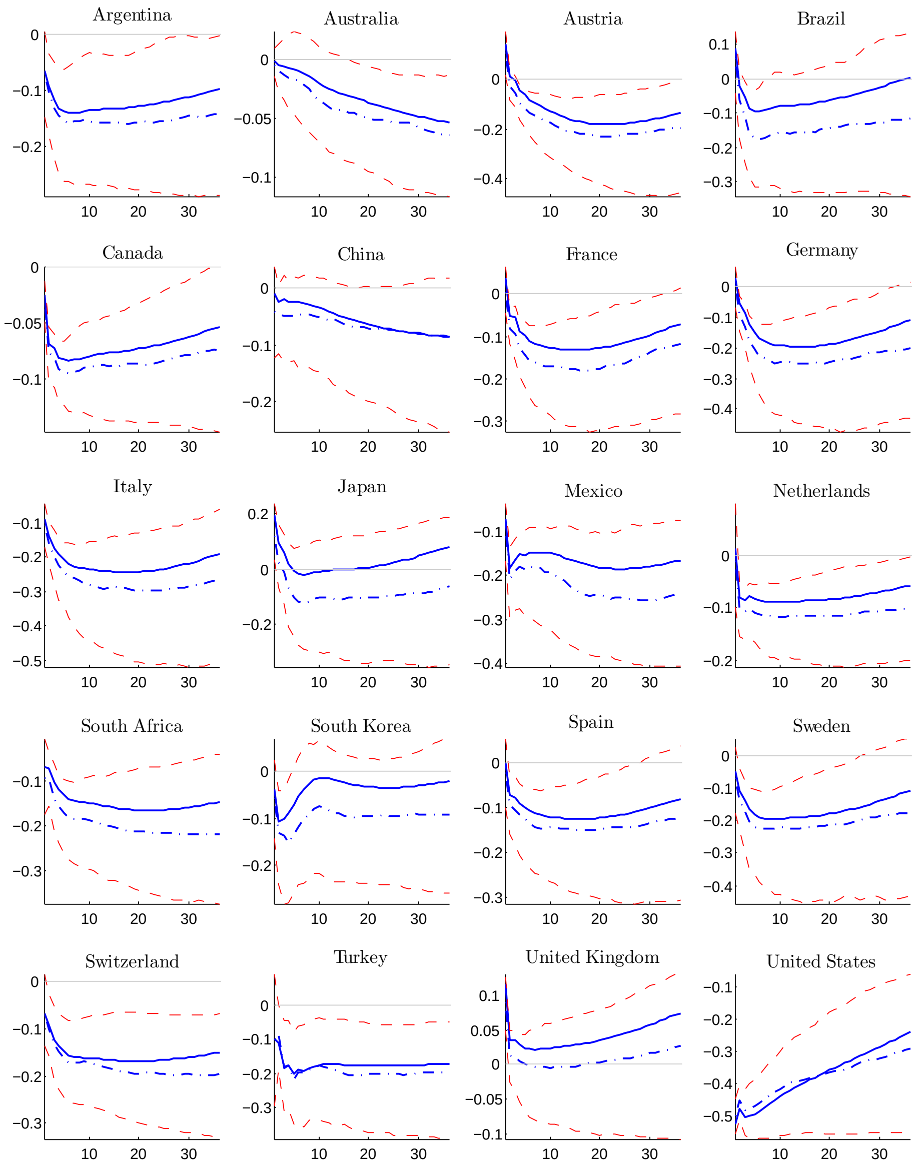
In the United States, industrial production recovers gradually from the initial drop of activity. In other countries, the demand shock triggers a slowdown in industrial production such that the level declines persistently. For some countries, such as the United Kingdom and Japan, the economic contraction is not significant. The strongest effect of an economic contraction in the United States can be expected in Germany and Italy, where the level of industrial productions falls by approximately 0.2 percent after one year.

Figure 5.6.a: *Generalized impulse responses for financial stress to a negative shock in industrial production in the US*



NOTES: The solid blue line represents the mean impulse response, the dashed-dotted blue line the median impulse response, and the dashed red lines represent the 66 percent bias-corrected bootstrap error bands.

Figure 5.6.b: *Generalized impulse responses for industrial production to a negative shock in industrial production in the US*



Notes: The solid blue line represents the mean impulse response, the dashed-dotted blue line the median impulse response, and the dashed red lines represent the 66 percent bias-corrected bootstrap error bands.

5.4 Conclusion

This chapter analyzes the international transmission of financial stress and its effects on economic activity for 20 countries. Using a dynamic approximate factor model, we construct country-specific financial stress indexes (FSI) from 1970 until 2012 on a monthly basis. The FSI are composed by financial indicators such as volatilities on stock markets, bond markets and the foreign exchange market. The FSIs succeed in signaling exceptional events that occurred on financial markets in the recent past. An empirical investigation shows that the correlation of financial stress across countries increased notably over the past four decades. Furthermore, the cross-country correlation of financial stress is particularly high during global financial crises. In addition, financial stress is stronger correlated in countries with a high degree of financial openness.

Subsequently, we estimate a GVAR model to analyze the international transmission of financial stress and the propagation of financial stress on economic activity. We show that financial stress significantly reduces economic activity; the negative effects are persistent and the maximum impact lags the shock to financial stress by about one year. Likewise, a shock to financial stress in the United States spreads quickly to financial markets in other countries and has a lagged but persistent effect on economic activity in the other countries. Furthermore, we find that a slowdown in economic activity (demonstrated by a shock to industrial production in the US) leads to a sustained increase in financial stress in most countries of our sample. The effects in this direction are not so large, however, that a financial crisis could be triggered by a prototype recession alone.

Our results indicate that financial stress should be a major concern when analyzing international business cycles. In addition, the result have important implication for economic policy. Because of the strong economic impact of financial shocks, the results implicate that monitoring of financial stress should be of interest for both monetary and fiscal policy makers. Since the financial cycle and the business cycle are significantly synchronized internationally, it is crucial to consider the global dimension of financial stress even from the perspective of a national policy maker.

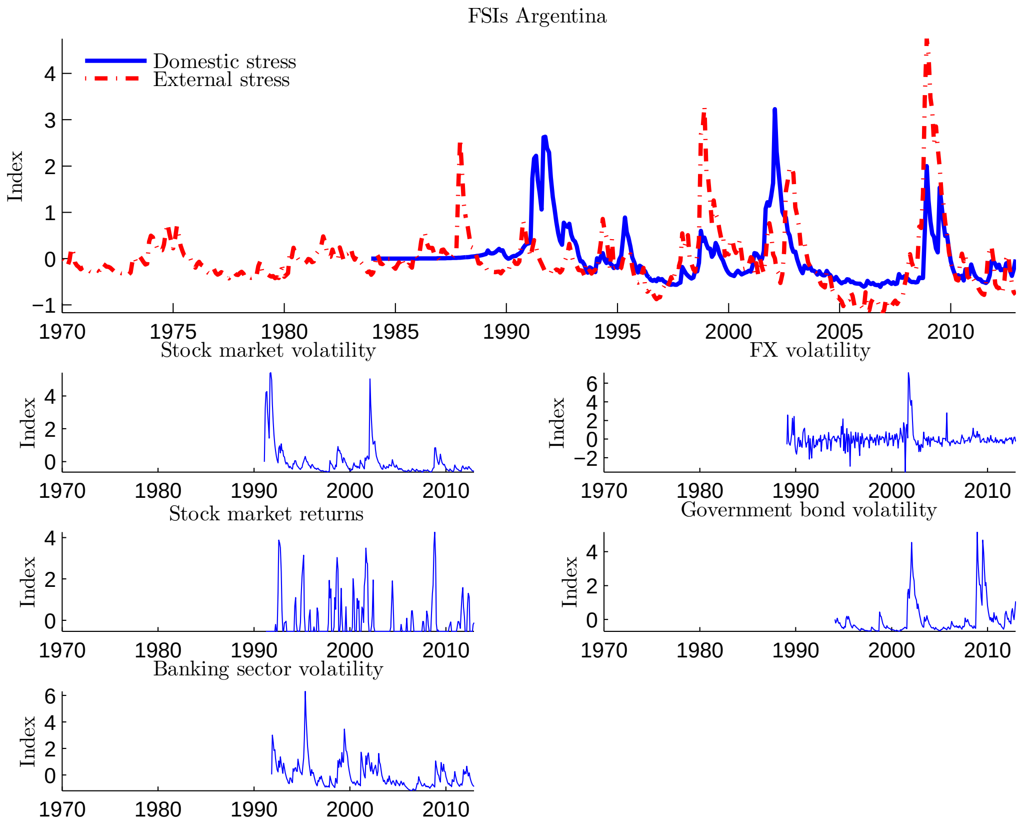
D Appendix

D.1 Data and economic history

In this section we describe important events in all considered countries and we show how the FSI relates to these events. For each country, we present the FSI as well as the data that we include in the estimation. In addition, we identify major events using short tables and shortly describe them for each country.

Argentina

Figure D1: *FSI and stress components for Argentina*



Notes: The solid blue line in the upper panel represents the the domestic FSI; the red dashed-dotted line the external (trade-weighted) FSI.

After a decade of economic stagnation and high inflation rates, Argentina fell into hyperinflation in 1989, which lasted until the convertibility plan of the domestic currency was introduced. The convertibility plan, which was put in place in April 1991, fixed the domestic currency to the U.S. Dollar at par in order to restrict monetary policy to be expansionary. It was designed to stabilize the economy through drastic, and almost irreversible, measures. Soon afterward the financial system in Argentina stabilized and the economy began to recover quite quickly. The Mexican Peso crisis (Tequila crisis) in 1994-1995 and the Asian and Russian crisis had relatively little impact on financial stress in Argentina. Although output fell sharply and interest rates increased significantly during these events, the fixed currency regime could be sustained and the upcoming pressures and uncertainty on stock markets was very limited. Financial stability was safeguarded throughout this period. The strongest increase in the FSI is recorded during the Argentinian crisis, when a run on commercial banks tirggered one of the severest crises in the country's history. All indicators included in the Argentinian FSI contributed to an increase in the FSI. The recent global financial crisis also affected Argentina, but to a much lesser extent than the crisis in 2002.

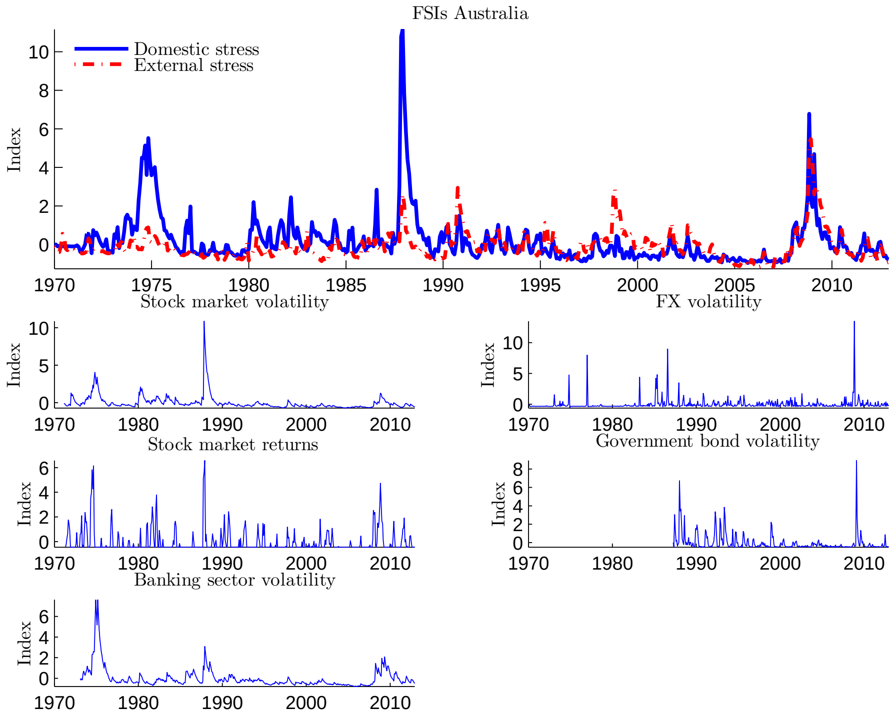
Table D1: *Selected events in Argentinean economic history*

1980-1989	Stagflation
1982	LDC crisis
1989	Hyperinflation
April 1991	Introduction of convertibility plan
1995	Mexican Peso crisis (Tequila crisis)
1998	Asian crisis / Russian default
August / September 1998	LTCM crisis
January 1999	Devaluation of the Brazilian Real
December 2001	Partial deposit freeze
2002	"Argentinian" crisis
2008-2009	Global financial crisis

Notes: LDC: Less-developed countries; LTCM: Long Term Capital Management.

Australia

Figure D2: *FSI and stress components for Australia*



Notes: The solid blue line in the upper panel represents the the domestic FSI; the red dashed-dotted line the external (trade-weighted) FSI.

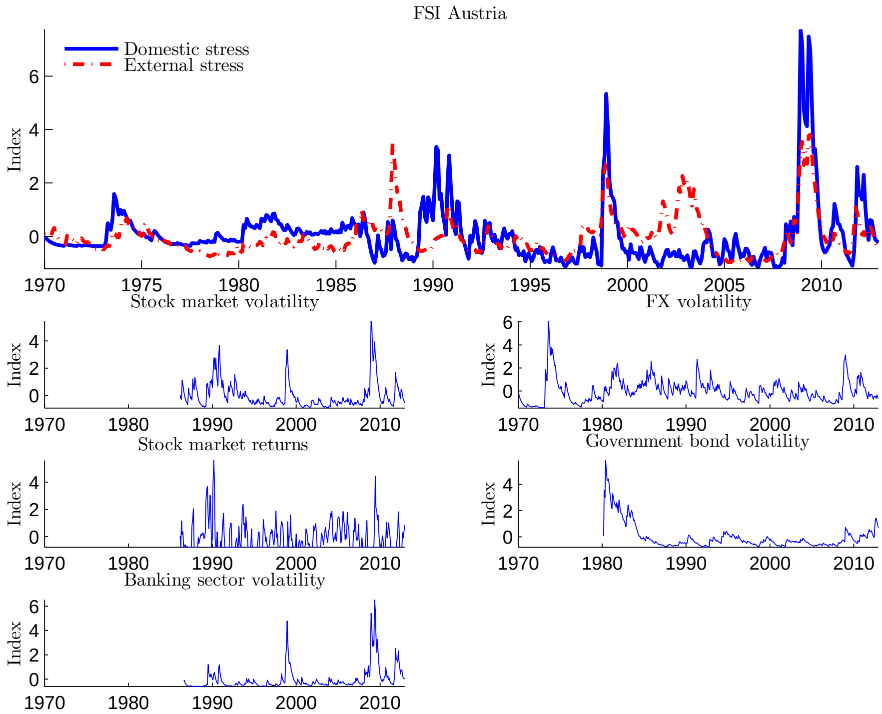
Australia experienced three episodes of financial stress. The first episode occurred during the first oil crisis in 1973-1974 and the second episode during the global stock market crash in 1987, when the FSI reached its highest level. During the third period, the recent global financial crisis, financial stress only rose slightly, because Australia was only marginally exposed to the turbulence on financial markets in other countries.

Table D2: *Selected events in Australian economic history*

1973-1974	Oil crisis
1987	Global stock market crash
2008-2009	Global financial crisis

Austria

Figure D3: *FSI and stress components for Austria*



Notes: The solid blue line in the upper panel represents the the domestic FSI; the red dashed-dotted line the external (trade-weighted) FSI.

Table D3: *Selected events in Austrian economic history*

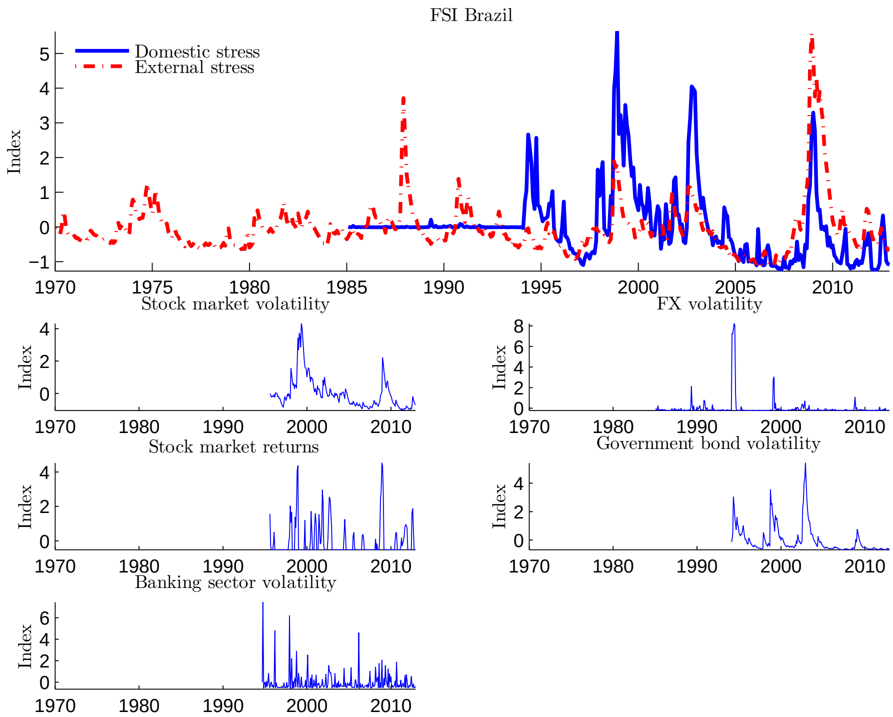
1973-1974	Oil crisis
1990-1992	German reunification / Collapse of Soviet regime
1997-1998	Asian crisis / Russian default
August / September 1998	LTCM crisis
2008-2009	Global financial crisis
2010-2012	European sovereign debt crisis

Notes: LTCM: Long Term Capital Management.

Austria experienced three periods of financial stress in the sample period. While financial stress was relatively subdued during the oil crisis 1973-1974, it significantly increased in the wake of the German reunification and the collapse of the Soviet regime from 1990 until 1992. Afterward, the Asian crisis led to a relatively sharp increase in the index. The highest stress in Austria was during the recent global financial crisis. Compared to this crisis, the European sovereign debt crisis affected financial markets in Austria only slightly.

Brazil

Figure D4: *FSI and stress components for Brazil*



Notes: The solid blue line in the upper panel represents the the domestic FSI; the red dashed-dotted line the external (trade-weighted) FSI.

The first financial stress events for Brazil that we can identify is the currency reform (Plano Real) in 1994 and the Mexican Peso crisis in 1995. During the Peso crisis, Brazil's trade deficit widened substantially, and the country had to bear strong net capital outflows. Economic policy reacted to the developments by shifting its policy focus primarily to the exchange rate and the trade balance.

The central bank announced interventions on foreign exchange markets with a narrow band, leading to a strong increase in dollar demand. The policy of a floating exchange rate regime with fixed nominal upper and lower bounds, resulted in a 10 percent devaluation of the nominal exchange rate, and was followed by a subsequent further devaluation under market pressures. At the same time, the government reversed the policy of rapid trade liberalization, using trade measures to curb imports, and an attempt was made to slow the

Table D4: *Selected events in Brazilian economic history*

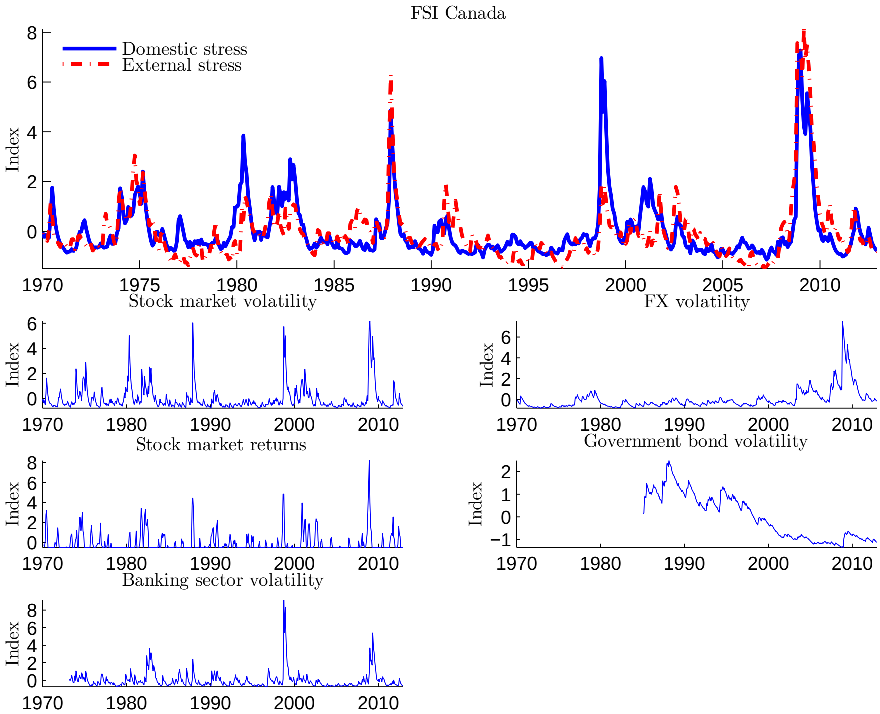
1980-1990	Stagflationary period
1981	LDC crisis
1990	Hyperinflation
July 1994	"Plano Real" - Currency reform
1995	Mexican Peso crisis (Tequila crisis)
1997-1998	Asian crisis / Russian default
August / September 1998	LTCM crisis
January 1999	Devaluation of the Brazilian Real
2002	"Argentinian" crisis
2008-2009	Financial crisis

Notes: LDC: Less-developed countries; LTCM: Long Term Capital Management.

economy to reduce inflationary pressures and check the deterioration of the trade balance. The next strong increase in the Brazilian FSI was during the depreciation of the Brazilian Real in 1999. Financial markets in Brazil were also highly exposed to the Argentinian crisis in 2002. In contrast, although financial stress increased noticeably during the global financial crisis, the peak of the FSI remained substantially lower than in the events that occurred in Latin American in the decade before.

Canada

Figure D5: *FSI and stress components for Canada*



Notes: The solid blue line in the upper panel represents the the domestic FSI; the red dashed-dotted line the external (trade-weighted) FSI.

The financial system in Canada experienced a variety of financial stress events over the past 40 years. The most significant increases in financial stress were during the 1987 stock market crash, the Russian and LTCM crisis, and most importantly the global financial crisis 2008-2009. On Black Friday 1987, the Canadian stock market index TSE dropped by 17 percent in two trading days. The banking sector was relatively resilient during these events such that volatility on bank equities remained subdued. In 1998 during the dramatic losses of the high leveraged hedge fund Long Term Capital Management (LTCM), banks were heavily involved and had to bear large losses. In addition, financial stress in Canada's major trading partners rose sharply. During the global financial crisis all stress components, except government bond volatility, soared and reached all-time highs. In particular, exchange rate volatility, which had been relatively low over the whole sample period, increased significantly. For a detailed description of the events of financial stress in Canada see Illing and Liu (2006).

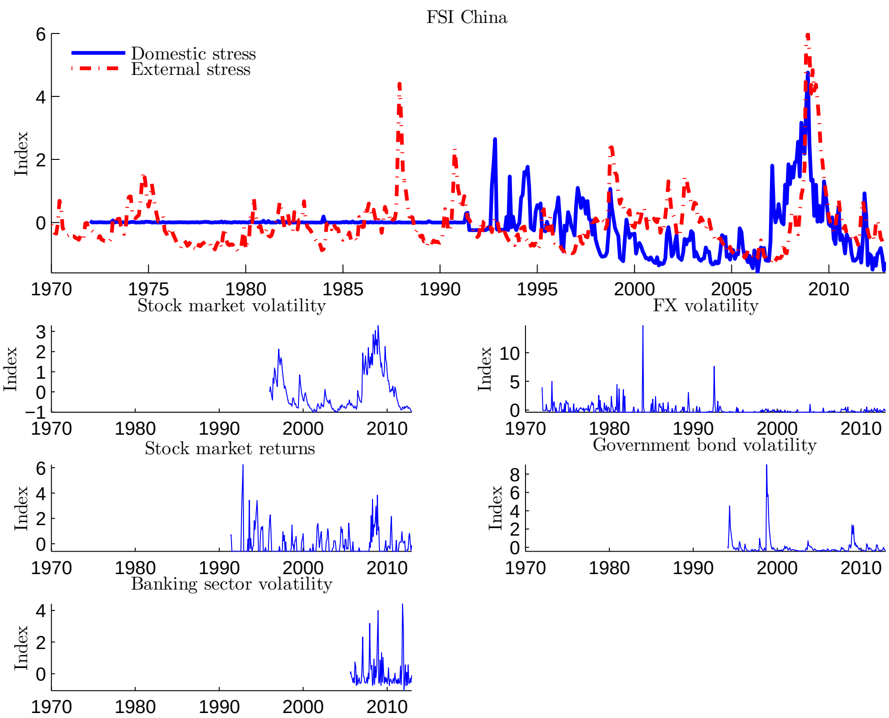
Table D5: *Selected events in Canadian economic history*

1973-1974	Oil crisis
1981	LDC crises
1987	Stock market crash
1991	Early-1990s bank losses (real estate price collapse)
2001	Terror attacks in the United States
1997-1998	Asian crisis / Russian default
August / September 1998	LTCM crisis
2008-2009	Global financial crisis

Notes: LDC: Less-developed countries; LTCM: Long Term Capital Management.

China

Figure D6: *FSI and stress components for China*



Notes: The solid blue line in the upper panel represents the the domestic FSI; the red dashed-dotted line the external (trade-weighted) FSI.

Since financial data for China has a relatively short history, visible movements in FSI begin at the beginning of the 1990's.[15] We identify the only great finan-

[15]The time series for the exchange rate volatility goes back further until 1972. However, the factor loading coefficient for the real exchange rate volatility index is very close to zero, such that it does not contribute significantly to the FSI.

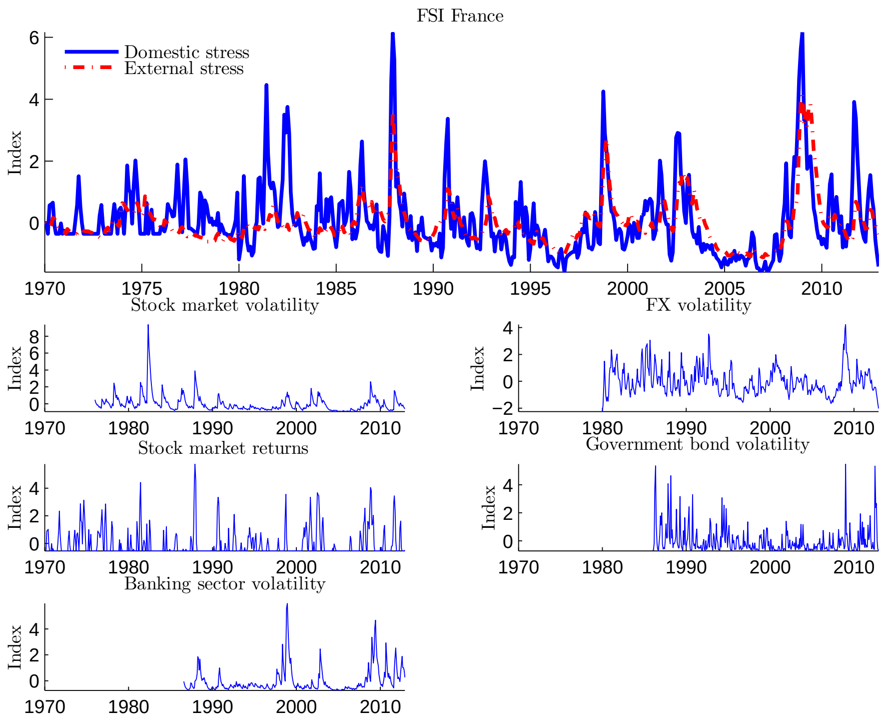
Table D6: *Selected events in Chinese economic history*

1997	Asian crisis
2008-2009	Global financial crisis

cial stress event in China during the global financial crisis, when stock market volatility and banking sector volatility reached record highs. Surprisingly, although stock and bond markets were noticeably affected during the Asian crisis in 1997, the FSI remains at very low levels, indicating that the financial system was not very strongly exposed to this event.

France

Figure D7: *FSI and stress components for France*



NOTES: The solid blue line in the upper panel represents the the domestic FSI; the red dashed-dotted line the external (trade-weighted) FSI.

The FSI for France is a relatively volatile index compared with the other countries in our analysis and points to various financial stress events over the past four decades. While the oil crisis had a relatively limited impact on financial stress in France, it soared the first time after the presidential election of François Mitterand on May 10, 1981. After an announcement of nationalization of private companies, the CAC40 dropped by more than 15 percent in just one day. The next strong increase in financial stress was during the stock market crash in 1987. One year later, the stock market had lost about 40 percent of its capitalization. The collapse of the Soviet Union and the crisis of the European exchange rate mechanism (ERM), when the French Franc came under pressure led to the next peaks of the FSI. During the Asian and Russian crisis as well as the collapse of the hedge fund LTCM the FSI increased significantly, particularly because French banks were involved considerably, such that volatility on bank equities jumped to a record high.

Table D7: *Selected events in French economic history*

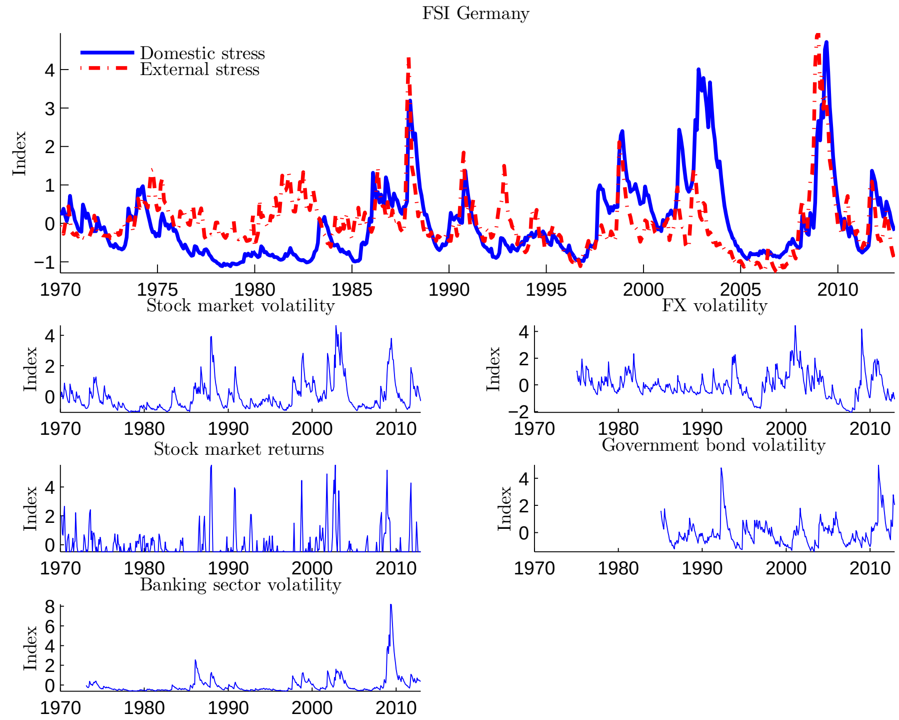
1973-1974	Oil crisis
1981	Stock market panic after presidential election
1981	LDC crisis
1987	Global stock market crash
1991	Collapse of Soviet Union, high political uncertainty
1992-1993	ERM crisis, Pressure on French Franc
1997-1998	Asian crisis / Russian default
August / September 1998	LTCM crisis
2001	Terror attacks in the United States
2004	Legacy of dotcom bubble
2008-2009	Global financial crisis
2010-2012	European sovereign debt crisis

Notes: LDC: Less-developed countries; LTCM: Long Term Capital Management; ERM: Exchange rate mechanism.

The low stress episode between 1998 and 2001 can be interpreted as investor's positive perception of the introduction of the Euro, mainly because exchange rate risk was reduced notably. The terror attacks in the United States on September 11, 2001 as well as the legacy of the burst of the dotcom bubble led to financial stress events, however with a moderate intensity. The highest peak of the FSI for France was during the global financial crisis 2008-2009. But also the European sovereign debt crisis led to widespread stress in the financial system in France, particularly, because government bonds came under pressure and French banks were strongly involved in crisis countries such as Greece. For a detailed description of the events of high financial stress in France see Aboura and van Roye (2013).

Germany

Figure D8: *FSI and stress components for Germany*



Notes: The solid blue line in the upper panel represents the the domestic FSI; the red dashed-dotted line the external (trade-weighted) FSI.

The major financial stress events for Germany are the 1987 global stock market crash, the legacy of the burst of the dotcom bubble and the global financial crisis 2008-2009.

While the 1987 crisis and the global financial crisis were also characterized by a strong increase in financial stress in the main trading partners, financial stress after the burst of the dotcom bubble was primarily a domestic phenomena. In particular, the volatility of the German stock market index DAX reached very high levels during this period. German reunification and the Asian and Russian crisis led a a slight increase in the index. In contrast, the ERM crisis had basically no major impact on financial stress in Germany. Along this line, the European sovereign debt crisis also had only slight effects on financial markets in Germany. In particular, compared to the crisis countries, government bond and banking sector volatility remained at low levels. For a detailed description of the events of high financial stress in Germany see van Roye (2013).

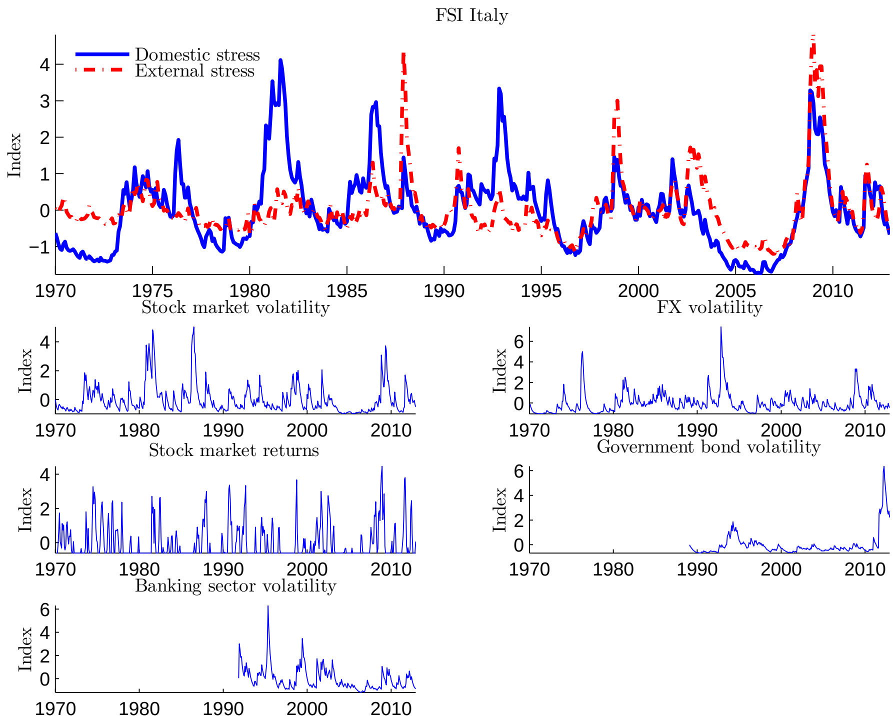
Table D8: *Selected events in German economic history*

1973-1974	Oil crisis
1987	Global stock market crash
1990-1991	Germany reunification; Collapse of Soviet Union
1992-1993	ERM crisis
1997-1998	Asian crisis / Russian default
August / September 1998	LTCM crisis
2001	Terror attacks in the United States
2004	Legacy of dotcom bubble
2008-2009	Global financial crisis
2010-2012	European sovereign debt crisis

Notes: LTCM: Long Term Capital Management; ERM: Exchange rate mechanism.

Italy

Figure D9: *FSI and stress components for Italy*



Notes: The solid blue line in the upper panel represents the the domestic FSI; the red dashed-dotted line the external (trade-weighted) FSI.

The FSI for Italy exhibits several peaks over the past four decades. The strongest increases in the FSI over the sample period was during the LDC crisis in 1982, the global stock market crash 1987, the ERM crisis , and the global

Table D9: *Selected events in Italian economic history*

1973-1974	Oil crisis
1981	LDC crisis
1987	Global stock market crash
1990-1991	Germany reunification; Collapse of Soviet Union
1992-1993	ERM crisis
1997-1998	Asian crisis / Russian default
August / September 1998	LTCM crisis
2001	Terror attacks in the United States
2004	Legacy of dotcom bubble
2008-2009	Global financial crisis
2010-2012	European sovereign debt crisis

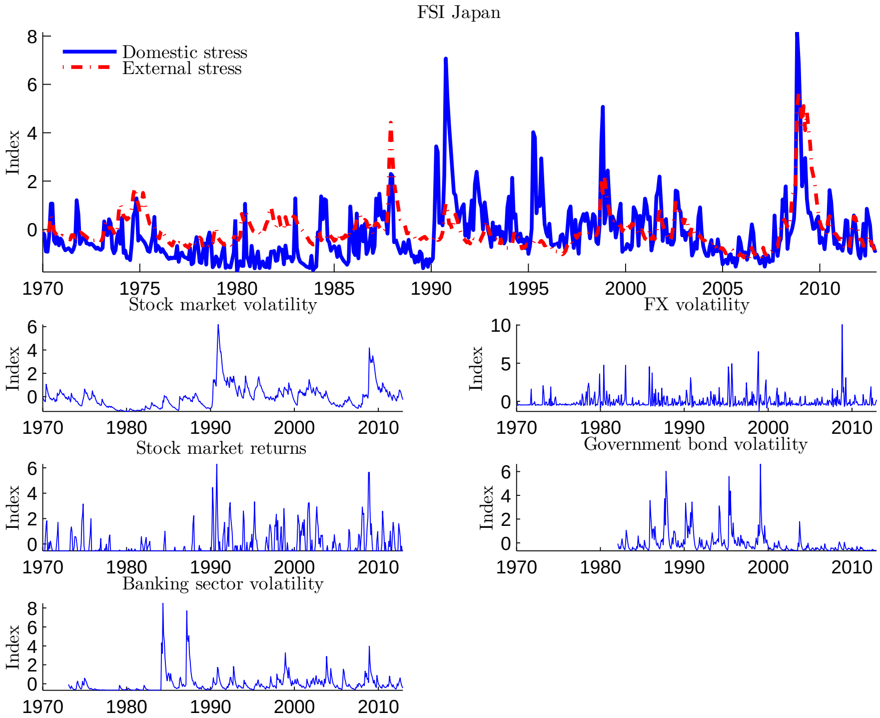
Notes: LDC: Less-developed countries; LTCM: Long Term Capital Management; ERM: Exchange rate mechanism.

financial crisis. The ERM crisis hit the financial system in Italy particularly hard. The Italian Lira devalued by 7 percent with the consequence that Italy withdrew from the European Monetary System in September 1992. Real effective exchange rate volatility soared in 1992 reaching a record high. Also returns on bank equities came under pressure as Italian banks held a large part of their liabilities in foreign currency. The global financial crisis had similar repercussions on financial markets in Italy, although the banking sector was affected to a much lower extent than those in France or Germany. Finally, the European sovereign debt crisis led to another increase in the FSI, principally because government bonds came under pressure. However, the impact of the crisis on the banking sector seems to have had a rather limited effect.

Japan

The FSI for Japan exhibits two very strong increases over the sample period. The first stress event was the Japanese stock market crash, when the Nikkei dropped by about 50 percent in 1990. THis event was the beginning of a persistent economic stagnation and Japan's lost decade. The second main stress event was the global financial crisis 2008-2009. Because of its regional vicinity to the other Asian countries, the Asian crisis was another noticeable financial stress event in Japan. Other international financial stress events such as the oil crisis 1973-1974 and the global stock market crash in 1987 had a rather limited impact on financial stress in Japan.

Figure D10: *FSI and stress components for Japan*



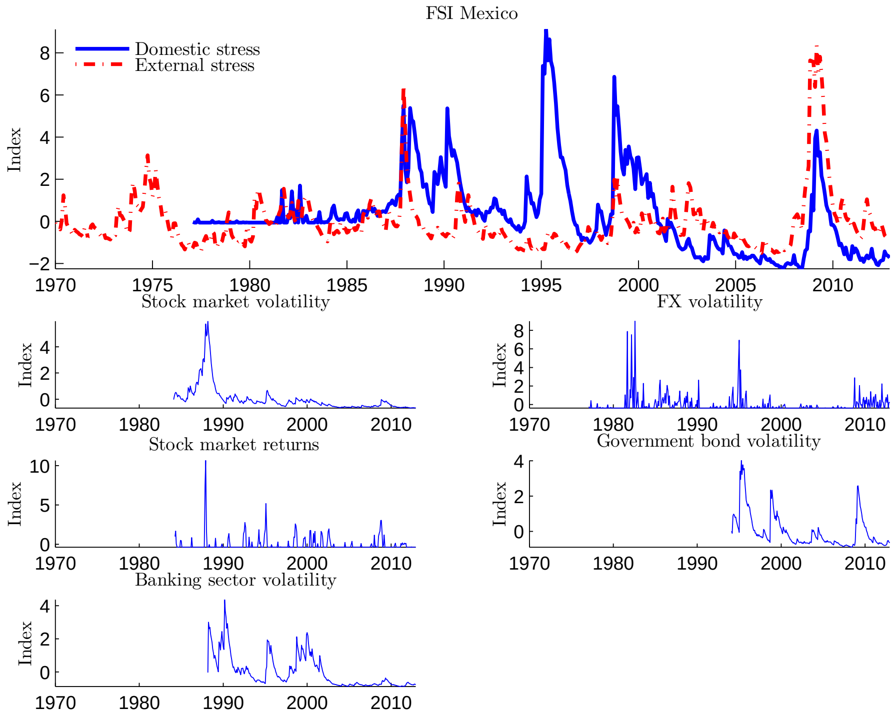
Notes: The solid blue line in the upper panel represents the the domestic FSI; the red dashed-dotted line the external (trade-weighted) FSI.

Table D10: *Selected events in Japanese economic history*

1973-1974	Oil crisis
1990	Nikkei crash – Tokyo stock market index falls by 50 percent
1990-1992	Banking crisis
2008-2009	Global financial crisis

Mexico

Figure D11: *FSI and stress components for Mexico*



Notes: The solid blue line in the upper panel represents the the domestic FSI; the red dashed-dotted line the external (trade-weighted) FSI.

In 1982, Mexico declared its inability to service the outstanding debt to their creditors and defaulted on its outstanding loans. The legacy of these events was reflected in financial stress increases in the following years: in 1987 stock markets in Mexico were heavily affected by the global stock market crash and banks still had to cope with balance sheet imbalances from the past decade. In the beginning of the 1990's, banking sector volatility significantly increased, which led to widespread strains in the financial system.

Table D11: *Selected events in Mexican economic history*

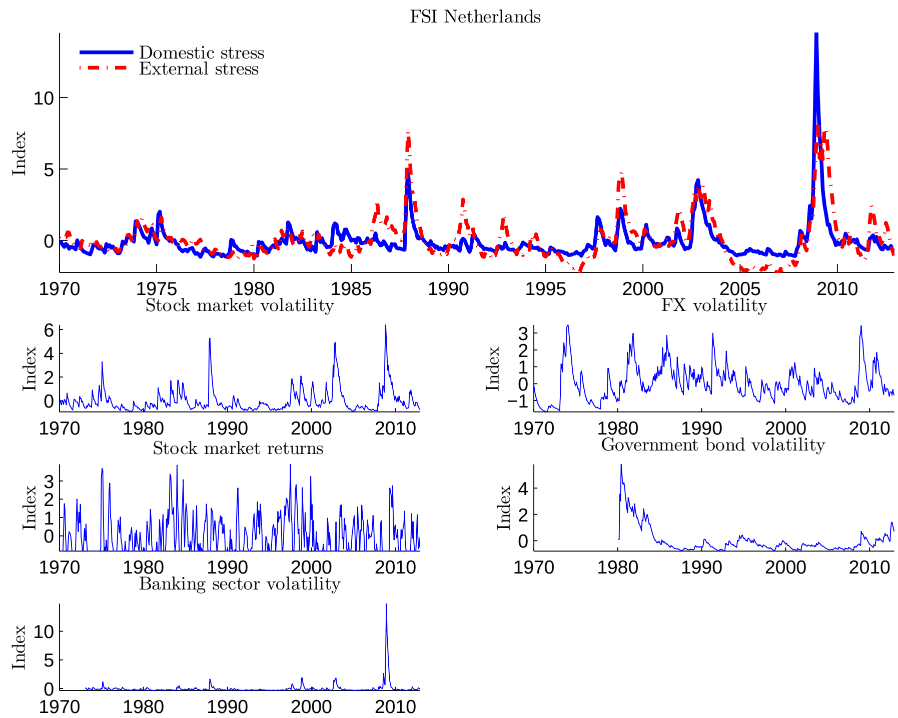
1982	Default on outstanding debt (LDC crisis), Peso currency turmoil
1995	Mexican Peso crisis (Tequila crisis)
1999	Brazilian crisis
2008-2009	Global financial crisis

Notes: LDC: Less-developed countries.

he Mexican Peso crisis was by far the most prominent increase in financial stress in Mexico. In 1994 the Mexican central bank had to give up the fixed exchange rate peg to the US-Dollar. This triggered a strong outflow of private capital and government bonds came under pressure. A standby credit agreement with the IMF and the World Bank finally led to appreciable decreases in the FSI in 1995. However, the devaluation of the Brazilian Real in 1999 led to pressures on government bonds again and to large losses in the banking sector. Finally, the global financial crisis had an impact on financial stress in Mexico. However, the magnitude of financial stress was rather limited and mainly due to the heavy financial market turmoils in Mexico's most important trading partner, the United States.

Netherlands

Figure D12: *FSI and stress components for the Netherlands*



Notes: The solid blue line in the upper panel represents the the domestic FSI; the red dashed-dotted line the external (trade-weighted) FSI.

The FSI for the Netherlands is mainly characterized by an outstanding increase of financial stress during the global financial crisis. All other events, such as the oil crisis in 1973-1974, the global stock market crash in 1987, the legacy

Table D12: *Selected events in Dutch economic history*

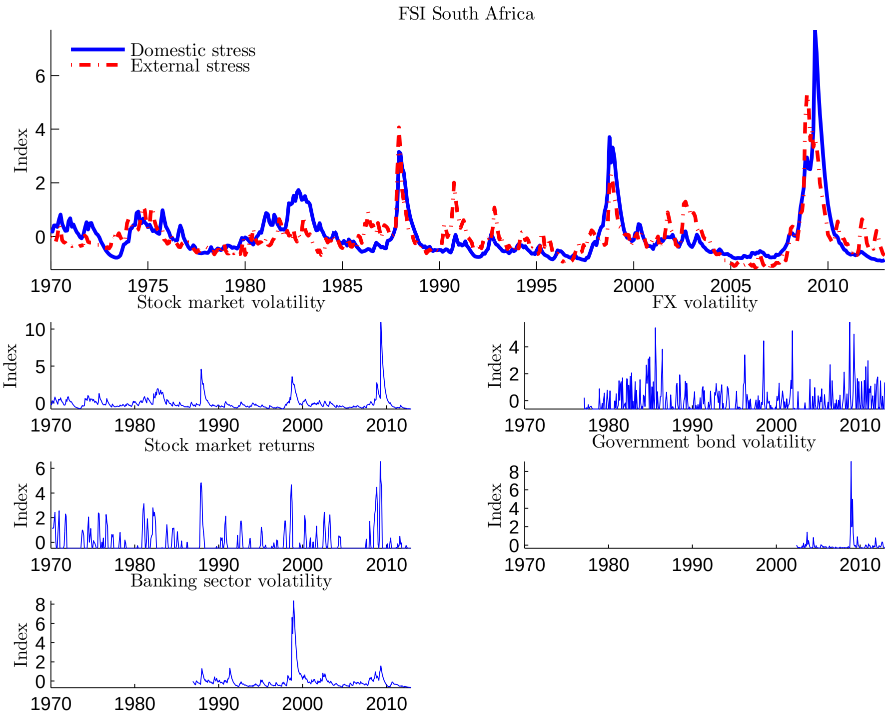
1973-1974	Oil crisis
1987	Global stock market crash
1997-1998	Asian crisis / Russian default
August / September 1998	LTCM crisis
2004	Legacy of dotcom bubble
2008-2009	Global financial crisis
2010-2012	European sovereign debt crisis

Notes: LTCM: Long Term Capital Management.

of the burst of the dotcom bubble and the European sovereign debt crisis had only minor effects. This is particularly due to the exceptionally high stress in the Dutch banking sector during the years 2008 and 2008.

South Africa

Figure D13: *FSI and stress components for South Africa*



Notes: The solid blue line in the upper panel represents the the domestic FSI; the red dashed-dotted line the external (trade-weighted) FSI.

The FSI of South Africa is strongly correlated to the external trade-weighted stress index. Although South Africa has a relatively low degree of financial openness, the financial system seems to be very vulnerable to external financial stress shocks. Outstanding global events that had a major impact on the South African financial system were the global stock market crash 1987, the Asian and Russian crisis 1997-1998, and the global financial crisis 2008-2009.

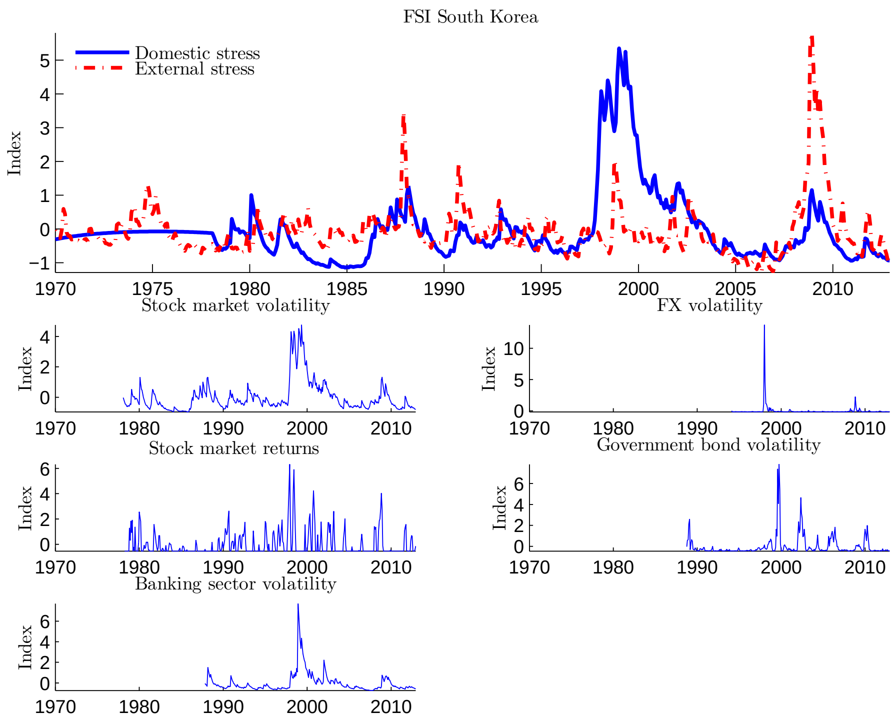
Table D13: *Selected events in South African economic history*

1987	Global stock market crash
1997-1998	Asian crisis / Russian default
August / September 1998	LTCM crisis
2008-2009	Global financial crisis

Notes: LTCM: Long Term Capital Management.

South Korea

Figure D14: *FSI and stress components for South Korea*



Notes: The solid blue line in the upper panel represents the the domestic FSI; the red dashed-dotted line the external (trade-weighted) FSI.

The most important financial stress event for South Korea over the sample period was the Asian crisis in 1997/1998. Stock market volatility rose sharply, returns on equity plummeted, and government bonds came under pressure. Similarly to the global stock market crash in 1987, the global financial crisis had only a minor impact on financial stress in South Korea.

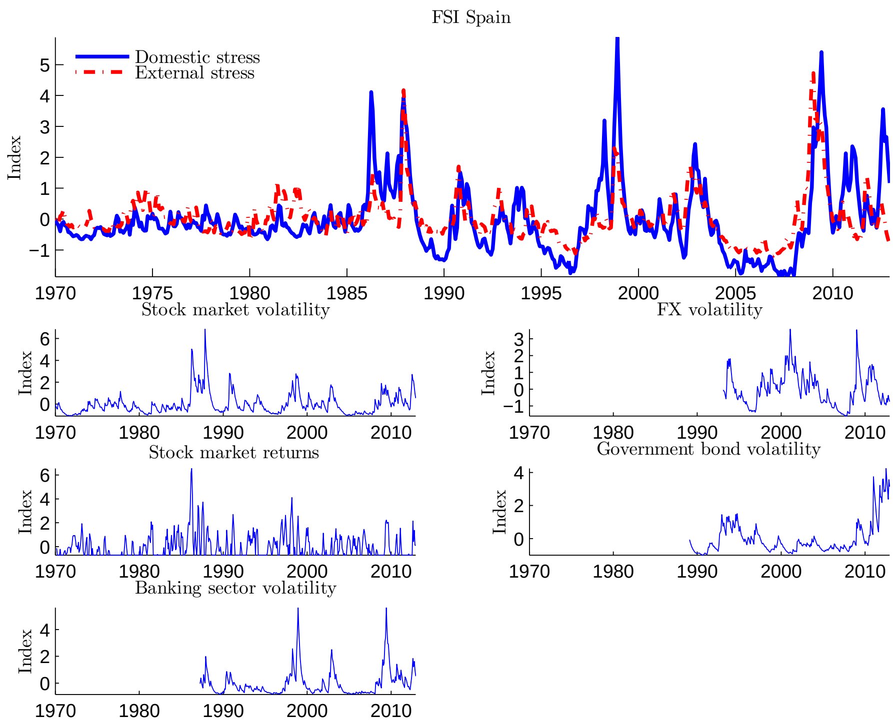
Table D14: *Selected events in South Korean economic history*

1987	Global stock market crash
1997-1998	Asian crisis / Russian default
August / September 1998	LTCM crisis
2008-2009	Global financial crisis

Notes: LTCM: Long Term Capital Management.

Spain

Figure D15: *FSI and stress components for Spain*



Notes: The solid blue line in the upper panel represents the the domestic FSI; the red dashed-dotted line the external (trade-weighted) FSI.

Spain experienced several peaks of high financial stress in the past forty years. After a period of strong economic performance after the Franco regime, when financial markets were more and more opened, financial markets experienced a significant turmoil in 1987. Spain was mainly affected by this event due to its exposure to Latin American countries such as Argentina, Brazil, Mexico and Venezuela. During this time period both Argentina and Venezuela underwent a exchange rate crisis and tried to restructure their debt. Spanish investors were directly hit by these events. The ERM crisis also had significant repercussions on financial markets in Spain as the country had to bear significant losses in competitiveness vis-à-vis countries like Germany. The Asian and Russian crisis also hit the financial system hard. The FSI increased to a record high, mainly because the Spanish banking sector was strongly affected. Finally, the global financial crisis and the European sovereign debt crisis were main events that led a widespread financial stress in Spain. While the global financial crisis was primarily due to banking problems, the European sovereign debt crisis affected the Spanish government bond market.

Table D15: *Selected events in Spanish economic history*

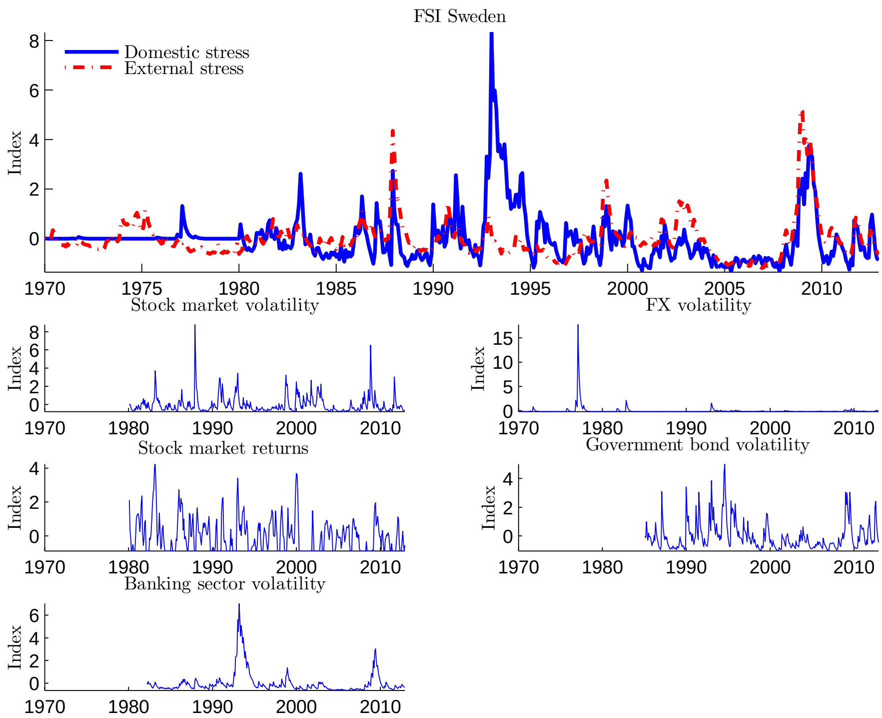
1987	Global stock market crash
1990-1991	German reunification; Collapse of Soviet Union
1992-1993	ERM crisis
1997-1998	Asian crisis / Russian default
August / September 1998	LTCM crisis
2001	Terror attacks in the United States
2004	Legacy of dotcom bubble
2008-2009	Global financial crisis
2010-2012	European sovereign debt crisis

Notes: LTCM: Long Term Capital Management; ERM: Exchange rate mechanism.

Sweden

The most important financial stress event in Sweden was the banking crisis in the early 1990's. By the end of 1990 reported credit losses had increased to around 1 per cent of lending, two to three times as much as during earlier years (Englund (1999)). Accordingly, volatility in the banking sector was extraordinarily high. When the crisis resolution had been completed, financial stress in Sweden remained at very low levels until the outbreak of the global financial crisis. However, the impact of this crisis on the Swedish financial systems remained relatively low, compared to the Swedish banking crisis in the early 1990's. The European sovereign debt crisis had almost no impact on the financial system in Sweden.

Figure D16: *FSI and stress components for Sweden*



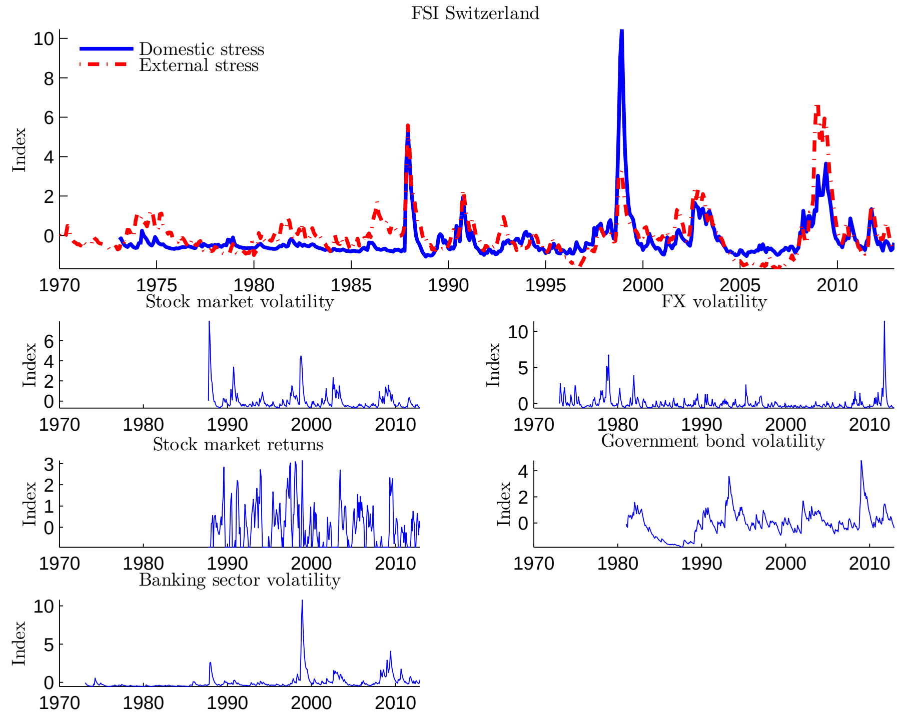
Notes: The solid blue line in the upper panel represents the the domestic FSI; the red dashed-dotted line the external (trade-weighted) FSI.

Table D16: *Selected events in Swedish economic history*

1987	Global stock market crash
1992-1994	Swedish banking crisis
2008-2009	Global financial crisis

Switzerland

Figure D17: *FSI and stress components for Switzerland*



Notes: The solid blue line in the upper panel represents the the domestic FSI; the red dashed-dotted line the external (trade-weighted) FSI.

The FSI for Switzerland can be characterized by three major peaks in the sample period.

Table D17: *Selected events in Swiss economic history*

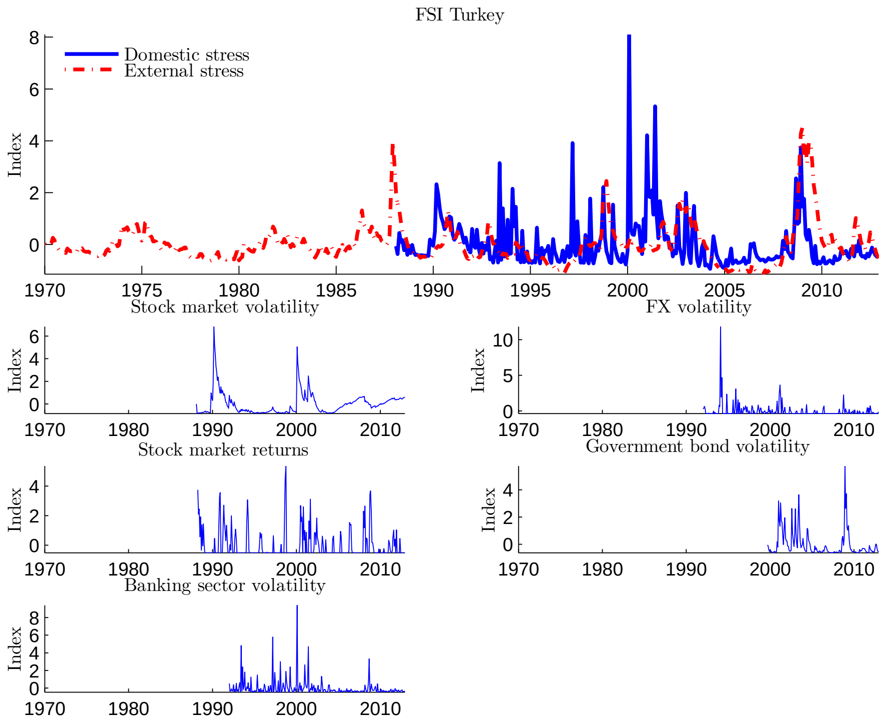
1987	Global stock market crash
1997-1998	Asian crisis / Russian default
August / September 1998	LTCM crisis
2008-2009	Global financial crisis

Notes: LTCM: Long Term Capital Management.

First, the global stock market crash in 1987 had a relatively strong effect on Swiss financial markets, especially on stock markets. Second, the collapse of LTCM had strong repercussions on the banking sector in Switzerland. The FSI indicates its record high during this stress event. Third, the global financial crisis had a noticeable impact o financial stress, although the level remained significantly below the aforementioned financial stress events. The European sovereign debt crisis seems to have had a negligible impact on financial markets in Switzerland.

Turkey

Figure D18: *FSI and stress components for Turkey*



Notes: The solid blue line in the upper panel represents the the domestic FSI; the red dashed-dotted line the external (trade-weighted) FSI.

The first period of financial stress for Turkey occurred in the beginning of the 1990's, when especially stock market volatility was very high. Afterward, the FSI peaks during the ERM crisis when the volatility of the Turkish lira sharply increased. While the Asian and Russian crisis had also a significant effect on financial markets in Turkey, the highest peak of financial stress was during the Turkish crisis in 2001. After the acceptance of the Turkish government to a standby agreement with the IMF, the index strongly declined, but it rose again after the terror attacks in the United States in September 2001 and the beginning of the second gulf war shortly afterward. The global financial crisis had a rather external influence of financial stress in Turkey. While the domestic FSI increased only slightly, the external financial stress index rose

Table D18: *Selected events in Turkish economic history*

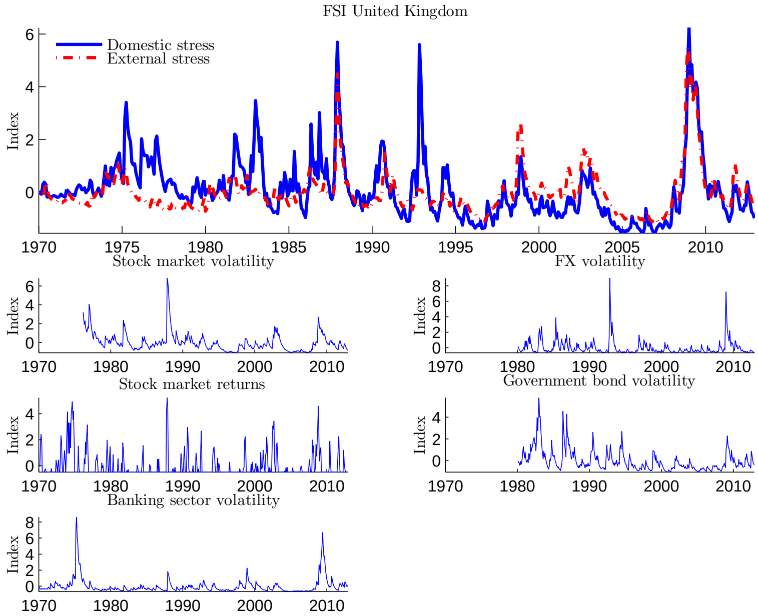
1991	Stock market turbulences
1992/1993	ERM crisis, Pressure on Turkish lira
1997-1998	Asian crisis / Russian default
August / September 1998	LTCM crisis
2001	Terror attacks in the United States
2003	Beginning of second gulf war
2008-2009	Global financial crisis

Notes: LTCM: Long Term Capital Management; ERM: Exchange rate mechanism.

sharply. Regarding the domestic stress variables, solely the volatility on Turkish government bonds soared during the global financial crisis. The European sovereign debt crisis had almost no influence on financial stress in Turkey. For a more detailed description of the events of high financial stress in Turkey see Cevik et al. (2013).

United Kingdom

Figure D19: *FSI and stress components for the United Kingdom*



Notes: The solid blue line in the upper panel represents the the domestic FSI; the red dashed-dotted line the external (trade-weighted) FSI.

Table D19: *Selected events in British economic history*

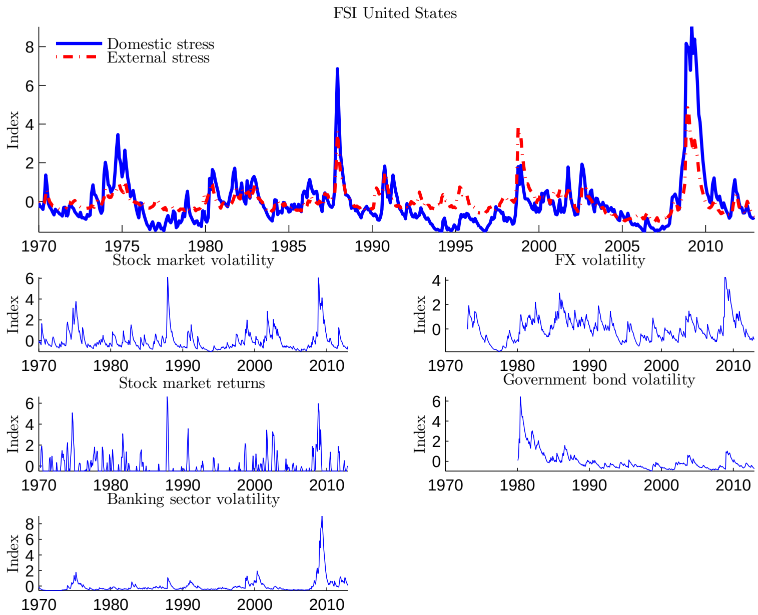
1973-1974	Oil crisis
1981	LDC crisis
1987	Global stock market crash
1992-1993	ERM crisis
1997-1998	Asian crisis / Russian default
August / September 1998	LTCM crisis
2001	Terror attacks in the United States
2008-2009	Global financial crisis

Notes: LDC: Less-developed countries; LTCM: Long Term Capital Management; ERM: Exchange rate mechanism.

The financial system of the United Kingdom experienced several periods of financial stress over the sample period. Being an industrial country dependent on oil, the oil crisis 1973-1974 had noticeable effects on financial stress. Over the course of time, the global stock market crash in 1987 was an event that hit the financial system in the United Kingdom particularly hard. The British stock market index dropped by the end of October by about 27 percent. Subsequently, the FSI exhibits a strong increase during the ERM crisis when exchange rate volatility soared. The collapse of LTCM in 1998 had only a very limited impact on financial stress in the United Kingdom. While the highest peak of the FSI was during the global financial crisis 2008-2009, the FSI remained at very low levels during the European sovereign debt crisis. For a more detailed description of the events of high financial stress in the United Kingdom see Christensen and Li (2013).

United States

Figure D20: *FSI and stress components for the United States*



Notes: The solid blue line in the upper panel represents the the domestic FSI; the red dashed-dotted line the external (trade-weighted) FSI.

Table D20: *Selected events in American economic history*

1973-1974	Oil crisis,
1981	LDC crisis
1982	Second oil crisis
1987	Global stock market crash
1997-1998	Asian crisis / Russian default
August / September 1998	LTCM crisis
2001	Terror attacks in the United States
2003	Beginning of second gulf war
2008-2009	Global financial crisis

Notes: LDC: Less-developed countries; LTCM: Long Term Capital Management.

In the United States, there were several remarkable periods of high financial stress in the past four decades. The oil crisis in 1973-1974 led to the first increase in the financial stress index. This event had mainly an impact on stock markets: stock market volatility rose sharply and firms had to bear serious losses. Although the United States were directly exposed to the LDC crisis as a main creditor to Latin American countries in 1982 and government bond volatility as well as interest rates were at record highs, financial markets were not excessively affected. This dramatically changed in 1987, when the stock market indexes hit rock bottom. Initiated by Black Monday 1987, return on assets of the US banking industry plummeted substantially, bringing down total total earnings for US banks for about two years. While the ERM crisis had no measurable effect on financial stress in the United States, the default of the hedge fund LTCM during the Asian / Russian crisis led to a sharp increase in the FSI. For a detailed description of the events of high financial stress see Hatzius et al. (2010), Hakkio and Keeton (2009), and Cardarelli et al. (2011).

Final remarks

This dissertation presents a theoretical and empirical analysis of the effects of macroeconomic uncertainty and financial stress on economic activity. It shows that a better understanding of the interdependencies of financial and macroeconomic developments are essential for business cycle analysis and policy advice. Moreover, it provides analytical tools for monitoring financial stability in real time using a broad set of financial stress indexes for several countries.

The results of this dissertation have important implications for economic policy. Due to the strong economic impact of financial shocks, monitoring financial stress should be of interest for both monetary and fiscal policy makers. Above all, it is important to identify financial imbalances and financial stress at an early stage in order to implement appropriate policy measures. The results provide a guidance for considering monetary and macroprudential policy decisions during times of financial stress. In addition, the results are relevant for macroeconomic forecasting. In a situation of macroeconomic uncertainty and financial stress, forecasters may take these developments into account and be more pessimistic for the economic outlook. Finally, since financial stress is significantly synchronized internationally, this dissertation claims that it is very important to consider its global dimension, even from the perspective of national policy makers. As a bottom line, the general intention of this dissertation is to improve the understanding between financial and macroeconomic developments.

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Eidesstattliche Erklärung

Ich erkläre hiermit an Eides Statt, dass ich meine Doktorarbeit *Financial Stress, Uncertainty, and Economic Activity* selbstständig und ohne fremde Hilfe angefertig habe und dass ich alle von anderen Autoren wörtlich übernommenen Stellen, wie auch die sich an die Gedanken anderer Autoren eng anlehnenden Ausführungen meiner Arbeit, besonders gekennzeichnet und Quellen nach den mir angegebenen Richtlinien zitiert habe. Im Fall der Abschnitte, die auf einzelnen Aufsätzen basieren, welche ich in Zusammenarbeit mit anderen Autoren verfasst habe, erkläre ich, dass ich eine angemessene anteilige Leistung beim Verfassen der jeweiligen Aufsätze erbracht habe.

Kiel, 18.06.2013

Ort, Datum

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Curriculum Vitae

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Info

Birth	28.08.1980 in Osnabrück, Germany
Citizenship	German

Experience

Working

2007-today **Research economist**, *Forecasting center and research area macroeconomic policies under market imperfections; The Kiel Institute for the World Economy*, Germany.
The Kiel Institute is an international center for research in global economic affairs, economic policy consulting, economic education and documentation. It is a renowned institution for forecasting and policy analysis in global economic affairs.
Special expertise: business cycle analysis; macroeconomic and econometric modeling; monetary economics; macro-financial linkages; emerging markets.

Projects

2012-today Enhancements and future development of the country monitoring framework at the Ministry of Finance. *Ministry of Finance, Germany.*

2012-today Consultancy and assistance to the Ministry of Finance within the Working Group on the Methodology to assess Lisbon related structural reforms (LIME). *Ministry of Finance, Germany.*

2007-today Joint Economic Forecast Project Team (Gemeinschaftsdiagnose). *Ministry of Economics and Technology, Germany.*

2012-2013 Report on macroprudential and fiscal policy options under a persistent expansionary monetary environment for the German economy. *Ministry of Finance, Germany.*

2012-2013 Report on a possible credit crunch in Germany during the Great Recession. *Ministry of Finance, Germany.*

2011-2012 Medium-term Economic Plan for Dubai 2011-2015 *Government of Dubai, Department for Economic Development.*

2011 Report on a possible credit crunch in Germany during the Great Recession. *Ministry of Finance, Germany.*

2007 Report on the weak economic performance for the Germany during the years 2005-2013. *Report for the Ministry of Economics and Technology.*

Conferences and workshops with own contributions

2013 Presentation of the *Kiel Policy Package to address the crisis in the euro area*, Kiel University, Germany.

2012 The Rimini Center for Economic Analysis in Canada: After (?) the Storm: Lessons from the Great Recession Rimini, Italy.

2012	Forecasting workshop at the Chinese Academy of Social Science (CASS), Beijing, China.
2012	5th Global Economic Symposium, Rio de Janeiro, Brazil.
2012	31th CIRET Conference, Vienna, Austria.
2012	3rd ZEW Conference on Recent Developments in Macroeconomics, Mannheim, Germany.
2012	9th EUROFRAME conference on economic policy issues in the European Union, Kiel.
2011	4th Global Economic Symposium, Kiel, Germany.
2011	Invited speaker at the ECB staff seminar of the external developments department, Frankfurt/Main, Germany.
2011	84th Kiel International Business Cycle Conference, Berlin, Germany.
2010	3rd Global Economic Symposium, Istanbul, Turkey.
2008	1st Global Economic Symposium, Pl¨on, Germany.

Education

2007-today	**PhD Program**, *Christian-Albrechts-Universität*, Kiel, Germany. PhD thesis: *Financial stress, uncertainty and economic activity*, Supervisor: Prof. Dr. Joachim Scheide
2001-2007	**Diploma**, *Humboldt Universität zu Berlin*, Germany. Graduate studies in economics and econometrics Diploma thesis: *Estimation Methods of the Gravity Model in International Trade*
2004-2006	**Diploma**, *Ecole Nationale de la Statistique et de l'Administration Economique (ENSAE)*, Malakoff, France. Graduate studies in econometrics and statistics

Scholarship and awards

2012	Honorable mention in the best paper award at the 2012 conference of the Centre for International Research on Economic Tendency Surveys (CIRET) in Vienna, Austria.
2004-2006	Graduate scholarship of the French-German University

Languages

Self-assessment European level CEFR (C2 maximum evaluation)

		Understanding		**Speaking**		**Writing**
		Listening	Reading	Interaction	Production	
English	**C2**	*C2*	*C2*	*C2*	*C2*	*C2*
French	**B2-C1**	*C1*	*C2*	*C1*	*B2*	*B2*
Spanish	**C1**	*C1*	*C2*	*C1*	*C1*	*C1*
German	**C2**	*C2*	*C2*	*C2*	*C2*	*C2*

Computer Skills

Econometrics Statistics: MATLAB, WinRats, EViews

Simulation Modeling: NiGEM, MATLAB, Dynare, Mathematica

Databases: Thomson Reuters Professional Datastream

Publications, submitted working papers and policy papers

Publications

van Roye, B. (2013). Financial stress and economic activity in Germany, Forthcoming in *Empirica*.

Kooths, S. and B. van Roye (2012). Nationale Geldschöpfung zersetzt den Euroraum, *Wirtschaftsdienst*, 92, Springer Verlag, 520-527.

Submitted working papers

Bonciani, D. and B. van Roye (2013). Uncertainty Shocks, banking frictions and economic activity. Unpublished manuscript.

Aboura, S. and B. van Roye (2013). Financial stress and economic dynamics: an application to France, *Kiel Working Paper*, 1834, The Kiel Institute for the World Economy.

Dovern, J. and B. van Roye (2013). The transmission of financial stress: Evidence from a GVAR model, Unpublished manuscript.

Kooths, S. and B. van Roye (2012). Single currency, national money creation, *Kiel Working Paper*, 1787, The Kiel Institute for the World Economy.

Utlaut, J. and B. van Roye (2010). The Effects of External Shocks on Business Cycles in Emerging Asia: A Bayesian VAR approach, *Kiel Working Paper*, 1668, Kiel Institute for the World Economy.

van Roye, B. and D. Wesselbaum (2009). Capital, Endogenous Separations, and the Business Cycle, *Kiel Working Paper*, 1561, Kiel Institute for the World Economy.

Policy papers

Snower, D., J. Boysen-Hogrefe, K.-J. Gern, H. Klodt, S. Kooths, C.-F. Laaser, C. Reicher, B. van Roye, J. Scheide, and K. Schrader (2013). The Kiel Policy Package to Address the Crisis in the Euro Area, *Kiel Policy Brief*, 58a, The Kiel Institute for the World Economy.

Gern, K.-J., B. van Roye, and J. Scheide (2011). Higher Inflation in China: Risks for Inflation and Output in Advanced Economies, *Kiel Policy Brief*, 36, The Kiel Institute for the World Economy.

Groll, D. and B. van Roye (2011). Price Competitiveness Divergence in the Euro Area: the Level Matters! *Kiel Policy Brief*, 24, The Kiel Institute for the World Economy.

Dovern, J., D. Groll, J. Boysen-Hogrefe, B. van Roye, and J. Scheide (2010). Droht in Deutschland eine Kreditklemme. *Kieler Diskussionsbeiräge 472/473*, 36, The Kiel Institute for the World Economy.

Boss, A., J. Dovern, K.-J. Gern, N. Jannsen, C.-P. Meier, B. van Roye and J. Scheide (2009). Ursachen der Wachstumsschwäche in Deutschland 1995- 2005. *Kieler Beiträge zur Wirtschaftspolitik 2.*, 24, The Kiel Institute for the World Economy.

van Roye, B. and D. Wesselbaum (2009). Estimating the Impact of Fiscal Stimulus Packages. In Klodt, H., and H. Lehment (2009). The Crisis and Beyond. *Kiel Institute E-Books (44-49)*, 24, The Kiel Institute for the World Economy.

Forecasting reports

2007-today Quarterly publication of forecasting reports of the world economy, the euro area and Germany. Publication list is available upon request.

Internships

11/2006-11/2007 Database management, Mortgage Backed Securities, CDOs, financial services at *Hypoport AG, The Finance Integrator*, Berlin, Germany

06/2006-08/2006 Time Series analysis, statistics, and project coordination at *ESCO Compañia de Servicios de Energia*, Lima, Peru

06/2004-07/2004 Financial Statistics and project planning at the *Deutsche Bundesstiftung Umwelt, DBU* in Osnabrück, Germany

08/2003-07/2003 Project Management, and writing proposals to the United Nations at *Eco Project Ltd*, Scarborough, Trinidad & Tobago

08/2002-07/2002 Assistant to the management board at *Siemens Ltd*, Bangkok, Thailand.

06/2001-07/2001 Assistance in Legal Affairs at the *Embassy of the Federal Republic of Germany* in Colombo, Sri Lanka.

References

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Dr. Stefan Kooths, *Deputy head of the forecasting center, The Kiel Institute for the World Economy, Berlin Office*, Germany. (E-Mail: stefan.kooths@ifw-kiel.de)

Interests and Hobbies

Traveling, Tennis, Soccer, Windsurfing, Kitesurfing, Guitar.