Università degli Studi di Cagliari

PHD DEGREE

Economics and Business

Cycle XXX

TITLE OF THE PHD THESIS

The predictive power of financial variables and the asymmetric impact of monetary policy in the euro area

Scientific Disciplinary Sector(s)

SECS-P/01

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Final exam. Academic Year 2016 – 2017

Thesis defence: February-March 2018 Session

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Marco Mandas gratefully acknowledges Sardinia Regional Government for the financial support of her PhD scholarship (P.O.R. Sardegna F.S.E. Operational Programme of the Autonomous Region of Sardinia, European Social Fund 2007-2013 - Axis IV Human Resources, Objective l.3, Line of Activity l.3.1.)”.

Contents

Abstract

This thesis contributes to several debates on the role of financial conditions in affecting monetary policy transmission and in predicting economic activity by providing new empirical evidence within linear and nonlinear frameworks.

The focus of the first chapter is to provide a comparison of the theoretical and empirical approaches that have been employed to investigate the nature of the nexus between financial and real economy. I concentrate more on the works that examine how financial imperfections are important in the monetary policy transmission mechanism and how financial information helps in forecasting the real economy. There is a large consensus that financial frictions lead to a rise in the persistence and the amplitude of monetary policy effects. Moreover, financial indicators have proved to be useful in predicting economic activity.

The second chapter studies the interaction between financial frictions and economic activity by investigating to what extent the information provided by financial stress indicators is useful in forecasting euro area economic activity, especially rare macroeconomic outcomes such as the Great Recession. To this end, I estimate a set of linear and non-linear Bayesian VAR models and evaluate their relative performance from both a point- and density-forecast perspective. In a pseudo real-time out-of-sample forecasting exercise, I find that financial stress indicators would have sent clear signals of significant downside risks for euro area economic activity well before the contraction of euro area GDP. Correspondingly, I find that their forecasting performance, when evaluated in terms of probability distribution, results superior to that of standard models that omit the link between finance and the macroeconomics.

The third chapter investigates the potential for the state-dependent nature of monetary policy transmission in the European Union within a framework that involves financial frictions. In

order to achieve this objective, I compare the different responses to a monetary policy shocks generated by a set of linear and nonlinear Bayesian VAR models. I find that financial conditions matter in the transmission of monetary policy and are crucial in determining a larger impact during periods of recession.

Introduction

My research interest focuses on how financial conditions affect the monetary policy transmission mechanism and to what extent the information provided by financial stress indicators is useful in forecasting euro area economic activity, especially rare macroeconomic outcomes such as the Great Recession. Indeed, the macroeconomic implications of the financial crisis that began in 2007 have motivated many economists to study the causes of the dramatic economic downturn within analytical frameworks that account for the interactions between financial markets and economic activity. Even before the recent events, some empirical facts as well as much formal research have stressed the crucial role of financial markets in affecting the economy. The beginning of this literature could be dated as far back as the 30's when Fisher developed the debt-deflation theory of Great Depression. In chapter 1, I survey the most influential papers of several decades of research on how financial conditions can affect short-term economic dynamics with the objective to provide a comparative assessment of the theoretical and empirical approaches that have been used to investigate how financial imperfections may preclude an economy from reaching its full potential. A great deal of attention is devoted to the literature that identifies the channels through which financial factors may determine and amplify the business cycle fluctuations (financial accelerator mechanism) and may affect the propagation mechanism of temporary monetary policy shocks (credit channel theory). With the presence of borrowing limits, many papers investigate to what extent a linear framework is appropriate and explore the possibility of a nonlinear and state-dependent link between financial and real economy since in normal circumstances financial frictions are not binding and therefore do not affect agents' decisions. The literature has delivered a mixed message so far, in the sense that it is not clear how these non-linear effects operate. I explore the different methodologies that have been applied to model non-linearity in time series.

My empirical work, developed in chapters 2 and 3, is directly related to the literature that I analysed in the first part.

In chapter 2, I contribute to the existing empirical literature on predicting euro area GDP growth by comparing the relative forecasting performance of a set of linear and nonlinear Bayesian vector autoregressive (BVAR) models that include financial indicators with standard BVAR models that omit the link between financial conditions and macroeconomics from both a point-wise and a predictive distribution perspective. I examine the link between macroeconomic outcomes and financial factors on euro area data by adopting a forecasting approach along the lines proposed by Alessandri and Mumtaz (2017) for the US. To further assess their performance, I compare the models with distributions of expectations derived from financial market participants surveyed by the European Central Bank within the Survey of Professional Forecasters (SPF). A key motivation behind the work presented in this chapter is the forecasting failure associated with the Great Recession and the large economic losses that led policy authority to pay more attention to financial stability issues aiming at preventing costly financial crisis. To this end, it has revealed to be more and more important to evaluate models' forecast performances in terms of density-forecast accuracy. Having at hand a predictive distribution allows a policy maker to check the likelihood of a recession event and take the appropriate precautions when the probabilities are above a predefined threshold. I find that, from a predictive distribution perspective, BVAR models with financial stress indicators outperform standard models and measures of risk derived from the SPF. This finding seems to be driven by the performance during periods of financial stress, while during tranquil periods models with financial stress indicators offer no advantage, in line with insights from theoretical models of occasionally binding constraints.

In chapter 3, I document empirically whether the impact of monetary policy depend on the state of the economy and whether financial conditions can affect its transmission. In this regard, the credit channel theory highlights how specific characteristics and imperfections of the financial system alter the transmission of monetary policy to the economy, but it is still not clear whether high financial stress during negative business cycle may prevent monetary interventions from reaching its objective to stabilize output and inflation or, conversely, it may increase its effectiveness through the additional capacity to mitigate adverse spirals that are typical during financial crisis. This strand of literature suggests the presence of non-linearity in the effects of monetary policy. The relevance of the debate led many authors to investigate to what extent monetary actions depend on the sign and size of the intervention and the state of the business cycle at the time of the intervention, but the results they obtained are ambiguous.

The objective of this chapter is to provide new empirical evidence that contributes to these debates by evaluating the role played by financial conditions in the propagation of monetary shocks in the European union within empirical models that capture non-linear interactions between the financial sector and the macroeconomics. First, I am interested in assessing the relevance of the credit channel by estimating two versions of a linear Bayesian VAR applied to euro area data in which one of them omit the existence of a credit channel in monetary policy transmission. The direct comparison between the impulse responses allows an intuitive way to achieve my objective. Thus, I apply a Bayesian Threshold VAR approach that allows for the possibility of two regimes determined by the lag of GDP growth in order to account for the asymmetric effects of monetary policy shocks on economic activity depending on the business cycle at the time the action is taken.

I find that financial conditions play a crucial role in amplifying the effects of monetary interventions and in determining the asymmetric impact across good and bad times, namely monetary policy shocks have larger and faster effects during periods of recessions.

Chapter 1

Monetary policy implications of financial frictions and the predictive power of financial measures: a survey

1.1 Introduction

The objective of this chapter is to survey the growing literature that studies how credit markets and economic activity interact. I concentrate more on the works that examine how these interactions are important in the monetary policy transmission mechanism and how financial information helps in forecasting the real economy.

In a frictionless economy, financial markets only help a modern economy to realize its full potential by allocating financial resources to most profitable projects. In most theoretical framework, the models abstract from financial frictions and study the dynamic relationships of the variables in a perfect capital markets context. The recent great recession has been a great reminder that financial factors play a crucial role in determining and amplifying business cycle fluctuations.

Starting with an analysis of the fundamental works on asymmetric information and principal-agent theory that provide the means to model financial frictions, I select and compare the most influential papers of several decades of research on how financial conditions can affect short-term economic dynamics. Researchers have devoted a great effort to identify the channels through which financial factors may affect the real economy. The general message of this literature is that changes in the creditworthiness of borrowers affect the cost of external funds that lead to a rise in the persistence and the amplitude of the business cycle (financial accelerator mechanism) and the monetary policy impact (credit channel theory). The presence of borrowing limits and the recent events shift the emphasis in this literature on the role of occasionally binding constraint in generating a nonlinear and state-dependent link between financial markets and real economy. Against this background, many economists study the power of financial market information in predicting economic activity. The focus of this survey is to provide a comparison of the theoretical and empirical approaches that have been employed to investigate the nature of the nexus between financial and real economy.

The structure of the chapter is as follows. Section 2 analyses the theoretical settings that the literature has proposed to study the link between real and financial economy, section 3 reviews the literature on the credit channel theory; section 4 summarizes the research on the asymmetric nature of monetary policy effects. Section 5 reports the papers that study the role of financial variables in predicting economic activity. Section 6 concludes.

1.2 The relationship between real and financial economy

Modigliani and Miller (1958) develop a theorem that states the value of a firm is independent of its capital structure (that is, its debt/equity ratio) and depend only on its ability to generate profits and the risk of its underlying assets in perfect capital markets. But many economists began to consider the assumption of perfect capital markets to be too strong and unrealistic. So, they take a new approach to study how financial and real economy interact and how the presence of asymmetric information between lenders and borrowers might have its part to prevent the efficient functioning of financial markets in allocating resources across firms and investors. With asymmetric information, many papers suggest that monitoring might improve financial markets efficiency by screening projects a priori in a context of adverse selection[1], by preventing moral hazard actions of the borrower once obtained the capital and, eventually, by punishing the borrower who fails to meet contractual obligation. Diamond (1984) develops the delegated monitoring theory where financial intermediation is useful in reducing the cost of controlling projects that resolve some incentive problems under conditions of imperfect information. Within a framework where banks diversify risk by financing many projects, each firm's project needs the funds of several investors and relative low cost of delegation, financial intermediation minimizes the cost of monitoring the borrower by exploiting scale economies. Holmstrom and Tirole (1997) explore the consequences of this monitoring activity in a very elegant model. They analyze the role of capital constraints in explaining the distribution of financial resources across differently informed agents (firms, intermediaries and investors). The main result is that all types of capital tightening – a credit crunch, a collateral and a saving squeeze- *hit poorly capitalized firms the hardest*. The financial frictions induced by information asymmetries highlighted by this paper are crucial for understanding the literature that studies their macroeconomic implications. Ludvigson (1999) finds that credit conditions play an important role in determining consumer decisions. He studies how changes in credit conditions affect consumption and what kind of theoretical framework can be employed to estimate how consumption might depend on credit conditions. He documents empirically the correlation of consumption growth with predictable credit conditions using a time-varying liquidity constraint model where credit limitations vary stochastically with consumers' income. Similarly, Zeldes (1989), testing the permanent income hypothesis against the alternative hypothesis that the optimal behavior of consumers is subject to a sequence of credit constraints, find that the

[1] Akerlof (1970) gave economists the tools to study the problems derived by this asymmetric information

assumption of inability to borrow in order to protect future shocks on personal income affects consumption choices of a significant portion of population.

The assumption of costly state verification[2] suggested by these papers is critical in determining the results obtained by Bernanke and Gertler (1989) and Carlstrom and Fuerst (1997)[3]. In their models a temporary shock generates much persistent effects on entrepreneurial net worth. The presence of financial frictions induces firms to deviate from first-best outcomes of their capital structure in response to any disturbances that affect the economy. Namely, a shock to borrowers' net worth increases financial frictions and forces them to invest less. This leads to a lower level of capital and lower entrepreneurs net worth in the following periods. This decrease results in a further drop in investments and net worth in the following periods making the effects of a shock much more persistent in a context of imperfect financial markets compared to the impact of the same shock in a standard setting that abstract from financial frictions. By introducing convex capital adjustment costs, Bernanke, Gertler and Gilchrist (1999) show that imperfections in the financial markets are important not only in determining much more persistency, but also in amplifying the propagation of shocks to economic activity. They analyze the role of credit market frictions in business cycle within a dynamic general equilibrium model that add several features to preceding framework. This setting exhibits the famous "financial accelerator mechanism" in the propagation of shocks to economy. Furthermore, they provide empirical evidence on how the financial accelerator influences

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[2] Townsend (1979) argues that the incentive to verify the state of the business derives from asymmetric information about future cash flows of the project.

[3] Bernanke and Gertler (1989) use an overlapping generations models where agents live for only two periods. Instead, agents are infinitely lived in the framework proposed by Carlstrom and Fuerst (1997).

business cycle dynamics with some quantitative simulations that show the responses of output and prices to monetary, technology and demand shocks.

Kiyotaki and Moore (1997) examine a model with two type of agents, farmers and gatherers, in which land is used both as a productivity factor and as a collateral for loans to farmers. With borrowing limits, a shock to the land value will affect the net worth of the farm and its capacity to invest. They conclude that the interactions between credit constraints and asset prices is important, both amplifying the effects of disturbances and generating cycles.

Even though Bernanke and Gertler (1989) already argued that the aggregate effects of productivity shocks might be asymmetric since the agency problem only bind on the "down" side, the authors I mentioned so far analyze the dynamics of log-linearized models around a steady state in which borrowing limits are binding, thus ignoring the potential for different responses to shocks depending on the state of the business cycle.

To this end, Brunnermeier and Sannikov (2014) develop a macroeconomic model to explore instabilities of the financial system in a volatile economy. They take a new approach that concentrate more on the impact of financial frictions instead of neo Keynesian price stickiness. By analyzing the full dynamics of the system, they find that the effects of shocks are greater during downturns driven by the more prominent financial instability that is characteristic when is more probable that agents are close to their credit limits. The behavior of the system away from the steady state best resembles crises episodes.

In line with the view of Brunnermeier and Sannikov (2014), Guerrieri and Iacoviello (2017) detect asymmetric responses to house price changes. They present a model with collateral constraints and show that the response of consumption and hours to house price changes is negative and large only when housing wealth is low and collateral constraints become tight. They provide empirical evidence from national, state-level, and metropolitan area-level data.

Thus, they suggest taking asymmetries into account to avoid underestimating the response to large house price collapses.

To sum up, the literature proposes different theoretical settings for financial frictions. The basic imperfections are mainly due to asymmetric information that determines problems of adverse selection and moral hazard. By integrating financial factors into rather standard dynamic general equilibrium models, many authors document how financial frictions are important in causing business cycle fluctuations with financial and credit shocks and in determining an amplification mechanism that accelerate the propagation of shocks to the real economy. An amplification mechanism that appears to be state-dependent. In normal times the amplification effects are not so relevant. However, the impact of shocks during downturn is exacerbated by the presence of financial frictions.

1.3 Monetary policy and the credit channel

The transmission mechanism of monetary policy to real economy is a central topic in macroeconomic literature. Within the traditional theoretical frameworks of investment, consumption and international trade that account for nominal wage and price rigidities, the conventional channels operate through the user cost of capital and wealth effects. By controlling the short-term policy rate, monetary authority affects directly money-market interest rates and, indirectly, lending and deposit rates applied by banks to their customers. This movements modify the cost of capital and hence influence firms and household investment decisions. In addition, consumption and investment are also affected by changes in asset prices. For example, as equity prices rise, households become wealthier and may choose to increase their consumption. Conversely, when equity prices fall, households may reduce consumption. On the other hand, the standard interest rate channel seems to be not sufficient to explain the large real effects generated by monetary actions. Moreover, the relevant role of financial intermediaries in the transmission mechanism and the imperfections in credit markets led many economists to seek for alternative or additional channels through which monetary policy might affect the economy[4]. Accordingly, Bernanke and Gertler (1995) decide to go inside the "black box" of monetary transmission to disentangle the different channels. They identify the so-called credit channel and provide a crucial contribution to the credit channel theory. In their opinion, financial frictions amplify the effects of conventional interest rate channel. Thus, they do not consider the credit channel as a parallel alternative, but as an enhancement mechanism to the existing neo classical channels. They distinguish two components of the broad credit channel: the balance-sheet and the bank-lending channels.

The balance-sheet channel of monetary policy is closely related to the idea of the financial accelerator that I have already examined. Changes in interest rates designed by the central bank affect the values of the assets and the cash flows of firms that serves also as collateral for loans. Consequently, the creditworthiness of potential borrowers and the external finance premium that they face are affected, generating an additional effect of monetary interventions. For example, according to this view, a tightening of monetary policy decreases the net worth of

[4] Boivin, Kiley and Mishkin (2010) provide an excellent survey that describe how monetary policy has changed over time and how researchers have developed new approaches to study how monetary interventions affect the economy, leading to further evolution in our understanding of monetary transmission mechanism.

borrowers and weaken their financial position. Since borrowers' financial position influences the effective cost of credit, changes in firms' reliability affect their investment decisions.

The bank-lending channel operates through additional changes in the supply of intermediated credit. Indeed, monetary policy seems to affect the supply of bank loans. The idea is that, in response to a negative monetary innovation, banks cannot easily replace lost deposits with other sources of funds and do not face a perfectly elastic demand for their open-markets liabilities. This leads to an increase in the banks' cost of funds that shift the supply of loans, excluding the bank-dependent borrowers and raising the external finance premium. Adrian and Shin (2008) document the procyclicality of leverage linked to the increased relevance of market based financial intermediaries in the supply of credit. They state that both these facts play a crucial role in amplifying the supply response to asset price changes and in closely interconnecting price and financial stability. Their analysis has important implications on how central banks should pursue his price stability objectives and suggests keeping continuously an eye on balance sheets size of security broker-dealers as they represent a good indicator of the overall funding conditions in a market-based financial system.

In the light of credit channel theory, a new theoretical framework that involve financial frictions turns to be necessary in order to study the responses of the economy to conventional and unconventional monetary policy. Bernanke, Gertler and Gilchrist (1999) has started to fill this gap in the literature by introducing financial frictions in a dynamic general equilibrium model. Gerali, Neri, Sessa and Signoretti (2010) extend the model in Iacoviello (2005) by adding a banking sector with imperfect competition and endogenous accumulation of bank capital that is very useful to evaluate the bank-lending channel of monetary transmission. Curdia and Woodford (2010) investigate the consequences of credit spreads for the effects of monetary policy shocks and identify the optimal policy responses to these shocks.

Moreover, the limits imposed by the zero lower bound to conventional monetary policy and the widespread use of unconventional monetary interventions led Gertler and Karadi (2015) to develop a quantitative monetary DSGE model that incorporate financial intermediaries with the objective to capture the key elements relevant in the transmission of unconventional monetary policy.

Empirically, the class of vector autoregressive (VAR) models represents a standard tool in monetary economics and is widely used for studying the monetary transmission mechanism. The main advantage is that it provides a very general representation allowing to capture the complex relationship between real, monetary and financial economy. The standard models include a set of real variables that denote the business cycle[5] and a short-term interest rate is used as a proxy for conventional monetary policy[6]. The small amount of information included in relatively small VARs has been criticized and alternative models, such as Factor Augmented VARs[7] and Large Bayesian VARs[8], are becoming more and more popular in order to span the whole information sets used by central banks, which actually contains hundreds of time series on financial and real variables. Ciccarelli Maddaloni and Peydrò (2013) use a Panel Bayesian VAR to examine how financial fragility has affected the transmission of euro area monetary

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[5] Most of the papers includes Gross Domestic Product (GDP) for output and Consumer Prices Index (CPI) for prices, but also Industrial Production and GDP components as Gross Capital Formation and Consumption depending on research purposes.

[6] 3-month Euribor rate, EONIA and Main Refinancing Operations rate (MRO) are the short-term interest rate mostly used to identify monetary policy actions in the euro area.

[7] Bernanke, Boivin and Eliasz (2005) is the most cited paper that measure the effects of monetary policy by adopting a factor-augmented VAR approach.

[8] See Banbura, Giannone and Reichlin (2010) for further details on large Bayesian VARs.

policy. They account for several dimensions of heterogeneity and credit conditions by using a recursive panel estimation approach and by including the responses of the Bank Lending Survey among the endogenous variables. The different types of information on borrowers and lenders included in this survey allow them to distinguish the effects of both balance sheet and bank lending channels in the propagation of monetary shocks. They find that the amplification effects of monetary shock have been induced by the balance-sheet channel over throughout the whole period after the Lehman bankruptcy, while bank lending channel has been statistically significant only in 2008 and 2009. Hartmann et al. (2015) estimate a Markov-switching VAR to investigate how financial shocks propagate to the economy and find that both the variances of the shocks and the parameters that describe the dynamic system change regime during systemic financial instability suggesting the presence of nonlinearity in the transmission of shocks. Kremer, instead, models linearly the dynamic interactions between financial instability and the macroeconomy and assesses the role played by standard and non-standard monetary policy measures in driving the economy within this context.

The literature provides empirical and theoretical evidence in favor of the existence of a credit channel in the monetary policy transmission to economic activity.

1.4 The asymmetric impact of monetary policy

Since the seminal work by classical economists who experienced the Great Depression like Fisher (1933) and Keynes (1936), the presence of some adverse feedback loops and negative spirals during crisis episodes that lead to non-linear effects has been at the core of the macroeconomic debate. A growing number of works has devoted more attention to study whether the effects of monetary policy depend on the size and direction of the action and vary over the business cycle. There is empirical evidence that support the asymmetric nature of monetary transmission mechanism, but it is not clear how these asymmetric effects operate and how financial fragility matter in triggering non-linearity. From an empirical point of view, various strategies have been employed to model non-linearity in time series. The Markov regime switching and Threshold VAR are the most popular non-linear models applied in the literature.

Balke (2000) estimate a threshold vector autoregressive (TAR) model, in which a credit variable separate the observations into different credit regimes, to study whether credit conditions play a role in the non-linear propagation of shocks. He finds that the effects of shocks are larger when financial conditions are tight. Weise (1999) investigates whether monetary policy has an asymmetric impact using a logistic smooth transition VAR (a multiple equation extension of Granger and Terasvirta, 1994). The switching variable is the economy's position in the business cycle identified by the growth rate of real output. This paper suggests that monetary shocks have different effects depending on the state of the economy, but they do not consider financial frictions. A smooth transition technique applied to a local projection model instead of vector autoregression is also used by Tenreyro and Thwaites (2013) to allow impulse responses of economic activity to depend on the state of the business cycle. Contrary to previous results, they find strong evidence that the effects of monetary policy on real and nominal variables are more powerful in expansions than in recession. This conclusion is shared by Mumtaz and Surico (2015). An application on US economic activity and interest rates suggests the presence of asymmetries in the propagation mechanism across good and bad times. They study this issue using a methodologically innovative strategy based on instrumental variable quantile regression, where the dynamics of the system vary with the state of the economy that represent the source of heterogeneity. The unobserved state of the economy is determined within the estimation process and is the key difference relative to other models.

This additional flexibility appears to be particularly useful in situations where the results are heavily affected by the choice of switching variables.

Alessandri, Conti and Venditti (2016) focus more on asymmetries related to the sign of the monetary shock and the policy implications of these asymmetries on financial stability. They account for the important link between the financial sector and the transmission of monetary policy by including the Gilchrist-Zakrajšek excess bond premium in a multivariate model augmented with local peaks of the endogenous variable to capture the non-linear impact of credit shocks on economic activity. The local projections method of Jordà (2005) is used to estimate the impulse response function. This approach is less stringent than the standard identification scheme of VAR models. Output does not respond asymmetrically with respect to the sign to changes in credit spreads.

Lo and Piger (2005) and Barnichon and Matthes (2014) explore the possibilities of several manifestations of asymmetries related to the direction, the size and the existing business cycle of the monetary policy action. The former paper uses a Markov regime-switching model driven by transition probabilities to capture time variation in the coefficients. They provide empirical evidence in support of a different impact of monetary policy across the state of the economy, but much less evidence of any asymmetry related to the direction and the size of the action. The latter work suggests a Gaussian basis function to identify the impulse responses to monetary policy shock. They identify the shocks in a multivariate model where the coefficients depend on the values of endogenous variables at the time of the shock. They find that contractionary policy produces larger effects on output than expansionary policy. Moreover, the lower the output growth the larger the effect of monetary shock.

Peersman and Smetz (2001) provide an application on euro area that suggests the effects of monetary policy are state-dependent. They estimate a VAR model with exogenous variables and identify the business cycle with a two state Markov switching regime with fixed coefficient, but state-dependent means. They identify monetary shocks in a linear VAR and thus they include the resulting new measure of monetary innovation to the auto regressive specification. Finally, they test whether the ß-coefficient of this indicator is different across regimes. The results suggest that monetary actions are more effective during recessions. This methodology has the limit to impose strong assumptions on the dynamics of the propagation of monetary shocks across regimes.

Another important contribution to this field of research is given by the work of Jannsen, Potjagailo and Wolters (2015) that study in detail the transmission mechanism of the monetary policy during financial crises. They include two dummy variables in a panel VAR that allow them to distinguish between four regimes. A dummy serves for identifying the acute and recovery phase of a financial crisis and the other one for separating between expansions and recession.[9] They find that the monetary policy is more effective during the acute phase of the financial crisis as it is able to mitigate some negative adverse loop that characterize this kind of event.

This analysis of the literature allows us to recognize the differences that have displayed the numerous approaches applied to study the asymmetric dynamic of the monetary policy transmission mechanism. The results are mixed. It is worth emphasizing how each author chooses a specific methodology depending on its own assumptions about the specific features of the system he intends to examine. The main differences regard the strategies used to identify the states of the economy and the different regimes[10], the methods to calculate the impulse

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[9] They use the systematic banking crises identified by Laeven and Valencia (2013) to date financial crises and the Harding and Pagan (2002) version of the Bry-Boschan algorithm to identify recessions and expansion.

[10] I refer to the choice between Markov switching, threshold model or, again, smooth transition techniques, dummy variables, strategies based on quantile regression and so on.

responses[11], the identification of monetary shocks[12], the estimation of the parameters[13], the set of endogenous and exogenous variables included in the models. Moreover, each empirical framework has a different degree of flexibility within the estimation process that might be crucial to have more efficient parameters.

1.5 The role of financial variables in predicting economic activity

The overall failure of market participants and institutions to predict the financial crisis that began in 2007 associated with the subsequent Great Recession has led economics profession to question the adequacy of macroeconomic and forecasting models routinely used. These facts in combination with the relationship between financial and economic activity suggested by the papers I analyzed in the second section constitute a theoretical framework and an important motivation for economists who study and analyze the role of financial variables in predicting real economy.

Here, in this perspective, the contribution of Stock and Watson (2003) is significant. They state that, based on the idea that financial variables incorporate news about the future of the economy faster than real variables, asset prices information is useful in predicting economic fluctuations and, especially, output and inflation. Their work consists of an econometric analysis that describes the interactions between a broad set of financial variables and output and inflation. Gilchrist and Zakrajšek (2012) build a financial indicator based on the corporate credit spread and present evidence on the predictive power of this indicator for real economy. They

[11] Local projection methodology, impulse responses function in VAR models, Gaussian basis function.

[12] See Ramey (2016) for further details on identification strategy of monetary shocks.

[13] For example, Bayesian against OLS estimation.

estimate VAR models where real and financial variables are included, and find that their indicator improve the real variables forecasts. Their forecast analysis is mainly based on the impulse response function of output, inflation, consumption and investment to a shock on the financial indicator. As such, they focus on the accuracy of point forecasts in linear models. Following the same approach but accounting for the differences on financial structure between US and euro area, Gilchrist and Mojon (2014) construct a credit spread indicator to measure financial stress in the European Union. By analyzing the impulse responses to shocks in credit spreads in a Factor-augmented VAR (FAVAR) model, they show how this indicator helps in predicting euro area economic activity. The predictive power of credit and government spreads on GDP dynamics (Italy) is also evaluated by Nicoletti and Passaro (2012) over time and over different horizons. They use Dynamic Model Averaging that takes the features of italian credit market into account. They find that banks information and government spread are particularly useful during periods of crisis.

Hollò, Kremer and Lo Duca (2012) calculate the Composite Indicator of Systemic Stress (CISS) for the whole euro area and each single country. This index is based on a broad set of financial time series that describe the economy's financial system and present many methodological innovation. They show the ability of this index to identify in a satisfactory manner financial regimes in a threshold VAR. Besides Alessandri and Mumtaz (2017) estimate linear and non-linear Bayesian vector autoregressive models and compare the models' performances both from a point forecasting and a distribution forecasting perspective in order to evaluate not only the models' ability to predict "means", but also to predict "tails", namely deviations from their expected paths. Furthermore, using some suitable performance indicators allows them to evaluate which model works better in "real time".

Predictive densities have received less attention than point forecasts in macroeconomics. Clements and Smith (2000) examine how evaluate density forecasts of linear and nonlinear models in predicting output and unemployment, presenting evidence that non-linear models are better than linear models in distribution forecasts rather than in point forecasts. This result is consistent with Alessandri and Mumtaz (2017). Cogley, Morozov and Sargent (2005) estimate predictive densities from a Bayesian VAR model for inflation and output and analyze the advantages that these distributions provide to evaluate and implement monetary policy. But only Alessandri and Mumtaz (2017) estimate density forecasts to examine the interactions between financial markets and output and prices. They also investigate the possible state-dependent nature of financial shock using a non-linear Bayesian TAR model. In fact, with the Bayesian TAR they can identify two regimes of high and low financial stress based on the value assumed by the financial indicator, that is the threshold variable. The results obtained by Alessandri and Mumtaz (2017) present evidence that the Bayesian TAR model dominates other models on the accuracy in predicting distributions in terms of Log Scores.

The literature delivers a rich set of financial stability indexes that account for different financial segments or different measures of financial stress, such as volatilities and spreads. Kliesen, Owyang and Vermann (2012) provide a useful survey of the financial stress indexes developed so far. They analyze to what extent they are correlated and compare the relative performance in predicting economic activity by using VAR models.

The general message delivered by this literature is that financial indicators help in predicting economic activity, but some results suggest that no financial indicator works for a long period of time.

1.6 Conclusion

This chapter provides a survey that link the literature on the macroeconomic implications of financial frictions with the research on the credit channel theory within a framework that account for the nonlinear and state-dependent effects of shocks induced by the presence of imperfections in the financial markets. From a theoretical point of view, I compare the different approaches to incorporate financial frictions into dynamic general equilibrium models and describe the different channels through which financial factors affect real dynamics. Then, I emphasize how these findings have been influential for the credit channel theory. From an empirical point of view, I distinguish the various strategies have been employed to model non-linearity in the propagation mechanism of monetary policy innovations and to evaluate the forecasting performance across models that include different measures of financial conditions. I find some open debates on how the asymmetric effects of monetary policy operate and how financial fragility affect the transmission of monetary policy.

Chapter 2

Do financial stress indicators help predicting GDP? Evidence from the euro area Great Recession

2.1 Introduction

The financial crisis that began in 2007 has led to one of the most dramatic and unforeseen economic recession ever recorded, leading the economics profession to question the adequacy of macroeconomic and forecasting models routinely used by market participants and institutions. In recent years, economists have embarked into new directions of research. The interaction between financial market imperfections agents' decisions and macroeconomic outcomes has received a great deal of attention[14]. From a theoretical point of view several recent general equilibrium models have stressed the role of occasionally binding borrowing constraints and/or other type of financial frictions in altering investment and consumption decisions of households and firms (Bianchi, 2011; Jermann and Quadrini, 2012; Brunnermeier and Sannikov, 2014). Financial frictions indeed can affect the persistence of the response of economic activity to temporary shocks. Furthermore, these frictions can also amplify the reaction of GDP to the same initial temporary shock through feedback loop between agents' net-worth and asset prices. Empirically, several papers (starting with the seminal paper by

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[14] Bernanke and Gertler (1989) develops a theoretical framework where financial frictions modify the persistence of demand shocks. Bernanke, Gertler and Gilchrist (1999) derive a model with financial sector that features the financial accelerator mechanism. Brunnermeier and Sannikov (2014) find that this amplification effects could lead to rich volatility dynamics and explain the instability of financial systems.

Bernanke, Gertler and Gilchrist, 1999) have documented the role of financial frictions in affecting the propagation mechanism of temporary demand shocks. Yet from a forecasting perspective it is difficult to find a significant and stable relationship between financial conditions and economic activity. This is primarily due to the fact that in normal circumstances financial frictions are not binding and therefore do not affect agents' decisions.

At the same time, following the forecasting failure associated with the Great Recession but also in response to the increased attention paid to financial stability issues, the emphasis is moving from assessing forecast performances only in terms of point-forecast accuracy to including evaluations in terms of density-forecast accuracy. As financial crises are rare but dire events leading to large economic losses a policy authority aiming at insuring financial stability might be more interested in preventing rare but costly financial crises than in predicting correctly normal business cycle fluctuations. This chapter contributes to the existing empirical literature, examining the link between macroeconomic outcomes and financial factors on euro area data by adopting a time series/forecasting reduced form approach along the lines proposed by Alessandri and Mumtaz (2017) for the US. I estimate a set of linear and non-linear BVAR models with financial stress indicators and compare their relative forecast performance for euro area GDP growth both from a point-wise and a predictive distribution perspective with standard BVAR models that omit the link between financial conditions and macroeconomics. To further assess their performance, I compare the models with distributions of expectations derived from financial market participants surveyed by the European Central Bank within the Survey of Professional Forecasters (SPF). The results of the survey are often used to measure market's perception of risks.

My main results are five. First, from a point forecast perspective, models exploiting information from financial stress indicators do not outperform standard BVAR models that overlook this type of information nor mean forecasts by professional forecasters. Second, from a predictive distribution perspective, BVAR models with financial stress indicators outperform standard models and measures of risk derived from the SPF. Third, this average (over the whole period) finding is driven by the performance during periods of financial stress, while during “tranquil” periods models with financial stress indicators offer no advantage, in line with insights from theoretical models of occasionally binding constraints. Fourth, I find that including information from financial markets leads to more accurate density forecasts both in a linear as well as in a non-linear framework. Fifth, measures of uncertainty about future GDP growth derived from the SPF are a poor indicator of economic activity risks.

The paper is organized as follows. Section 2 review the existing literature, section 3 presents the models; section 4 introduces the indicator of financial stress exploited in the analysis. Section 5 reports the results of the forecast comparison exercise. Section 6 sums up my results and concludes.

2.2 Literature review

Several recent studies for the euro area focus on the nexus between financial stress and economic activity by employing both structural models and forecasting models. Kremer (2015) adopts a monetary policy VAR model and adds a composite index of financial stress to analyse the effects of the latter on economic activity as well its interaction with the ECB conventional and unconventional monetary policies. Gilchrist and Mojon (2014)[15] construct credit risk indicators for euro area banks and non-financial corporations and find that they have a statistically significant predictive content for economic activity. Using the same indicator,

[15] Gilchrist and Zakrajšek (2012) perform a related analysis about the US economy.

Alessandri et. al (2016) investigate the relationship between monetary policy, financial stress and economic activity, finding evidence of strong non-linearities. Van Roye (2011) derives a financial market stress indicator and shows that its inclusion into a Bayesian VAR model significantly improves the out-of-sample forecasting performance in predicting German GDP from a point-forecasting perspective. Nicoletti and Passaro (2012) use Dynamic Model Averaging to evaluate the predictive power of interest rate spreads for Italian GDP and argue that these indicators help predicting economic activity, particularly during crises episodes. Darracq Paries et al (2014) incorporate a financial condition index into a VAR and estimate that financial shocks caused one-fifth of the decline in euro-area manufacturing production during the Great Recession. While these papers mainly employed structural impulse-response analysis and/or standard statistics to evaluate the models (point-) forecast performance, Del Negro and Schorfheide (2012) move beyond point-forecasts and evaluate density-forecasts for US GDP derived from a structural model with and without financial frictions. They find that a standard DSGE model with financial frictions (in the forms of occasionally binding financial constraints) and informed with interest rate spread data would have given more probability to the realization of such an extreme event as the Great Recession than the same model without financial frictions. The same model with financial frictions compares well also with Blue chip real-time forecasts. Alessandri and Mumtaz (2017) estimate small linear and non-linear BVAR models to assess the predictive power of financial condition indexes for US macroeconomic activity and compare the models' forecasting performances placing more emphasis on density forecasts. The authors argue that financial conditions matter for economic activity but only during specific episodes. Using a set-up similar to Alessandri and Mumtaz (2017) framework, this chapter focuses on evaluating the forecasting accuracy of linear and non-linear BVAR models with and without financial stress variables from a point and density forecast perspective. The models employed belong to the VAR family, however compared to Alessandri and Mumtaz (2017) closed economy BVAR, I extend the set of variables on which forecasts are conditioned in order to account for information on global inflationary pressures and global demand. Indeed, omitting such important variables for the euro area business cycle could lead to overrate the role of financial variables especially during globally synchronized events as financial crises. Therefore the models I employ are similar to Burlon et al. (2015) who estimate a BVAR-X model for the euro area and find that, in a "pseudo" real-time forecasting exercise, its performance is similar to that of a DSGE model and compares well with the forecasts made by the ECB. Indeed, following the authors I start from a very similar reduced form BVAR-X model for the Euro area and add a composite index of systemic financial stress among the endogenous variables. I then depart from the path taken by the authors and look mainly at density forecasts accuracy both on average and during periods of high financial stress.

2.3 The forecasting models

2.3.1 The linear models

The class of linear models that I use in this chapter are BVARX models. While very simple, these models are found to compare well in many forecasting applications with more complex structural models (see Burlon et al. 2015; Koop, 2013). Furthermore, they allow us to appreciate in a very clear and direct way the additional information content of financial indicators. The models are defined as:

$$Y_t = c + \sum_{p=1}^{P} A_p Y_{t-p} + \sum_{q=0}^{Q} B_q X_{t-q} + \Omega^{1/2} e_t \,, \qquad e_t \sim N(0,1)$$

where Y_t denotes the vector endogenous variables, X_t is the vector of exogenous variables, A and B are the reduced form coefficients and, finally, Ω is the error covariance matrix. I estimate the model by using a Bayesian approach. In setting the prior distribution, I follow the procedure developed by Banbura et al. (2010).[16] I use two versions of this model, differing only in terms of the variables entering Y_t. The benchmark model (BVARX) is a standard BVAR that does not consider the interaction between macroeconomic variables and financial factors, augmented with a set of exogenous variable considered important drivers of the euro area business cycle. It contains the following endogenous (Y) variables: GDP, the private Consumption Deflator (specified in difference) and the EONIA interest rate. The exogenous (X) variables are the euro area foreign demand (in difference) and the oil price (in log-levels). The alternative model (BVARX-FF) differs from the benchmark model as I add an indicator of financial stress among the Y variables. The direct comparison between these two models forecast performances allows a simple and intuitive way to quantify the relevance of the link between financial factors and economic activity.

The models are specified with 4 lags for the endogenous variables and one for the exogenous ones (for the latter, also contemporaneous values are included).

2.3.2 *The non-linear model*

In order to account for the possibility of non-linear interactions among financial stress and economic activity as suggested by the economic theory, I estimate a Threshold-VAR (TAR-FF) defined as:

$$Y_t = \left[c_1 + \sum_{p=1}^{P} B_{1,p} Y_{t-p} + \Omega^{1/2} e_t \right] S_t + \left[c_2 + \sum_{p=1}^{P} B_{2,p} Y_{t-p} + \Omega^{1/2} e_t \right] (1 - S_t),$$

where

[16] See Appendix for details about implementation of prior distributions using dummy observations.

$$e_t \sim N(0,1)$$

$$S_t = 1 \leftrightarrow Z_{t-d} \leq Z^*$$

As before Y_t denotes the vector of endogenous variables and includes GDP, the private consumption deflator, the EONIA interest rate and the financial stress indicator. Following Alessandri and Mumtaz (2017), I allow for the possibility of two financial regimes characterized by different dynamics ($B_1 \neq B_2$), where the regime prevailing at each time *t* is determined by the value assumed at time *t-d* by the financial stress indicator relative to a threshold value (Z^*, endogenously determined), where the delay *d* is assumed to be an unknown parameter. As in the BVAR framework, I impose a natural conjugate prior on the VAR parameters in the two regimes[17].

2.4 Regimes of financial stress

In this section I describe the indicator of euro area financial stress included in the BVARX-FF and the TAR-FF models. The CISS indicator, compiled and maintained by the ECB, measures financial systemic stress by aggregating 15 proxies for financial market stress (such as volatilities, risk spreads and cumulative valuation losses) describing the five most important segments of modern financial systems[18]: (1) money markets, (2) equity markets, (3) financial intermediaries sector, (4) bond markets and (5) foreign exchange markets. I have chosen this index for several reasons. As suggested by Nicoletti and Passaro (2012), it wouldn't be wise to rely on one single indicator to forecast GDP dynamics. Indicators that can convey reliable information in "normal times" can be useless in crisis periods. Also Alessandri and Mumtaz

[17] See Alessandri and Mumtaz (2017) for further details on TAR model structure.

[18] See Hollò, Kremer and Lo Duca (2012)

(2017) highlight the importance of using broad based indicators such as financial condition indexes. Among this class, the CISS appears particularly suited for my purposes. It concentrates on capturing the systemic dimension of financial instability by, first, covering the main classes of financial markets and intermediaries in a systematic fashion and, second, by considering the time-varying dependence of stress between these major segments of the financial system[19]. As documented by Hartmann et al. (2015), these features allow the CISS to offer a better performance than alternative measures of financial stress[20] in identifying well-known stress events, increasing in response to occurred periods of financial turmoil. Moreover, the inclusion among the components of the indicator of measures of stress among financial intermediaries may be quite important in the context of my analysis since the euro area is a more bank-based financial system than the US. Looking at its statistical properties, the indicator is found to have strong linkages with euro area GDP as reported in figure 1 where the dynamic correlation between the indicator and Euro area GDP growth is reported.

Hollò et al. (2012) estimating the impulse responses from a Threshold VAR, find that the real economic impact of financial stress shocks is significantly different across the regimes. The TAR-FF model, similar to Hollò et al (2015), when estimated over the period 1987-2015, delivers the following classification of regimes (see figure 2). According to the model median estimates, two periods of financial stress are identified (by grey bands in the figure). The first

[19] Hollò, Kremer and Lo Duca (2012) apply the standard portfolio theory to the aggregation of sub-indices referred to every financial segment. This methodological innovation put more weight to the CISS during periods in which stress prevails in several market segments at the same time, capturing episodes of widespread financial instability with systemic implications.

[20] Hartmann et al. (2015) find that alternative measures of financial stress, inter alia stock market volatility and corporate bond spread, are less able than CISS to identify known episodes of financial instability.

one emerged in 2001-2002 but was not associated to a decline in euro area GDP. The second and most important period of high financial stress took place between 2007 and 2012 covering both the Great Recession (2008-09) and the Sovereign Debt Crisis (2010-2012). Interestingly, the model does not distinguish between the two crises, despite the markedly different intensity of GDP contraction during the two episodes. One reason could be that the properties of financial cycles are different from those of business cycles. There is a great agreement that house prices and credit cycles are longer than regular business cycles. Hence, from a business cycle perspective, the two recessions can be distinguished, but, from a financial cycle perspective, the source of financial instability during the two episodes might be part of a unique cycle. Moreover, as I will document in the next section, the information content of the CISS indicator for euro area GDP growth was much more significant during the Great Recession than the Sovereign Debt Crisis.

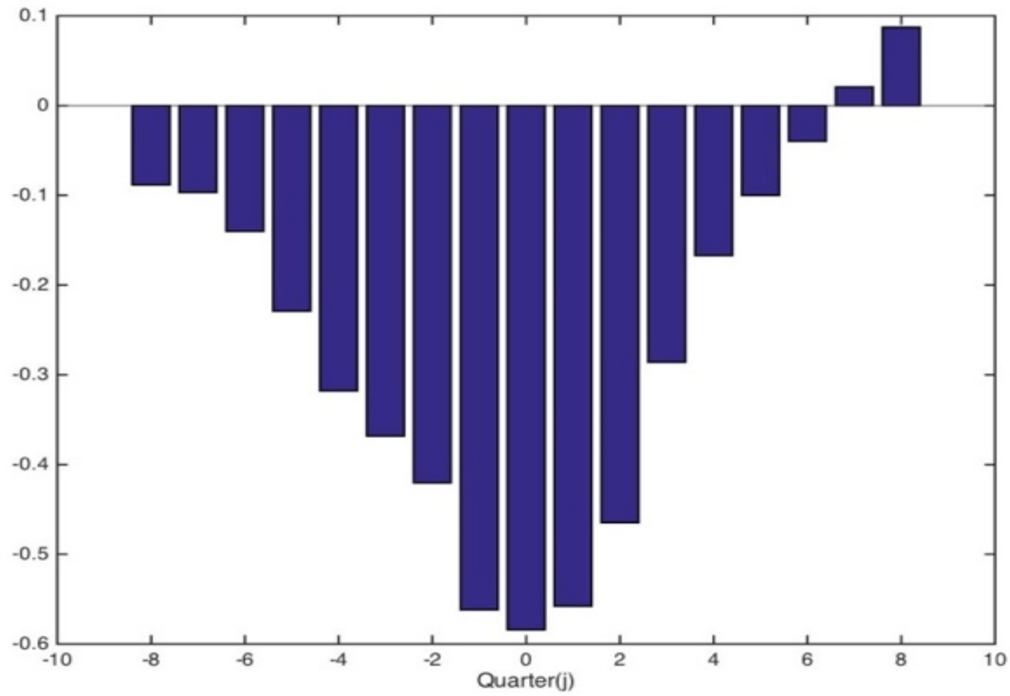

Figure 1: Dynamic correlations between GDPt and CISSt+j, 1987Q1:2015Q4

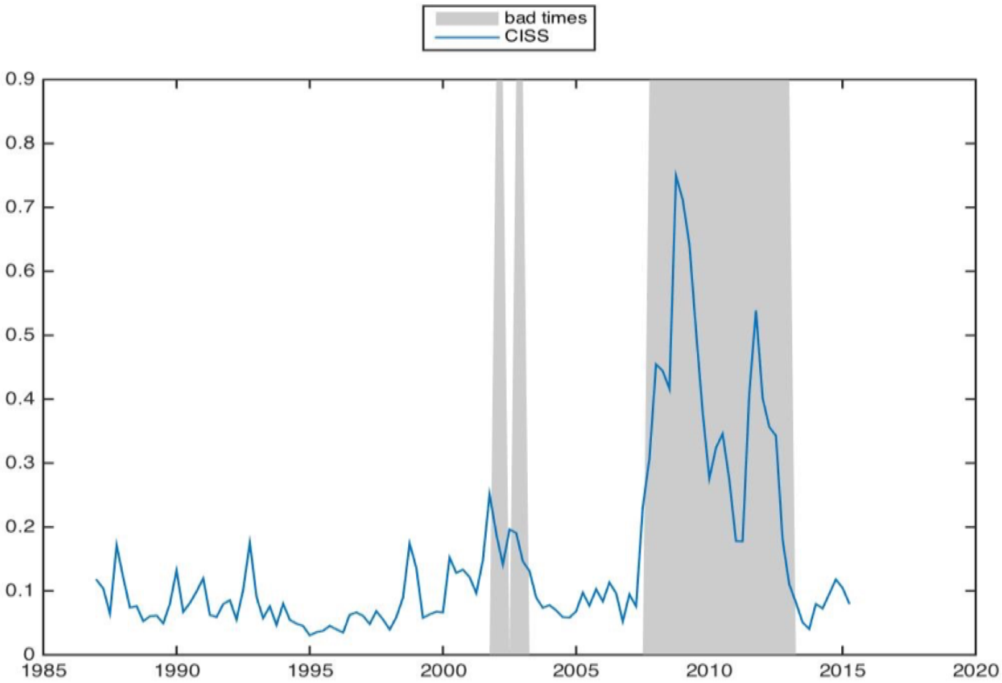

Figure 2: Composite Index of Systemic Stress (blue line) and periods of high financial stress (grey bands), identified by a Threshold BVAR with two states driven by the level of the CISS, that represents the threshold variable of the model

2.5 The results of the forecast comparison exercise

In order to compare the forecast performance of the models, I adopt a “pseudo” real-time framework. The models are estimated recursively over an expanding window, mimicking in each period the information content available to forecasters at that time. The first “pseudo” real time forecast is produced by estimating the models over the window 1987:Q1 to 2001:Q4 and forecasting up to 8 quarter ahead, based on the information for the endogenous and exogenous variables available in the first quarter of 2002. The last estimation sample covers the period 1987:Q1-2015:Q4. At each iteration forecasts are conditional on the expected path for oil prices as extracted by futures markets at that time and on the expected evolution of the euro area external demand as available to market participants[21]. In this way, the models' forecasts are conditional on the same information set available to market participants [22,23].

I compare the forecasting performance of my models at 4 and 8 quarters ahead horizons[24]. Point forecasts are calculated as the arithmetic mean of the density forecasts and evaluated in terms of Root Mean Squared Errors (RMSE). Density forecasts are estimated using kernel methods and their accuracy is evaluated in terms of weighted log-scores (Amisano and Giacomini, 2007) in order to focus the attention on the models' ability to predict extreme events.[25]

I start the forecast analysis by examining the average performance calculated over the full set of 56 out-of-sample forecasts. Besides comparing models' forecasts, I also report the corresponding median forecast and forecast distribution derived from the ECB Survey of Professional Forecasters (SPF) as an indicator of market participants forecast record.

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[21] More specifically, for the oil price I use the 10 working day average price prevailing in spot and future oil markets between the 1st and 15th of the second month of the quarter (February, May, August and November). For the euro area external demand, I use the same assumptions used by the Eurosystem staff in their forecasts and usually embedding information up to the second month of the quarter.

[22] In order to mimic as close as possible the available information set, I also condition on short-term indicators of economic activity by substituting the model 1 quarter-ahead forecast with that embedded in the corresponding Eurosystem projection exercise and usually based on short-term "bridge models" (see also Burlon et al., 2015).

[23] To be precise, in each quarter I compare the forecast produced by the BVAR models with the first SPF survey round conducted after the end of that quarter (for instance the ECB survey conducted at the beginning of April 2002 for the first pseudo real time forecast discussed in the main text). This way, SPF forecasts enjoy an informational advantage of around 1 month.

[24] Forecasts at horizons greater than one quarter are cumulated.

[25] The weights are a way to focus attention on different regions of the probability distribution of the variable, in this case I focus on left-tails of the distributions.

Table 1 reports the average root mean squared errors (RMSE) and the average log-scores for real Gross Domestic Product generated by the BVARX with financial frictions (BVARX-FF), the Threshold VAR (TAR-FF) and the ECB Survey of Professional Forecasters (SPF)[26] relative to the benchmark BVARX. This table shows some interesting results. First, in terms of point forecast accuracy (RMSE), models with information on financial stress underperform the benchmark BVARX model. On the contrary, the median SPF forecast outperform the benchmark, highlighting the limit of "small" models[27]. While these findings do not lend support to the hypothesis of an important macro-finance feedback loop, when I look at the performance in terms of density accuracy (log-scores), I find that the BVARX-FF and the TAR-FF models outperform the benchmark at the 4-quarter horizon and that the SPF forecasts underperform the benchmark. However, average results are not statistically different from each other as results of the tests of equal predictive ability suggest (values in squared brackets).

Table 2 reports weighted log-scores based on the weighting schemes proposed by Amisano and Giacomini (2007). The results suggest that, even in a linear context, financial indicators prove to be useful in predicting "tails", that is, GDP realizations that fall into the tail of the forecast distribution, while they bring no additional information to forecast "means", namely realizations near the centre of the forecast distribution.

Overall, my results are broadly in line with Alessandri and Mumtaz (2017) results for the US. The fact that forecast performances are not significantly different on average over the whole sample leaves open the possibility that financial stress indicators help predicting economic activity only in specific periods. This hypothesis which will be discussed in the next section is

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[26] As SPF forecasts, I use the mean point estimate across analysts surveyed.

[27] In fact, the superior performance of SPF mean forecast could be due partly to the informational advantage compared to BVAR models.

actually consistent with several theoretical models which focus on occasionally binding borrowing constraints. According to these models, under "normal circumstances" financial frictions do not affect economic agents' decision. It is only during specific periods that financial variables become relevant for forecasting purposes[28]. As such periods are rather infrequent, average results over large sample tend to hide the information content of financial stress indictors.

	RMSE		LogScores	
	4Q	8Q	4Q	8Q
BVARX-FF	1.16 [0.133]	1.30 [0.111]	0.78 [0.433]	1.04 [0.472]
TAR-FF	1.25 [0.154]	1.37 [0.209]	0.77 [0.393]	1.18 [0.13]
SPF	0.84 [0.097]	0.96 [0.37]	2.33 [0.152]	1.30 [0.206]

Table 1: Average root mean squared errors (RMSE) and log-scores of the models relative to the average root mean squared error and log-score of the benchmark model BVARX on 4 and 8 quarters ahead predictions of GDP growth. Values greater than 1 mean that BVARX performs better than the corresponding model and vice versa. Between brackets, P-values for the null hypothesis of equal pairwise unconditional predictive ability based on RMSE and log-score criteria

[28] The model built by Brunnermeier and Sannikov (2014) shows that the financial system exhibits some instability due to non-linear effects that arise only in downturns. Moreover, Del Negro and Schorfheide (2012) examine DSGE model forecasts during 2008-09 suggesting that models with financial frictions are preferable to the Smets and Wouters (2003) model without financial sector.

	Weighted log scores	
	Left tail	Both tails
BVARX-FF	0.43	0.29
	[0.345]	[0.308]
TAR-FF	0.42	0.27
	[0.297]	[0.234]
SPF	1.74	2.06
	[0.144]	[0.139]

Table 2 Weighted log scores. Average scores of the models relative to the weighted log scores of BVARX and pvalues for the null hypothesis of equal pairwise predictive ability based on the weighting schemes suggested by Amisano and Giacomini (2007).

2.5.1 Subsample analysis

In order to investigate which model works better at each moment of time from a density forecast perspective, I look at the models' performance over shorter selected subsamples. I focus my analysis on 4 quarters ahead predictions of GDP growth. In table 3, I calculate RMSEs and log-scores over "low financial stress" regime and the "high financial stress" regime determined by the TAR-FF model. Two results are worth commenting. First, I confirm the inferior performance of the BVARX-FF and (to a minor extent) TAR-FF models in terms of point forecast accuracy, a result which holds true both in "low-" and "high stress" periods. Second, I find that in terms of log-scores, the full-sample performance of the BVARX-FF and TAR-FF models are driven by the large improvement of their performances during high financial stress periods. Figure 3 reports the evolution of the log-scores over time and clearly shows that the performance of all models except those of the BVARX-FF and the TAR models deteriorates tremendously between the end of 2008 and the beginning of 2009 when euro area

GDP contracted significantly. Figure 5 shows the forecast distribution produced by each model 4 quarters in advance for the period 2008Q4-2009Q3, and again it can be noticed that the only models associating a non-negligible probability to the realization of GDP growth actually observed are the BVARX-FF and TAR-FF models.[29]

Finally, the results confirm that while the median forecast derived from the SPF survey performs relatively well from a point forecast perspective both in good and bad times, its performance in terms of probability distribution is rather poor, suggesting caution in quantitatively assessing risk and uncertainty on the basis of such survey. This is also confirmed by figure 4 which shows that actual outcomes often lie outside the ±2 standard deviation uncertainty bands around median SPF forecasts[30].

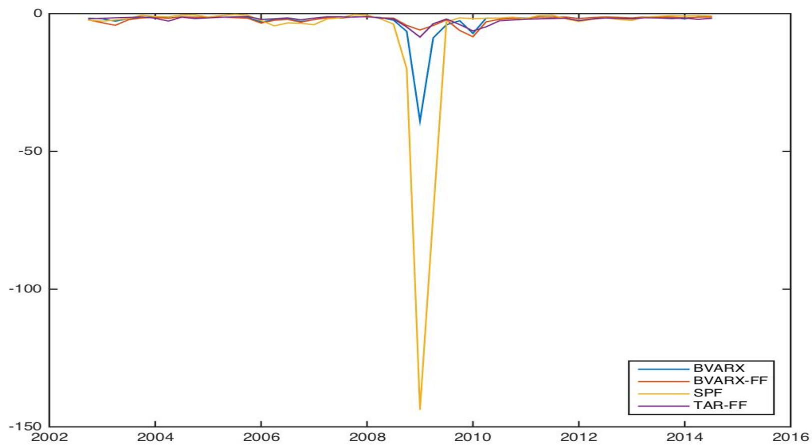

Figure 3: Log-scores associated to the corresponding 4 quarters ahead predictions of GDP cumulated growth

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[29] In appendix 2.B I provide the density forecasts associated to the 4-quarters ahead prediction of GDP cumulated growth generated by all the models for each quarter taken into consideration in the out-of-sample analysis.

[30] Notice that the probabilities of observing a negative year-on-year real GDP growth at each date are *ex ante* probabilities based on 4 quarters ahead predictive distributions generated by my models and SPF.

	RMSE		LogScores	
	4Q		4Q	
	Low Financial Stress	High Financial Stress	Low Financial Stress	High Financial Stress
BVARX-FF	1.17	1.16	1.10	0.65
TAR-FF	1.04	1.35	1.00	0.68
SPF	0.81	0.88	0.96	2.87

Table 3: Average root mean squared errors (RMSE) and log-scores of the models relative to the average root mean squared error and log-score of the benchmark model BVARX on 4 quarters ahead predictions of GDP growth during the periods of low financial stress and high financial stress identified by the TAR-FF model estimated over the whole sample as in section 3.

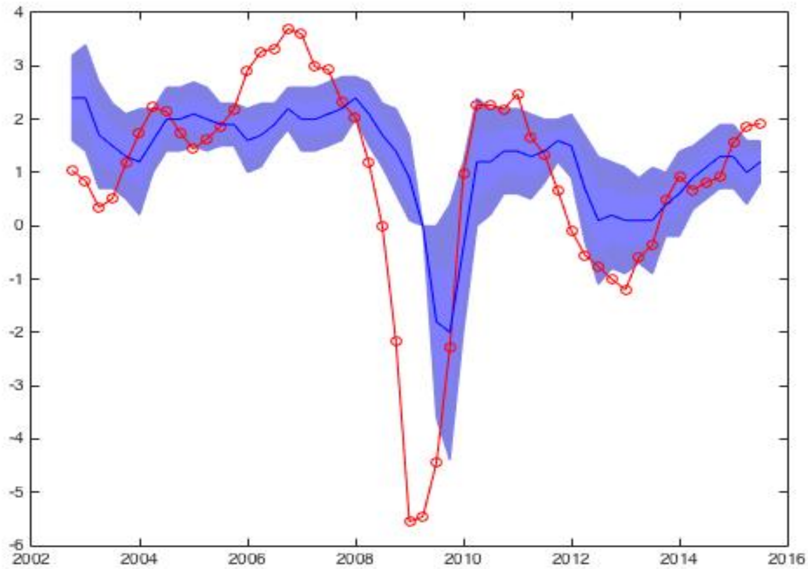


Figure 4: Red line with circles is the actual outcome of 4 quarters GDP cumulated growth, blue line is the 4 quarters ahead real GDP cumulated growth central projection provided by SPF and the width of the ranges is twice the standard deviation of the central projection.

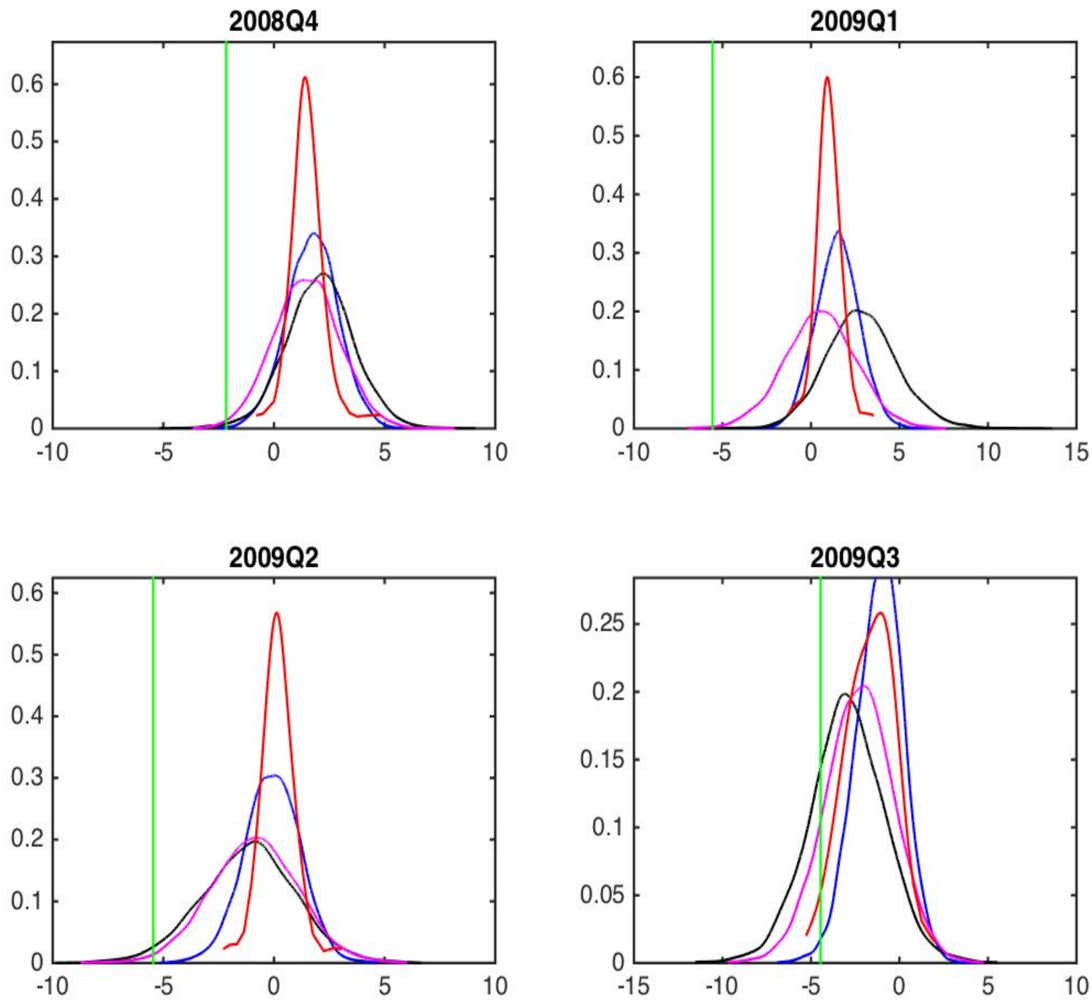


Figure 5: Density forecasts associated to the 4-quarters ahead prediction of GDP cumulated growth generated by, BVARX (blue line), BVARX-FF (purple line), TAR-FF (black line) and SPF (red line) at each quarter from 2008Q4 to 2009Q3. The green line is the actual outcome.

2.6 Conclusion

This chapter provides a quantitative assessment of the predictive power of a financial stress index for forecasting euro area real GDP. I analyse the relative forecasting performance of a set of linear and non-linear BVAR models evaluated over a broad set of metrics that allow us to compare the relative accuracy in point and density forecasting and to highlight to what extent and at which point of time the discrepancies between models emerged. The analysis delivers the following results. First, the presence of the financial stress indicator helps in predicting probability distributions of GDP growth during the 2008-09 Great Recession. However, the same models do not enjoy any advantage from a point forecasting perspective. Overall my results lend support to theoretical models of the nexus between imperfect financial markets and macroeconomics. Furthermore, they suggest the presence of a trade-off between point forecast and density forecast accuracy.

2.A The prior distribution of the parameters

I use the Minnesota prior[31] for the VAR coefficients, incorporating the belief that the endogenous variables follow an AR(1) process, under the hypothesis that there is a greater amount of information in recent own lags than both distant ones and those of other variables. I let the prior on the intercept be diffuse and set the following moments for the prior distribution of the coefficients:

$$E\left[\left(\beta_{p,q}\right)_{ij}\right] = \begin{cases} \partial_i, & j = i, p = 1 \\ 0, & otherwise \end{cases}$$

$$V\left[\left(\beta_{p,q}\right)_{ij}\right] = \begin{cases} \dfrac{\lambda^2}{p^2} & if\ i = j, \\ \dfrac{\lambda^2 \sigma_i^2}{p^2 \sigma_j^2} & if\ i \neq j, \\ \dfrac{\lambda \varphi \sigma_i^2}{(q+1)^2 \sigma_j^{x\,2}} & if\ j\ exogenous. \end{cases}$$

where ∂_i denotes the OLS estimates of the coefficients of an AR(1) regression estimated for each endogenous variable using a training sample. The scaling factors σ_i are set using the standard deviation of the error terms from those preliminary AR(1) regressions and σ_j^x are set using the standard deviation of the exogenous variables. The hyperparameter λ controls the

[31] See Litterman (1986) and the modifications proposed by Kadiyala and Karlsson (1997) for details.

overall tightness of the prior on the VAR coefficients and φ governs the tightness of the prior on the VAR coefficients of the exogenous variables.[32]

I implement the prior using the following dummy observations:[33]

$$Y_D^X = \begin{pmatrix} \frac{diag(\partial_1\sigma_1 \ldots \partial_N\sigma_N)}{\lambda} \\ 0_{(N+M)*(P+Q)\times N} \\ \ldots\ldots\ldots\ldots\ldots\ldots \\ diag(\sigma_1 \ldots \sigma_N) \\ \ldots\ldots\ldots\ldots\ldots\ldots \\ 0_{1\times N} \end{pmatrix}$$

$$X_D^X = \begin{pmatrix} \frac{J_P \otimes diag(\sigma_1 \ldots \sigma_N)}{\lambda} & 0_{(N*P)\times(M*(Q+1))} & 0_{(N*P)\times 1} \\ 0_{(M*(Q+1))\times(N*P)} & \frac{J_{Q+1} \otimes diag(\sigma_1{}^x \ldots \sigma_M{}^x)}{\varphi} & 0_{(M*(Q+1))\times 1} \\ \ldots\ldots\ldots & \ldots\ldots\ldots.. & \ldots\ldots.. \\ 0_{1\times(N*P)} & 0_{1\times(M*(Q+1))} & \varepsilon \end{pmatrix}$$

where ε is the tightness of the prior on the constant term.[34]

Given the natural conjugate priors, the conditional posterior distributions of the VAR parameters $\beta = vec([c, A_1, A_2, \ldots, A_P, B_0, B_1, \ldots, B_Q,])$ and Ω are defined as:

$$G(\beta/\Omega) \sim N(\beta^*, \Omega \otimes (X^{*\prime}X^*)^{-1})$$

$$G(\Omega/\beta) \sim IW(S^*, T^*),$$

[32] I follow the BVAR literature in setting hyperparameter $\lambda = 0.15$ and $\varphi = 10\lambda$, indicating a flat prior on coefficients associated to exogenous variables.

[33] I also refer the reader to Alessandri and Mumtaz (2017) and Blake and Mumtaz (2012) for investigating about the technique of implementing priors using dummy observations.

[34] I set $\varepsilon = 0.01$, letting a flat prior on the constant.

where:

$$\beta^* = (X^{*\prime}X^*)^{-1}(X^{*\prime}Y^*)$$

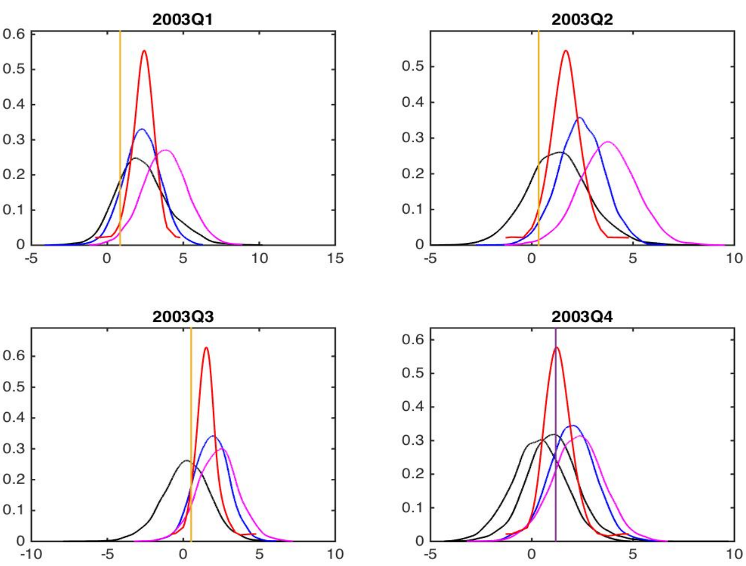
$$S^* = \left(Y^* - X^*\tilde{\beta}\right)'\left(Y^* - X^*\tilde{\beta}\right)$$

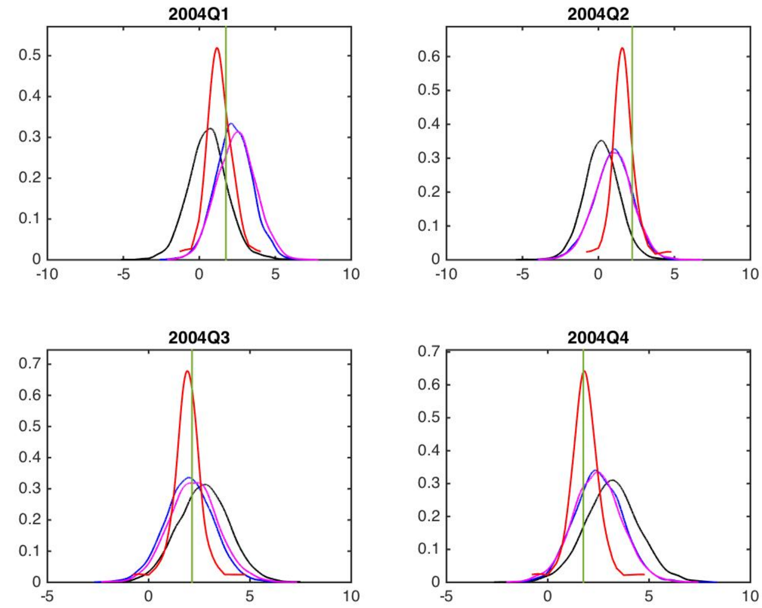
with $Y^* = [Y; Y_D^X]$, $X^* = \left[\left(Y_{t-1}\, Y_{t-2} \dots Y_{t-P}\, X_t\, X_{t-1} \dots X_{t-Q}\, c\right); X_D^X\right]$. and $\tilde{\beta}$ denoting the draw of the VAR coefficients β reshaped to be conformable with X^*. T^* denotes the number of rows of Y^*.

I use a Gibbs sampler to estimate the posterior distribution of the parameters by drawing successively from the conditional posteriors.

2.B Density forecasts for each year

The following figures include the density forecasts associated to the 4-quarters ahead prediction of GDP cumulated growth generated by, BVARX (blue line), BVARX-FF (purple line), TAR-FF (black line) and SPF (red line) at each quarter from 2002 to 2013. The yellow line is the actual outcome.




2004Q1
0.5
0.4
0.3
0.2
0.1
0
-10
-5
0
5
10
2004Q2
0.6
0.5
0.4
0.3
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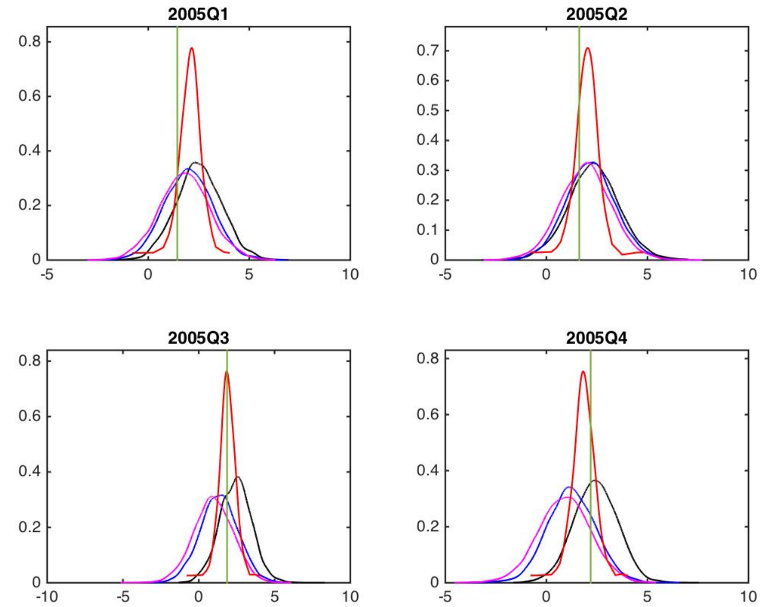
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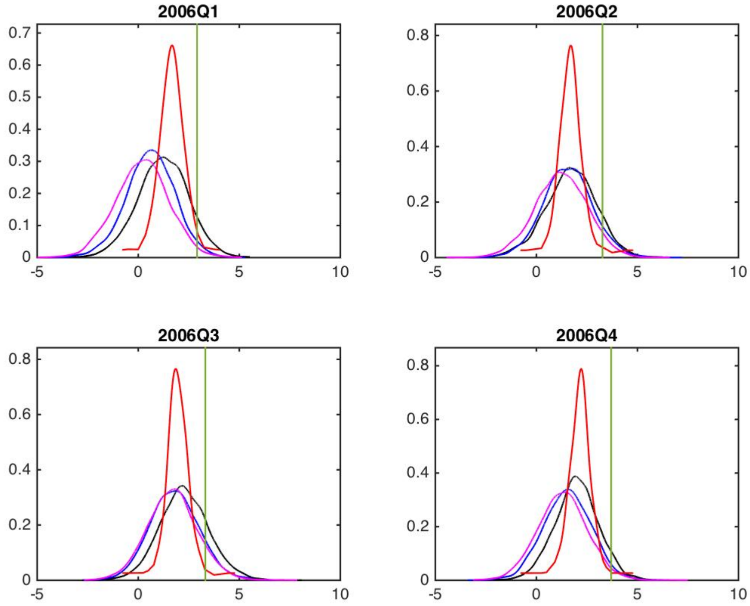
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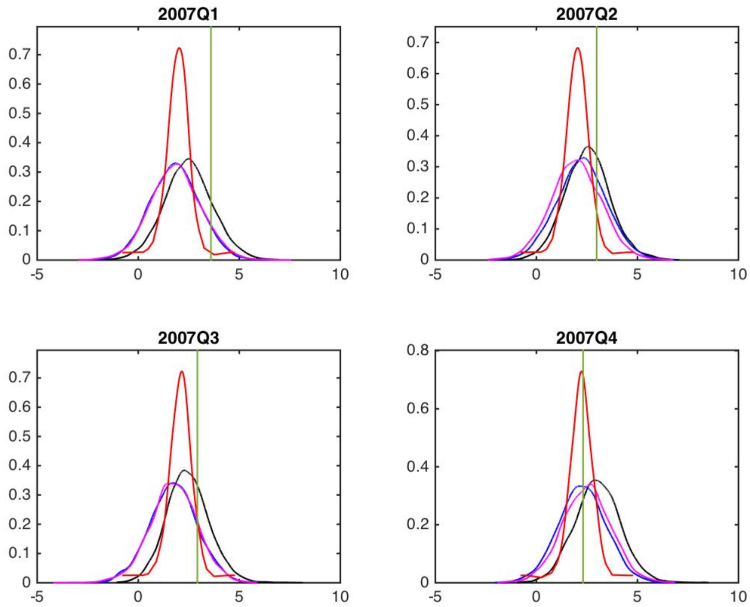
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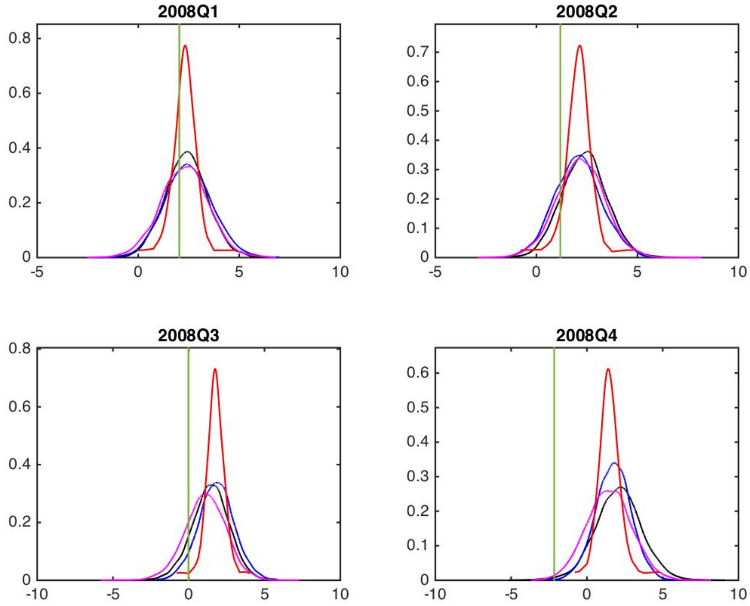
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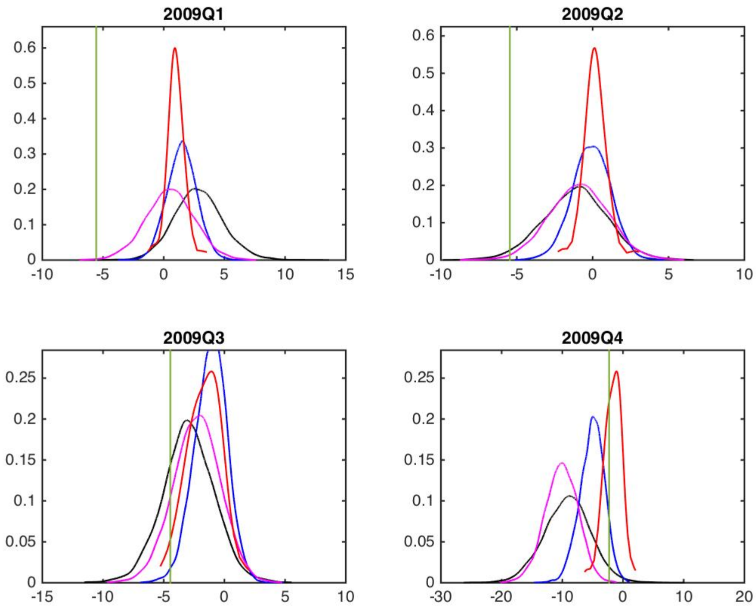
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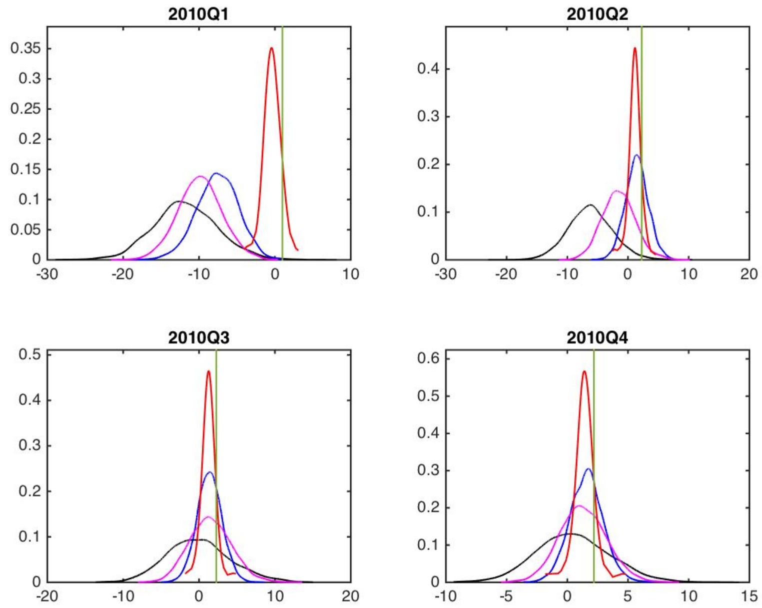
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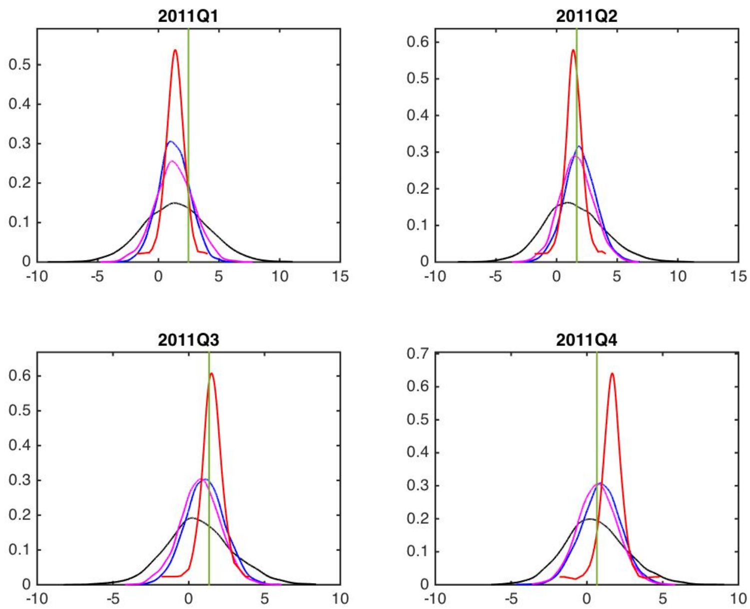
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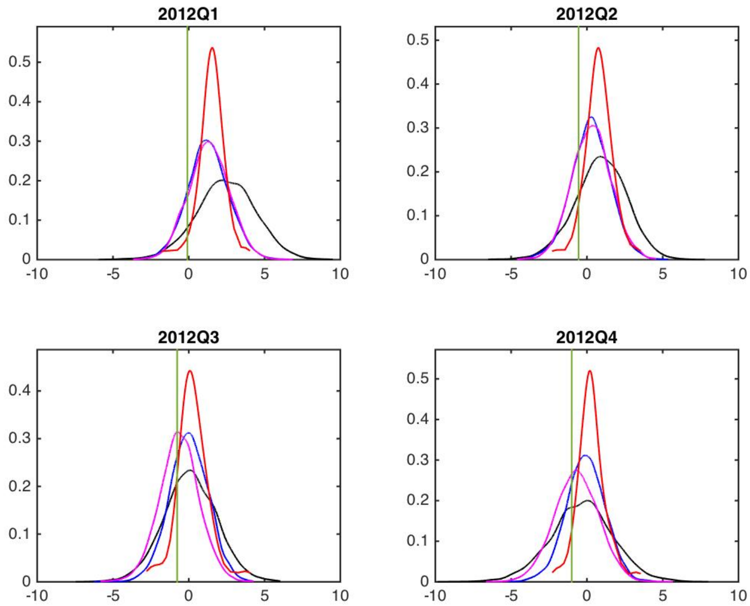
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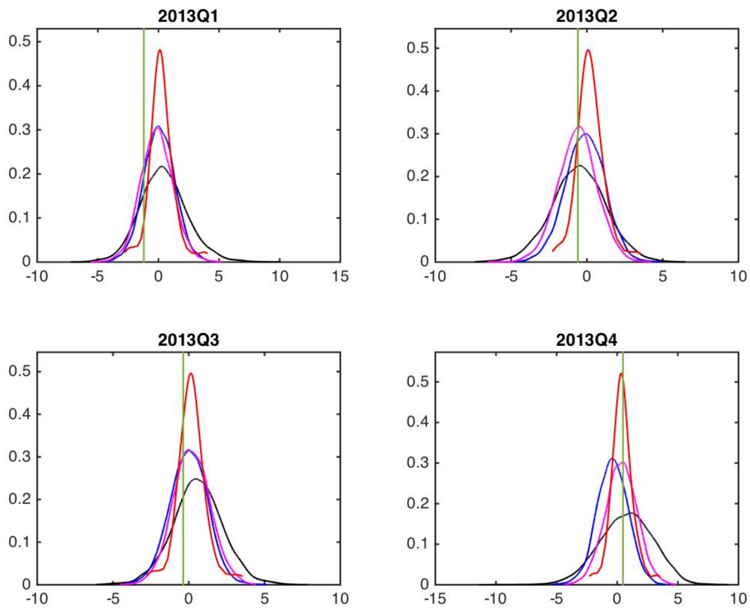
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Chapter 3

The credit channel and the state-dependent nature of the monetary policy transmission

3.1 Introduction

In most DSGE literature, the models of monetary policy assume frictionless financial markets and identify the neoclassical channels of the monetary transmission mechanism[35]. Consequently, from a conventional point of view, credit markets are neutral and do not play any role in the propagation of monetary shocks to the real economy. Otherwise several papers have shown that the financial markets are not so perfect, but rather based on imperfect information that affect the efficient distribution of financial resources across firms and investors and lead temporary shocks to have much stronger persistence through feedback effects to economic activity.[36] It is against this background that Bernanke and Gertler (1995) explore whether those frictions in credit markets can help in explaining the potency of monetary policy and develop the idea of the credit channel of monetary transmission as a set of factors that

[35] A large class of DSGE models (Clarida, Gertler and Gali, 1999; Christiano, Eichenbaum and Evans, 2005 among many other references) abstract from financial frictions and have been very influential in providing a theoretical guidance when formulating monetary interventions. For example, the European Central Bank has incorporated the Smetz and Wouters (2003) model into the monetary policy process.

[36] Diamond (1984), Holmstrom and Tirole (1997), Bernanke and Gertler (1989) are only ones of the most important contribution to this field of research.

amplify the conventional interest rate effect[37]. From this perspective, financial conditions are a crucial link in the transmission mechanism of monetary policy and many economists have been motivated to provide a new theoretical framework that incorporates financial market frictions to evaluate the response of the economy to monetary shocks from both a quantitative and a qualitative perspective (Bernanke, Gertler and Gilchrist, 1999; Brunnermeier and Sannikov, 2014; Gerali, Neri, Sessa and Signoretti, 2010; Gertler and Karadi, 2011). In most of these works, the authors have analysed the dynamics of log-linearized models around a steady state in which borrowing constraints are binding, thus ignoring the potentially nonlinear, state-dependent nature of the mechanism through which shocks are propagated.

The events that have occurred since 2007, when the financial crisis has quickly turned into an economic recession, whose scale and consequences were not witnessed since the famous 1929, have led many economists to revisit the related issues in the light of financial crisis and the great recession. By studying the full equilibrium dynamics, Brunnermeier and Sannikov (2014) find that financial system exhibits instability due to highly non-linear effects that are asymmetric and arise only during downturns when is more probable that agents are close to their credit limits.[38]

Hence, following the theoretical and empirical evidence in favor of the credit channel and the non-linear nexus between financial markets and real economy, there is an open debate on

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[37] It is worth emphasizing that the credit channel in their point of view is not a parallel channel but it is crucial in stimulating an enhancement mechanism to traditional monetary transmission channel.

[38] A growing literature stresses the role of occasionally binding constraints in generating asymmetric effects of temporary shocks. Guerrieri and Iacoviello (2017) provide theoretical evidence on this kind of asymmetries generated by collateral constraints. Empirically, the contribution of Balke (2000) is important in identifying credit regimes that determine business cycle asymmetries in the propagation of shocks.

whether the impact of monetary policy is asymmetric and how financial turmoil can affect its transmission. Indeed, monetary policy literature has largely ignored the potential for the state-dependent nature of the propagation mechanism of monetary shock and has delivered mixed messages so far.

The objective of this chapter is to evaluate the role played by financial conditions in the propagation effects of monetary shocks in the European union within empirical models that are able to capture both linear and non-linear interactions between the financial sector and the macroeconomy. First, I estimate two versions of a linear Bayesian VAR applied to euro area data. The benchmark one includes conventional measures of economic output, inflation and monetary policy and the alternative one add a composite indicator measuring the state of systemic financial stress, that is the Composite Indicator of Systemic Stress (CISS). The direct comparison between the impulse responses allows an intuitive way to quantitatively assess the relevance of the credit channel. Thus, I apply a Bayesian Threshold VAR approach that allows for the possibility of two regimes determined by the lag of GDP growth in order to account for asymmetries of monetary policy shocks on economic activity depending on the state of the business cycle at the time the action is taken.

I find that financial conditions play a crucial role in amplifying the effects of monetary interventions and in determining the asymmetric impact across good and bad times, namely monetary policy shocks have larger and faster effects during periods of recessions.

This work contributes to the debate mainly in two ways. First, I provide new empirical evidence in support of the existence of a credit channel in the propagation of monetary policy. Secondly, I assess the possibility of a state-dependent nature of the effects of monetary shocks by applying a Threshold VAR approach that take the credit channel and the non-linear dynamic interaction between real and financial economy into account.

The chapter is organized as follows. Section 2 analyse the existing literature, section 3 presents the data and the models; section 4 describes the regimes identified by the Threshold model. Section 5 and 6 reports the results of the structural analysis. Section 7 and 8 sums up the results, future lines of research and concludes.

3.2 Literature review

Many economists have devoted an outstanding effort in studying how monetary transmission mechanism works and whether the effects that are generated depend on the size, the direction of the action and vary over the business cycle. There is quite widespread agreement about the asymmetric nature of monetary transmission mechanism. A broad literature has produced empirical evidence in support of this view. There is far less agreement about how these asymmetric effects operate and how financial fragility affect the transmission of monetary policy. An important debate regarding these points is still open.

On the one hand, some recent studies agree that monetary policy is more effective during booms than during crisis. Tenreyro and Thwaites (2013) use a local projection model with the smooth transition regression method of Granger and Terasvirta (1994) to allow impulse responses of economic activity to depend on the state of the business cycle and find strong evidence that the effects of monetary policy on real and nominal variables are more powerful in expansions than in recession. This conclusion is shared by Mumtaz and Surico (2015). They study this issue using a strategy based on quantile regression and an application on US economic activity and interest rates suggests the presence of asymmetries in the propagation mechanism across good and bad times.

On the other hand, Lo and Piger (2005), Barnichon and Matthes (2014) and Peersman and Smetz (2001) find that monetary policy is more effective in recessions than in expansions. Lo and Piger (2005) use a time-varying transition probabilities framework to evaluate the evidence for asymmetries related to the direction, the size and the existing business cycle of the monetary policy action. Their results suggest that policy interventions taken during recessions have larger effects than those taken during booms. Barnichon and Matthes (2014) propose a new method to identify the possibly non-linear effect of monetary policy by using Gaussian basis functions to parametrize impulse response functions and find that the lower the output growth the larger the effect of an expansionary policy. Peersman and Smetz (2001) is one of the few papers that studies the asymmetric effects of monetary policy in the euro area. They estimate a VAR model with exogenous variables and identify the business cycle with a two state Markov switching regime with fixed coefficient and state-dependent means. They then identify monetary shocks and use their historical contribution to the euro area interest rate as a measure of monetary policy. Finally, they extend the basic specification with the new monetary policy indicator and test whether the ß-coefficient of this indicator is different across regimes. The results suggest that monetary actions are more effective during recessions. This methodology has the limit to ignore the potential for spillovers between interdependent economies and for differences across regimes in the propagation of monetary shocks.

The results I obtained are in line with the latter point of view I examined.

Moreover, there is not a clear answer to the question of whether the transmission of monetary policy is impaired due to financial crisis. From a theoretical perspective, some studies argue that monetary policy might be less effective during financial turmoil because the standard transmission channel are weakened. Jannsen, Potjagailo and Wolters (2015) provide empirical evidence that monetary policy is more effective during financial crises as it is able to mitigate some negative adverse loop that characterize this kind of event. Recent studies show how financial fragility of financial intermediaries and borrowers has affected transmission mechanism of the single Euro area monetary policy during the Great Recession and the

Sovereign Debt crisis (see Ciccarelli et al., 2013) and suggest including variables that capture banking and financial conditions in order to correctly distinguish the transmission channel of the monetary policy. My model account for this by including the Composite Indicator of Systemic Stress (CISS). This indicator appears to be particularly suitable for my purposes as it exploits a large information set by covering the main classes of financial markets and concentrates on capturing the systemic dimension of financial instability by putting more weight on situations in which stress prevails in several markets segments at the same time.

3.3 Data

I use quarterly data covering the period from April 1990 to October 2014. Data are taken from the Area-Wide Model (AWM) database. The macroeconomic variables included in the models are the real Gross Domestic Product growth (GDP), the overall Harmonized Index of Consumer prices (HICP) and the EONIA Interest rate (STR). GDP and HICP are seasonally adjusted. I decided to exclude the period from the end of 2014 on as the ECB key interest rate was at its zero lower bound and the aim of this analysis is to address the macroeconomic implications of changes on such measure implemented by the central bank.

In the euro area, the European Central Bank's most important decisions to implement conventional monetary policy relate to the key interest rates in line with the Governing Council's preferences. Figure 6 shows how the EONIA rate stayed relatively close to the Main Refinancing Operations minimum bid rate (MRO) and, consequently, it represents a valid proxy for monetary policy decisions. Even so, it is worth noting that, since the financial crisis at the end of 2008, the ECB started to adopt non-standard policies, creating conditions of excess liquidity such that the EONIA was no longer keeping up the MRO rate.

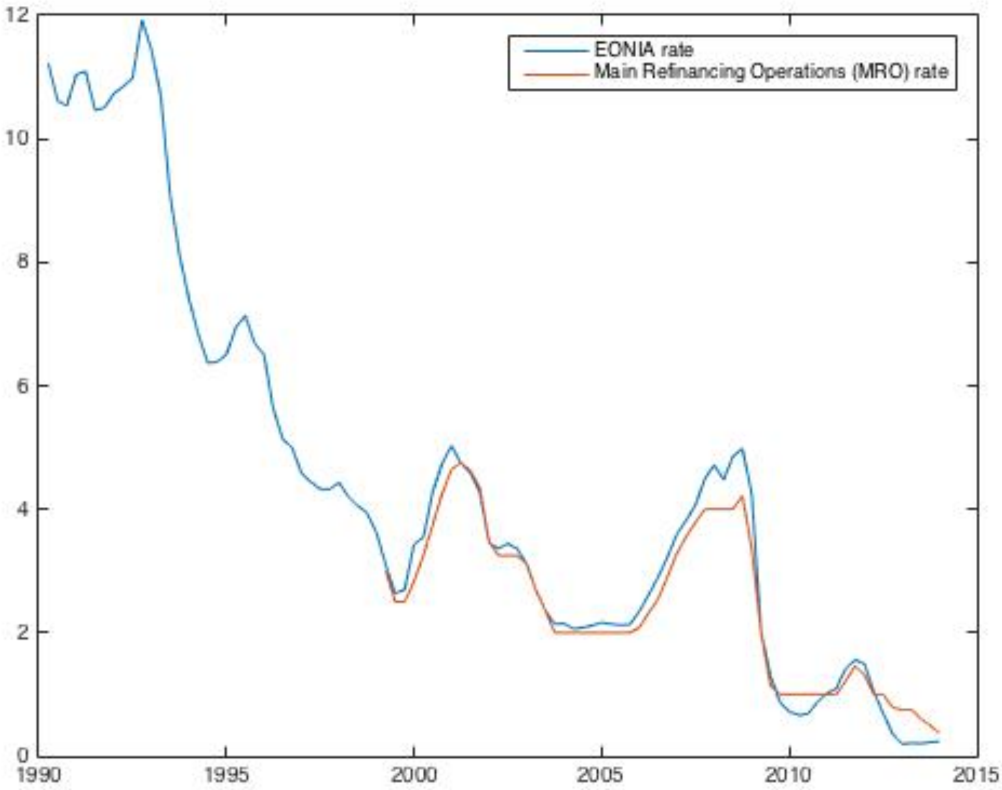


Figure 6: EONIA rate (blue line) and Main Refinancing Operations (MRO) rate (red line) from Q1:1990 to Q3:2014

I have chosen the Composite Indicator of Systemic Stress (CISS), compiled and maintained by ECB, to describe the financial market conditions. The time series of this index is available in the Statistical Data Warehouse of the ECB. This indicator captures systemic risk, uncertainty, liquidity and leverage that characterize the financial system in the Euro Area from a broad set of series describing money, equity, financial intermediaries, bond and foreign exchange markets. The key motivation that led me to prefer it among other candidates[39] is its ability to give a real-time picture of financial conditions that cover the main channels by which the funds

[39] The Volatility Index (VIX) and the credit risk indicators constructed by Gilchrist and Mojon (2014) concentrate on selected financial segment and feature of financial stress.

of savers are reallocated to borrowers. Hence, it represents a good proxy for the broad credit channel identified by Bernanke and Gertler (1995).

3.4 Models and Identification strategy of structural shocks

3.4.1The linear models

The class of linear models that I estimate are Bayesian VAR models. These models represent the most used methodological tool in identifying monetary policy shocks. In fact, they provide a simple framework that summarize in a satisfactory way the dynamic relationships included in the system and allow us to simulate the response of any variable to disturbance to the short-term interest rate equation (monetary policy shock). The models are defined as:

$$Y_t = c + \sum_{p=1}^{P} A_p Y_{t-p} + \Omega^{1/2} e_t\,, \qquad e_t \sim N(0,1)$$

where Y_t denotes the vector endogenous variables, A is the reduced form matrix of coefficients and Ω is the error covariance matrix. I estimate the model using a Bayesian approach. In setting the prior distribution I follow the procedure developed by Banbura et al. (2010). I use two versions of this model, differing only in terms of the variables entering Y_t. The benchmark model (BVAR) is a standard BVAR that does not consider the interaction between macroeconomic variables and financial factors. It contains GDP, HICP and STR. The alternative model (BVAR-FF) differs from the benchmark model as I add the CISS among the Y variables. By comparing the impulse responses of output and prices generated by the two different models, I can appreciate the relevance of the credit channel in the transmission of monetary policy.

The models are specified with 4 lags for the endogenous variables.

3.4.2 The non-linear models

I apply a Bayesian Threshold VAR approach in order to model time series non-linearity. This model has the feature to separate observations into two different regimes based on a threshold variable and provide a useful context to evaluate the asymmetries of monetary policy shock depending on their timing with respect to the business cycle. It is particularly suitable for my purposes as it can empirically identify non-linearities in the form of regime switches in the dynamic system that links key macroeconomic and financial variables. Alternative models to identify non-linearities such as time-varying parameter models allow for time variation in parameters and shocks but in a smoother and recursive manner. This framework does not reflect my idea of discrete shifts in the state-dependent dynamic structure that transmits monetary policy shocks to the economy.

The model is defined as:

$$Y_t = \left[c_1 + \sum_{p=1}^{P} B_{1,p} Y_{t-p} + \Omega^{1/2} e_t \right] S_t + \left[c_2 + \sum_{p=1}^{P} B_{2,p} Y_{t-p} + \Omega^{1/2} e_t \right] (1 - S_t),$$

where

$$e_t \sim N(0, 1)$$

$$S_t = 1 \leftrightarrow Z_{t-d} \geq Z^*$$

As in the BVAR framework, I impose a natural conjugate prior on the VAR parameters in the two regimes[40] and estimate two versions of this model that differs in the endogenous variables entering Y_t as before. I allow for the possibility of two regimes characterized by different dynamics ($B_1 \neq B_2$), that identify the business cycle as at each time *t* the regime is

[40] See Chen and Lee (1995) and Alessandri and Mumtaz (2017) for further details on TAR model structure.

determined by the value assumed at time *t-d* by real GDP growth relative to a threshold value (Z^*, endogenously determined), where the delay *d* is assumed to be an unknown parameter.

Following Koop, Pesaran and Potter (1996), I estimate the impulse response functions that are based on the following definition:

$$IRF_t^S = E(Y_{t+k} \backslash \psi_t , Y_{t-1}^s , \mu) - E(Y_{t+k} \backslash \psi_t , Y_{t-1}^s)$$

where ψ_t denotes all the parameters and hyperparameters of the VAR model, *k* is the horizon under consideration, *S= 0,1* denotes the regime and μ denotes the shock. The impulse response functions are calculated as the difference between two conditional expectations. The first term is a forecast of the endogenous variable conditioned on one of the structural shock μ. The second one is a forecast of the same endogenous variable when the shock is equal to zero. To identify the structural shocks, I use a standard Cholesky decompositions methodology. Indeed, I consider that zero contemporaneous restrictions are less stringent than a priori sign restrictions within a macro-financial context where the effects of monetary policy in different regimes are not so clear from a theoretical perspective. I order the short-term interest rate after GDP and HICP based on the conventional view that contemporaneous values of these variables are relevant in determining the monetary policy process, but they can react only with a lag to exogenous disturbances. The CISS is ordered last based on the assumption that financial variables move quickly in response to any news and contemporaneous values do not contain any marginal information that is useful in formulating the monetary policy.[41]

[41] Bernanke, Gertler and Gilchrist (1999) and Alessandri and Mumtaz (2017) use the same identification strategy of structural shocks.

3.5 Regimes

It is useful to examine features of cyclical regimes identified by the threshold VAR model. Figure 7 shows the estimated regimes. The periods in which *GDP* is below the critical threshold correspond to periods of bad times; instead, when it is above corresponding to regime of good times. Apart from sporadic event, the model has identified four past recessions for the euro area economy. From the third quarter of 1992 to the fourth quarter of 1993 a significant decline in the level of overall economic activity is reported.

In addition, the period from the first quarter of 2002 to the fourth quarter of 2003 has been characterized as a prolonged pause in the growth of economic activity rather than an authentic recession.

Then, the 2007 is the year when began the great financial crisis, which was followed by the great economic recession from the second quarter of 2008 to the end of 2009. Finally, after a brief period of recovery, the European Sovereign Debt crisis emerged.

It is worth emphasizing how every recession identified by this model can be associated with some event of financial stress. In fact, in 1992 the European financial system was hit by the breakdown of the European Exchange Rate Mechanism. At the end of 2001 real and financial global economy was shaken by the terrorist attacks and the WorldCom bankruptcy occurred in 2002. Eventually, the most recent financial crisis and the concerns about sovereign credit risk are intimately linked with the two periods of recession identified by the model.

To sum up, it emerges that the Threshold VAR appropriately distinguishes sub-periods of recession characterized by negative growth and financial stress.

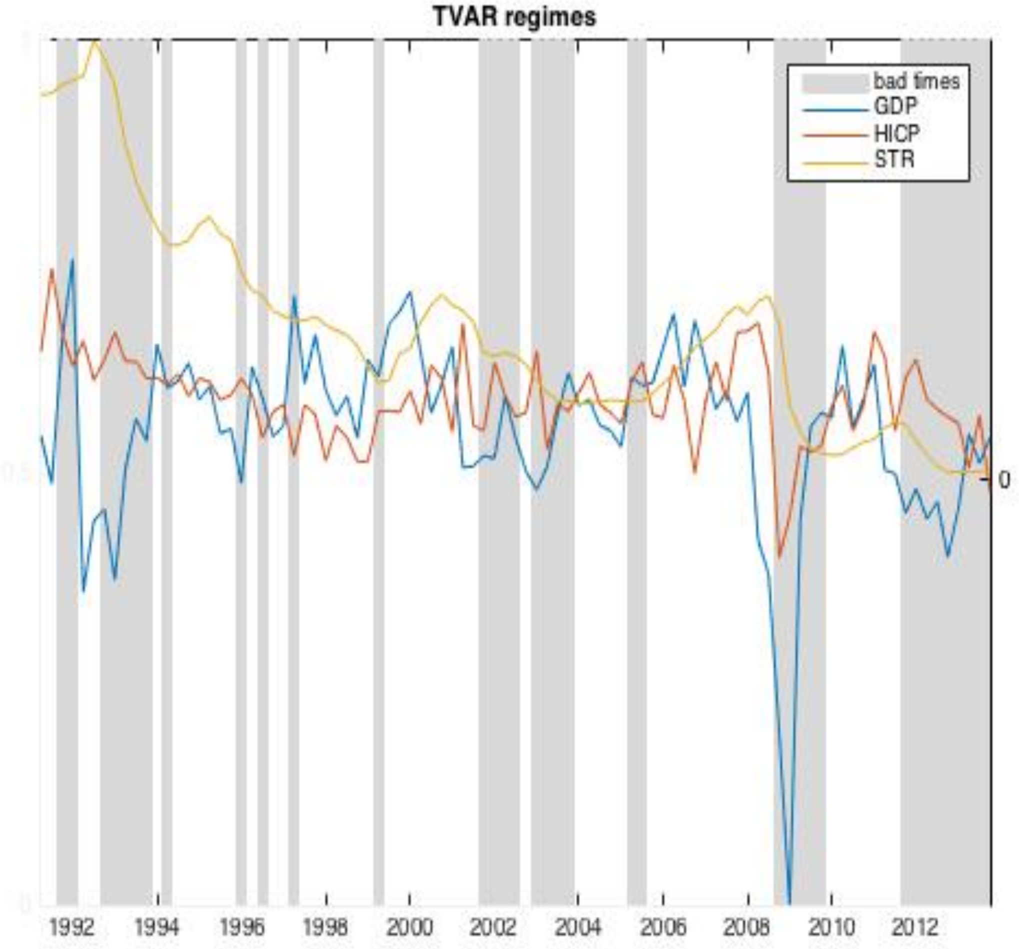


Figure 7: The endogenous variables GDP (blue line), HICP (red line) and STR (yellow line) with the periods of bad times (grey bands), identified by a Threshold BVAR with two states driven by the level of the GDP growth, that represents the threshold variable of the model.

3.6 The relevance of the credit channel

The first experiment I analyse is the comparison between the impulse responses generated by the two linear models described above in order to assess the relevance of the credit channel and the adequacy of the financial index I include to take these additional effects into account.

Figure 8 shows the reaction of output and prices to a monetary policy shock[42] in the two models. The baseline simulation (dotted blue line) is based on a model in which the amplifying effect of monetary transmission through the credit channel is shut down. I can see that the inclusion of credit market frictions magnifies the effects of conventional channel of the monetary transmission mechanism on GDP as the drop in output is deeper than the one that occurs in the system that does not involve financial variable. This result is in line with the empirical evidence provided by several papers and with the hypothesis that the credit channel works as an enhancement mechanism in the propagation of traditional interest rate effect. I can note that the monetary policy shock increases the systemic stress of financial sector turning out to be important in determining an additional effect on output in the transmission of the monetary policy innovation.

The response of prices appears to be similar in both the simulations I propose and present the so-called "price-puzzle" that is typical within this framework. Indeed, an unexpected tightening in monetary policy leads to an increase rather than a decrease in the price level. This result suggests including other variables such as commodity price index to solve it. In addition, monetary policy shock has a more persistent effect on short-term interest rate in the baseline

[42] I analyse the effect of an unanticipated raise in the short-term interest rate that result in a tightening of monetary policy.

framework, pointing out the possibility for the inability to correctly distinguish monetary from financial pressure.

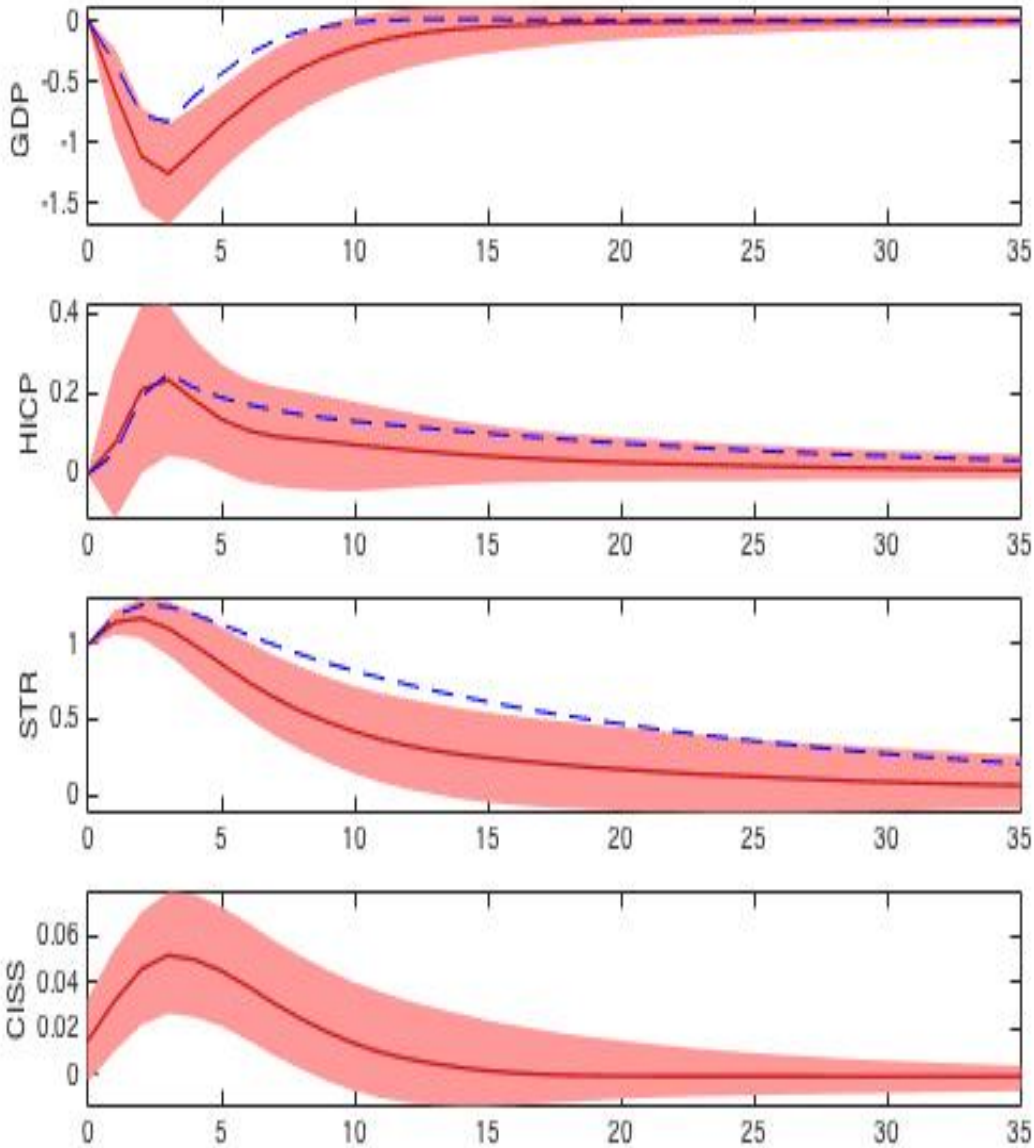


Figure 8: Impulse responses of a 1 % positive monetary policy shock on the variables included in the linear models. The blue dotted lines identify the responses generated by the baseline model (BVAR). The red lines are the one produced by the alternative version with the financial index (BVAR-FF) with the ranges that correspond to the 16th and 84th quantile of the distribution.

3.7 The state-dependent nature of monetary transmission

Figure 9 shows the responses to a monetary shock generated by the Threshold models. The dynamics are qualitatively similar in the two regimes within both the frameworks proposed. In the baseline simulations, the impact of monetary shock on GDP does not show any asymmetric nature even from a quantitative perspective, but as I include financial friction in my setting a quantitative difference begins to emerge. The fall in output is almost twice during the periods of recession in the alternative version of the model compared to the baseline one and, within the financial friction framework, the impact of monetary shocks is greater during bad times than during good times. Interestingly, the unexpected tightening of monetary policy produces larger effects on the measure of financial stress during recessions and it seems that the revealed asymmetric nature of the monetary policy is driven by the existence of the credit channel in the transmission mechanism. Moreover, it is worth noting how the decline in output reaches a deeper trough whether the shock hit the economy during bad times, but, on the other hand, the recovery appears to be faster than during good times. This difference might be due to the much stronger persistency of the effects on the policy rate in the good times than recession times. These results are in line with the literature that shares the conclusion that monetary policy is more effective during crisis times.

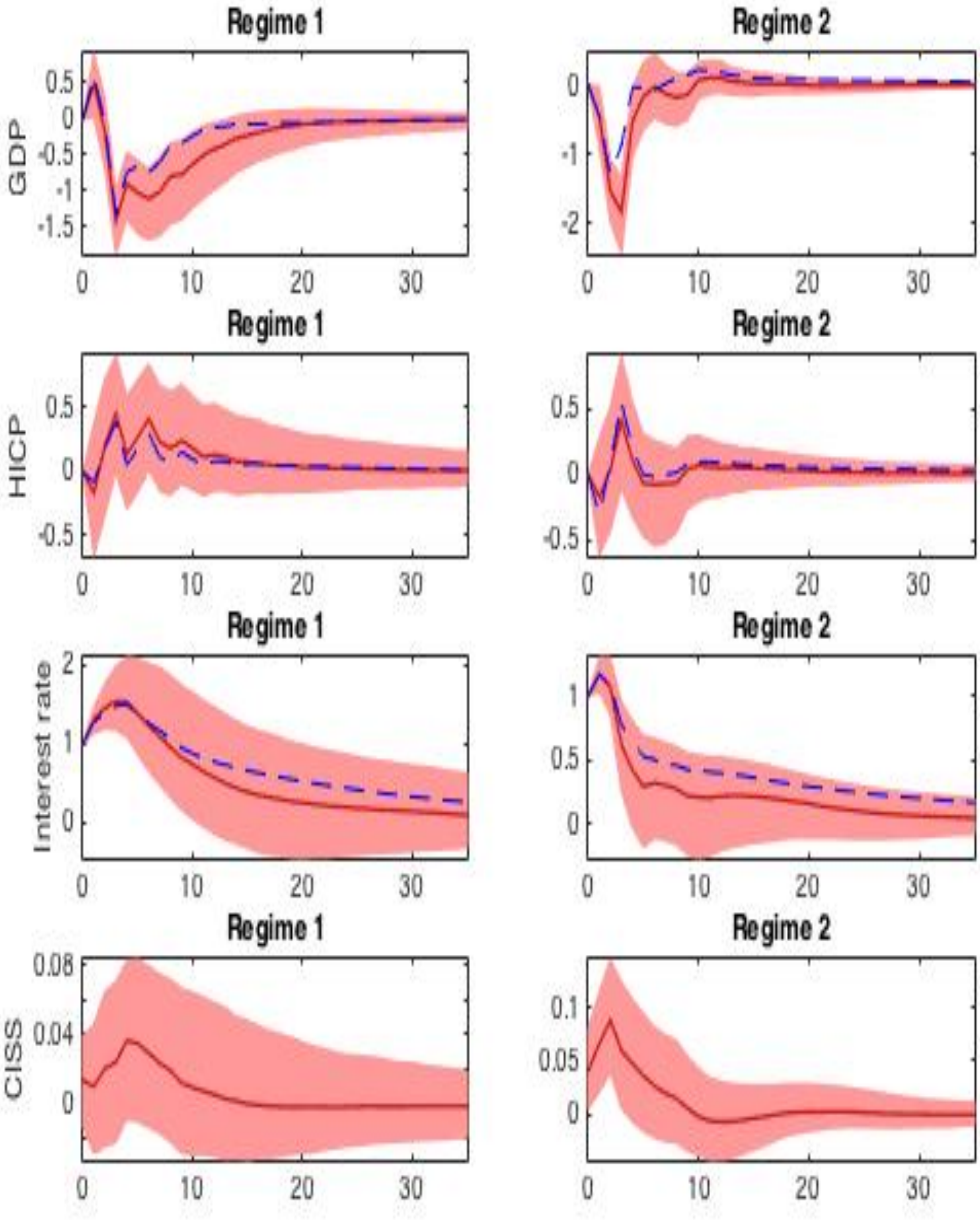


Figure 9: Impulse responses of a 1 % positive monetary policy shock generated by the Threshold models. The blue dotted lines identify the responses generated by the baseline model (TVAR). The red lines are the one produced by the alternative version that includes financial frictions. Regime 1 and 2 correspond to period of good and recession times.

3.7 Future lines of research

I would like to take a new approach to analyse the potential for asymmetries of the transmission mechanism of European monetary policy by estimating a hierarchical panel Threshold VAR model.[43] Monetary union and trade and financial market integration have induced closer interdependencies between euro area countries, making panel VAR models particularly suitable for studying the propagation effects of monetary policy in the European union as they are able to capture both static and dynamic interdependencies and to account for cross-sectional heterogeneities.[44] The fact that Euro area member countries are subject to common monetary policy shocks and share a high degree of commonality in business cycle and financial market dynamics is of crucial importance for the choice to adopt a panel estimation technique. The advantage of this approach is that I allow impulse responses not only to depend on the state of the economy but also to take spillover effects between countries into account. Such a framework is able to capture average effects of monetary policy shocks across regimes and to characterize country specific differences relative to the average by exploiting both state-dependent nature and cross-sectional effects of the transmission mechanism of the European monetary policy.

Moreover, empirical literature provides various way to identify and estimate monetary policy shocks. It would be worth to consider the narrative approach proposed by Romer and Romer

[43] The estimation algorithm of the Bayesian hierarchical Panel VAR is very well-explained step by step in the paper by Perez (2015). I show in appendix 3.A the details of the algorithm for the panel threshold VAR with a simulation on artificial data.

[44] Canova and Ciccarelli (2013) provide an exhaustive survey of Panel vector autoregressive models used in macroeconomy and finance

(2004) or the high frequency proxy SVAR method used by Gertler and Karadi (2015) in a recent paper. Eventually, it would be important to extend the set of variables included in the system in order to account for information that capture the stance of unconventional monetary policy, global inflationary pressures and global demand. Indeed, omitting such important variables for the euro area business cycle could lead to overrate the role of financial variables in the transmission of conventional monetary policy.

3.8 Conclusion

This work provides new empirical evidence that sustain the relevance of the credit channel in the propagation of monetary policy. In addition, it gives a quantitative assessment of the state-dependent nature of the effects of monetary shocks by applying a Threshold VAR approach that take the credit channel and the non-linear dynamic interaction between real and financial economy into account. The results suggest that financial conditions play an important role in amplifying the propagation of monetary effects in the European Union and in generating asymmetries in the impact on overall economic activity across the various states of the economy. Indeed, the unexpected tightening of monetary policy has a greater impact on financial stress during recessions that appears to be the crux in determining asymmetries in the transmission mechanism of monetary policy. Overall the results are in line with the empirical evidence of several papers and theoretical models that describe dynamic interaction between imperfections in financial markets and the macroeconomy.

3.A The hierarchical panel threshold VAR model

I assume that each economy can be modeled as an individual threshold VAR model and then I combine the information to estimate the panel model.

With $n = 1, \dots, N$, each country n is represented by a threshold VAR model defined as:

$$Y_n = \left[X_{1,n}B_{1,n} + W_{1,n}\Gamma_{1,n} + \mathrm{U}_{1,n}\ \right]S_t + \left[X_{2,n}B_{2,n} + W_{2,n}\Gamma_{2,n} + \mathrm{U}_{2,n}\ \right](1 - S_t),$$

with

$$S_t = 1 \leftrightarrow \ Z_{t-d} \leq Z^*$$

where Y_n is a $T_n \times M$ matrix of endogenous variables, $X_{i,n}$ is a $T_{i,n} \times K$ matrix that include the P lags of the endogenous variables and the Q exogenous variables specific to each country, with $K = MP + Q$. $W_{i,n}$ is a $T_{i,n} \times R$ matrix of exogenous variable common to all countries. $U_{i,n}$ is a $T_{i,n} \times M$ matrix of reduced form shocks. The model allows for the possibility of two regimes determined by the level of the threshold variable Z_{t-d} relative to the threshold level Z^* that we need to estimate.

3A.1 Prior assumptions

I impose a natural conjugate prior on the VAR parameters as in Perez (2015) in the two regimes. I suggest reading this work for details on the derivation of the posterior distribution for both τ, that is the overall tightness parameter, and $\bar{\beta}$, that is the common mean of the specific betas, in a hierarchical context.

Moreover, I assume a normal prior for $Z^* \sim N(\bar{Z}, \bar{V})$ where $\bar{Z}$ is the mean of the threshold variable and $\bar{V}$ is set 10.

3A.2 The algorithm

I assume starting value for $Z^* = mean(Z_t)$. I set $k = 1$ and denote K as the total number of draws. Then follow the step below:

Step 1:

Separate the sample into two regimes by using the dummy variable $S_t = 1 \leftrightarrow Z_{t-d} \leq Z^*$.

Step 2:

Draw $\beta_{i,n}$ from the posterior distribution that is $N\left(\tilde{\beta}_{i,n}, \tilde{\Delta}_{i,n}\right)$ for $i = 1, 2$ that identifies the regime. $\tilde{\beta}_{i,n}$ and $\tilde{\Delta}_{i,n}$ are defined as:

$$\tilde{\Delta}_{i,n} = \left(\Sigma_{i,n}^{-1} \otimes X'_{i,n}X_{i,n} + \tau_i^{-1}O_n^{-1}\right)^{-1}$$

$$\tilde{\beta}_{i,n} = \tilde{\Delta}_{i,n}\left(\left(\Sigma_{i,n}^{-1} \otimes X'_{i,n}\right)\left(Y_{i,n} - \left(I_M \otimes W_{i,n}\right)\gamma_{i,n}\right) + \tau_i^{-1}O_n^{-1}\bar{\beta}_i\right)$$

where O_n is the covariance matrix of the Minnesota prior. If the candidate draw is stable, I keep it, otherwise I discard it.

Step 3.

Draw $\gamma_{i,n}$ from the posterior distribution that is $N\left(\tilde{\gamma}_{i,n}, \tilde{\Gamma}_{i,n}\right)$. $\tilde{\gamma}_{i,n}$ and $\tilde{\Gamma}_{i,n}$ are defined as:

$$\tilde{\Gamma}_{i,n} = \left(\Sigma_{i,n}^{-1} \otimes W'_{i,n}W_{i,n}\right)^{-1}$$

$$\tilde{\gamma}_{i,n} = \tilde{\Gamma}_{i,n}\left(\left(\Sigma_{i,n}^{-1} \otimes W'_{i,n}\right)\left(Y_{i,n} - \left(I_M \otimes X_{i,n}\right)\beta_{i,n}\right)\right)$$

Step 4.

Draw $\Sigma_{i,n}$ from the posterior distribution that is Inverted-Wishart centered at the sum of squared residuals $U_{i,n}$.

Where:

$$U_{i,n} = Y_{i,n} - X_{i,n}B_{i,n} + W_{i,n}\Gamma_{i,n}$$

$$\Sigma_{i,n} \sim IW\left(U'_{i,n}U_{i,n}, T_{i,n}\right)$$

Step 5.

Draw Z^* from its conditional distribution by using a random walk Metropolis algorithm. I draw a candidate value of Z^*_{new} from $Z^*_{new} = Z^*_{old} + \psi^{1\backslash 2}\epsilon,\ \epsilon \sim N(0,1)$. The acceptance probability is given by $\frac{f(Y_t|Z^*_{new},\Xi)}{f(Y_t|Z^*_{old},\Xi)}$ where $f(.)$ denotes the posterior density and Ξ represents all other parameters in the model. I choose the scaling factor ψ to ensure that the acceptance rate remains between 20% and 40%. The posterior density is proportional to the product of the likelihood of the VAR in each regime times the prior.

Then, repeat steps 1 to 5 for $n = 1, \dots, N$.

Step 6.

Draw $\bar{\beta}_i$ from its posterior distribution that is $N(\bar{\bar{\beta}}, \bar{\Delta})$, where:

$$\bar{\Delta} = \left(\sum_{n=1}^{N} \tau_i^{-1} O_n^{-1}\right)^{-1}$$

$$\bar{\bar{\beta}} = \bar{\Delta}\left[\sum_{n=1}^{N} \tau_i^{-1} O_n^{-1}\, \beta_{i,n}\right]$$

Step 7.

Draw τ_i from its posterior distribution that is an Inverse Gamma defined as:

$$\tau_i \sim IG\left(\frac{NMK + v}{2}, \frac{\sum_{n=1}^{N}(\beta_{i,n} - \bar{\beta}_i)' O_n^{-1}(\beta_{i,n} - \bar{\beta}_i) + s}{2}\right)$$

I set $v = -1$ and $s = 0$.

A complete cycle of these steps generates a draw of the parameters $\left\{\left[\beta_{i,n}, \gamma_{i,n}, \Sigma_{i,n}\right]_{n=1}^{N}, \bar{\beta}_i, \tau_i\right\}$ for each regime i. If $k < K$ set $k = k + 1$ and return to step 1. Otherwise stop. [45]

[45] For further details on the estimation setup, prior distributions and the derivation of the posterior distribution of each parameter to estimate, I refer the reader to Perez (2015).

3A.3 Testing the model with artificial data

I consider the following panel threshold VAR model based on 300 artificial observations for each of $N = 2$ cross sections, with $P = 2$ lags and $M = 2$ endogenous variables:

Regime 1

$$\begin{bmatrix} Y_{1,t}^1 \\ Y_{2,t}^1 \end{bmatrix} = \left[\begin{bmatrix} -0.1 & -0.3 & 0 & 0 \\ +0.2 & +0.7 & 0 & 0 \end{bmatrix}\right] \begin{bmatrix} Y_{1,t-1}^1 \\ Y_{2,t-1}^1 \\ Y_{1,t-2}^1 \\ Y_{2,t-2}^1 \end{bmatrix} + \begin{bmatrix} e_{1,t}^1 \\ e_{2,t}^1 \end{bmatrix}$$

$$\begin{bmatrix} Y_{1,t}^2 \\ Y_{2,t}^2 \end{bmatrix} = \left[\begin{bmatrix} +0.3 & +0.3 & 0 & 0 \\ -0.3 & +0.5 & 0 & 0 \end{bmatrix}\right] \begin{bmatrix} Y_{1,t-1}^2 \\ Y_{2,t-1}^2 \\ Y_{1,t-2}^2 \\ Y_{2,t-2}^2 \end{bmatrix} + \begin{bmatrix} e_{1,t}^2 \\ e_{2,t}^2 \end{bmatrix}$$

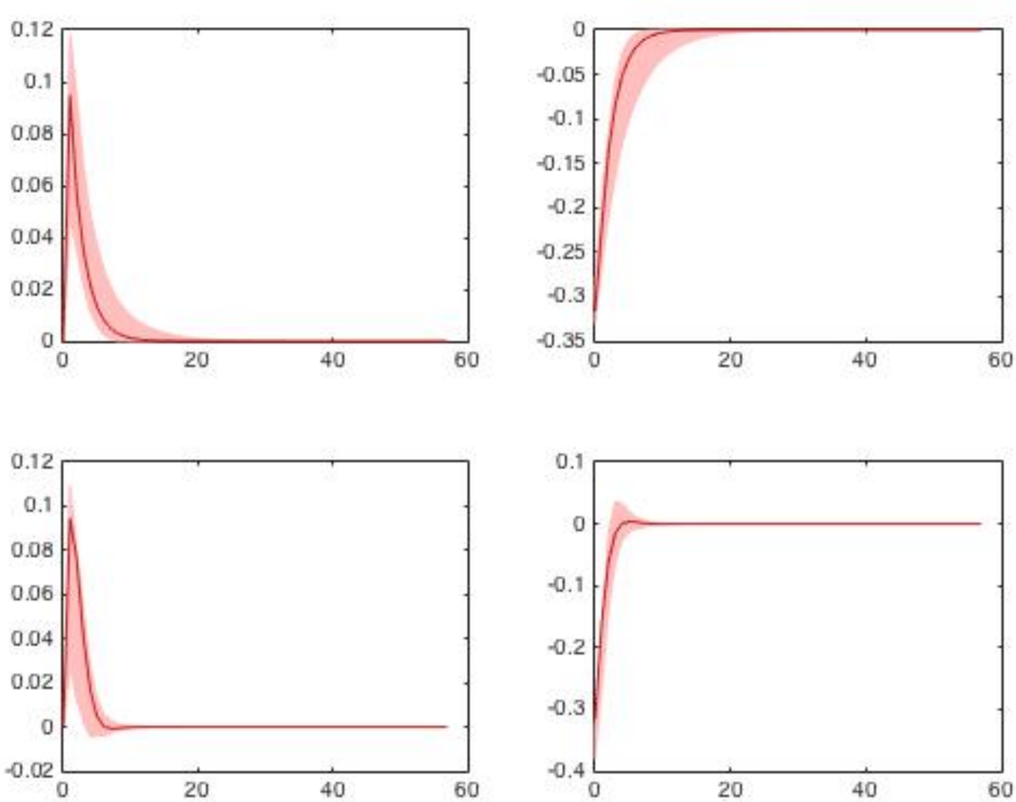
Regime 2

$$\begin{bmatrix} Y_{1,t}^1 \\ Y_{2,t}^1 \end{bmatrix} = \left[\begin{bmatrix} +0.3 & -0.3 & 0 & 0 \\ +0.2 & +0.5 & 0 & 0 \end{bmatrix}\right] \begin{bmatrix} Y_{1,t-1}^1 \\ Y_{2,t-1}^1 \\ Y_{1,t-2}^1 \\ Y_{2,t-2}^1 \end{bmatrix} + \begin{bmatrix} e_{1,t}^1 \\ e_{2,t}^1 \end{bmatrix}$$

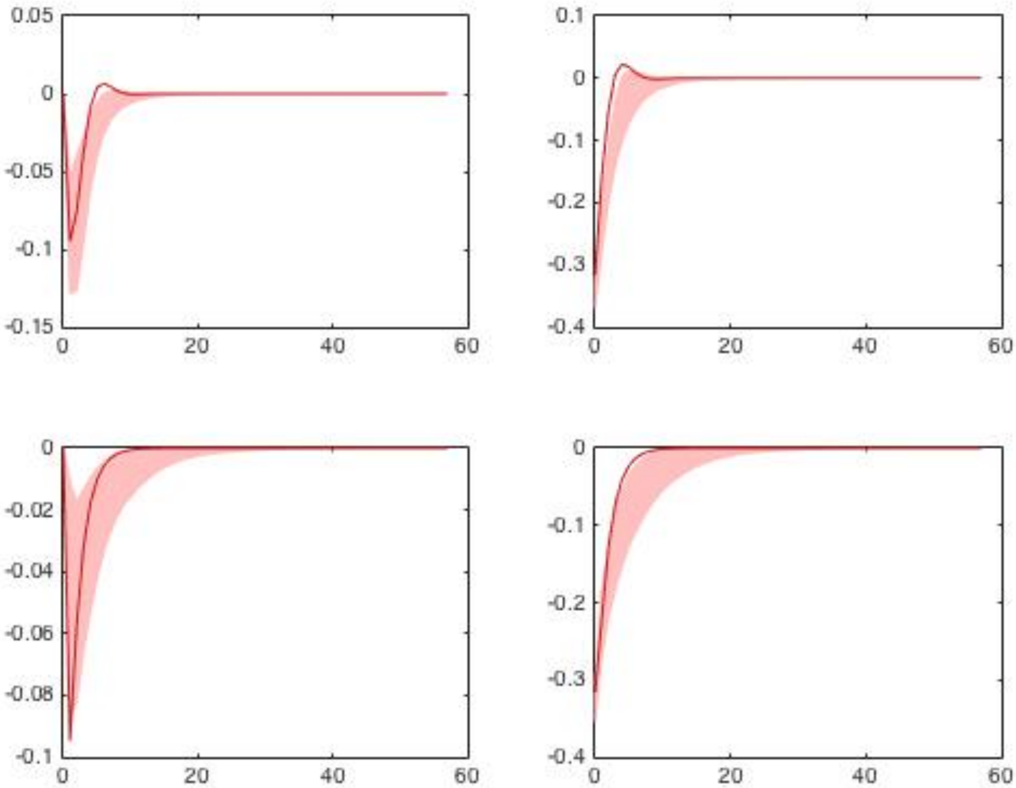
$$\begin{bmatrix} Y_{1,t}^2 \\ Y_{2,t}^2 \end{bmatrix} = \left[\begin{bmatrix} -0.1 & +0.3 & 0 & 0 \\ -0.3 & +0.7 & 0 & 0 \end{bmatrix}\right] \begin{bmatrix} Y_{1,t-1}^2 \\ Y_{2,t-1}^2 \\ Y_{1,t-2}^2 \\ Y_{2,t-2}^2 \end{bmatrix} + \begin{bmatrix} e_{1,t}^2 \\ e_{2,t}^2 \end{bmatrix}$$

The figures below show the impulse response functions to a one standard deviation negative shock on the second endogenous variable. The red line is the true artificial impulse response while the upper and the lower bound of the bands correspond to the 84th and 16th quantile of the response functions distributions generated by the panel threshold VAR:

<u>Regime 1</u>



Regime 2


0.05
0
-0.05
-0.1
-0.15
0
20
40
60
0.1
0
-0.1
-0.2
-0.3
-0.4
0
20
40
60
0
-0.02
-0.04
-0.06
-0.08
-0.1
0
20
40
60
0
-0.1
-0.2
-0.3
-0.4
0
20
40
60

Conclusion

This thesis contributes to the field of forecasting and monetary policy, focusing specifically on their link with financial frictions.

The first chapter surveys the literature on the macroeconomic implications of financial frictions. I concentrate more on works related to the credit channel theory, the predictive power of financial variables and the nonlinear and state-dependent effects of shocks induced by the presence of imperfections in the financial markets. I compare the different approaches to incorporate financial frictions into dynamic general equilibrium models and the various empirical strategies to model non-linearity for both macroeconomic and forecasting purposes. I find some open debates on how the asymmetric effects of monetary policy operate and how financial fragility affect the transmission of monetary policy that have motivated my empirical exercises that I develop in the following chapters.

In chapter 2, I provide a quantitative analysis of the role played by a financial stress index in forecasting euro area real GDP growth. I examine the relative forecasting performance of a set of linear and non-linear Bayesian VAR models evaluated over a broad set of metrics that allow us to compare the full-sample and real-time relative accuracy in point and density forecasting. The estimation of predictive distributions allows us to show how the models that include the financial stress indicator would have sent a credible advance warning on the upcoming Great Recession by implying higher ex ante probability to the recession event compared to the models that omit the financial variable. On the other hand, the same models do not enjoy any advantage from a point forecasting perspective.

The third chapter resorts to structural impulse responses analysis to investigate the relevance of the credit channel in the propagation of monetary policy shocks and to provide a quantitative assessment of the state-dependent nature of the effects of monetary shocks. I apply a Threshold

VAR approach that take the credit channel and the non-linear dynamic interaction between real and financial economy into account. The results suggest that financial conditions play an important role in amplifying the propagation of monetary effects in the European union and in determining asymmetries in the impact on overall economic activity across the various states of the economy. Indeed, the unexpected tightening of monetary policy has a greater impact on financial stress during recessions. The more adverse financial conditions affect the transmission mechanism of monetary policy and induce asymmetries depending on the state of the economy when the shock hits the economy.

Overall the results lend support to theoretical models of the nexus between imperfect financial markets and macroeconomics and suggest macroprudential and monetary policy authority to pay more attention to the role of financial factors in macroeconomic and forecasting analysis.

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