Macroeconomic effects of monetary policy shocks: Credit and inflation expectation transmission channels.

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Abstract

After the introduction, this thesis comprises three chapters that examine the monetary policy transmission channels in the European Union. The chapters focus on two channels of monetary policy transmission: credit supply and expectation channels including periods of unconventional monetary policy.

Chapter 2 analyses the effects of a monetary policy shock on the euro area with a focus on disaggregated inflation expectations. The key finding is that the responses of inflation expectations in the euro area have become weaker in magnitude and less dispersed over time. There is evidence of convergence among consumer expectations after 2012 during the zero lower bound period. The responses of inflation expectations after 2012 take more time to react (more than six quarters compared with the four quarters before 2008) and are weaker, on average, in the long run than the responses before 2008. The heterogeneity in the responses of EA countries and various demographic groups is substantially reduced after 2012 following the implementation of unconventional monetary policy. The determinants of the heterogeneity among countries are partly explained by the share of manufacturing and degree of unemployment protection.

Chapter 3 finds a positive effect of the PSPP, a leading component of the ECB's monetary policy, on the volume of small loans received by SMEs, especially the smallest category of below 0.25 million euros, and small changes in the costs of borrowing. There is a corresponding change in SMEs' cost of borrowing perception estimated from the survey data. Using the fixed effects model and a panel of EU countries, I find that an increase in the PSPP's monthly net purchases of 1% of GDP is associated with the volume of loans rising by 47 million for loans below 0.25 million euros, with the cost of borrowing falling by 174 basis points.

Chapter 4 forecasts MFVAR, which has a lower root mean squared forecast error than a random walk forecast. This study extends the mixed frequency methodology into a new domain of survey variables and argues for their importance in tracking monetary policy transmission through the credit channel. In addition to short-term forecasts, I produce monthly estimates of the perception of economic activity obtained from the bank lending survey. The resulting monthly series for the survey variables capture the perceptions of economic activity from the perspective of bank managers. These forecasts of bank lending conditions can thus capture the drastic changes in lending conditions amid the sovereign debt crisis in the euro area ahead of the official quarterly release.

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Statement of originality

I, Vladislav Skovorodov, confirm that the research included within this thesis is my own work or that where it has been carried out in collaboration with, or supported by others, that this is duly acknowledged below and my contribution indicated. Previously published material is also acknowledged below.

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Acronyms

ABSPP Asset-Backed Securities Purchase Programme

APP Asset Purchase Programme

BLS Bank Lending Survey

BoE Bank of England

BoJ Bank of Japan

CBPP Covered Bond Purchase Programme

CPI Consumer Price Index

CSPP Corporate Sector Purchase Programme

EA Euro Area

EC European Commission

ECB European Central Bank

EMU European Monetary Union

EONIA Euro Overnight Index Average

FAVAR Factor-Augmented Vector Autoregression

Fed Federal Reserve

GDP Gross Domestic Product

IP Interest Rate Pass-Through

IRF Impulse Response Function

LSAP Large-Scale Asset Purchase

MFI Monetary Financial Institution

MFVAR Mixed Frequency Vector Autoregression

MIDAS Mixed Data Sampling

MP Monetary Policy

PPI Producer Price Index

PSPP Public Sector Purchase Programme

QE Quantitative Easing

SAFE Survey on the Access to Finance of Enterprises

SME Small and Medium-sized Enterprise

SMP Securities Market Programme

UMP Unconventional Monetary Policy

VAR Vector Autoregression

ZLB Zero Lower Bound

Chapter 1

Introduction

Two survey measures, one of consumers and one of senior loan officers, capture the perception of economic agents and highlight differences among EA countries. The literature has not thus far assessed a particular monetary policy (MP) channel using these surveys. Yet, the tools for such an analysis are well developed and can provide new insights. The following chapters bridge this gap. The remainder of this section briefly outlines the latest developments and challenges in the MP literature and positions this thesis chapter with their corresponding contributions to this strand of the literature.

The global financial crisis of 2007 forced central banks to engage in UMP when interest rates reached their zero lower bound (ZLB). As a result, the European Central Bank (ECB) implemented a number of unconventional tools, which were followed by theoretical and empirical studies that aimed to analyse their effectiveness.

The ZLB should be expected to last long into the future, which emphasises the importance of a ZLB MP investigation (Kocherlakota, 2019). There are two reasons for a prolonged ZLB period. First, empirical estimates of the natural real interest rate have been decreasing over the past decade. This smaller buffer makes an economy more vulnerable to even small shocks and thus pushes rates towards the ZLB. Second, in the event of another financial crisis, as interest rates fall, there will be no room for central banks to protect the economy from adverse shocks, which might reduce aggregate output and further deepen the recession.

Unconventional tools can be broadly separated into forward guidance and large-scale asset purchases (LSAPs). Forward guidance refers to communication by MP authorities that aims to form public beliefs about central bank policy (Rossi, 2019, p. 2). For instance, announcements that interest rates are being kept lower for longer would change the market's belief about the future path of interest rates. The mechanism of announcement effects is described by Eggertsson et al. (2003, p. 44). Quantitative easing (QE) summarises changes in both the size and the composition of a central bank's balance sheet.

The main challenge faced by the researcher was the identification of the unconventional policy rates, as standard methods did not apply or described the data poorly Wright (2012). Five approaches have been used in the literature to identify unconventional policy Rossi (2019): the shadow rate approach, heteroscedasticity-based identification, high frequency identification, use of external instruments, and use of functional vector autoregression (VAR).

To place the following chapters in the context of the literature, chapter 2 uses the shadow rate approach to find the heterogeneous effects of UMP on inflation expectations in the EA. Chapter 3 discusses an alternative approach that uses large panel data to analyse the Public Sector Purchase Programme (PSPP), which lowers the agreed interest rates for loans under 0.25 million euros and reduces the perceived credit constraints for small and medium-sized enterprises (SMEs). Finally, Chapter 4 shows the importance of the bank lending survey (BLS) for the EA and conducts a forecasting exercise that produces monthly values for the survey outcomes as well as one-step ahead forecasts that perform better then naive forecasts.

1.0.1 European Monetary Union (EMU)

To discuss the motivation for these chapters, it is important to highlight the goals of the EMU. The Treaty creating the monetary union put price stability as a primary objective of MP in the EA (Article 127). The European Economic and Monetary Union is a historic project that first aimed to unite 11 economies (now 19 at the time of writing). These are diverse countries that possess the additional challenge of assessing MP in the form of the potential heterogeneity of causal relationships. There is evidence that the underlying fundamentals for their business cycles are not synchronised (Granville and Hussain, 2017; Bagnai et al., 2017).

The two main challenges in the initial stage of the monetary union were to establish the credibility of the institution and set up a consistent approach to conduct MP. These challenges re-emerge at the time of crisis and are still worthy of further scrutiny. A number of tools have been used to deal with the above challenges. Most importantly, price stability has become the main measurement of a bank's accountability. From the very beginning, the ECB emphasised the importance of communicating policy and the economic reasoning behind its actions. The main publicity event has become the press conference held by the president and vice-president immediately right after the governing council meeting.

The underlying premise for the forthcoming chapters is the ECB's primary mandate, namely medium price stability for the EA, which is implied to be 2–5 years according to Trichet (2003): 'monetary policy needs to focus on the period covering the whole transmission process'. The price stability mandate was further reinforced by the ECB introducing an explicit forward guidance on the future paths of interest rates in July 2013.

The price stability target is applied to a collection of historically different countries, which motivates these chapters to investigate whether the MP transmission channel has the same effects across Europe and over time.

Chapter 2

Effects of unconventional monetary policy (UMP) on disaggregated consumers' inflation expectations in the euro area (EA)

Since 1999, the ECB has overseen the implementation of the EMU, which is composed of a group of economies that are culturally, historically, and demographically heterogeneous. This study analyses one of the channels of MP transmission, which runs through forming consumer expectations of future prices.

The ability of EA member countries to withstand negative macroeconomic shocks such as the global financial crisis in 2007 and European sovereign debt crisis was identified as a major barrier to the success of the monetary union from its initiation. In particular, the responses of inflation expectations are relevant to changing the real interest rate during the ZLB period.

The inflation expectation transmission channel is particularly relevant during periods of UMP. For instance, as shown by D'Acunto et al. (2017), inflation expectations are closely linked to willingness to spend; yet, they substantially vary across demographics. Furthermore, the seminal study by Mankiw and Reis (2002) highlighted the uneven information dissemination across the population. Inattentive consumers explain the sluggishness in the responses of consumption to an income shock (Reis, 2006).

Central banks' communication has changed dramatically in the past two decades (Gürkaynak et al., 2005; Haldane and McMahon, 2018). Therefore, studying consumers' inflation expectations is necessary for understanding the propagation of MP shocks to consumption, especially during a period of UMP. Moreover, Koop et al. (2009) found evidence that the MP transmission channel changes over time—even during periods of conventional MP.

The contribution of this study is twofold: it finds declining heterogeneity in the responses of consumers' inflation expectations in the EA and it includes the period of the financial crisis in the sample to assess the effectiveness of UMP in the post-2012 period. Additionally, this study focuses on disaggregated consumer expectations, as opposed to market-derived expectations or professional forecasts.

Consumer expectations are preferred to the alternatives for three reasons. First, consumers' inflation expectations have less incentive to provide disingenuous information about their opinions, which are correlated with their financial decisions (Arnold et al., 2014; Armantier, Bruine de Bruin, Topa, van der Klaauw, and Zafar, Armantier et al.; Coibion et al., 2017). Second, consumer forecasts fit the Phillips curve better, as found by Coibion and Gorodnichenko (2015). Third, inflation expectation data are segmented into age categories only at the level of consumer surveys, which allows me to analyse different demographics. For the remainder of the thesis, inflation expectations refer to consumers' inflation expectations.

This study bridges a gap in the literature by exploring how the formation of inflation expectations has evolved over time at the country level and by demographic group. I investigate the MP transmission channels using consumers' inflation expectations and their variation across various demographics for 10 EA countries. Figures A.2 and A.3 illustrate the diversity of inflation expectations disaggregated by age group and country. While the inflation expectations series remained relatively stable, the inflation index, overall, dropped from 2.3 to 1.4 percent and its standard deviation rose from 0.3938 to 1.0896.

Following this introduction, Section 2 presents the methodology and covers the latest developments in incorporating inflation expectations into structural models. Section 3 describes the data and empirical analysis. Section 4 concludes and highlights the limitations and areas for further research.

2.1 Methodology

Traditionally, small VARs have been used to analyse MP (see, for instance, Christiano et al. (1999)). However, this methodology has two limitations. First, it incorporates only a small selection of macroeconomic variables. Second, omitted variables can lead to bias. Bernanke et al. (2005) (BBE) outlined the issue of econometricians using a smaller dataset than the one used by MP authorities. BBE argued that this may lead to structural shocks being misspecified because MP reacts to variables that are omitted from small models. Benati and Surico (2009) made a case for MP's contribution to the period of the Great Moderation and concluded that omitted variable bias may be present in the VAR estimates of the impact of an MP shock.

The problem with omitted variable bias, also noted in the literature as 'non-fundamentalness' Sargent and Hansen (1981); Lippi and Reichlin (1994); Canova and Hamidi Sahneh (2017), is particularly acute in the context of estimating the effects of a structural MP shock on inflation expectations. This is because the adopted methodology should be able to accommodate the key macroeconomic variables as well as variables representing inflation expectations. Section 2.3.3 demonstrates the failure of small VARs with zero restrictions and sign restrictions to identify shocks precisely. Therefore, an empirical model should be able to fulfil two requirements. First, as numerous variables are necessary to estimate a disaggregated series of inflation expectations, researchers can stay doubtful about the formation of inflation expectations. Second, the empirical model should be able to capture the time variation of inflation expectations to test the hypothesis that the formation of inflation expectations has changed in the past two decades.

It is difficult to justify a constant relationship between inflation expectations and inflation given that the sample from 1990Q1 to 2017Q4 includes the global financial and sovereign debt crises. Factor-augmented VAR (FAVAR) with time-varying coefficients and stochastic volatility meets the above criteria because it can address both issues, namely the number of variables and changing inflation expectations. Furthermore, this methodology can estimate disaggregated series in a unified framework.

In the seminal paper that outlined the limitations of small VARs, BBE introduced a FAVAR model that summarises the dynamics of a large dataset into a smaller number of common factors. Building on BBE, Baumeister et al. (2013) (BLM) proposed a time-varying version of the FAVAR model that incorporates all the necessary components for estimating the MP transmission channels. This model can handle large numbers of variables, includes observed factors, and allows the coefficients to vary over time.

Since the introduction of methodologies that can handle large datasets, the literature on MP transmission channels has used them to include disaggregated series. For example, in the case of inflation, researchers have included breakdowns of the widest available Consumer Price Index (CPI) data. In this vein, Altissimo et al. (2009) used a dynamic factor model to examine the period from 1985 to 2005 with 404 CPI indices in the United States.

BLM estimated the effects of MP on disaggregated price dynamics using the FAVAR model, taking 138 US series from 1975Q1 to 2008Q1. They reported the price puzzle to be present only for some of the series, diminishing gradually after the 1980s. BLM's findings coincide with those of the decline of the real effects of MP surprises at the aggregate level. Studies adopting FAVAR methodologies mostly concentrate on US data, such as Bernanke et al. (2005); Favero et al. (2005); Stock and Watson (2005). Among those studies focusing on European data are McCallum and Smets (2007); Eickmeier (2009); Galariotis et al. (2018). Bils and Klenow (2004) also found that the frequency of price changes varies significantly across different type of goods. They compared data with the results of sticky price models to find that actual inflation rates are more volatile and short-lived. Balke and Wynne (2007) estimated the disaggregated producer price index (PPI) response to an MP shock, which has a significant relative price response. Similarly, Clark (2006) found the average persistence of disaggregated prices to be lower than the persistence of aggregate inflation in the United States for 1984-2002.

Altissimo et al. (2009) aggregated 404 sub-indices of inflation in the EA to examine the dynamics of inflation persistence. They found that idiosyncratic shocks explain most of the variance of sectoral prices. However, one common factor was found to be the main driver of aggregate dynamics. Additionally, they found that the slow propagation of MP shocks on the prices of services explains persistence in aggregate series. Boivin et al. (2009) found that disaggregated prices respond quickly to sector-specific shocks, whereas aggregate shocks produce effects only in the medium to long run. Boivin et al. (2008) estimated an EA-wide structural model. Lastrapes (2006) and Balke and Wynne (2007) demonstrated that money supply shocks have long-run effects on the commodity price distribution.

De Graeve and Walentin (2015) considered sectoral pricing behaviour and estimated a dynamic factor model to find that both the variance and the persistence of inflation are driven by aggregate and sector-specific shocks. Bianchi and Civelli (2015) investigated the globalisation hypothesis, pinning down inflation stability using a time-varying parameter VAR. They found that the contribution of the global effect has increased over time in some countries' inflation, but that this cannot explain recent inflation dynamics.

There are, however, some criticisms of the FAVAR methodology. Boivin and Ng (2006) criticised rich data models and showed that including too many variables in a factor model can distort the factor estimates. The justification for a large model in this study is based on the assumption that consumers form their inflation expectations by observing the policy rate and extracting information from a number of key published macroeconomic and financial variables. Boivin and Ng (2006) developed a test for the identification of a number of factors, which I discuss further in the empirical application.

Most studies adopting this methodology rely on US data (Bernanke et al., 2005; Favero et al., 2005; Boivin et al., 2009). The literature on the implementation of FAVAR models in the European Union (EU) is scarcer than in the United States. For instance, Galariotis et al. (2018) estimated the effects of conventional MP and UMP using FAVAR and two alternative models. They found a weaker effect of both MPs on peripheral EA countries compared with the core group. This chapter also incorporates time variation into the model to account for the ZLB period and possible structural change in the MP transmission channel.

The recent literature has also taken advantage of time-varying models. Variation over time is used both in time-varying factor loadings and in time-varying factor dynamics. Del Negro and Otrok (2008) introduced a model incorporating time-varying factor loadings and stochastic volatility. Mumtaz and Surico (2012) estimated time-varying factor dynamics to analyse changes in the common components of inflation in the industrialised world. Baumeister et al. (2013) provided another example of the implementation of time-varying factor dynamics into a model.

2.1.1 A time-varying FAVAR model with stochastic volatility

The model is estimated using Bayesian methods. Appendix A.1.1 describes the estimation and demonstrates the numerical methods. In this section, I highlight a few of these details.

FAVAR models incorporate extra information into traditional VAR models by assuming that a number of factors (fewer than the number of variables) capture most of the co-movement of the series. Furthermore, recent extensions of these models incorporate time variation within the coefficients and stochastic volatility. Baumeister et al. (2013) and Ellis et al. (2014) described the methodology of time-varying parameter FAVAR with stochastic volatility. The considered model has the following form:

$$X_{i,t} = \Gamma_i Z_t + e_{i,t} \tag{2.1}$$

$$Z_t = \phi_{1,t} Z_{t-1} + \phi_{2,t} Z_{t-2} + ... + \phi_{L,t} Z_{t-L} + v_t \tag{2.2}$$

where $X_{i,t}$ is a panel of N variables over the T time horizon; $Z_t = F_t^1, ..., F_t^j, R_t$ is a matrix that includes j latent factors that summarise the co-movement of the variables of interest and an observed factor R_t; $e_{i,t}$ are idiosyncratic components with variance/covariance diagonal matrix $\mathbb{E}[e_{i,t}^{'} e_{i,t}] = \Sigma$; and Γ_i is a vector of the factor loadings. A model that incorporates a large amount of information is less likely to suffer from omitted variable bias.

Since this study focuses on examining the impulse responses of consumer expectations over time, the model is extended using time-varying coefficients and stochastic volatility. Time variation allows for changes in the dynamics of shock propagation coming from changes in consumer behaviour. Stochastic volatility incorporates the variation in the volatility of the underlying series.

In the recent literature, time variation has been applied to both factor loadings and factor dynamics. Del Negro and Otrok (2008) studied changes in the international business cycle and were the first to incorporate time-varying factor loadings and stochastic volatility. They found a decline in volatility in 19 countries. Mumtaz and Surico (2012) applied a dynamic factor model with time variation in the dynamics of the factors to study the evolution of common and country-specific inflation components. The time-varying FAVAR model estimated in this work is closely related to that of Del Negro and Otrok (2008), Mumtaz and Surico (2012) and Baumeister et al. (2013). Equation (2.1) of the time-varying FAVAR model can be written as follows:

$$\begin{pmatrix} X_{1,t} \\ \vdots \\ X_{N,t} \\ R_t \end{pmatrix} = \begin{pmatrix} \Lambda^{11} & \cdots & \Lambda^{1j} & \Psi^{11} \\ \vdots & \cdots & \vdots & \vdots \\ \Lambda^{N1} & \cdots & \Lambda^{Nj} & \Psi^{N1} \\ 0 & \cdots & 0 & 1 \end{pmatrix} \begin{pmatrix} F_{1,t} \\ \vdots \\ F_{N,t} \\ R_t \end{pmatrix} + \begin{pmatrix} e_{1,t} \\ \vdots \\ e_{N,t} \\ 0 \end{pmatrix} \tag{2.3}$$

where Λ are the factor loadings and Ψ are the loadings on the observed variable. The structure of the loadings matrix allows for observed variables to be loaded, and Equation (2.2) then has the following form:

$$Z_t = \sum_{l=1}^{L} \phi_{l,t} Z_{t-l} + v_t \tag{2.4}$$

where Z_t is $F_t^1, F_t^2, ..., F_t^j, R_t$ and L is the lag length. I adopt the number of lags $L = 2$ following the works of Cogley and Sargent (2005) and Primiceri (2005). The law of motion for $\phi_t = \phi_{t-1} + \eta_t$ and innovation for $VAR(v_t) \equiv \Omega_t = A_t^{-1} H_t (A_t^{-1})'$, where H_t and A_t evolve as random walks.

Two alternative specifications can be used to implement time variation. Del Negro and Otrok (2008) allowed for time variation in factor loadings Γ and Φ. Alternatively, time variation was implemented by Mumtaz and Surico (2012) and Baumeister et al. (2013) to allow for the changing dynamic of the transition equation. This study follows the latter approach. Time-varying factor loadings imply time-invariant coefficients in the transition equation, which determines the dynamics between the state of the economy and policy rate. This assumption would be highly implausible with the sample that covers the 2007–08 crisis and sovereign debt crisis. On the contrary, the time-varying dynamics of the factors have the flexibility to allow for structural breaks in the factor dynamics.

MCMC methods

I estimate the joint posterior density of the parameters of interest by sampling iteratively from the conditional densities using the Markov chain Monte Carlo (MCMC) method. The model is estimated using Bayesian methods (see Appendix A.1.1 for the details on the algorithms). After discarding the first 100,000 iterations, the results presented in Figure 8 are based on 1000 iterations of Gibbs' sampling algorithm. Evidence of convergence is presented in the Appendix Figure (A.1). The model is estimated using the Bayesian methods described in Kim and Nelson (1999).

The MCMC algorithm has the following steps:

1. Set the priors and starting values (described in Appendix A.1.1).
2. Conditional on the factors, Z and observed variables, X, sample the factor loadings Γ.
3. Conditional on the factors, Z and factor loadings, Γ, sample the variance of the error terms of the observation equation, Σ from the IW distribution.
4. Conditional on the factors, Z and error covariance, obtain the VAR coefficients in the transition equation using the Carter-Kohn algorithm ϕ.
5. Conditional on the factors, Z and VAR coefficients, ϕ, sample the error covariance following Cogley and Sargent (2005): the diagonal elements of the VAR covariance matrix are sampled using the methods described in Jacquier et al. (2002).
6. Given the factor loadings, Γ, error covariance matrix in observation equation, Σ, VAR coefficients in the transition equation, and error covariance matrix in the transition equation, Ω, obtain the factors using the Carter–Kohn algorithm. Given Γ and Z_t, draw R.

Iterate steps 2 to 6 M times. When M and M_0 are sufficiently large but $M > M_0$, the marginal posterior distribution of each parameter can be approximately obtained from the last $(M - M_0)$ iterations.

2.1.2 Identification

Following the methodology proposed by Uhlig (2005), restrictions are imposed on the contemporaneous response of the three observed variables following Ellis et al. (2014). Tightening MP is identified as an increase in the interest rate, but a decrease in output and inflation:

$$
\begin{aligned}
(IRF)^{Y}_{(t,h=0)} &< 0 \\
(IRF)^{\pi}_{(t,h=0)} &< 0 \\
(IRF)^{\text{MPR}}_{(t,h=0)} &> 0
\end{aligned}
$$

I calculate the impulse responses of factors Γ_i to monetary shock R_t. The normalisation of the shock implies a change in the shadow rate by 100 basis points. As a robustness check, this study also follows the recursive identification of Bernanke and Blinder (1992); Bernanke et al. (2005); Baumeister et al. (2013), with the MP variable ordered last. The Cholesky identification achieves similar structural responses in inflation expectations, yet is more sensitive to the selection of lags and factors.

Following BBE, the factors are identified by fixing a $K \times K$ block of Δ^f as an identity matrix, and the upper $K \times 1$ block of Ψ^R is zero.

The impulse responses are calculated according to Koop et al. (1996, p. 122) and Fry and Pagan (2011, p. 950):

$$(IRF)^Z_{t,h} = \mathbb{E}[Z_{t+h}|\omega_t, Z^{t-1}, \mu_{MP}] - \mathbb{E}[Z_{t+h}|\omega_t, Z^{t-1}] \tag{2.5}$$

where ω_t represent all the parameters in the model and μ_{MP} is the MP shock. This approach is aimed at obtaining a single value θ, which denotes a single IRF and minimises the criterion in Fry et al. (2005). The procedure, also known as median target method (MT), chooses such $\theta^{(k)}$ that the impulse response is closest to the median response. The algorithm proceeds as follows:

- Obtain impulse response function for a set of models (100) that satisfies sign restrictions. Obtain this for each time period in the case of the time-varying model.
- The standardised impulse responses are stored in a vector $\phi^{(l)}$ for each value $\theta^{(l)}$.
- Choose l such that $MT = \phi^{(l)'}\phi^{(l)}$ and use that l to calculate the impulse responses.

2.2 Data and Empirical Analysis

2.2.1 Data

To have a balanced panel, I restrict the sample of inflation expectations to 10 EA countries (Belgium, Germany, Greece, Spain, France, Italy, the Netherlands, Austria, Portugal, and Finland). Following Bańbura et al. (2015), I extend the dataset using the Area Wide Model dataset for the EA (Fagan et al., 2005). These extensions allow me to use the period from 1990q1 to 2000q1 as a training sample to set up the priors, as in Baumeister et al. (2013) and Ellis et al. (2014). Table A.1 in the Appendix lists the macroeconomic variables. The results of the alternative specification that follows the dataset of BBE, with a shorter sample from 2000Q1 and 148 variables, are comparable to the baseline results presented in the next section.

Following Galariotis et al. (2018), I use the shadow rate of Wu and Xia (2017) for Europe (see also the shadow rate for the United States Wu and Xia (2016)) as a proxy for the MP stance. The data span from 1990q1 to 2017Q4. This period was chosen to maximise the number of observations for the selected countries. Several countries were not included because of a large number of missing observations. Note that the shadow rate of Wu and Xia (2017) for Euro Area is constructed based on a term structure model, exploiting the non-binding zero lower bound for the long term bonds. This methodology might not continue to be an effective policy rate tool when the term structure flattens further.

2.2.2 Quantifying survey data on inflation expectations

The data on consumer surveys in the EA are provided by the European Commission (EC). Unlike data from the Survey of Professional Forecasters, EC data do not contain point estimates and only present the proportions of the respondents making an open interval statement (prices would: increase more rapidly, increase at the same rate, increase at a slower rate, stay about the same, or fall).

There are ways to quantify the qualitative data from surveys on inflation expectations. The main two methodologies, which provide the point estimates of expected inflation, are the probability (Carlson and Parkin, 1975) and regression approaches (Pesaran, 1985, 1987). Furthermore, there extensions to the above approaches, notably, the correlation approach was proposed by Batchelor (1982). For the literature review of the above methodologies see Smith and McAleer (1995) and Batchelor (2009). Based on the forecast root mean square error, they concluded that a regression approach is preferable for all variables, except for prices for which the probability approach was superior. However, the results of the above approaches require strong assumptions about perceived inflation (i.e. what inflation consumers have observed in the past 12 months) to answer the survey question. Therefore, in this article I consider the simplified balance statistic to avoid making additional assumptions while maintaining interpretability of the inflation expectations measure.

To avoid making these assumptions, I consider the balance statistic presented in the EC dataset:

$$Balance = PP + P/2 - M/2 - MM$$

where PP, P, M, and MM are the answers regarding inflation increasing more rapidly, increasing at the same rate, staying about the same, and falling, respectively. Additionally, I derive a simplified balance, which is the sum between the proportions of consumers expecting prices to rise:

$$InflationExpectations = PP + P$$

This simplification allows the impulse responses of this variable to be interpreted more easily. For instance, a positive (negative) value of 10 would imply that an additional 10% of consumers expect prices to rise (fall) in the next 12 months. Here, I follow the balance statistic in the EC survey to interpret the 'stay the same' answer with a negative connotation.

For a further discussion, it is useful to distinguish two terms: price perception and price expectations. The former is understood as being backward-looking and underlines the ability to see past price changes effectively, while the latter are forward-looking, describing consumers' predictions of price level changes (Fuhrer and Moore, 1995; Malmendier and Nagel, 2015). This provides evidence that forming inflation expectations depends on the inflation the individual has observed in his/her lifetime. Malmendier and Nagel (2011) similarly found a link between observed stock market performance during the lifetime of the individual and his/her risk-taking activity.

However, these expectations are not always rational; beliefs may deviate from rationality, as shown by Fuster et al. (2010). These authors introduced the notion of natural expectations, which are defined as the weighted average of rational and intuitive expectations. Survey experiments suggest that rational inattention may be an important source of information frictions (Cavallo et al., 2017). They also show that even in the presence of accurate information, agents place significant weight on inaccurate sources of information. In addition, inflation expectations seem to vary by demographic group and education level (Inoue, Kilian, and Kiraz, Inoue et al.; Madeira and Zafar, 2015).

Figure A.3 illustrates the simplified balance statistic for the group of 10 EA countries. For the remainder of the thesis, I adopt a simplified balance to measure inflation expectations, hereafter referred to as balance or inflation expectations. This figure illustrates the heterogeneity among the four age groups, which dips, to some degree, during the financial crisis and returns to the pre-2008 level after 2012.

Table 2.1: Summary statistics of consumers' inflation expectations

	DE		ES		FR		IT	
	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.
Pre-EMU	71	4.6	63.1	4.1	38.1	3.1	43.6	7.4
Post-EMU	58.9	7.7	62.1	4.3	59.8	6.2	41.4	8.9
Post-crisis	48.4	6.3	42.7	4.7	56.7	5.6	27.8	3.7

Note: Pre-EMU sample 1993q1–1998q4; Post-EMU sample 2002q1–2008q2 following (Ehrmann et al., 2011); Post-sovereign debt crisis sample 2012q2–2017q4 following (Lane, 2012).

There is suggestive evidence that personal experiences determine the dynamics of inflation expectations. The literature provides two major explanations.

First, studies address inflation expectations based on the inflation individuals have observed throughout their lifetime. Second, the literature sees media coverage as the source of imperfect inflation expectation updating. However, it has been unable to distinguish between the two. Lamla and Lein (2014) showed empirically that the amount and tone of media coverage affect inflation expectations. Badarinza and Buchmann (2009) assessed the degree of heterogeneity of consumers' inflation perceptions and expectations in the EA. Coibion et al. (2017) presented evidence that firms update their inflation expectations in a Bayesian manner.

2.3 Empirical Results

2.3.1 Aggregate responses to an MP shock

Before moving to the inflation expectations by demographic group, it is informative to examine the aggregate responses of EA macroeconomic variables to an MP shock. The responses of gross domestic product (GDP), inflation, and unemployment have received the most attention in previous studies and are useful to compare the performance of the model.

Figure 2.1 displays the estimated impulse responses of the level of aggregate real activity measures, consumer prices, number of unemployed, and inflation expectations to an MP contraction. The left panels of the figure show the median responses in each quarter over 2000Q1–2017Q4. The two middle panels compare the responses at the beginning and end of the sample, as representative dates. The last column considers the relative importance of time variation in the impulse responses following the approach proposed by Cogley et al. (2010) and Baumeister et al. (2013).

The last panel plots the joint posterior distribution of the accumulated responses at the one-year horizon with the values for 2000Q1 plotted on the x-axis and those for 2017Q4 on the y-axis. Shifts in the distribution relative to the horizontal line indicate a systematic change over time Baumeister et al. (2013). Figure A.4 displays the impulse response functions (IRFs) with no accumulation over time.

Figure 2.1 shows that a 100 basis points increase in the EA shadow rate reduces the growth rate of GDP at market prices by around 1.2% at a horizon of two years in more recent times, which is about half the magnitude relative to the first half of the sample (2%). The second row of Figure 3 displays the responses of consumer prices. After an unexpected positive MP shock, the price level falls by around 1.7% in the long run during the 2000s, while it currently levels off at 1.1% below the baseline. The evolution of the unemployment rate

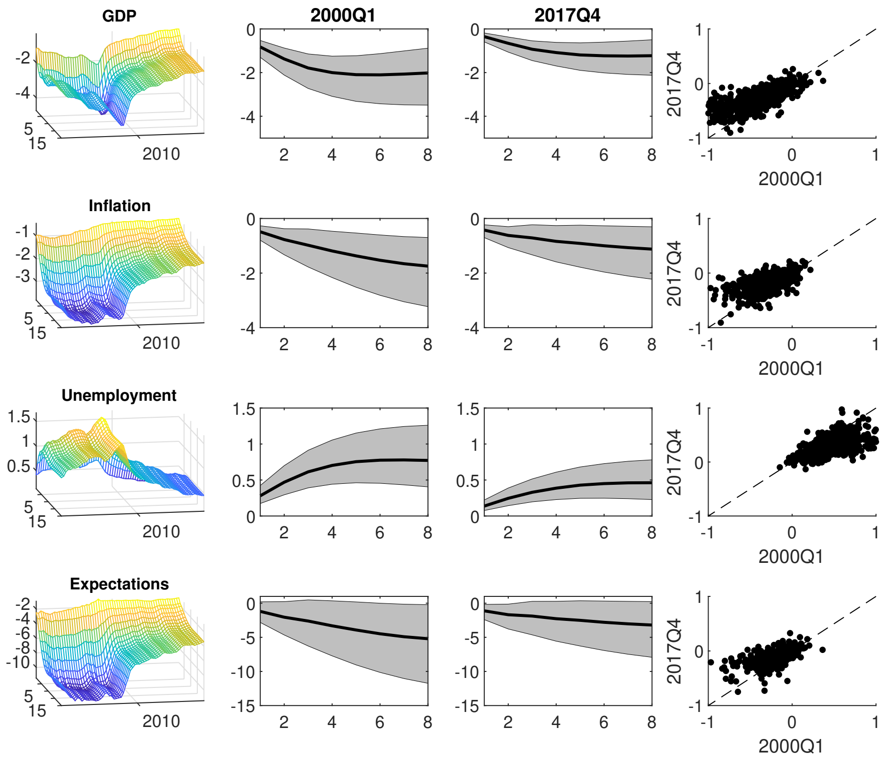

Figure 2.1: Accumulated impulse responses of GDP, inflation, unemployment, and inflation expectations.

Note: Time-varying median IRFs of selected aggregate variables at each point in time (first column) and in 2000Q1 and 2017Q4 (second and third columns) with the 16*th* and 84*th* percentiles (shaded areas) to a 100 basis point shock to a shadow rate and joint distribution of the accumulated responses one year after the MP shock in 2000Q1 and 2017Q4 (fourth column). IRF horizon in quarters (x-axis); Time period (y-axis); Percentage point (z-axis).

responses shows time variation too, decreasing from 0.7% to 0.4%. Inflation expectations exhibit a similar shift after 2010, dropping from 5% decrease in respondents expecting a higher inflation in the next 12 months, to a drop of 3%. The difference in responses is more striking at a three-year horizon, with a drop from 10.8% to 3.4% throughout the sample.

The last column of Figure 2.1 indicates that the milder reaction of real GDP, unemployment, and inflation expectations in more recent times is a non-negligible feature at the four-quarter horizon since at least 75% of the joint distribution lies above the 45-degree line for all measures (except for the unemployment, which lies below because of the positive response to MP shock).

Owing to the large uncertainty around the median estimates, evidence of time variation is less clear-cut for the longer horizon.

The alternative specification with the Cholesky identification of the shocks supports the analysis of Castelnuovo and Surico (2010), who argued that the price puzzle in structural VARs may be a symptom of omitted variable bias that may arise when the Taylor principle is violated. In particular, they showed that when the economy is operating under indeterminacy, an additional unobserved variable characterises the dynamics of the economy. The factors included in our model summarise a large amount of information that may proxy for this latent variable. The fact that the price puzzle is absent from the alternative Cholesky identification throughout the sample lends support to this idea (Bernanke et al., 2005).

2.3.2 Disaggregated responses to an MP shock

Figure 2.2 demonstrates the accumulated responses of inflation expectations disaggregated by demographic group. The first row depicts the responses of the four age groups regarding their inflation expectations. The responses are not restricted by the identification strategy. The specification with the disaggregated age groups exhibits similar behaviour to a price puzzle, with an initial increase in the level of consumers that expect prices to rise, levelling off after the one-year horizon. The median responses retain the same order as the corresponding age groups, with younger demographics showing the weakest response.

The median impulse responses in the second row of Figure 2.2 capture the individual components of inflation expectations by income group after a contractionary MP shock of 100 basis points at our two representative points in time: 2000Q1 and 2017Q4. The behaviour of these responses is in line with the aggregate measure of inflation expectations from Figure 2.1. The long-run response is lower in 2017q4 and the order of the income quartiles is maintained in the level of responses: the lowest quartile income group exhibiting the lowest updating of inflation expectations. The last row in Figure 2.2 captures a similar dynamic within the education groups, with the lowest education group having the lowest level of inflation expectation updating. To test the significance of the differences of inflation expectations across groups, I augment the MCMC algorithm to record these differences at each of 1000 iteration after the discarding the first $100,000$. The credible sets of IRFs of the differences across demographic groups always include zero.

While the disaggregated series for inflation expectations do not exhibit clear-cut heterogeneity within the demographic groups, the time variation of IRFs

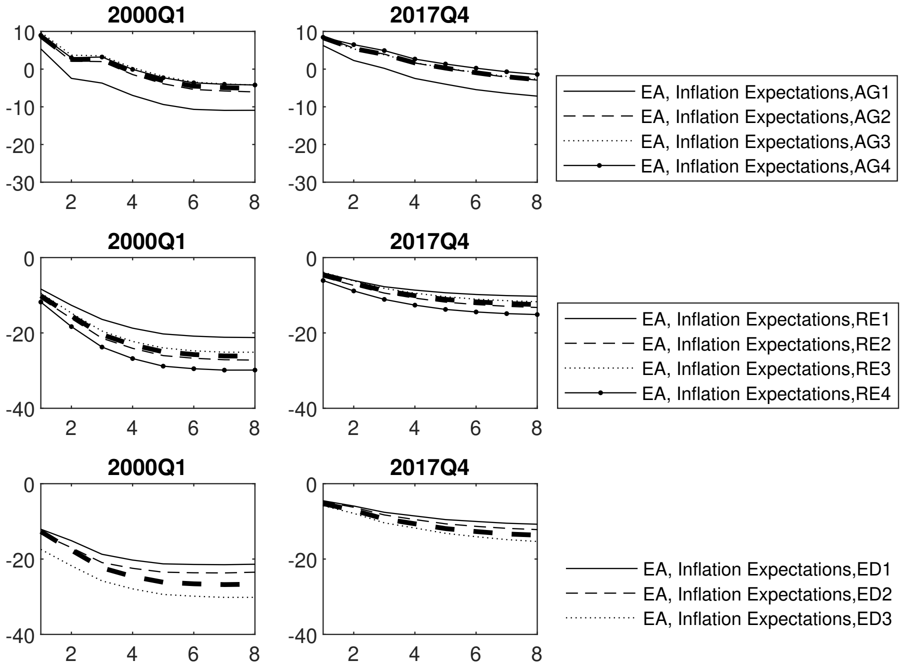

Figure 2.2: Accumulated impulse responses of inflation expectations by demographic group.

Note: Accumulated IRFs at the disaggregated level. The first row contains the specifications with expectations by age group (16–29, 30–49, 50–64, and 65+ years, respectively). The second row contains the specifications with expectations by income group (first, second, third, and fourth quartiles, respectively). The third row contains the specifications with expectations by education group (primary, secondary, and further education, respectively).

shows a consolidating trend among all the specifications. There is a general trend among the sampled countries of the increasing persistence of inflation expectation responses from 2012. This outcome is in line with Coibion and Gorodnichenko's (2015) earlier findings, who argued that the relative stability of inflation expectations has kept inflation stable since 2012.

The procedure that finds IRFs is aimed at obtaining the responses of variables caused by an unanticipated monetary policy shock. The distinction should be made between this theoretically unanticipated shock and shocks due to announcements or unanticipated implementation changes. In order to empirically separate the effects of different kinds of shocks, further research might consider different identification strategy (i.e. proxy identification).

2.3.3 VAR performance

The literature on the MP transmission channel often relies on the VAR methodology. Therefore, it is instructive to demonstrate the performance of VAR using the EA sample with popular identifications. Figure 2.3 presents the results for the VAR estimation with $[Y_t, \pi_t, I_t]$ identified with the recursive scheme, the augmented recursive scheme with the inflation expectations variable, following the order Castelnuovo and Surico (2010) with $[\mathbb{E}[\pi_{t+1}], Y_t, \pi_t, I_t]$, and the sign restrictions in the third column. The contemporaneous zero restriction pre-

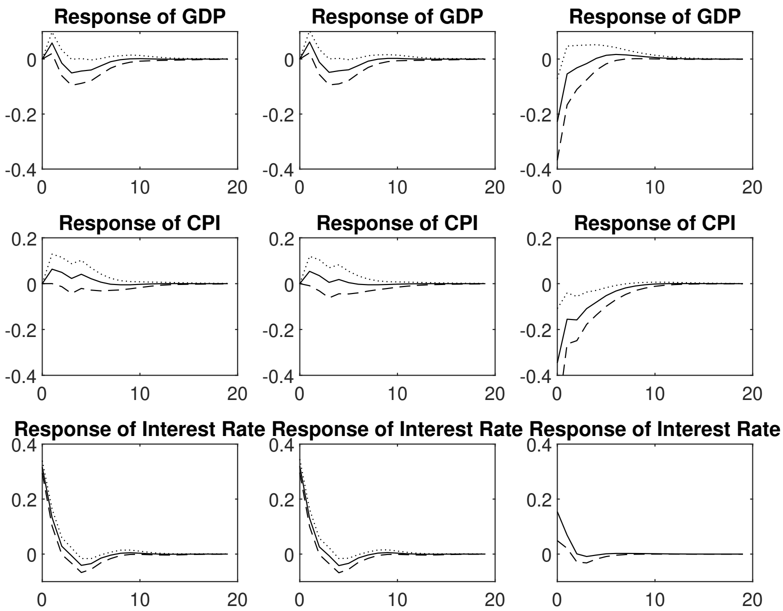

Figure 2.3: IRFs from the VARs with zero and sign restrictions.

Note: The first column contains the IRF from the VAR with four lags and three variables with the Cholesky identification, ordered GDP, CPI, and interest rate; the second column contains the IRF from the VAR with four lags and four variables with the Cholesky identification, ordered inflation expectations, GDP, CPI, and interest rate; and the third column contains the IRF from the VAR with four lags and three variables with the contemporaneous sign restrictions, GDP (-), CPI (-), and interest rate (+).

sented in the first column exhibits a price puzzle, as in much of the literature. The second column presents similar results to those in the first column, and the forward-looking inflation expectations variable does not change the responses, as in Castelnuovo and Surico (2010). Finally, the last column shows that the IRFs with sign restrictions exhibit the correct responses despite them being endogenously imposed.

2.3.4 Determinants of cross-country asymmetries in MP transmission

Following Carlino and DeFina (1999), this section tests whether the empirical findings of the asymmetric responses among EA members (Figure A.11) could be explained by the variables capturing industry structure and labor market rigidities. To account for the fact that the dependent variable is an estimated value itself, I follow the procedure suggested by Hong and Li (2017, p. 161) and use Ordinary Least Squares with heteroskedasticity robust standard errors to estimate the following regression:

$$\begin{aligned}\hat{I}_{i,t}^{h=8} =& \alpha + \gamma_1 * manufacturing_{i,t} + \gamma_2 * protection_{i,t} \\ &+ \gamma_3 * union_{i,t} + FE_{time} + \varepsilon_{i,t}\end{aligned} \tag{2.6}$$

Recent discussions of MP propagation in the EA has used the industry structure, labour, and wage rigidities to explain the variation in the output responses to a monetary shock Georgiadis (2015). These analyses broadly conclude that the lower share of manufacturing, higher level of unemployment protection, and lower level of unionisation somewhat mitigate the responses of output. The variables capturing manufacturing share and the number of small firms are measured based on the number of employees, as opposed to total value-added or gross product as in Carlino and DeFina (1999); Georgiadis (2015), because the dependent variable in this analysis is inflation expectations and it is measured by the ratio of consumer expecting inflation to go up.

Figure 2.4 presents the structure of industries in terms of firm size (measured by the number of employees). There is a high proportion of small firms (i.e. those with fewer than nine employees). Notably, the construction sector, which is largely represented by smaller firms, is argued to be sensitive to the credit channel of MP.

The regression results of Equation (2.6) in Table 2.2 suggest that more than 40% of the variation in inflation expectation responses could be explained by the industry and labour market composition of EA countries. The key determinants are the share of manufacturing and level of unemployment protection. The signs of the estimated coefficients go in line with the findings in the literature Carlino and DeFina (1999); Georgiadis (2014, 2015).

Recall that the responses of inflation expectations are negative to a positive MP shock, with the negative value for manufacturing suggesting a stronger response to such a shock. Similarly, in Table 2.2 columns 1 and 2 unemployment protection and union density have a significant positive sign, which impedes the response of inflation expectations in line with earlier findings (Georgiadis, 2015). Following Carlino and DeFina (1999), columns 3 and 4 test whether the number of small firms has explanatory power over the variation in responses of inflation expectations. Evidence concerning the number of small firms being a significant factor is very limited.

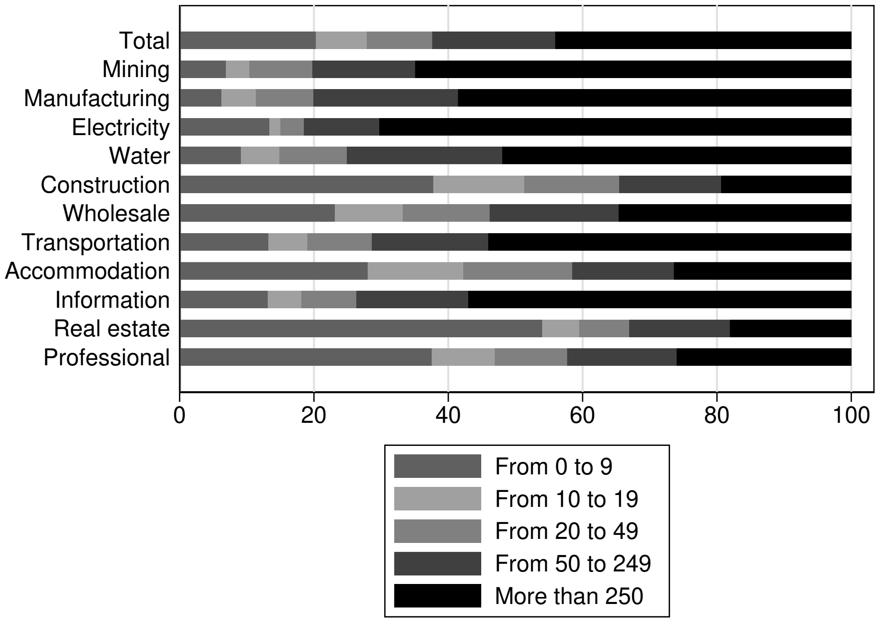

Figure 2.4: Value added by industry and number of employees.
Note: Number of employees is defined as the total number of people who work in the observation unit. Value added at factor costs is gross income from operating activities after adjusting for operating subsidies and indirect taxes. Source: Eurostat.

2.4 Conclusions

This study investigated the MP transmission channel using consumers' inflation expectations and how it varies across four demographic groups (16–29, 30–49, 50–64, and 65+ years) and 10 EA countries. This research thus bridges a gap in the literature by exploring how the formation of inflation expectations has evolved over time at both the aggregate level and by demographic group.

I find heterogeneity in the responses of disaggregated consumers' inflation expectations in the EA based on a time-varying FAVAR model. The results indicate some heterogeneity in the responses of different age groups to an EA-wide MP shock, although not significant for most of the countries. Younger agents (16–29 years) exhibit a higher level of updating inflation expectations

Table 2.2: Regression results for the determinants of the MP transmission.

	Inflation expectation responses at h=8 (2 years)			
Specification	(1)	(2)	(3)	(4)
manufacturing	-0.125*	-0.114**		
	(0.0668)	(0.0568)		
protection	1.112**	1.337***		
	(0.560)	(0.471)		
union	0.119***	0.121***		
	(0.0153)	(0.0138)		
smallfirms			0.0998	0.101*
			(0.0626)	(0.0589)
Constant	-5.420*	-7.327***	-11.32*	-10.27*
	(3.232)	(1.742)	(5.879)	(5.429)
Observations	139	139	39	39
R-squared	0.453	0.402	0.091	0.045
Time FE	YES	NO	YES	NO

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The results are based on annual data from 1999 to 2018, using a sample of eight countries: Belgium, France, Germany, Greece, Italy, the Netherlands, Portugal, and Spain. Manufacturing is presented as the ratios of total employment in each country. Protection is an index of unemployment protection recorded by the OECD. Union is the percentage of unionisation recorded by the OECD.

than older groups. Similarly, a larger share of consumers with a higher education level and higher income would update their inflation expectations. This finding concurs with those in the literature.

The key finding is that the responses of inflation expectations have weakened over time. Inflation responses after 2010, during the ZLB period, take more time to react, making them weaker on average than the responses before 2008. The dynamics of inflation expectations could therefore be a possible cause of inflation persistence in the EA.

One of the questions with which economists are concerned is the particularly subdued behaviour of inflation in the past decade in the EA Miles et al. (2017). Only a few explanations of why inflation remains anchored in a post-2010 period have been proposed. One of the explanations was proposed by Blanchard et al. (2015). They explored two issues regarding the financial crisis. First, they observed that output in advanced countries is below pre-crisis levels, which they explained with the hysteresis hypothesis. Second, they captured a flatter Phillips curve in the post-2008 period. These two facts suggest that the economies of advanced countries are not yet in a recovery regime.

Coibion and Gorodnichenko (2015) argued that the relative stability of inflation expectations has kept inflation stable since 2010. This study expands on the point of inflation expectations playing a key role in inflation dynamics in the past decade. For monetary authorities, it is crucial to know the effects of their interventions on inflation expectations. Coibion et al. (2017) further highlighted the importance of expectations by stating that 'first and most practically, we lack direct empirical evidence on the real-time beliefs of firms, those agents whose expectations play a central role in price-setting, hiring, and investment decisions'.

The determinants of the heterogeneity in the responses of inflation expectations suggest that industry structure and labour market rigidities play a significant role in the propagation mechanism of MP. The results also go in line with earlier findings suggesting that a lower share of manufacturing and higher unemployment protection and union share mitigate the effects of credit channels, which calls for further investigation.

There are a number of dimensions upon which further research can improve. First, several novel identification strategies could help pin down MP shocks more precisely. Second, there is concern over the rather small sample for the EU to estimate a model with a large number of parameters. Third, introducing a panel structure, for instance by estimating dynamic factor models with restricted factor loadings for countries, is an interesting possibility. Fourth, estimating individual countries with a smaller VAR to analyse the historical decomposition of inflation expectations might reveal which variables contribute to the formation of inflation expectations.

Chapter 3

The effect of the ECB's PSPP on the cost and perception of credit availability for SMEs

This chapter examines the MP transmission mechanism for SMEs. The analysis estimates the effect of the public sector purchase programme (PSPP), a leading instrument of the ECB's MP, on SMEs' access to credit and their perception of credit availability. The latter is assessed using the survey on the access to finance of enterprises (SAFE). The survey variables are useful to analyse the policy propagation mechanism as well as heterogeneity of policy effects (Jappelli and Pistaferri, 2014, p. 109).

The PSPP was introduced on 22 January 2015 and conducted between 9 March 2015 and 19 December 2018 to complement the EA asset purchase programme (APP), by improving borrowing conditions for households and non-financial corporations (Part 4 ECB decision 2015/774) (Andrade et al., 2016). The PSPP has by far the largest volume of assets purchased, peaking at 79 billion euros of monthly purchases (May 2016) compared with the next largest monthly purchase of 12 billion euros (March 2015) associated with the third covered bond purchase programme (CBPP3).

Given that the PSPP aims to ease borrowing conditions for non-financial corporations and households, I focus on SMEs, which account for a large proportion of employment and output in the EA, representing 99.8% of EA enterprises, 60% of turnover, and 70% of employment (ECB, 2015, p. 44).

This chapter investigates whether the restoration of liquidity in the interbank market led to an expansion in credit supply for SMEs by examining the effectiveness of the PSPP and its impact on the cost of borrowing. The APPs of the Euro system include not only the PSPP and CBPP, but also the asset-backed securities purchase programme (ABSPP) and corporate sector purchase programme (CSPP). These differ substantially in their implementation of other countries' UMP, with the exception of the PSPP. The PSPP resembles the UMP of most other countries, as it directly affects long-term borrowing costs by purchasing sovereign bonds (Andrade et al., 2016).

The contribution of this chapter is twofold. First, it presents evidence of the effect of the PSPP on lending volumes and interest rates for households and non-financial enterprises. Second, it uncovers the positive effect on the perceptions of SMEs, which evaluate the PSPP with regard to credit standards and the availability of credit.

I first discuss whether the PSPP affects the cost and volume of borrowing for households and non-financial enterprises. I then investigate whether SMEs' perceptions of these effects are accurate by analysing the SAFE. This survey is conducted semi-annually across EU SMEs to assess various aspects of credit availability, interest rates, and economic outlook. Firm-level data from the SAFE allow me to identify the loan supply effects on these enterprises.

I find a positive effect of the PSPP on the volume of small loans received by

SMEs, especially the smallest category of below 0.25 million euros, and small changes in the costs of borrowing. I estimate a fixed effects model with a panel of EU countries and obtain the following result: an increase in the PSPP's monthly net purchases of 1% of GDP of the corresponding country is associated with the volume of loans rising by 47 million for loans below 0.25 million euros and the cost of borrowing falling by 174 basis points. Evidence from the estimation with the survey variables also shows the positive effect of the PSPP for small enterprises. There is a 2.12% increase in respondents who record an interest rate decrease after a 1% of GDP increase in the PSPP's net purchases.

SMEs are particularly vulnerable to credit supply shocks (Ferrando et al., 2015). Carbo-Valverde et al. (2016) assessed the credit constraints that SMEs experienced during the credit crunch and highlighted the importance for them to access credit.

To distinguish conventional MP and UMP, this chapter adopts the following definition for the latter: UMP directly affects long-term borrowing costs by purchasing sovereign bonds (Andrade et al., 2016). This definition captures the latest monetary interventions by the Bank of England (BoE), ECB and Federal Reserve (Fed), and Bank of Japan (BoJ) since the early 2000s.

The EU was exposed to a crisis of comparable magnitude to that in the United States because of the large holdings of US asset-backed securities and dependence on the dollar supply (Lane, 2012, p. 52). The EU's position was worsened by its own credit and housing bubbles, most prominently developed in Greece, Ireland, and Spain (Lane, 2012, p. 54). These events led to shortages of liquidity and loan losses (Lane, 2012, p. 55).

Jäger and Grigoriadis (2017, p. 4) argued that three main reasons drove the high debt levels in the EU. The first was its premature assumption of the convergence of all Eurozone countries towards Germany (Arghyrou and Kontonikas, 2012, p. 670), which translated into sovereign bond spreads becoming relatively similar across EU members (Mody and Sandri, 2012, p. 2012). The second was that the adoption of a single currency focused the responsibility of anticyclical policies on national fiscal authorities (Lane, 2012, p. 54). The third was that southern European countries experienced relatively low interest rates before the crisis and became excessive net borrowers (Lane, 2012, p. 54). The original design of European treaties was supposed to mitigate excessive imbalances by establishing the Stability and Growth Pact and the 'no bailout' clause, which, consequently, proved to be insufficient (Lane, 2012, p. 49).

During the crisis, the ECB first lowered interest rates through conventional measures (Lenza et al., 2010, p. 16). It then engaged in less conventional measures, which changed the composition (qualitative easing) and size (QE) of the balance sheet (Lenza et al., 2010, p. 18). The predominant part of those unconventional measures was aimed at banks, because they are the key institutions in the credit creation process, specifically private credit (Lenza et al., 2010, p. 28).

The effect of UMP on the economic sentiment of US investors was highlighted by Lutz (2015). Similarly, one can argue that firms' investment decisions are guided by their perceptions of credit availability. For instance, Cingano et al. (2016) found evidence of the real effects of bank lending channels on Italian banks during the liquidity shortage in 2007. Banks' exposure to interbank markets explains the 40% investment decrease after 2007. Their findings suggest pre-crisis exposure to interbank markets and predict banks' subsequent credit supply. In turn, the lack of liquidity in banks is passed on to reduce lending to businesses. Ryan et al. (2014, p. 497) provided empirical evidence that the financing constraints of small enterprises explain most of the variation in the employment dynamic during the Great Recession. They also provided a link between a fall in the supply of credit and timing of UMP interventions.

Joyce et al. (2012) noted that the ECB balance sheet expansion came largely from an increase in the provision of loans, which were provided in exchange for collateral (mostly bank loans, not government bonds) contrary to the Fed, BoE, and BoJ. The PSPP thus resembles QE programmes in that it expands the balance sheet to stimulate and stabilise credit.

A body of the literature analyses other APPs in the EU. For instance, Eser and Schwaab (2016, p. 16) analysed the strong effects of purchases on the yields of the securities market program (SMP) and attributed them to reduced default risk premia, a lower liquidity risk premium, and local supply effects. Other studies such as Haitsma et al. (2016, p. 106) also find that the ECB's UMP had a significantly negative effect on the German–Italian yield spread as well as elevating returns from the EURO STOXX 50 index.

Gibson et al. (2016) analysed the SMP and CBPPs by estimating the effects on bond spreads using a fixed effects regression controlling for time and country, similar to the methodology presented in this chapter. Their results indicated that these two APPs reduced sovereign spreads and raised covered bond prices.

Finally, a large strand of the literature analyses the effects of long-term refinancing operations (LTROs). For example Crosignani et al. (2019, p. 19) concentrated on three-year LTROs and showed their significant role in alleviating liquidity and funding risks in the banking sector, which in return stimulated the economy. Moreover, LTROs appear to support the financing of the economy through QE rather than lowering the cost of financing.

Following this introduction, Section 2 describes the methodology and data on the PSPP, cost of borrowing, and perception of the availability of credit. Section 3 provides the empirical results and relevant discussions. Section 4 presents concluding remarks and the limitations of this research.

3.1 Credit Channel of Monetary Transmission

MP uses its influence over short-term interest rates to change the cost of capital. In turn, spending on durable goods such as fixed investment, housing, and inventories is affected. These changes in aggregate demand then affect the level of production. Bernanke and Gertler (1995, p. 2) argued that this 'textbook' role of the MP credit channel is incomplete, as neoclassical models have difficulty pinning down the effect of the cost of capital on aggregate spending because most explanatory power rests within the lagged values of output, sales, and cash flow.

Unanticipated MP tightening typically has only transitory effects on interest rates and is followed by a sustained decline in real GDP and prices (Bernanke and Gertler, 1995, p. 4). Final demand absorbs the initial impact of the MP contraction, falling relatively quickly after the change. The earliest and sharpest declines in final demand are related to residential investments, followed by consumer goods. Fixed business investment declines with a delay, lagging behind housing and consumer spending.

The impact of conventional MP on credit volume has been studied extensively, with notable research by Bernanke and Blinder (1992); Gertler and Gilchrist (1994); Kashyap and Stein (2000); Jiménez et al. (2012). MP rate changes may affect the credit quality of the pool of borrowers through the interest rate channel and the firm balance sheet channel of MP by changing firm investment opportunities, net worth, and collateral Bernanke and Gertler (1995). Moreover, MP, by affecting bank liquidity, may influence the volume of credit supplied through the bank balance sheet channel of MP (Kashyap and Stein, 2000, p. 420).

In early 2009 in the United States, the supply of credit in industrialized countries appeared to be tightening substantially Diamond and Rajan (2009). For example, about 65% of US banks reported having tightened lending standards on commercial and industrial loans to large and middle-market firms over the past three months, a continuation of a pattern seen in the previous quarter. This percentage was above the previous peaks reported in 1990 and 2001.

Ivashina and Scharfstein (2010, p. 320) found that new loans to large borrowers fell by 47% in the last quarter of 2008. They also showed that term lending fell by considerably more than lending to revolving credit facilities (67% vs. 27%). The use of a three-month interest rate is in line with many studies such as Angeloni and Ehrmann (2003) that also use European data.

This chapter is related to the growing literature that studies the EA economy. However, to the best of my knowledge, this is the first work to examine the PSPP and a broad set of interest rates (as well as senior loan managers' perceptions of them). Peersman and Straub (2009) also examined aspects of financial intermediation in the EA to assess the role of credit shocks but did not distinguish pre- and post-crisis developments. Other researchers have studied the monetary transmission mechanism using EA data before the crisis. In particular, the ECB promoted a set of studies providing many interesting results (see the collection of studies in Angeloni and Ehrmann (2003)).

3.2 Data

I use two datasets. The first dataset comprises the interest rates applied by monetary financial institutions (MFIs) to households and non-financial institutions. The second dataset is a survey of the availability of finance for SMEs.

3.2.1 Borrowing costs and volumes

The MFI dataset was created as a result of the ECB's regulation in 2001 and it contains interest rate data from MFIs to non-financial organisations and households. MFIs belong to the following sectors of activity: central banks, credit institutions, deposit-taking corporations, and money market funds.

The statistics on interest rates are presented as 'agreed rates', which correspond to the interest rate agreed between an MFI and its customer, averaged across the period and converted into an annualised rate. The statistic for the volume of loans is presented as loans other than revolving loans and overdrafts in millions of euros. The dataset starts in 2003m1. I estimate the effects of the PSPP from 2015m1 to 2017m3, from the beginning of its intervention to the latest available data point. More detailed data have been collected since 2010m6, which allowed me to distinguish two more sizes of loans: below 0.25 million and between 0.25 and 1 million euros.

Figure 3.1 displays the monthly business volumes of loans from 2003m1 to 2017m3. The volumes of below 0.25 million euros and between 0.25 and 1 million euros diverge from 2015. The increase in lending activity after 2007 is mainly attributed to loans larger than 1 million euros. Loans below 1 million euros remained at about the same level (below 100 billion every month). As a further analysis, I assume that loans below 1 million euros are issued to SMEs and test this assumption in Section 3.4.

Statistics on interest rates are divided into fixed and floating rates, a period of fixed interest rates, and the presence of collateral. Figure 3.2 presents the interest rate on a loan with fixed interest rates for more than one year. Other interest rates exhibit similar behaviour (see Figure A.12 in the Appendix).

The interest rates in Figure 3.2 exhibit similar behaviour to the volume of

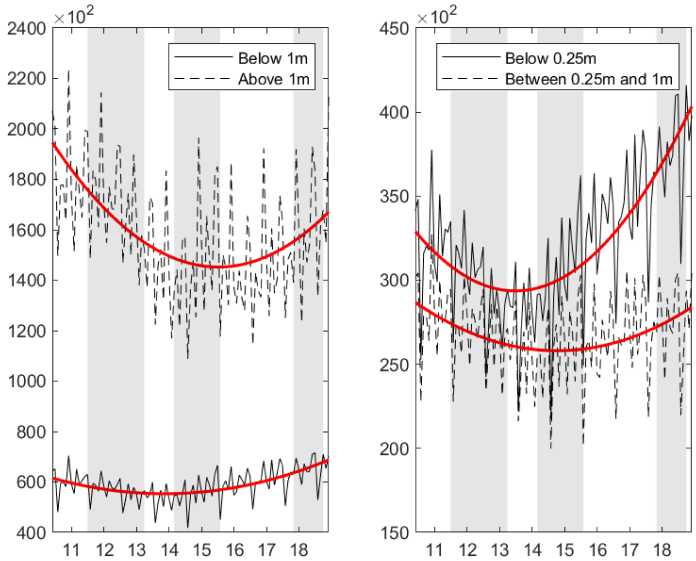

Figure 3.1: Bank business volumes: Loans to corporations of various sizes (new business).

Note: Business volume (outstanding amount/new business), Credit and other institutions (MFIs except money market funds and central banks) reporting sector - Loans other than revolving loans and overdrafts, convenience and extended credit card debt, Total initial rate fixation, New business coverage, EA (changing composition), Non-financial corporations sector, denominated in euros. The data for the 0.25 m euro breakdown are only available from 2010m6. The shaded area is the OECD-based recession indicators for Germany following the peak through the trough.

credit. The spike in 2008 is a risk premium after the financial crisis unfolded. The following fall in interest rates, until the beginning of 2010, coincides with the increased activity of open market operations.

3.2.2 Description of the survey and interventions

The SAFE is a survey of EU companies conducted by the EC and ECB every six months from June 2009 (which investigated from January to June 2009). The dataset is a pooled cross-section based on the first 15 waves of the survey. It focuses on autonomous profit-oriented enterprises capable of independent financial decisions, which represent 84.2% of the dataset. Based on the number of employees, the EC's website classifies SMEs into three groups: micro, small, and medium-sized that have fewer than 10, between 10 and 50, and between 50 and 250 employees, respectively. The SAFE dataset has an almost equal representation of each group, namely micro (35.2%), small (31.1%), and medium-sized (25.7%), with the remaining 8.5% attributed to larger firms. To differentiate

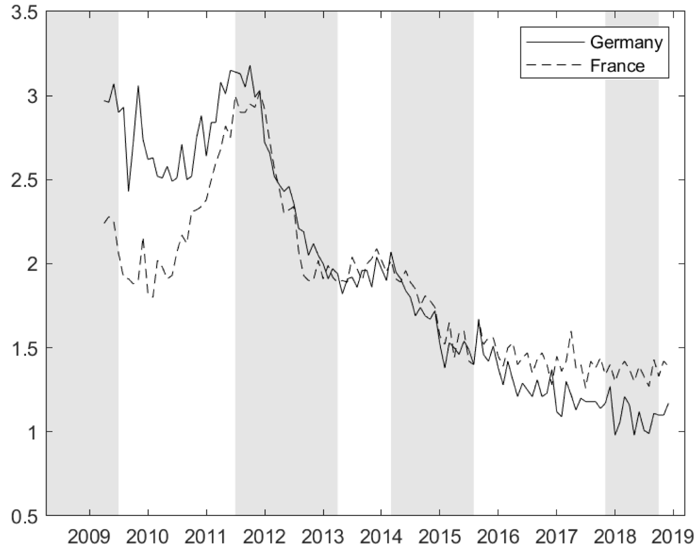

Figure 3.2: Interest rate on loans with an IRF period greater than one year.
Note: Statistics Bulletin, MFI. The shaded area is the OECD-based recession indicators for Germany following the peak through the trough.

respondents by annual turnover, the survey sets up thresholds of 2, 10, and 50 million euros. Four sectors are presented in the survey: industry (24.1%), construction (11.4%), trade (27.4%), and services (37.1%). The majority of enterprises are older than 10 years (78%).

The survey includes a number of questions, which can be used to evaluate and capture changes in the availability of finance to SMEs before and after the start of asset purchases. Participants (SMEs) were asked to assess the forms of financing available to them, interest rates at which funds could be acquired, and other credit lines available to them.

As demonstrated in Figure 3.3, the first asset purchases started under the CBPP in the first quarter of 2009, which coincides with the start of the SAFE. Another pivotal point is the first quarter of 2015, which marks the official start of the QE programme.

There are 16 waves in the survey, each corresponding to a six-month period (see Table A.5). The 16*th* wave was released in May 2017 and is the latest included in my empirical analysis. The survey timing allows for investigating 11 periods before the PSPP's intervention and five periods while it unfolded.

The PSPP started in January 2015, which falls in the middle of the 12th wave's reference period. According to the survey, in this period SMEs considered access to finance to be the least worrying problem, with only 11% mentioning it

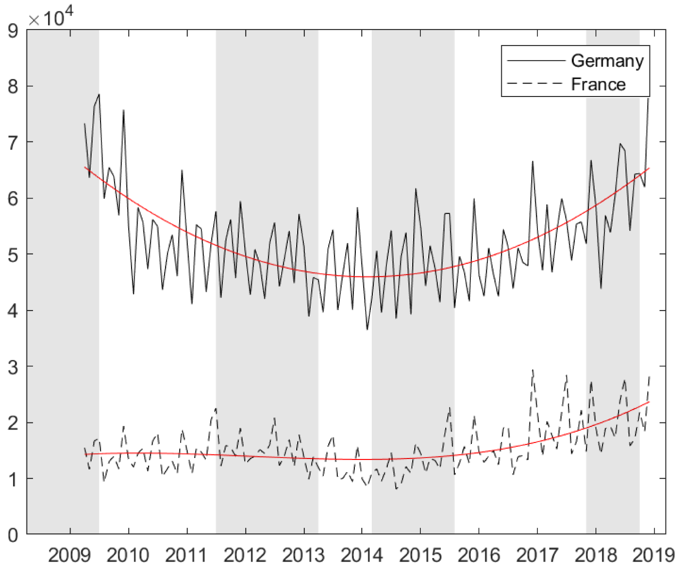

Figure 3.3: Purchases under the PSPP (flow).
Note: Fitted lines are third-order polynomials. Shaded area is OECD-based recession indicators for Germany following the peak through the trough.

as such, down from 13% in the previous period. However, 3% reported the need to access bank loans, which was a threefold increase from previous periods. This is the first time since 2009 when, on balance, an improvement in the availability of bank loans was recorded. Similarly, there was a record of perceived lower interest rates and an increase in the available size and maturity of loans.

For the empirical analysis, the survey questions were converted into dummy variables. Table A.9 describes the dummy variables and the corresponding survey questions and programme responses. Figure 3.4 presents the summary statistics for the key dummy variables, which are used as dependent variables.

3.3 Methodology

I estimate the model using a panel dataset comprising two sets of countries, namely those affected and those not affected by the PSPP (i.e. EA and non-EA countries). The panel data model is based on a two fixed effects framework (country and time fixed effects). This approach accounts for unobserved time-invariant variables, which could lead to misleading inferences about unconventional interventions. I estimate the following linear regression with the country and time fixed effects:

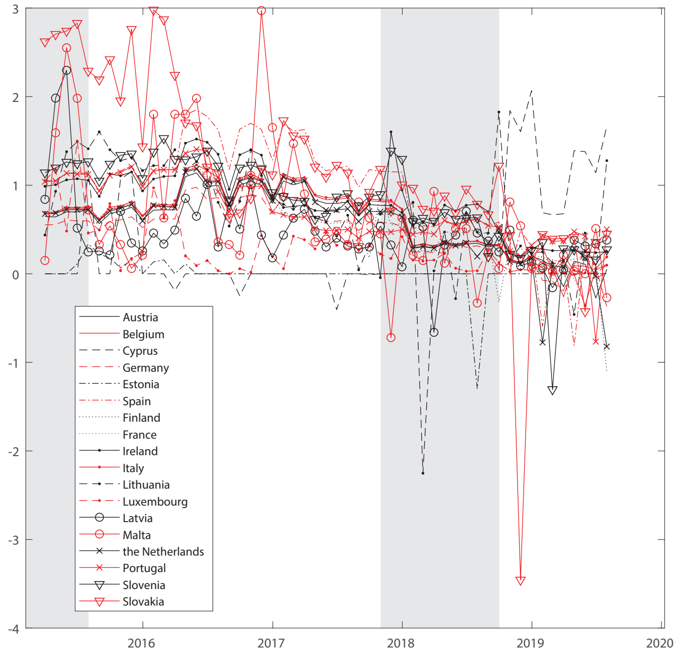

Figure 3.4: PSPP as a share of GDP.
Note: The shaded area is the OECD-based recession indicators for Germany following the peak through the trough.

$$Y_{it} = \beta X_{i,t} + \alpha_i + \gamma_t + e_{i,t}$$

where Y_{it} is the interest rate for SMEs in the first specification (Table 3.1) and a dummy variable constructed from the SAFE (Table 3.2) dataset for each country i and time period t. The survey wave spans six months, and for the last two specifications it is the cost of borrowing loans under 1 million euros. X_{it} is a variable indicating the ratio of net semi-annual purchases under the PSPP over semi-annual GDP (2009 base year) for country i and time t. Finally, the variables α_i and γ_t correspond to the country and time fixed effects, respectively.

3.4 Empirical Results

I present two sets of results for the PSPP's effects: the effects on the actual volume and agreed interest rates for loans of different sizes and the effects on the perceptions of SMEs on the availability of credit.

Table 3.1 presents the results of the estimation of borrowing costs and interest rate perception. These specifications use the interest rate as the dependent variable. The results are significant for loans under 0.25 and under 1 million euros as well as for the 0.25–1 million euro category but with the opposite sign. Similarly to the results with loan volumes, the smallest loans are affected the most, with a drop of 174 basis points after a 1% of GDP increase in the PSPP's net purchases. Loans below 1 million euros decreased by 47 basis points and loans between 0.25 and 1 million euros actually rose by 71 basis points.

The monetary policy transmission channel to SMEs was studied by Berger and Udell (2006). One possible explanation of the difference in signs obtained in Table 3.1 could be the asymmetry in the interest rate pass-through mechanism in the Euro Area. For instance, Sander and Kleimeier (2004) show that there are significant differences in pass-through mechanisms to corporate loans and current account. A monetary stimulus might shift the loan supply curve. The adjustment in the lending rates then depends on the elasticity of the loan demand curve and degree of lending rate stickiness or credit rationing (Sander and Kleimeier, 2004, p. 486). The less competitive the credit market, and less elastic the demand for loans (fewer alternatives available), the larger is the decrease in the lending rates. Additionally, Sander and Kleimeier (2004) show that market imperfections in the Euro Area, such as credit rationing play an important role in the interest rate pass-through mechanism. This mechanism contains a partial explanation of the asymmetries presented in Table 3.1, with interest rates for loans above 1m seeing an increase in the interest rate. Berger and Udell (2006) suggests identification of the monetary transmission channels in order to single out the effects for particular loan sizes, which would require a more detailed dataset on loan issuance.

Table A.3 presents the specifications that use loan volume as the dependent variable for different loan sizes. The smallest loan sizes have significant results. Note that the data on loans below 0.25 million euros start in 2010m6 and have fewer observations. An increase in the PSPP's monthly net purchases of 1% of each country's GDP is associated with the volume of loans rising by 52 million euros for loans below 1 million euros. The main driver of this increase in loans below 0.25 million euros, which increase by 47 million. This result indicates a positive effect of the PSPP on volumes of small loans, especially the smallest category of below 0.25 million euros. By contrast, the coefficients of larger loans are not significant. While the aggregated results contain clear effects of PSPP on the interest rates and volumes of loans, the differences between PSPP effects on the groups of countries (i.e. troubled vs non-troubled) are not significant. This result goes in line with earlier findings of Hristov et al. (2014) and confirmed with exercise in Section 4.5.

My last finding is the effect of the PSPP on the survey variables (interest)

Table 3.1: PSPP's effects on interest rates

	Interest rates on loans with an IRF period of >1 year			
	(1)	(2)	(3)	(4)
Variable	Below 1 m euros	Above 1 m euros	Below 0.25 m euros	Between 0.25–1 m euros
PSPP/GDP (c)	-0.0482*	0.0149	-0.174***	0.0718**
	0.0285	0.0566	0.0428	0.03
Constant	3.029***	2.621***	3.412***	2.820***
	0.135	0.211	0.152	0.174
Observations	307	265	252	246
R-squared	0.858	0.559	0.786	0.749
Country FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Note: Interest rates on loans with an IRF period of greater than one year acquired from the MFI Interest Rate Statistics, measured in percent (mean=3.74) (c) PSPP/GDP is the percentage of the PSPP's net monthly purchases over average monthly GDP for 2009q1 (mean=10.70). Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

for small, medium-sized, and large firms estimated separately (Table 3.2). The results show the positive effect of the PSPP for small enterprises. The negative coefficient in column 1 indicates that 2.12% more respondents acknowledge an interest rate decrease after a 1% of GDP increase in the PSPP's net purchases. On the contrary, for enterprises with more than 250 employees (column 3), there is a 3.48% increase in respondents recording an interest rate rise.

Table A.4 presents the estimation results for the perception of finance availability from the SAFE dataset. The singled out dependent variables are the percentage of SMEs that acknowledged an interest rate increase (Specifications 1 and 2) and the percentage of SMEs that acknowledged a financial cost increase (Specifications 3 and 4). The results are significant for Specifications 2 and 4, namely those without time fixed effects and those with country fixed effects, respectively.

These findings concur with the effects of the PSPP on the cost of borrowing in Table 3.1. One possible interpretation of these effects is that small enterprises take out loans below 0.25 million euros. This finding also suggests that the assumption of a link between loans below 0.25 million euros and SMEs is reasonable in the setup of this chapter. The credit channel in the conventional

Table 3.2: PSPP's effects on interest rates by firm size

	(1)	(2)	(3)	(4)
Variable	Small	Medium	Large	All
PSPP/GDP(b)	-0.0212***	0.0104	0.0348***	0.00812
	0.00638	0.00711	0.0105	0.00529
Constant	0.363***	0.603***	0.593***	0.527***
	0.0814	0.0924	0.0585	0.0636
Observations	16,986	9,839	3,629	30,454
R-squared	0.259	0.319	0.295	0.286
Country FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Note: Dependent variable 'interest' is a dummy variable for the percentage of respondents who perceive the interest rate to have increased; (b) 'PSPP/GDP' is the change in the share of purchases under the PSPP over a half year (wave) and the GDP of the corresponding country over half a year (wave) with 2009 as the base year. 'Small', 'Medium', and 'Large' refer to enterprises with 0–50, 50-250, and more than 250 employees, respectively. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

MP setting is described by Bernanke and Blinder (1992).

3.5 Conclusions

This chapter evaluated the effects of UMP in the EA. I focused on the PSPP, which has conducted asset purchases since the first quarter of 2015. I estimated the effects of the PSPP on the availability of finance for SMEs, both in perceived and in actual terms. Since the PSPP started in 2015, it provides few observations to estimate its effects with time series. The panel setup allows me to overcome this limitation.

Two datasets were merged for this analysis: a survey on the availability of finance, which provided the percentage of SMEs that perceive interest rates as rising, and the MFI dataset on borrowing costs for non-financial organisations and households. The latter dataset provided borrowing costs by country for loans below 1 million euros.

My findings can be summarised as follows. There is a positive effect of the PSPP on the volume of small loans, especially the smallest category of below 0.25 million euros, and small changes in the costs of borrowing. For a 1% of GDP increase in monthly net purchases under the PSPP, the volume of loans rises by 47 million, whereas the cost of borrowing falls by 174 basis points for loans below 0.25 million euros.

In addition, for the reasons discussed in this chapter, there is a corresponding effect of the PSPP on the survey variables. For a 1% of GDP increase in monthly net purchases under the PSPP, there is a 2.12% increase in enterprises with fewer than 50 employees that perceive interest rates as decreasing. There are at least two interpretations of these findings. First, the MP information channel is functioning effectively. Second, which was also an initial assumption, enterprises with few employees mostly take out loans below 0.25 million euros.

Further research could account for countries' heterogeneity, as UMP affected EU countries to different degrees. A different dataset could be used to analyse the link between SMEs and their typical size of loans by adopting a bank level MIR dataset. Further events of potential interest are when the ECB announced 36-month LTROs in December 2011 and when a new programme for buying sovereign debt, namely outright monetary transactions, was announced in September 2012. As the number of observations for the PSPP grows, it may also be possible to estimate the time series for individual EA countries.

Chapter 4

Forecasting the BLS outcomes using mixed frequency VAR (MFVAR).

4.1 Forecasting the BLS Outcomes

This chapter applies MFVAR to forecast BLS outcomes. The BLS captures the perceptions and expectations of bank managers about economic activity and credit supply. I provide evidence in favour of bivariate MFVAR over a benchmark naive forecast of expecting the last observed value.

The BLS, which is released quarterly, provides valuable information to policymakers. Decision making is a function of agents' perceptions and expectations Coibion et al. (2017, p. 7). Therefore, survey data are useful to assess whether contractionary MP and adverse economic conditions reduce the supply of bank loans (Bernanke and Gertler, 1995, p. 40) or whether business cycle fluctuations and MP stance affect the credit spread (Gilchrist and Zakrajšek, 2012, p. 1714). These questions are crucial not only for macroeconomics in general but also for policymaking, especially when dealing with crisis periods.

This study is motivated by the need for policy authorities to have real-time information on the credit supply channel of MP transmission (Jiménez et al., 2012, p. 2324). Additionally, there is evidence that interest rate pass-through (IP) at the level of bank lending changed during the crisis: Von Borstel et al. (2016); Hristov et al. (2014). The BLS captures the last stage of the IP mechanism, which is argued to drive the shift in IP during the financial crisis.

To analyse the MP propagation mechanism and track economic indicators in general, studies have developed various models, including those for short-term forecasting. Previous work emphasises the importance of building indicators to track the economy more frequently Stock and Watson (1988); Giannone et al. (2008); Mariano and Murasawa (2010). However, while these studies have developed powerful methodologies, indicators of real activity have received most research attention, leaving a gap in producing real-time indicators at intermediate stages between changes in MP and credit supply.

This study bridges that gap by estimating commercial banks' perceptions of economic activity in real-time. This is motivated by Coibion et al. (2017), who stated the following: 'First and most practically, we lack direct empirical evidence on the real-time beliefs of firms, those agents whose expectations play a central role in price-setting, hiring, and investment decisions'. This allows me to track MP propagation through the lending channel to enterprises.

The contribution of this study is twofold. The first contribution is the application of a bivariate version of MFVAR, which can produce monthly series and forecasts of commercial banks' perceptions of economic activity from 2008. Second, the article compares the forecasting performance of MFVAR with the random walk benchmark. The lack of long-time series for commercial banks' perceptions motivates the choice of the model (i.e. MFVAR), which relies on more frequently published monthly series. In general, VARs are useful forecasting tools. In particular, Bayesian VARs allow for a natural estimation of conditional and unconditional forecasts as well as credible sets around the forecasted series. For instance, Schorfheide and Song (2015) focused on the Bayesian estimation of a state-space model to produce multivariate predictive distributions.

The rest of the article is structured as follows. Section 4.2 describes the data and presents the empirical results. Section 4.3 contains the estimation methodology. Section 4.5 discusses the empirical implications of the estimated monthly BLS outcomes.

4.2 Data

For all data except BLS the frequency is monthly and the sample period is 2000M1 to 2018M5. Figure 4.1 illustrates the commonly used macroeconomic variables for estimating monthly economic activity indexes and the survey variable of interest (i.e. the BLS). The survey variable corresponds to a question that evaluates economic activity and has similar trends to common macroeconomic variables. Their frequency, however, does not allow MP authorities to track the transmission of policy changes to understand commercial bank managers' perceptions on a monthly basis.

4.2.1 Selection of indicators

The primary focus here is placed on forecasting the BLS, which reflects bank managers' perceptions of economic activity. Since this variable is highly correlated with other measures of activity and more frequent survey variables of economic activity, I narrow the data to the variables presented in Table 4.1. Figure 4.1 presents evidence of the co-movement between the variable of interest and other economic indicators. The dataset resembles the one used by Camacho and Perez-Quiros (2010, p. 667), who estimated a single-factor model for a real-time short-term indicator of EA growth.

To have a parsimonious model, I use bivariate MFVAR. As a robustness check, I also apply MFVAR that includes more variables but the RMSE is larger for those models. Equivalently, the multivariate specification does not improve the forecasts. A large number of indicators is thought to add more noise and cross-correlation of the idiosyncratic shocks (Boivin and Ng, 2006, p. 188). Evidence in Figure (4.2) and Figure (A.19) suggests a wider credible set for multivariate MFVAR. Moreover in a multivariate model RMSE is higher (5.63) than for a bivariate model (3.39) (see Figures (4.3) and (A.20)).

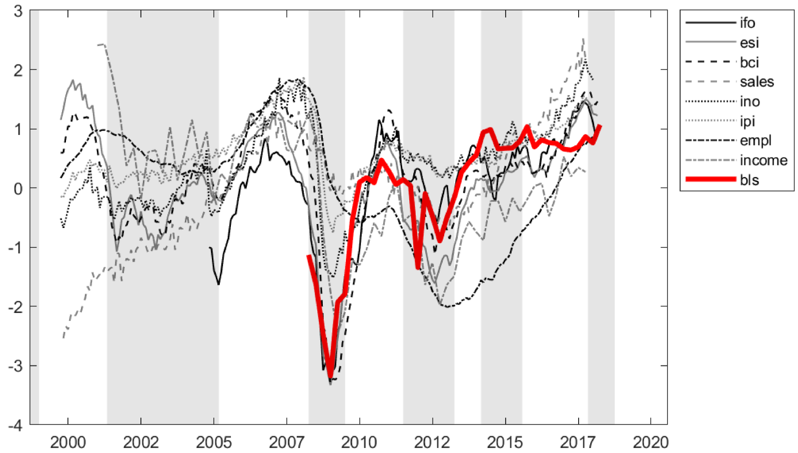

Figure 4.1: Economic indicators for the EA and economic perception indicator
Note: 'BLS' is a variable from the EA BLS, which evaluates credit standards (eased=1, tightened=0); 'income' is the real growth in actual final consumption per capita in the EA; 'ifo' is a time series for the economic climate in the EA; 'esi' is the EA economic sentiment indicator; 'bci' is the EA business climate indicator; 'sales' is retail sales volume (annual growth rate); 'ino' is industrial new orders; and 'empl' is the unemployment rate, divided into total (all ages) and total (male and female). The shaded area is the OECD-based recession indicators for Germany. All variables are standardised. The unemployment rate was inverted with the opposite sign.

European institutions collect a number of soft indicators with monthly, quarterly, and semi-annual frequencies. Table 4.1 presents the time series chosen for empirical analysis.

A bank's ability to access market financing is an indicator of the BLS that is collected quarterly and that captures credit availability from the supply-side point of view. It is thus the first indicator that shows the resurgence of credit in the EA in the first quarter of 2010.

Table 4.2 shows a typical problem of information availability, namely that the release date for the key variables is usually delayed. For instance, the release of the BLS quarterly series is delayed by one or two months. For instance, the 2012q1 value for the BLS was published on 25 April 2012. This lag in the publication is taken into account when estimating the forecast.

4.3 Econometric Approach

4.3.1 Mixed frequency models

In this section, I describe a model that addresses mixed frequency data and missing observations. The estimation focuses on forecasting the BLS variable,

Table 4.1: Data sources

ID	Source	Description	Type
		Quarterly	
BLS	EA BLS.	Credit standards (eased +, tightened −).	Soft
		Monthly	
IFO	Germany IFO Business Climate Index	Long time series for the Economic Climate for the EA	Soft
Bnb	Belgium Overall Business Indicator	Belgium Overall Business Indicator	Soft
Esi	EC. Business and consumer surveys	EA Economic Sentiment Indicator	Soft
Bci	EC. Business and consumer surveys	EA Business Climate Indicator	Soft
Sales	Eurostat	Retail Sales Volume, Annual Growth Rate	Hard
Ino	Eurostat	Industrial New Orders	Hard
Ipi	Eurostat	Industrial Production Index	Hard
Empl	Eurostat	Unemployment Rate, Total	Hard

which is released at a quarterly frequency. The remaining variables have a monthly frequency. There are a number of alternatives to the MFVAR. Most notably MIDAS approach by Ghysels et al. (2004) and Ghysels et al. (2007), which was proven to be useful for various forecasting purposes. MIDAS is a time series regression tool that permits different frequencies for model variables. (Bai et al., 2013, p. 801) compare the forecasting performance of MIDAS and state-space models applied to a mixed –frequency data and concluded Kalman filter forecast to perform slightly better. (Kuzin et al., 2011, p. 536) compare the performance of AR-MIDAS against MFVAR by evaluating Euro Area GDP forecasts. Their conclusion suggests the outperforming methodology is unclear and the results depend on predictors and forecast horizon.

While the literature does not provide evidence of clear outperforming forecasting methodology the MFVAR has another important result. The state-space models allow the estimation of the missing high-frequency data by using the Kalman Filter (Foroni and Marcellino, 2013, p. 25), which in this paper is considered to be a useful object.

This chapter thus builds on the literature on economic indicators estimated using mixed frequency models. The need to provide short-term forecasting of the key macroeconomic indicators has motivated the development of a number of methodologies such as state-space models, mixed data sampling models, and bridge equations. Foroni and Marcellino (2013) reviewed the literature dis-

Table 4.2: Stylised information sets of the soft indicators

Information available in 2012m1 (January 1)									
Year	Quarter	Month	bls	esi	bci	sales	ino	ipi	empl
2011	Q4	M12		x	x	x	x	x	x
2012	Q1	M1							
2012	Q1	M2							
2012	Q1	M3							
2012	Q2	M4							

Information available in 2012m2 (February 1)									
Year	Quarter	Month	bls	esi	bci	sales	ino	ipi	empl
2011	Q4	M12		x	x	x	x	x	x
2012	Q1	M1		x	x	x	x	x	x
2012	Q1	M2							
2012	Q1	M3							
2012	Q2	M4							

Information available in 2012m3 (March 1)									
Year	Quarter	Month	bls	esi	bci	sales	ino	ipi	empl
2011	Q4	M12	x	x	x	x	x	x	x
2012	Q1	M1		x	x	x	x	x	x
2012	Q1	M2		x	x	x	x	x	x
2012	Q1	M3							
2012	Q2	M4							

Note: ‘safe’ corresponds to Q11 in the EA Survey on the access to finance of enterprises, which evaluates the general economic outlook, insofar as it affects the availability of external financing; ‘income’ is the real growth in actual final consumption per capita in the EA.

cussing bridge equations, mixed data sampling models, mixed frequency factor models, and, most recently, MFVARs Schorfheide and Song (2015). The latter methodology is extended for the structural analysis Schorfheide et al. (2018).

4.3.2 State space representation

The model is closely related to that of Schorfheide and Song (2015). The state space representation of the model has the following form:

$$y_t = H\beta_t + \epsilon_t \tag{4.1}$$

The transition equation is

$$\beta_t = H\beta_{t-1} + \varepsilon_t \tag{4.2}$$

$$\epsilon_t \sim iidN(0, \Omega_\epsilon)$$

$$\varepsilon_t \sim iidN(0, \Omega_\varepsilon)$$

When the variable Y is observed, Equation (1) has the following form:

$$\begin{pmatrix} 0 & x_1 \\ 0 & x_2 \\ y_3 & x_3 \\ 0 & x_4 \\ 0 & x_5 \\ y_6 & x_6 \\ \vdots & \vdots \\ y_T & x_T \end{pmatrix} = \begin{pmatrix} \frac{1}{3} & 0 & \frac{1}{3} & 0 & \frac{1}{3} & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{pmatrix} \times \begin{pmatrix} \hat{y}_t \\ x_t \\ \hat{y}_{t-1} \\ x_{t-1} \\ \hat{y}_{t-2} \\ x_{t-2} \end{pmatrix} \tag{4.3}$$

which implies that the quarterly data can be represented as an average of the monthly variables:

$$Y_3 = (1/3Y)_t + (1/3Y)_{t-1} + (1/3Y)_{t-2}$$

When the observation is unavailable, Equation (1) takes the following form:

$$\begin{pmatrix} 0 & x_1 \\ 0 & x_2 \\ y_3 & x_3 \\ 0 & x_4 \\ 0 & x_5 \\ y_6 & x_6 \\ \vdots & \vdots \\ y_T & x_T \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{pmatrix} \times \begin{pmatrix} \hat{y}_t \\ x_t \\ \hat{y}_{t-1} \\ x_{t-1} \\ \hat{y}_{t-2} \\ x_{t-2} \end{pmatrix} + \begin{pmatrix} \varepsilon_t \\ 0 \end{pmatrix} \tag{4.4}$$

When observations are missing, the row in matrix H means that the variable is zero and an error term is a large number. From the point of view of the Kalman filter, these observations would be ignored when calculating a new estimated value of $\hat{Y}$. The transition equation has the following form:

$$\begin{pmatrix} \hat{y}_t \\ x_t \\ \hat{y}_{t-1} \\ x_{t-1} \\ \hat{y}_{t-2} \\ x_{t-2} \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} + \begin{pmatrix} b_1 & b_2 & b_3 & b_4 & b_5 & b_6 \\ d_1 & d_2 & d_3 & d_4 & d_5 & d_6 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix} \times \begin{pmatrix} \hat{y}_{t-1} \\ x_{t-1} \\ \hat{y}_{t-2} \\ x_{t-2} \\ \hat{y}_{t-3} \\ x_{t-3} \end{pmatrix} + \begin{pmatrix} v_1 \\ v_2 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} \tag{4.5}$$

The variance of the error term is

$$Q = \begin{pmatrix} q_{11} & q_{12} & 0 & 0 & 0 & 0 \\ q_{21} & q_{22} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \tag{4.6}$$

The question of how many variables should be chosen in z_t raises various issues, as it is assumed that a better specification is obtained when a large number of variables is present Giannone et al. (2008). However, the risk of using a large number of variables is that this may violate the weak cross-correlation hypothesis and increase noise. Boivin and Ng (2005) argued that the selection of variables with statistical criteria generates biased estimates. Another concern with the model estimation is the feasibility of a large number of time series included. While the model can be extended to include a large number of series, I follow Camacho and Quiros (2011), who argued that small models are relatively easier to test for assumptions in an empirical setup. Figure 1 shows that the variables of interest have visually similar dynamics to the monthly series in the model, whereas such a visual inspection would not be feasible in a larger setup.

An important task in a VAR estimation is to cope with the high dimensionality of β. The MFVAR in this article is equipped with Minnesota prior and estimated with Bayesian methods. The Minnesota prior is based on Sims and Zha (1998), applied in Bańbura et al. (2010) and Giannone et al. (2015). The implementation follows a textbook chapter of Del Negro and Eusepi (2011, p. 12) and Blake et al. (2012, p. 31). The main notion of the Minnesota prior is to centre the distribution of β around the value that entails random walk behaviour of variables in the model. The version of Minnesota prior used in this article is proper and belongs to a family of multivariate Normal inverse Wishart distributions. I implement the Minnesota prior using the dummy variables approach Blake et al. (2012), which in turn is based on Bańbura et al. (2010). The artificial observations used in a dummy variable approach are a computationally more convenient way to implement priors.

4.4 Empirical Results

To respond to the ever-increasing need for the monetary authorities to timely respond to shocks in an informed manner, MFVAR produces monthly estimates of the survey variables, which are available at a quarterly frequency from the EC website.

This section conducts the following forecasting exercise. For each period t, where the BLS variable is available, the model produces a one-step-ahead forecast given the information available at $t-1$, replicating the real-time dataset available to a forecaster at the time the forecast is made. The forecast estimation follows the work of Schorfheide and Song (2015), who used another iteration of the prediction step of the Kalman filter to obtain the one-step-ahead forecast. I evaluate the forecasting performance of MFVAR against the benchmark of the random walk process as follows:

$$y_t = y_{t-1} + \varepsilon_t$$

I compare the forecast from the model with a benchmark, which expects the same value for the BLS variable as in the previously published quarter:

$$RMSE = \sum_{t=1}^{T} \mathbb{E}(BLS_t|\Omega_{t-1}) - BLS_t$$

where $RMSE$ is the root mean squared error (RMSE), BLS_t is the realised value of the survey variable, $\mathbb{E}(BLS_t)$ is the expected value of the survey variable, Ω_{t-1} is the information set available at time $t-1$, and the mean squared errors are 3.39 and 10.75, respectively. Figure 4.3 illustrates the performance of MFVAR forecast throughout the sample.

The result is a one-step-ahead forecast and a confidence interval for the perceptions of economic activity estimated using pseudo samples. The forecast is based only on the information available at the time of the forecast. The importance of the forecasts is highlighted when the BLS variables change drastically (e.g. during the sovereign default crisis in the EU). The value of 2011q4 is -12.1, followed by a deterioration of the economic outlook to -41.3.

Lane (2012, p. 50) outlined three major problematic periods during the sovereign default crisis: the divergence of Greek yields in 2010, Irish and Portuguese yield co-movement in 2010 and first two quarters of 2011, and the spreads of Italy and Spain against Germany rising above 300 basis points in 2011m7 and staying at a heightened level thereafter. During that period, the BLS reported sharp credit tightening in 2012q1. The three outlined events are the periods when MFVAR outperformed naive forecasting by a large margin (see Figure 4.3). The proposed model could capture this drop from 2012m1. Figure 4.2 illustrates the performance of the forecasts compared with the quarterly observed series.

4.5 Structural Analysis of IP

This section shows that the BLS variable plays an important role in the IP mechanism. I provide evidence that the BLS can explain the variation in the interest rates and the responses of interest rates to an MP shock across countries.

The forecasting exercise produced monthly observations for the BLS variable. However, the produced time-series might not be useful in economic modelling and does not contain information about the monetary policy transmission channel. The regression exercise's aim is to test this hypothesis whether the BLS variable from the forecasting exercise has significant explanatory power over the various interest rates in the Euro Area. This exercise estimates the following regression:

$$i_t = \alpha_t + \phi BLS_t + \varepsilon_t \tag{4.7}$$

Where i_t is a matrix containing interest rates (Table 4.3) and a matrix of IRFs of interest rates (Table 4.4), BLS_t is a monthly variable of Bank lending survey responses estimated in the previous section. The second part of the exercise provides evidence that the BLS variable contains information that could explain the variation in the responses of the interest rates. Von Borstel et al. (2016)

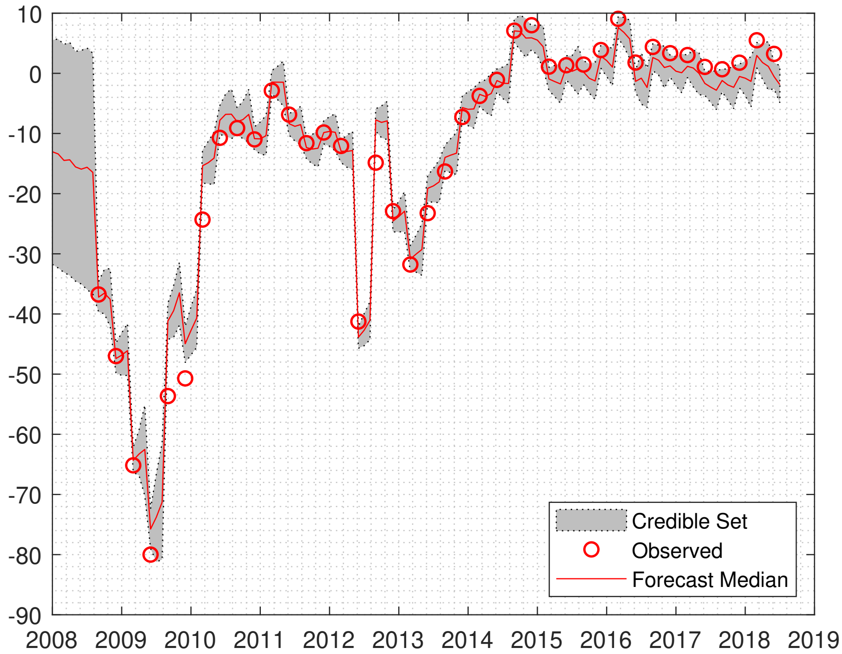

Figure 4.2: Perceptions of economic activity, one-step ahead forecast
Note: The 'BLS' variable is the survey question on credit standards (eased=positive, tightened=negative). The credible set is 68%.

showed that the response of bank lending rates did not significantly change between the pre-2007 crisis period and the sovereign debt crisis (January 2010 to December 2013), except for one component of IP, the bank lending margin. Therefore, the survey variable might contribute to explain the last step of the IP mechanism.

Table 4.3 highlights the relationships among the interest rates on loans to corporations and households, long-term debt securities, and BLS outcomes. The results indicate that an increase in BLS variable, which corresponds to a perceived improvement of economic activity, is negatively related to the interest rates on loans to corporations and long term debt securities. For a 10% of BLS increase, there is a 39 basis points decrease in interest rates on loans to corporations and 40 basis points decrease in interest rates for long term debt securities. The results for loans to households are less significant and have a positive relationship. One of the reasons for the difference in signs of the relationship between loans to corporations and households might be the asymmetries in the IP channel discussed in Section 3.4.

The second part of the regression exercise estimates IRFs of interest rates on

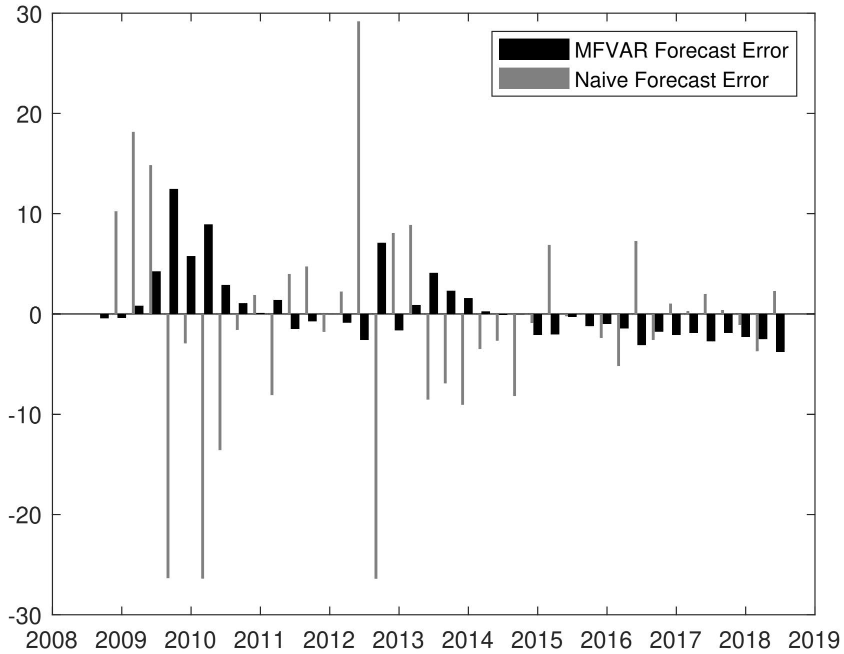

Figure 4.3: Forecast error comparison: MFVAR and random walk

Note: Error is calculated as the difference between the realised value and median forecast produced by MFVAR using the pseudo sample. RMSE for bivariate MFVAR is 3.39 and for naive forecast 10.75.

loans to corporations and households, long-term debt securities as a dependent variable. The IRFs are obtained from the FAVAR estimation with a recursive identification and are presented in Appendix Figures A.13, A.14, and A.15. I extend the FAVAR model of Von Borstel et al. (2016) using time-varying coefficients and stochastic volatility, as described in Chapter 2. I keep the same recursive identification scheme (Von Borstel et al., 2016, p. 390). Table 4.4 presents the results of the second part of the regression exercise. The significant relationship between the BLS variable and responses of interest rates on loans to corporations in column 1, suggests that an improvement in economic outlook (increase in the BLS variable) is associated with the amplified response of interest rates to a monetary policy shock. The opposite holds true for the responses of interest rates on loans to households. Overall, I find that the variation in the interest rate responses could be explained by the BLS variable, which captures the perception of MP changes at the level of senior loan officers. It highlights the importance of the information contained in the BLS outcomes.

Table 4.3: Regression results for the BLS and interest rates

	(1) Business	(2) Household	(3) Government
BLS	-0.00392***	0.00178*	-0.00402***
	(0.00132)	(0.00108)	(0.00109)
Constant	3.262***	4.221***	2.570***
	(0.235)	(0.256)	(0.127)
Observations	301	301	301
R-squared	0.807	0.907	0.831

Note: The panel includes Austria, Belgium, Germany, Spain, Greece, Italy, and Portugal. 'Business' means the annualised agreed rate for deposits from corporations with an agreed maturity of up to one year; 'Household' refers to the annualised agreed rate for deposits from households with an agreed maturity of up to one year; 'Government' refers to a long-term interest rate for convergence purposes (10-year maturity). All specifications include the country and time fixed effects. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.6 Conclusion

Owing to the lack of real-time indicators for the survey values, this study estimates a monthly series for banks' perceptions of economic activity in the EA between 2008 and 2018, producing one-step-ahead forecasts based on the available data at each point in time. The forecasting performance of MFVAR is able to beat a random walk benchmark. However, the gains in the RMSE come from periods of drastic changes in the BLS indicator during the financial crisis. These gains are captured by the availability of monthly series within the mixed frequency model.

The importance of the information contained in the BLS outcomes is demonstrated by two examples. The first piece of evidence comes from a panel estimation of business, household, and government borrowing rates and the BLS variable highlighting its significance. The second piece of evidence comes from the extension of the FAVAR methodology of Von Borstel et al. (2016) with time variation and stochastic volatility. This extension produces time-varying impulse responses for eight EA countries. The variation over time and between countries is also explained by the BLS outcomes. While the above articles evaluated the effects of the ECB's monetary policy, the analysis did not consider the spillover effects of other CBs.

Table 4.4: Regression results with the BLS and estimated responses of the interest rates

Variable	(1) Business	(2) Household	(3) Government
BLS	-0.0172***	0.00845***	0.00388
	(0.00332)	(0.00261)	(0.00269)
Constant	-1.797***	-5.663***	-7.189***
	(0.553)	(0.452)	(0.403)
Observations	301	301	301
R-squared	0.070	0.045	0.031

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The panel includes Austria, Belgium, Germany, Spain, Greece, Italy, and Portugal. The dependent variable is the accumulated impulse response at the 24-month horizon. All specifications include the time fixed effects. Robust standard errors in parentheses.

Chapter 5

Conclusions

This thesis analyses the two channels of MP transmission: credit supply and expectation channels including the periods of UMP. In the second chapter, I find heterogeneity in the responses of disaggregated consumers' inflation expectations in the EA based on time-varying FAVAR. The results indicate some heterogeneity in the responses of different age groups to an EA-wide monetary policy shock, although these are not significant for most countries. Younger demographics (16–29 years) exhibit a higher level of updating inflation expectations than older groups. Similarly, a larger share of consumers with a higher education level and higher income would update their inflation expectations. This finding concurs with those in the literature.

The key finding is that the responses of inflation expectations have weakened over time. The responses of inflation expectations after 2010, during the ZLB period, take more time to react, making them weaker on average than the responses before 2008. The dynamics of inflation expectations could therefore be a possible cause of inflation persistence in the EA.

The determinants of the heterogeneity in the responses of inflation expectations suggest that industry structure and labour market rigidities play a significant role in the propagation mechanism of MP. The results also go in line with earlier findings suggesting that a lower share of manufacturing and higher unemployment protection and union share mitigate the effects of credit channels.

The third chapter finds a positive effect of the PSPP on the volume of small loans, especially the smallest category of below 0.25 m euros, and small changes in the costs of borrowing. For a 1% of GDP increase in monthly net purchases under the PSPP, the volume of loans rises by 47 million, whereas for loans below 0.25 million euros, the cost of borrowing falls by 174 basis points.

Owing to the lack of real-time indicators for the survey values, the fourth chapter estimates a monthly series for banks' perceptions of economic activity in the EA between 2008 and 2018, producing one-step ahead forecasts based on the available data at each point in time. The forecasting performance of MFVAR is able to beat a random walk benchmark. However, the gains in the RMSE come from periods of drastic changes in the BLS indicator during. These gains are captured by the availability of monthly series within the mixed frequency model.

A potential interest for future research is to improve the identification strategy of the monetary policy shocks to evaluate not only unanticipated shocks but also the effects of the announcements and unannounced changes in the implementation of unconventional policies. Furthermore, it might be useful to include the MP shocks from Japan, USA, Canada, Sweden and Switzerland to evaluate and compare their contributions to the effects found in the chapters above.

Appendix A

Appendix

A.1 Appendix Chapter 2

A.1.1 Estimation steps

1. Set the priors and starting values.

2. Conditional on the factors and observed variables, sample the factor loadings.

3. Conditional on the factors and factor loadings, sample the variance of the error terms of the observation equation from the IG distribution.

4. Conditional on the factors and error covariance, obtain the VAR coefficients in the transition equation using the Carter-Kohn algorithm.

5. Conditional on the factors and VAR coefficients, sample the error covariance from the IW distribution.

6. Given the factor loadings, error covariance matrix observation equation, VAR coefficients in the transition equation, and error covariance matrix in the transition equation, obtain the factors using the Carter–Kohn algorithm.

Similarly, the above could be expressed using the following notation:

- Γ (Factors loadings)
- R (Covariance matrix X)
- $\{\beta_t\}_{t=1}^{T}$ (VAR coefficients in the transition equation)
- Q (Covariance matrix for β_t)
- $\{a_{ij,t}\}_{t-1}^{T}$ (Off diagonal elements of A_t)
- D covariance matrix for A
- Diagonal elements of H_t
- Variance of $ln(h_{i,t})$
- $\{F_t^j\}_{t-1}^{T}$ Factors

Steps:

1. Set the priors and initial values for the model parameters: parameters in the transition equation, parameters in the random walk process for $\{a_{ij,t}\}$, parameters in the observation equation, and parameters in the random walk process for $ln(h_{i,t})$.

2. Given R, draw Γ.

3. Given Γ and Z_t, draw R.

4. Given Z_t, Q, $\{a_{ij,t}\}$, and $h_{i,t}$, draw β_t.

5. Given β_t, draw Q.

6. Given Z_t, β_t, $h_{i,t}$, and D, draw $a_{ij,t}$.

7. Given $a_{ij,t}$, draw D.

8. Given Z_t, β_t, and g_i, draw $h_{i,t}$.

9. Given $h_{i,t}$, draw g_i.

10. Given Γ, R, β_t, $a_{ij,t}$, and $h_{i,t}$, draw F_t.

11. Iterate steps 2 to 10 M times. When M and M_0 are sufficiently large but $M > M_0$, the marginal posterior distribution of each parameter can be approximately obtained from the last $(M - M_0)$ iterations.

Priors and Convergence

Time-varying parameter models, namely time-varying parameter FAVAR SV, are not parsimonious and contain a large number of coefficients. (Koop et al., 2010, p. 5) argued that without informative priors, precisely estimating coefficients might be challenging. Following Primiceri (2005), this problem could be mitigated using the first 10 years of data as a training sample.

In Chapter 2, the first 10 years (40 observations, from 1999:I to 1999:IV) are used to calibrate the prior distributions.

Following Baumeister et al. (2013) to assess convergence of the Markov Chain, Figure A.1 illustrates the recursive mean across the retained draws of key model parameters and shows that the means are relatively stable.

Calculating IRFs (Fry and Pagan, 2011)

This section describes the steps for obtaining IRFs according to Fry and Pagan (2011). This approach is aimed at obtaining a single value θ, which denotes a single IRF and minimises the criterion in Fry et al. (2005). The procedure, also known as median target method (MT), chooses such $\theta^{(k)}$ that the impulse response is closest to the median response. The algorithm proceeds as follows:

- Obtain impulse response function for a set of models (100) that satisfies sign restrictions. Obtain this for each time period in the case of time varying model.

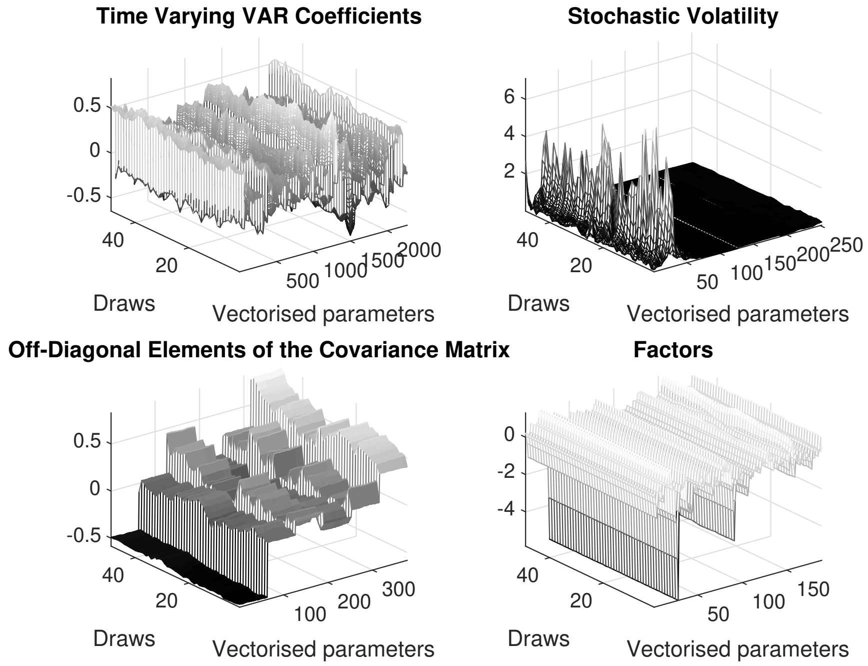

Figure A.1: Recursive means of key model parameters to assess convergence of the Markov chain to the ergodic distribution.

- The standardised impulse responses are stored in a vector $\phi^{(l)}$ for each value $\theta^{(l)}$.
- Choose l such that $MT = \phi^{(l)\prime}\phi^{(l)}$ and use that l to calculate the impulse responses.

Algorithms

The algorithms described below closely follow Blake et al. (2012); Kim and Nelson (1999); Koop (2003).

Sampling from the normal distribution

To obtain sample x with the dimensions $k \times 1$ from a normal distribution $N(m, v)$, generate the $k \times 1$ vector z from the standard normal distribution. Then, transform vector z by adding mean m and scaling by variance v with the following formula:

$$x = m + z \times v^{1/2}$$

Sampling from the inverse Gamma

To obtain a sample x with the dimensions $k \times 1$ from an inverse Gamma distribution $\Gamma^{-1}(S/2, T/2)$, where $S/2$ and $T/2$ are the degrees of freedom and scale parameters, respectively, generate the $k \times 1$ vector z from the standard normal distribution. Then, find $x = D/([z^0]' z^0)$.

Sampling from the inverse Wishart

See the description in (Zellner, 1971, p. 389).

Sampling from the lognormal

To sample from the lognormal distribution $z \sim log - normal(\mu, \sigma)$, sample z_0 from the normal density $N(\mu, \sigma)$ and then transform $z = exp(n)$.

Gibbs sampling

Suppose the researcher is given a joint density $f(x, y_1, y_2, ...y_n)$ and he/she is interested in obtaining the characteristics of marginal density

$$f(x) = \int ... \int f(x, y_1, y_2, ...y_n) dy_1 ... dy_n$$

In other words, he/she wants to integrate out all the y variables. The most straightforward approach would be to calculate $f(x)$ and use it to obtain the desired statistics. Yet, the integration of the expression above is often extremely difficult to perform either analytically or numerically.

In Monte Carlo integration, the algorithm takes random draws from $p(\theta|y)$ and finds an average to estimate $\mathbb{E}[g(\theta|y)]$ for any function of interest $g(\theta)$. In many models, it is not easy/feasible to draw from $p(\theta|y)$. However, it is easy to draw from

$$p(\theta_{(1)}|y, \theta_{(2)}, \theta_{(3)}, ..., \theta_{(B)}),$$
$$p(\theta_{(2)}|y, \theta_{(1)}, \theta_{(3)}, ..., \theta_{(B)}), ...$$
$$p(\theta_{(B)}|y, \theta_{(1)}, \theta_{(2)}, ..., \theta_{(B-1)})$$

Suppose $f(x_1, x_2, ..., x_k)$ is a joint distribution of k variables. The interest of a researcher is $f(x_i)$, $i = 1...k$. However, a standard procedure of integrating a joint distribution might be unfeasible. Assume that conditional distribution $f(x_i|x_j)$ for $i \neq j$ is known; then, Gibbs sampling is a way to approach an approximation of the marginal distribution.

Gibbs sampling is an MCMC algorithm, a numerical method that approximates the joint and marginal distributions by drawing from the conditional distributions. Suppose there is a distribution with K variables, and the researcher is interested in finding the joint and marginal distributions, given that we know the functional form and moments of all the conditional distributions.

Randomly draw x_1 from its conditional distribution holding all other x_s constant at their starting value. In the first iteration of Gibbs sampling, we draw a random sample of parameters for x_1 to x_p; as the number of iterations goes to infinity, the joint and marginal distributions converge. The second iteration is $(x_1^2, x_2^2 ... x_p^2)$.

As the number of draws rises, the samples from the conditional distributions converge towards the joint and marginal distributions of x_t at an exponential rate (Casella and George, 1992, p. 170). In other words, if one runs Gibbs sampling for M iterations and considers the last H number of iterations, the researcher would obtain H values for $x_1, x_2, ..., x_k$. The histogram of these H draws is an approximation of the marginal density of $x_1, x_2, ..., x_k$. Consequently, the estimate of the mean of the marginal posterior distribution is a sample mean of the H retained draws from Gibbs sampling.

Metropolis–Hastings

This algorithm follows Koop (2003) and Blake et al. (2012) closely. Let y be a matrix of observations and Φ be a vector of parameters. Then, $p(y|\Phi)$, $p(\Phi)$, and $p(\Phi|y)$ are the likelihood, prior, and posterior, respectively. Let Φ^* denote a draw from a density, called candidate generating density. Candidate generating density is denoted as $q = (\Phi^{(s-1)}; \Phi)$, where Φ is a random variable and its density depends on $\Phi^{(s-1)}$. The Metropolis -Hastings algorithm is an MCMC algorithm, which draws values Φ^s for $s = 1...S$.

In Metropolis–Hastings, the draws are weighted equally; however, not all draws are accepted. Consider a function of interest $\pi(\Phi)$ and the estimate of this function $\mathbb{E}(\pi(\Phi)|y)$, and denote this by $(\pi)(\Phi)$. Then, $\pi(\Phi) = 1/S \sum_{s=1}^{S} \pi(\Phi)$.

Considering the above, Metropolis–Hastings contains the following steps:

- Chose starting value Φ^0
- Take candidate draw Φ^* from candidate density $q = (\Phi^{s-1}; \Phi)$.
- Calculate the probability of the acceptance of draw $\alpha = (\Phi^{s-1}; \Phi^*)$.
- Change Φ^s to Φ^* with probability $\alpha(\Phi^{s-1}; \Phi^*)$ and set $\Phi^s = \Phi^{s-1}$ with probability $1 - \alpha(\Phi^{s-1}; \Phi^*)$.
- Repeat steps 1-3 S times, and calculate the average of the S draws $\pi(\Phi^1), ..., \pi(\Phi^S)$.

- The acceptance probability has the following form: Matrix σ determines how the exploration of the distribution is conducted. If it is too low, then it does not explore the distribution sufficiently; on the contrary, if it is too high, then it would sample a considerable amount from the tails of the distributions. Choose σ that such the acceptance rate is between 20% and 40%.

Kalman filter

Consider a general state space model (with the notation following Hamilton (1994)):

$$\underset{r\times 1}{y_t} = \underset{n\times k}{A'} \times \underset{k\times 1}{x_t} + \underset{n\times r}{H'} \times \underset{r\times 1}{\xi} + \underset{n\times 1}{w_t} \tag{A.1}$$

$$\underset{r\times 1}{\xi_{t+1}} = \underset{1\times 1}{\mu} + \underset{r\times r}{F} \times \underset{r\times 1}{\xi_t} + \underset{r\times 1}{v_{t+1}} \tag{A.2}$$

where $\mathbb{E}[v_t v_t'] = Q$ and zero otherwise; $\mathbb{E}[w_t w_t'] = R$ and zero otherwise.

Assume that Y and X are observed. For simplicity, assume that the values F, Q, H, H, R are also known with certainty. This assumption is relaxed later. The following algorithm calculates the linear least squares forecasts of the state vector:

$$\hat{\xi}_{t+1|t} = \mathbb{E}(\xi_{t+1}|Y_t) \tag{A.3}$$

where $\mathbb{E}(\xi_{t+1}|Y_t)$ is a linear projection of ξ_{t+1} on Y_t and a constant. The Kalman filter produces these projections recursively for each time period. The mean squared error associated with each forecast is calculated as follows:

$$P_{t+1|t} \equiv \mathbb{E}[(\xi_{t+1} - \xi_{t+1|t})(\xi_{t+1} - \xi_{t+1|t})'] \tag{A.4}$$

If the eigenvalues of F are all inside the unit circle, the state process (transition equation) is covariance-stationary. Then, unconditional moments are given by $\xi_{0|0} = (I_r - F)^{-1}\mu$ and $vec(P_{0|0}) = (I - F \otimes F)^{-1} vec(Q))$. If the state process is not stationary and the eigenvalues of F lay outside the unit circle, no unconditional moments exist; hence, the starting value for the mean is arbitrary and the variance is a diagonal matrix with large entries to reflect the uncertainty.

Given the starting values for the state and its variance, we forecast the state, variance, and observed variable. We assume that the exogenous variables x contain no information about the state beyond the already realised observed variables:

$$\xi_{t|t-1} = \mu + F\xi_{t-|t-1} \tag{A.5}$$

$$P_{t|t-1} = FP_{t|t-1}F' + Q \tag{A.6}$$

$$\eta_{t|t-1} = y_t - A'x_{t|t-1} + H'\xi_{t|t-1} \tag{A.7}$$

$$f_{t|t-1} = H'P_{t|t-1}H + R \tag{A.8}$$

Equation (A.21) updates the state according to the transition equation; Equation (A.22) updates the state variance (which includes the error value from the transition equation); Equation (A.23) calculates the forecast error (i.e. the difference between the forecasted $\hat{y}$ and its realised counterpart); and Equation (A.24) calculates the forecast error variance (which includes the error value from the observation equation).

The next step is updating the inference about the state (finding $\hat{\xi}_{t|t}$):

$$\hat{\xi}_{t|t} = \underbrace{\hat{\xi}_{t|t-1}}_{\text{old forecast}} + \underbrace{P_{t|t-1}}_{\text{old variance}} \underbrace{H(H'P_{t|t-1}H + R)^{-1}}_{f_{t|t-1}} \underbrace{(y_t - A'x_{t|t-1} + H'\xi_{t|t-1})}_{\eta_{t|t-1}} \tag{A.9}$$

Alternatively, combining the old variance with the forecast error variance, the updating equation could be expressed using the Kalman gain expression:

$$\hat{\xi}_{t|t} = \underbrace{\hat{\xi}_{t|t-1}}_{\text{old forecast}} + \underbrace{P_{t|t-1}H'f_{t|t-1}^{-1}}_{\text{kalman gain}} \underbrace{\eta_{t|t-1}}_{\text{forecast error}} \tag{A.10}$$

Similarly, for the variance of the state,

$$P_{t|t} = \underbrace{P_{t|t-1}}_{\text{old variance}} - \underbrace{K}_{\text{kalman gain}} HP_{t|t-1} \tag{A.11}$$

The forecasts of the state and observed variables ($\hat{\xi}_{t|t-1}$ and $\hat{y}_{t|t-1}$) are optimal within the set of forecasts that are linear in x_t, X_{t-1}, Y_{t-1} (Hamilton, 1994, p. 385). If the initial state and innovations are multivariate Gaussian, the forecasts are optimal among any functions of x_t, X_{t-1}, Y_{t-1}. Furthermore, if the initial state and innovations are Gaussian, the distribution of y_t conditional on

x_t and X_{t-1}, Y_{t-1} is also Gaussian: /

$$y_t|x_t, X_{t-1}, Y_{t-1} \sim N((A'x_t + H'\hat{\xi}_{t|t-1}), (H'P_{t|t-1}H + R)) \tag{A.12}$$

Then, the sample log likelihood is the sum of the log likelihoods for each time period, consisting of the values from the Kalman filter algorithm:

$$\sum_{t=1}^{T} log f_{y_t|X_{t-1},Y_{t-1}}(y_t|X_{t-1}, Y_{t-1}) \tag{A.13}$$

where

$$f_{Y_t|X_{t-1},Y_{t-1}}(Y_t|X_{t-1}, Y_{t-1}) =$$

$$\frac{2}{\pi}\left|H'P_{t|t-1}H + R\right|^{-\frac{1}{2}} \times exp(\frac{1}{2}(A'X_t + H'\hat{\xi}_{t|t-1})'(H'P_{t|t-1}H + R)^{-1}) \times exp(A'X_t + H'\hat{\xi}_{t|t-1})$$

Carter–Kohn algorithm

The algorithm developed by Carter and Kohn (1994) considers the factorisation of the joint density $H(\beta_T|Y_T)$:

$$\begin{aligned} H(\beta_T|Y_T) &= H(\beta_T|Y_T) \times H(\beta_{T-1}|\beta_T, Y_T) \\ H(\beta_T|Y_T) &= H(\beta_T|Y_T) \times H(\beta_{T-1}|\beta_T, Y_T) \\ &\times H(\beta_{T-2}|\beta_T, \beta_{T-1}, Y_T) \end{aligned}$$

Then,

$$H(\beta_T|Y_T) = H(\beta_T|Y_T) \times H(\beta_{T-1}|\beta_T, Y_T) \times H(\beta_{T-2}|\beta_T, \beta_{T-1}, Y_T) \\ \times H(\beta_{T-3}|\beta_T, \beta_{T-1}, \beta_{T-2}, Y_T)$$

Finally,

$$H(\beta_T|Y_T) = H(\beta_T|Y_T) \times H(\beta_{T-1}|\beta_T, Y_T) \times H(\beta_{T-2}|\beta_T, \beta_{T-1}, Y_T) \\ \times H(\beta_{T-3}|\beta_T, \beta_{T-1}, \beta_{T-2}, Y_T) \times ... \times H(\beta_1|\beta_T, \beta_{T-1}, \beta_{T-2}, \beta_{T-3,...}, \beta_2, Y_T)$$

Or, more concisely,

$$H(\beta_T|Y_T) = H(\beta_T|Y_T) \times ... \times H(\beta_1|\beta_T, \beta_{T-1}, \beta_{T-2}, \beta_{T-3,...}, \beta_2, Y_T)$$

Following (Kim and Nelson, 1999, p. 191), Expression (1) can be simplified because β_T is an AR or Markov process. Then, β_T does not contain additional information on $\beta]_(T-2)$, which is already included in $\beta_(T-1)$. Expression (1) can thus be rewritten in the following way:

$$H(\beta_T|Y_T) = H(\beta_T|Y_T) \times H(\beta_{T-1}|\beta_T, Y_{T-1})$$
$$\times H(\beta_{T-2}|\beta_{T-1}, Y_{T-2}) \times H(\beta_{T-3}|\beta_{T-2}, Y_{T-3}) \times ... \times H(\beta_1|\beta_2, Y_1)$$

Or, more compactly,

$$(H(\beta_T|Y_T) = H(\beta_T|Y_T) \prod_{t=1}^{T-1} [H(\beta_T|\beta_{t+1}, Y_t)]) \tag{A.14}$$

Stochastic volatility

Consider the following model Jacquier et al. (2002):

$$y_t = \varepsilon_t \sqrt{(exp(ln(h_t))}$$

where h_t is a state variable and a time-varying variance. Since it cannot be estimated using the Carter–Kohn algorithm, we use the independent Metropolis–Hastings algorithm. Obtain a starting value for $h_t, t = 0, ..., T$ and set the priors μ and σ (e.g. μ could be the log of the ordinary least squares estimate of the variance of ε_t and σ could be set to a large number to reflect the uncertainty around the initial value). At $t = 0$, sample the initial value of h_0 from the log-normal density $f(h_0|h_1) = h^{-1}exp(-(ln(h_0) - \mu_0)^2/(2\sigma_0))$, where $\mu_0 = \sigma_0(\mu/\sigma + ln(h_1)/g)$ and $\sigma_0 = (\sigma g)/(\sigma + g)$ Jacquier et al. (2002, p. 11).

For $t = 1...T-1$ for each t, draw a new value for h_t from the candidate density and call the draw $h_(t, new)$: $q(\Phi^{G+1}) = h^{-1}exp(-(ln(h_t) - \mu)^2/(2\sigma_h))$ where $\mu = ln[h_{t+1} + ln[h_{t-1}]]/2$ and $\sigma = g/2$. The acceptance probability is then derived as

$$\alpha = min[((h_{t,new}^{-0.5} exp(-(y_t^2)/(2h_{t,new})))/(h_{t,old}^{-0.5} exp(-(y_t^2)/(2h_{t,old}))), 1)] \tag{A.15}$$

Draw $u \sim U(0, 1)$. If $u < \alpha$, set $h_t = h_{t,new}$; otherwise, retain the old draw.

For the last time period T, compute $\mu = ln[h_{t-1}]$ and $\sigma_h = g$ and draw $h_(t, new)$ from the candidate density

$$q(\Phi^{G+1}) = h^{-1}exp(-(ln(h_t) - \mu)^2/(2\sigma_h))$$

and the acceptance probability

$$\alpha = min[((h_{t,new}^{-0.5} exp(-(y_t^2)/(2h_{t,new})))/(h_{t,old}^{-0.5} exp(-(y_t^2)/(2h_{t,old}))), 1)] \tag{A.16}$$

Draw $u \sim U(0,1)$. If $u < \alpha$, set $h_t = h_{t,new}$; otherwise, retain the old draw.

Given the draw for h_t, compute the residuals of the transition equation $[v]_t = ln[h_t] - ln[h_{t-1}]$.

Draw g from the inverse Gamma distribution with scale parameter $(v_t^{'} v_t + g_0)/2$ and degrees of freedom $(T + v_0)/2$. This is a combination of the Gibbs and Hastings–Metropolis algorithms.

Repeat steps 2 and 3. The last L draws of h_t and g approximate the marginal posterior distributions.

A.1.2 Data

Details of the survey data

The Joint Harmonised EU Programme of Business and Consumer Surveys was introduced in 1961 and extended to the consumer sector in 1972. The survey is conducted each month. As of May 2016, the programme included 28 member states, of which 10 are of interest in this study: Belgium, Germany, Greece, Spain, France, Italy, the Netherlands, Austria, Portugal, and Finland. The questions of interest from the consumer survey include: Q5. How do you think consumer prices have developed over the last 12 months? They have:

- ++ risen a lot
- + risen moderately
- = risen slightly
- − stayed about the same
- −− fallen
- N don't know.

Q6 By comparison with the past 12 months, how do you expect consumer prices to develop in the next 12 months? They will:

- ++ increase more rapidly
- + increase at the same rate
- = increase at a slower rate
- − stay about the same

- $--$ fall
- N don't know.

A.1.3 Tables

Table A.1: Area Wide Model: List of the variables.

Variable	**Area Wide Model index**	**T**	**F**
GDP at Market Prices	YER	6	0
Individual Consumption Expenditure	PCR	6	0
General Government Final Consumption Expenditure	GCR	6	0
Gross Fixed Capital Formation	ITR	6	0
Exports of Goods and Services	XTR	6	0
Imports of Goods and Services	MTR	6	0
GDP, Income Side	YIN	6	0
Net Factor Income from Abroad as a Share of GDP	NFN_YEN	4	0
Unemployment Rate	URX	4	0
Nominal Short-Term Interest Rate 3	STN	4	1
Nominal Long-Term Interest Rate 10	LTN	4	1
Commodity Prices	COMPR	6	1
Non-oil Commodity Prices	PCOMU	6	1
World GDP	YWR	6	0
Nominal Effective Exchange Rate	EEN	4	1
EURUSD	EXR	4	1

Note: Column T denotes transformation: $6 = log - difference$,$4 - difference$; Column F denotes fast moving variables (BBE): $1 = fast$,$0 = slow$ (for the Cholesky identification only).

A.1.4 Figures

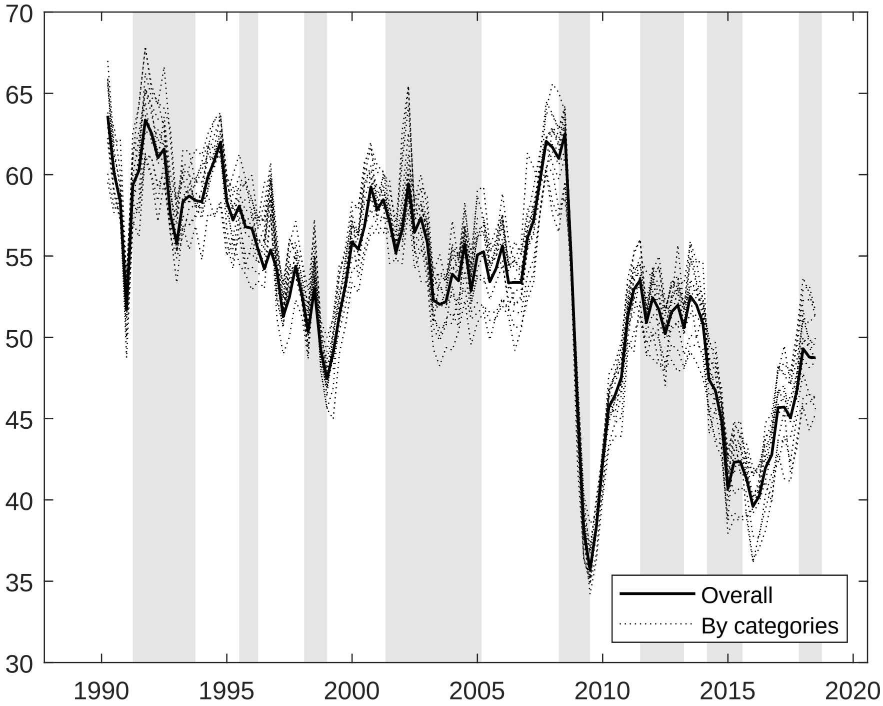

Figure A.2: Disaggregated inflation expectations by category.
Note: The solid line denotes overall inflation expectations. The dotted lines denote inflation expectations by age, gender, education, and income. The Values are calculated as the sum of the proportions of the populations reporting a price increase and price stability in the next 12 months. The shaded area is the OECD-based recession indicators for Germany following the peak through the trough.

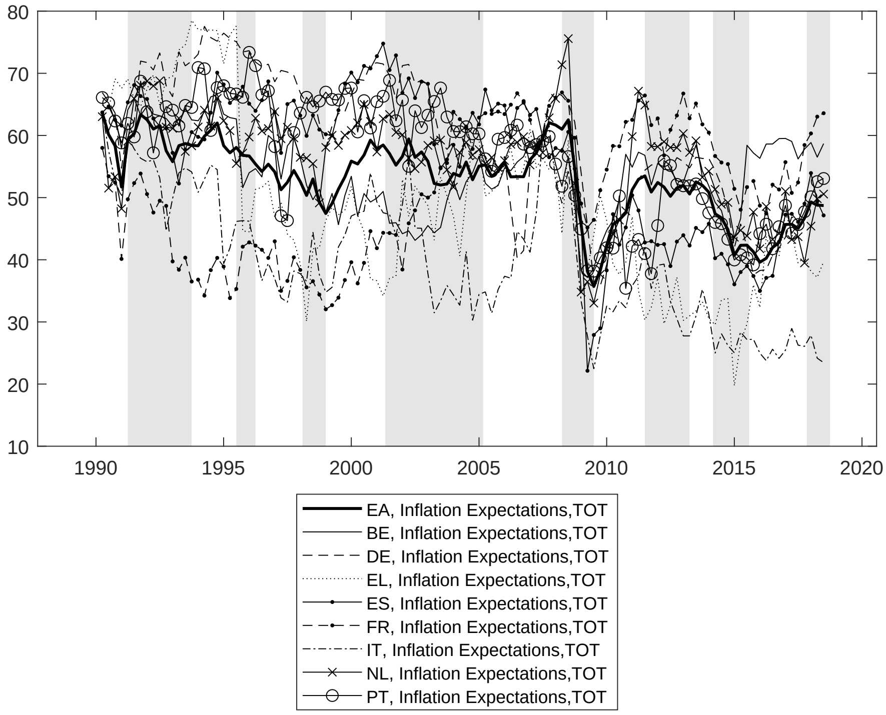

Figure A.3: Disaggregated inflation expectations by country.

Note: The solid line denotes overall inflation expectations. The values are calculated as the sum of the proportions of the populations reporting a price increase and price stability in the next 12 months. The shaded area is the OECD-based recession indicators for Germany following the peak through the trough.

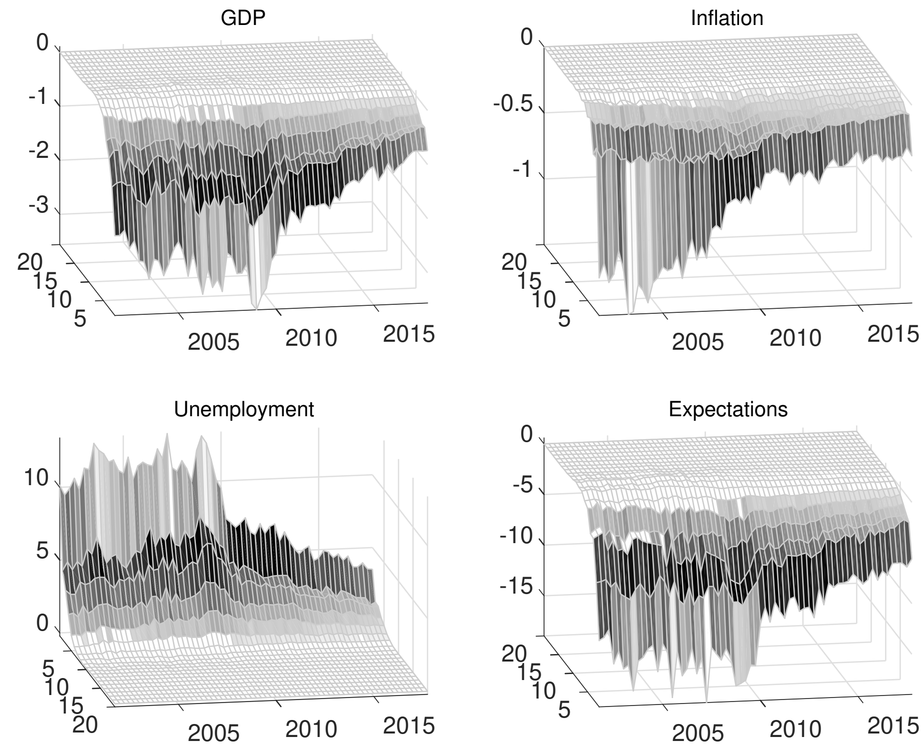

Figure A.4: Responses of GDP, inflation, unemployment, and inflation expectations to a contractionary MP shock.

Note: Time-varying median IRFs of the shadow rate (MP instrument). Identified with sign restrictions (see Section 2.1.2).

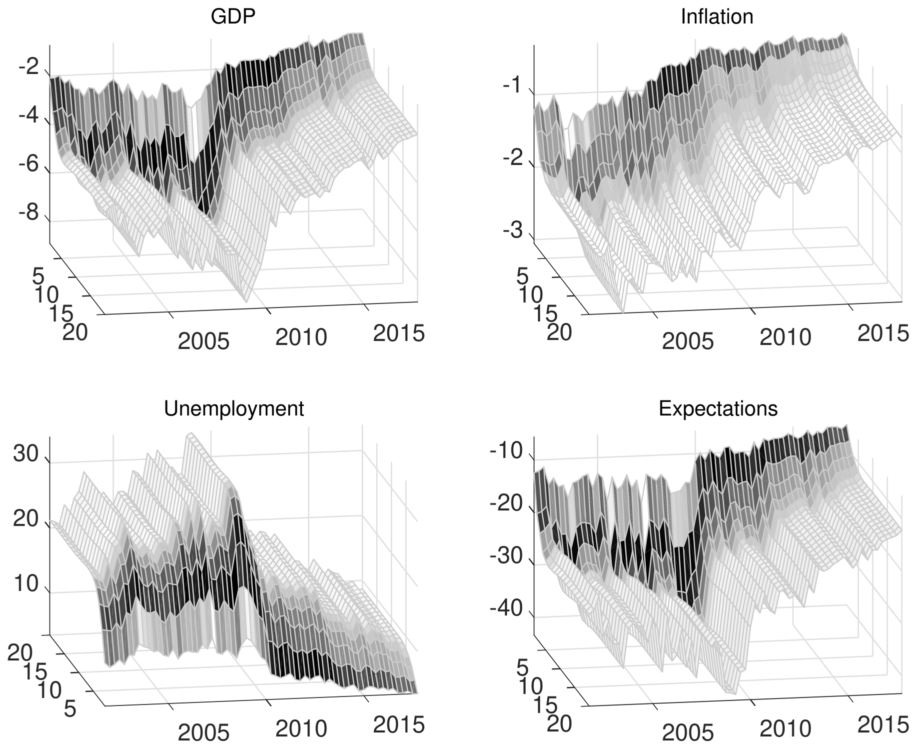

Figure A.5: Accumulated responses of GDP, inflation, unemployment, and inflation expectations to a contractionary MP shock.
Note: Time-varying median IRFs of the shadow rate (MP instrument). Identified with sign restrictions (see Section 2.1.2).

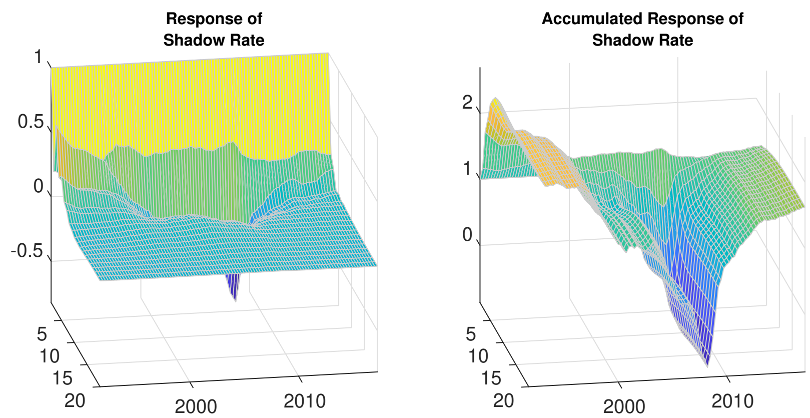

Figure A.6: Shadow rate response
Note: Time-varying median IRFs of the shadow rate (MP instrument). Identified with sign restrictions (see Section 2.1.2).

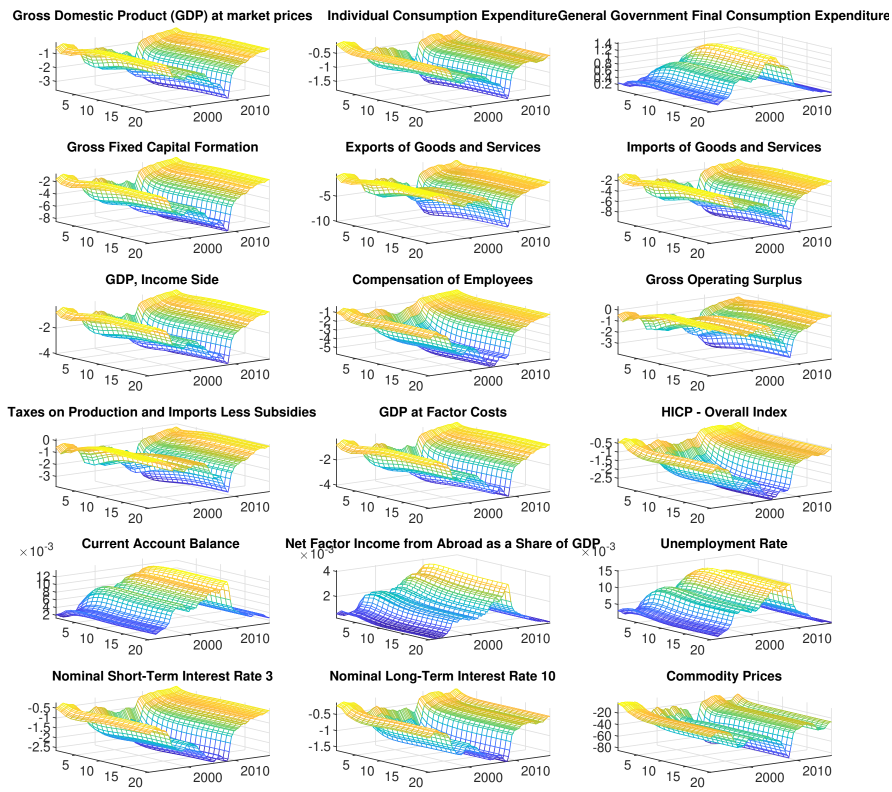

Figure A.7: Accumulated responses of the Area Wide Model variables (Fagan et al., 2005): Part 1.

Note: Time-varying median IRFs of the shadow rate (MP instrument). Identified with sign restrictions (see Section 2.1.2).

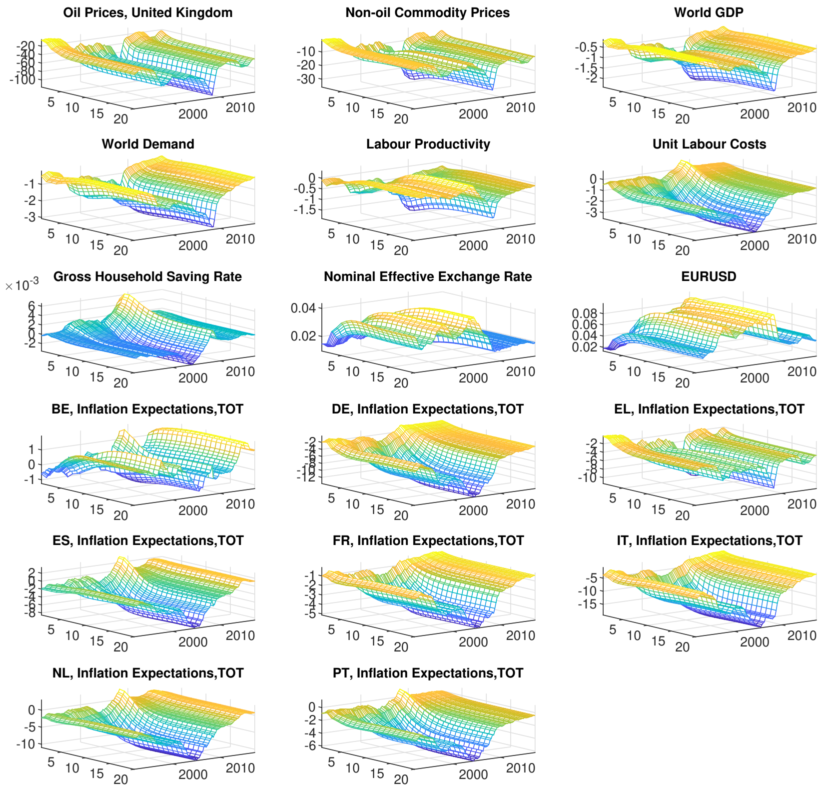

Figure A.8: Accumulated responses of the Area Wide Model variables (Fagan et al., 2005): Part 2.

Note: Time-varying median IRFs of the shadow rate (MP instrument). Identified with sign restrictions (see Section 2.1.2).

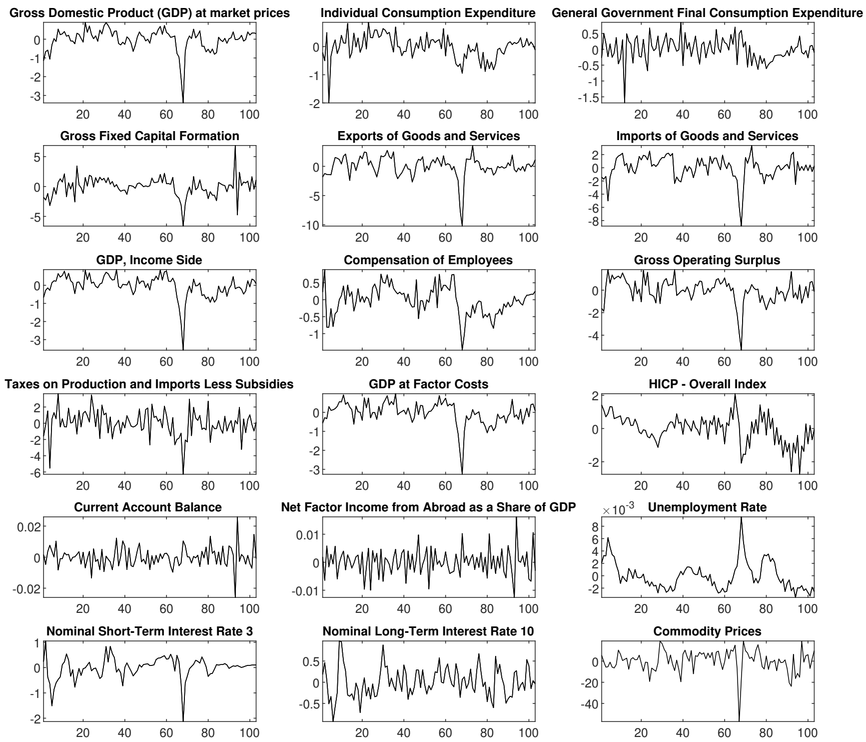

Figure A.9: Area Wide Model variables: Part 1.

Note: Data from the Area Wide Model (Fagan et al., 2005).

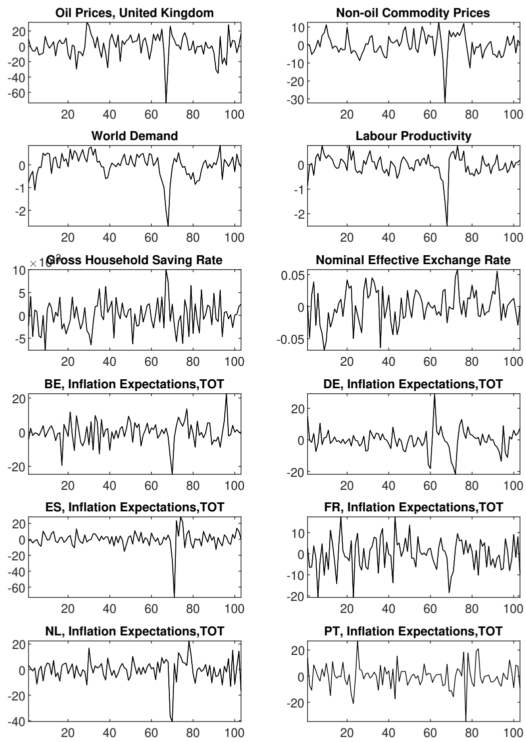

Figure A.10: Area Wide Model variables: Part 2.

Note: Data from the Area Wide Model (Fagan et al., 2005).

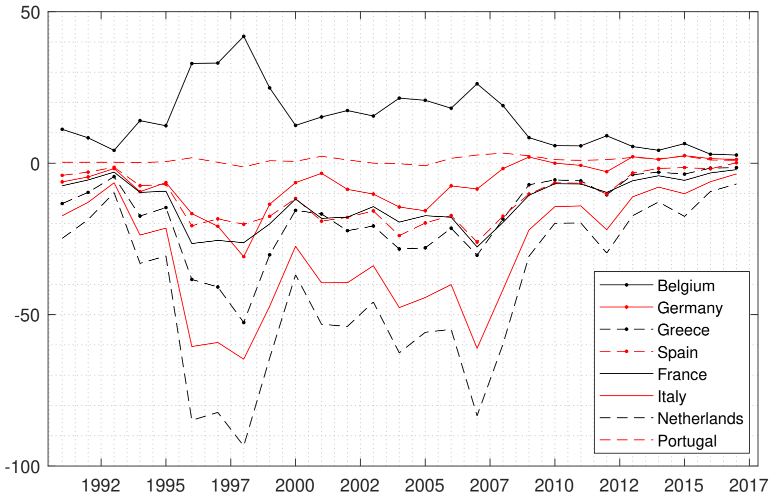

Figure A.11: Inflation expectation responses by country.

Note: Time-varying median responses of the inflation expectations by country, eight quarters after the shock.

A.2 Appendix Chapter 3

A.2.1 Tables

Table A.2: PSPP announcement and extensions

Wave	Reference period	PSPP Announcement	Duration	Size
1	January–June 2009			
11	April–September 2014			
12	October 2014–March 2015	22-Jan-15	March–end of September 2016	Monthly purchases of EUR 60 billion
13	April–September 2015			
14	October 2015–March 2016	03-Dec-15	Until the end of March 2017	Unchanged
15	April–September 2016			
16	October 2016–March 2017	08-Jun-17	Until the end of December 2017	Unchanged

Note: Data from the SAFE.

Table A.3: PSPP's effects on the volume of loans

	Loan volumes (a)			
Variable	(1) Below 1 m euros	(2) Above 1 m euros	(3) Below 0.25 m euros	(4) Between 0.25-1 m euros
PSPP/GDP (c)	52.46**	-81.73	47.36***	21.38
	(21.56)	(69.49)	(15.88)	(13.06)
Constant	1,025***	7,549***	146.5	872.7***
	(205.5)	(700.2)	(110.1)	(132.5)
Observations	352	337	319	317
R-squared	0.985	0.970	0.989	0.978
Country FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Note: Data from the SAFE.

Table A.4: PSPP's effects on the survey variables

	(1)	(2)	(3)	(4)
Variable	Interest (a)	Interest	Financial cost (b)	Financial cost
PSPP/GDP(c)	0.00812	-0.0761***	-0.00497	-0.0377***
	-0.00529	-0.0044	-0.00594	-0.00416
Constant	0.527***	0.574***	0.760***	0.851***
	-0.0636	-0.00254	-0.0911	-0.00237
Observations	30,454	30,454	25,581	25,581
R-squared	0.286	0.052	0.107	0.022
Country FE	YES	NO	YES	NO
Time FE	YES	NO	YES	NO
Individual FE	NO	YES	NO	YES
Number of respondents		22,592		19,312

Note: Data from the SAFE.

Table A.5: SAFE timeline

#	Survey wave	Fieldwork period	Publication date	Wave	Reference period: Past six months
1	2009H1	17 June 2009–23 July 2009	21-Sep-09	Common	January–June 2009
2	2009H2	19 November–18 December 2009	16-Feb-10	ECB wave	July–December 2009
3	2010H1	27 August–22 September 2010	22-Oct-10	ECB wave	March–September 2010
4	2010H2	21 February–25 March 2011	27-Apr-11	ECB wave	September 2010–February 2011
5	2011H1	22 August–7 October 2011	01-Dec-11	Common	April–September 2011
6	2011H2	29 February–29 March 2012	27-Apr-12	ECB wave	October 2011–March 2012
7	2012H1	3 September–11 October 2012	02-Nov-12	ECB wave	April–September 2012
8	2012H2	18 February–21 March 2013	26-Apr-13	ECB wave	October 2012–March 2013
9	2013H1	28 August–4 October 2013 *	14-Nov-13	Common	April–September 2013
10	2013H2	20 February–24 March 2014	30-Apr-14	ECB wave	October 2013–March 2014
11	2014H1	1 September–10 October 2014	12-Nov-14	Common	April–September 2014
12	2014H2	16 March–25 April 2015	02-Jun-15	ECB wave	October 2014–March 2015
13	2015H1	21 September–26 October 2015	02-Dec-15	Common	April–September 2015
14	2015H2	10 March–21 April 2016	01-Jun-16	ECB wave	October 2015–March 2016
15	2016H1	19 September–27 October 2016	02-Dec-16	Common	April–September 2016
16	2016H2	6 March–14 April 2017	24-May-17	ECB wave	October 2016–March 2017

Note: Data from the SAFE.

A.2.2 Figures

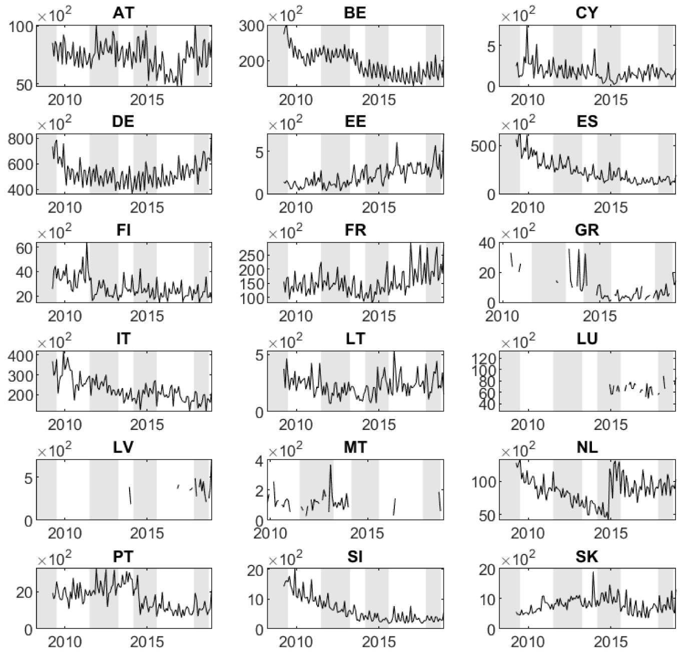

Figure A.12: Interest rate on loans with an IRF period of more than one year.
Note: Statistics Bulletin, MFI. The shaded area is the OECD-based recession indicators for Germany following the peak through the trough.

Table A.6: Description of interest rates

Code for the series	Description
A2A.A.B.	Bank business volumes - loans to corporations of up to 0.25 m euros (new business)
A2A.A.R.	Bank interest rates - loans to corporations of up to 0.25 m euros (new business)
A2A.F.R.	Bank interest rates - loans to corporations of up to 0.25 m euros with a floating rate and an IRF period of up to one year (new business)
A2A.K.R.	Bank interest rates - loans to corporations of up to 0.25 m euros with an IRF period of over one year (new business)
A2A.Q.R.	Bank interest rates - loans to corporations of up to 0.25 m euros with an IRF period of over three months & up to one year (new business)
A2A.Y.R.	Bank interest rates - loans to corporations of up to 0.25 m euros with an IRF period of up to one year & original maturity of over one year (new business)
A2AC.A.R.	Bank interest rates - loans to corporations with collateral of up to 0.25 m euros (new business)
A2AC.F.R.	Bank interest rates - loans to corporations with collateral of up to 0.25 m euros with a floating rate and an IRF period of up to one year (new business)
A2AC.Y.R.	Bank interest rates - loans to corporations with collateral of up to 0.25 m euros with an IRF period of up to one year & original maturity of over one year (new business)

Note: Data from the SAFE.

Table A.7: Difference-in-difference results with the survey outcomes

	(1)	(2)	(3	(4)
Variable	Interest	Interest	Financial cost	Financial cost
Treatment*Post(c)	-0.194***	-0.250***	-0.109***	-0.116***
	-0.0246	-0.0125	-0.0272	-0.0121
Constant	0.426***	0.587***	0.716***	0.855***
	-0.0665	-0.0028	-0.0887	-0.00268
Observations	30,454	30,454	25,581	25,581
R-squared	0.289	0.062	0.108	0.024
Country FE	YES	NO	YES	NO
Time FE	YES	NO	YES	NO
Individual FE	NO	YES	NO	YES
Number of respondents		22,592		19,312

Note: Data from the SAFE.

Table A.8: Difference-in-difference results with the survey outcomes by firm size

	(1)	(2)	(3)	(4)
Variable	Small	Medium	Large	All
Treatment*Post (b)	-0.268***	-0.174***	-0.101*	-0.194***
	-0.0303	-0.0361	-0.0518	-0.0246
Constant	0.259***	0.529***	0.587***	0.426***
	-0.084	-0.103	-0.0586	-0.0665
Observations	16,986	9,839	3,629	30,454
R-squared	0.265	0.322	0.294	0.289
Country FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Individual FE	NO	NO	NO	NO

Note: Data from the SAFE.

Table A.9: Description of the survey questions.

Type of question	Question number in the survey	Description	Dummy	Dummy=1
For each of the following actors, would you say that they have improved, remained unchanged, or deteriorated over the past six months?	Q11_a	General economic outlook, insofar as it affects the availability of external financing	outlook	improved
	Q11_b	Access to public financial support, including guarantees	pubfin	improved
	Q11_f	Willingness of banks to provide credit to your enterprise	bankcredit	improved
	Q11_h	Willingness of investors to invest	invest	improved
For each of the following types of financing, would you say that their availability has improved, remained unchanged, or deteriorated for your enterprise over the past six months?	Q9_a	Bank loans	loans	improved
	Q9_f	Credit line and overdrafts	overdraft	improved
We will turn now to the terms and conditions of bank financing, such as bank loans, overdrafts, and credit lines. Please indicate whether the following items increased, remained unchanged, or decreased in the past six months.	Q10_a	level of interest rates	interest	Was decreased by the bank
	Q10_b	cost of financing	fcost	Was decreased by the bank
	Q10_c	size of loan credit	loansize	Was increased by the bank
If you applied and tried to negotiate for this type of financing over the past six months, what was the outcome? Please provide a separate answer in each case.	Q7B_a	bank loan received	yesloan	received everything and received 75% and above
Have you applied for the following types of financing in the past six months?	Q7A_a	bank loan applied for	yesapplied	applied
What is the size of the last bank loan that your enterprise obtained or renegotiated in the past six months?	Q8_a	Size of bank loan	sloan	Small (under 25k euros)
What is the approximate number of employees?	D1_rec	number of employees	smallfirm	Under 50 employees
Indicate if your needs increased, remained unchanged, or decreased over the past six months.	Q5_a	Need for a bank loan	needloan	need of loan increased
	d1_rec	Number of employees		

Note: Data from the SAFE.

A.3 Appendix Chapter 4

A.3.1 Kalman filter

Consider a general state space model (with the notation following Hamilton (1994)):

$$\underset{r\times 1}{y_t} = \underset{n\times k}{A'} \times \underset{k\times 1}{x_t} + \underset{n\times r}{H'} \times \underset{r\times 1}{\xi} + \underset{n\times 1}{w_t} \tag{A.17}$$

$$\underset{r\times 1}{\xi_{t+1}} = \underset{1\times 1}{\mu} + \underset{r\times r}{F} \times \underset{r\times 1}{\xi_t} + \underset{r\times 1}{v_{t+1}} \tag{A.18}$$

where $\mathbb{E}[v_t v_t'] = Q$ and zero otherwise; $\mathbb{E}[w_t w_t'] = R$ and zero otherwise.

Assume that Y and X are observed. For simplicity, assume that the values F, Q, H, H, R are also known with certainty. This assumption is relaxed later. The following algorithm calculates the linear least squares forecasts of the state vector:

$$\hat{\xi}_{t+1|t} = \mathbb{E}(\xi_{t+1}|Y_t) \tag{A.19}$$

where $\mathbb{E}(\xi_{t+1}|Y_t)$ is a linear projection of ξ_{t+1} on Y_t and a constant. The Kalman filter produces these projections recursively for each time period. The mean squared error associated with each forecast is calculated as follows:

$$P_{t+1|t} \equiv \mathbb{E}[(\xi_{t+1} - \xi_{t+1|t})(\xi_{t+1} - \xi_{t+1|t})'] \tag{A.20}$$

If the eigenvalues of F are all inside the unit circle, the state process (transition equation) is covariance-stationary. Then, unconditional moments are given by $\xi_{0|0} = (I_r - F)^{-1}\mu$ and $vec(P_{0|0}) = (I - F \otimes F)^{-1} vec(Q))$. If the state process is not stationary and the eigenvalues of F lay outside unit circle, no unconditional moments exist; hence, the starting value for the mean is arbitrary and the variance is a diagonal matrix with large entries to reflect the uncertainty.

Given the starting values for the state and its variance, we forecast the state, variance, and observed variable. We assume that the exogenous variables x contain no information about the state beyond the already realised observed variables:

$$\xi_{t|t-1} = \mu + F\xi_{t-|t-1} \tag{A.21}$$

$$P_{t|t-1} = FP_{t-|t-1}F' + Q \tag{A.22}$$

$$\eta_{t|t-1} = y_t - A'x_{t|t-1} + H'\xi_{t|t-1} \tag{A.23}$$

$$f_{t|t-1} = H'P_{t|t-1}H + R \tag{A.24}$$

Equation (A.21) updates the state according to the transition equation; Equation (A.22) updates the state variance (which includes the error value from the transition equation); Equation (A.23) calculates the forecast error (i.e. the difference between the forecasted $\hat{y}$ and its realised counterpart); and Equation (A.24) calculates the forecast error variance (which includes the error value from the observation equation).

The next step is updating the inference about the state (finding $\hat{\xi}_{t|t}$):

$$\hat{\xi}_{t|t} = \underbrace{\hat{\xi}_{t|t-1}}_{\text{old forecast}} + \underbrace{P_{t|t-1}}_{\text{old variance}} \underbrace{H(H'P_{t|t-1}H + R)^{-1}}_{f_{t|t-1}} \underbrace{(y_t - A'x_{t|t-1} + H'\xi_{t|t-1})}_{\eta_{t|t-1}} \tag{A.25}$$

Alternatively, combining the old variance with the forecast error variance, the updating equation could be expressed using the Kalman gain expression:

$$\hat{\xi}_{t|t} = \underbrace{\hat{\xi}_{t|t-1}}_{\text{old forecast}} + \underbrace{P_{t|t-1}H'f_{t|t-1}^{-1}}_{\text{kalman gain}} \underbrace{\eta_{t|t-1}}_{\text{forecast error}} \tag{A.26}$$

Similarly, for the variance of the state,

$$P_{t|t} = \underbrace{P_{t|t-1}}_{\text{old variance}} - \underbrace{K}_{\text{kalman gain}} HP_{t|t-1} \tag{A.27}$$

The forecasts of the state and observed variables ($\hat{\xi}_{t|t-1}$ and $\hat{y}_{t|t-1}$) are optimal within the set of forecasts that are linear in x_t, X_{t-1}, Y_{t-1} (Hamilton, 1994, p. 385). If the initial state and innovations are multivariate Gaussian, the forecasts are optimal among any functions of x_t, X_{t-1}, Y_{t-1}. Furthermore, if the initial state and innovations are Gaussian, the distribution of y_t conditional on x_t and X_{t-1}, Y_{t-1} is also Gaussian:

$$y_t|x_t, X_{t-1}, Y_{t-1} \sim N((A'x_t + H'\hat{\xi}_{t|t-1}), (H'P_{t|t-1}H + R)) \tag{A.28}$$

Then, the sample log likelihood is the sum of the log likelihoods for each time period, consisting of the values from the Kalman filter algorithm:

$$\sum_{t=1}^{T} log f_{y_t|X_{t-1},Y_{t-1}}(y_t|X_{t-1}, Y_{t-1}) \tag{A.29}$$

where

$$f_{Y_t|X_{t-1},Y_{t-1}}(Y_t|X_{t-1}, Y_{t-1}) =$$

$$\frac{2}{\pi}\left|H'P_{t|t-1}H + R\right|^{-\frac{1}{2}} \times exp(\frac{1}{2}(A'X_t+H'\hat{\xi}_{t|t-1})'(H'P_{t|t-1}H+R)^{-1}) \times exp(A'X_t+H'\hat{\xi}_{t|t-1})$$

A.3.2 Figures

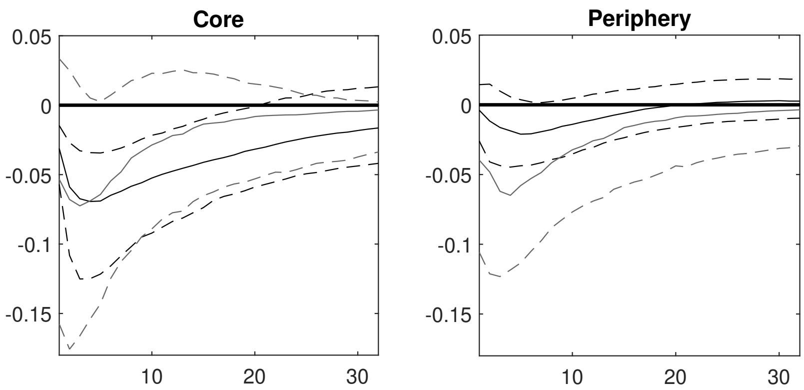

Figure A.13: Business lending rates: Accumulated responses from FAVAR with the recursive identification

Note: The solid lines are the median responses to a shock normalised to lower the EONIA by 1 percentage point on impact; the dotted lines are the 68% credible set. Black: pre-2007 crisis, Grey: sovereign debt crisis (January 2010 to December 2013).

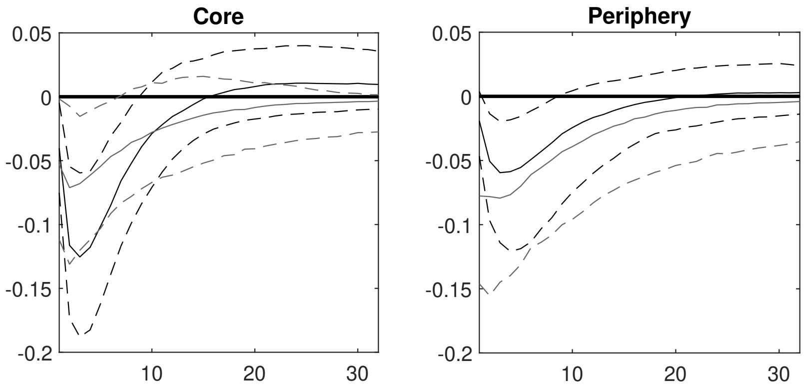

Figure A.14: Household lending rates: Accumulated responses from FAVAR with the recursive identification.

Note: The solid lines are the median responses to a shock normalised to lower the EONIA by 1 percentage point on impact; the dotted lines are the 68% credible set. Black: pre-2007 crisis, Grey: sovereign debt crisis (January 2010 to December 2013).

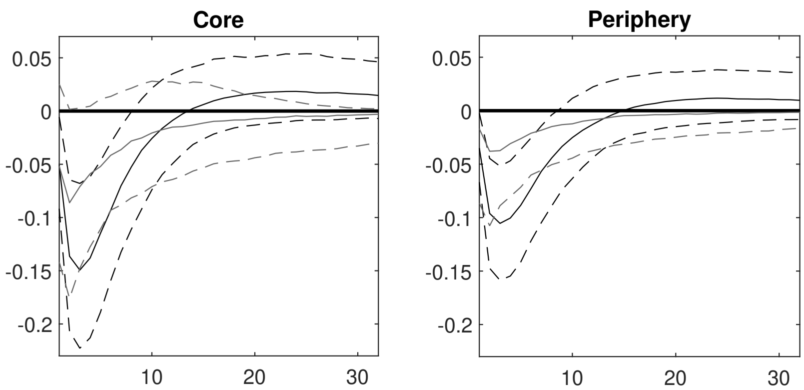

Figure A.15: Long-term lending rates: Accumulated responses from FAVAR with the recursive identification.

Note: The solid lines are the median responses to a shock normalised to lower the EONIA by 1 percentage point on impact; the dotted lines are the 68% credible set. Black: pre-2007 crisis, Grey: sovereign debt crisis (January 2010 to December 2013).

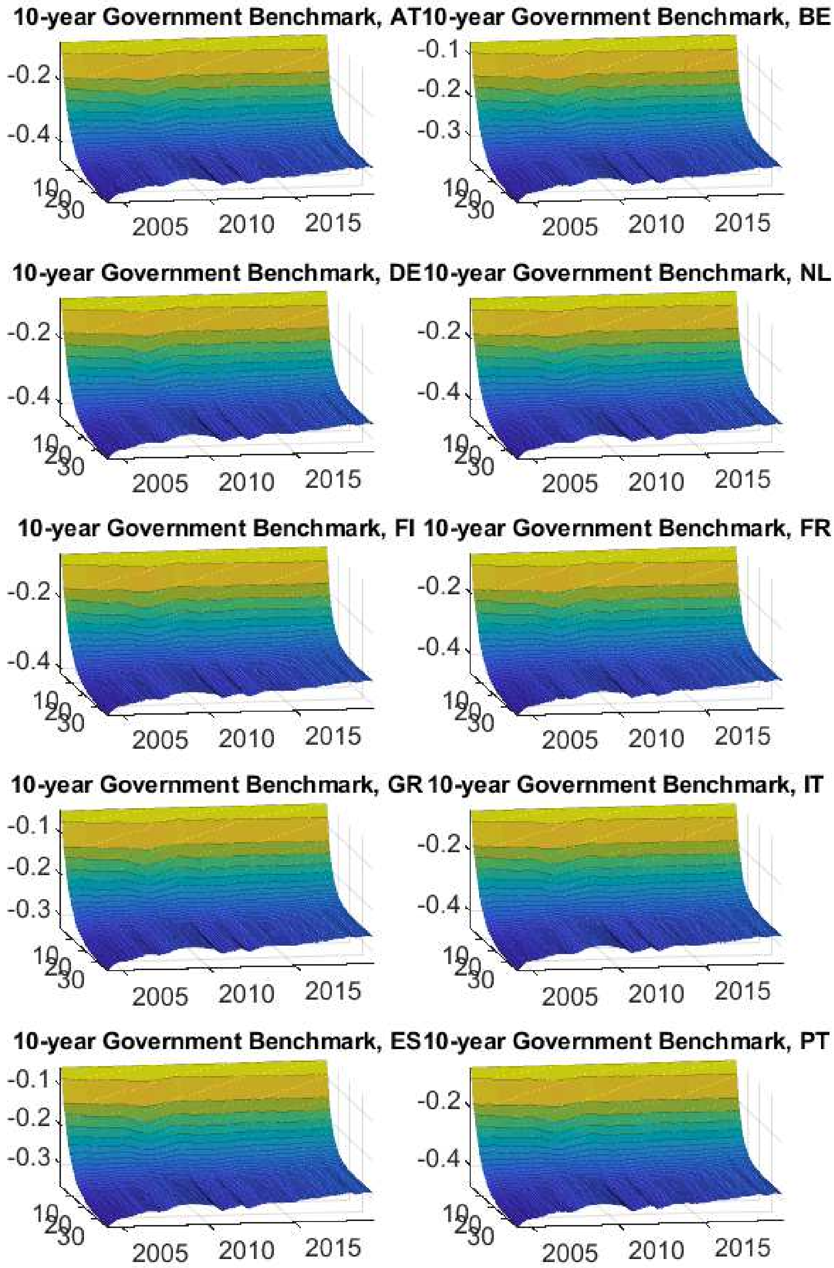

Figure A.16: Long-term lending rates: Accumulated responses from time-varying parameter FAVAR SV with the recursive identification.

Note: Time-varying median impulse response to a shock normalised to lower the EONIA by 1 percentage point on impact.

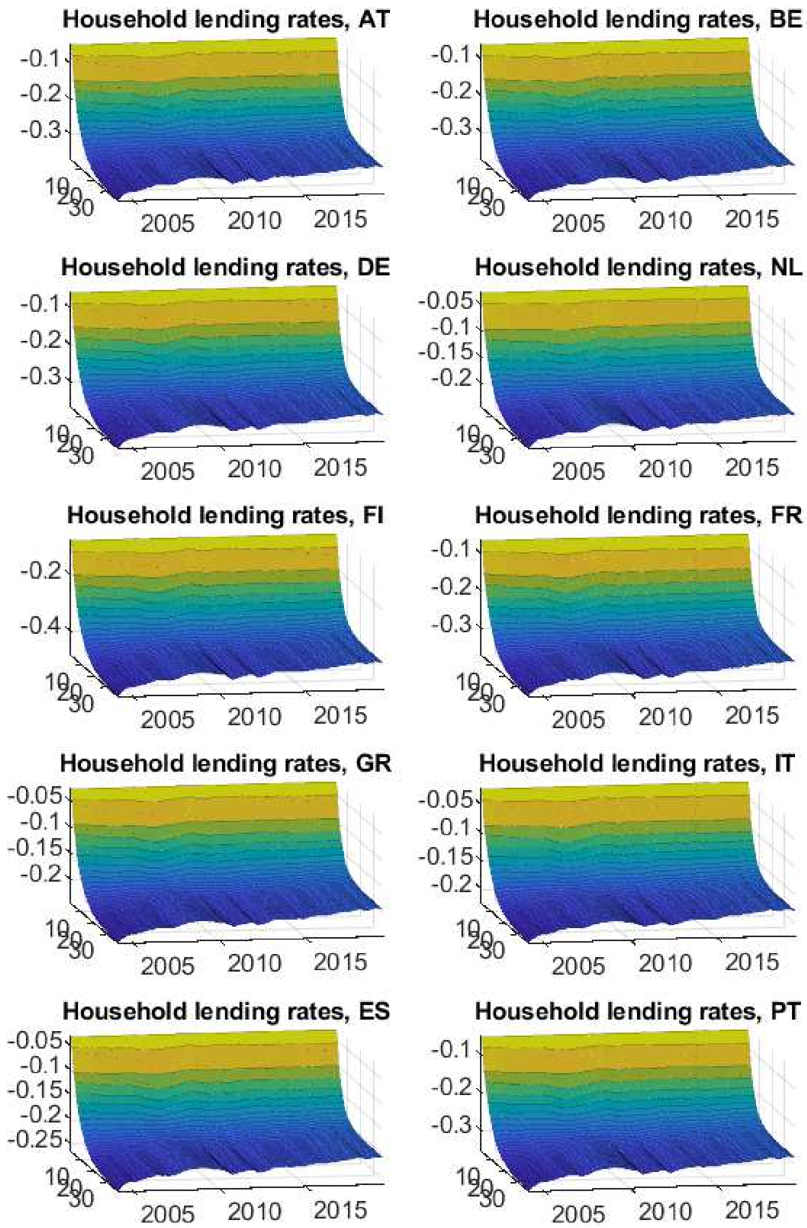

Figure A.17: Household lending rates: Accumulated responses from time-varying parameter FAVAR SV with the recursive identification.

Note: Time-varying median impulse response to a shock normalised to lower the EONIA by 1 percentage point on impact.

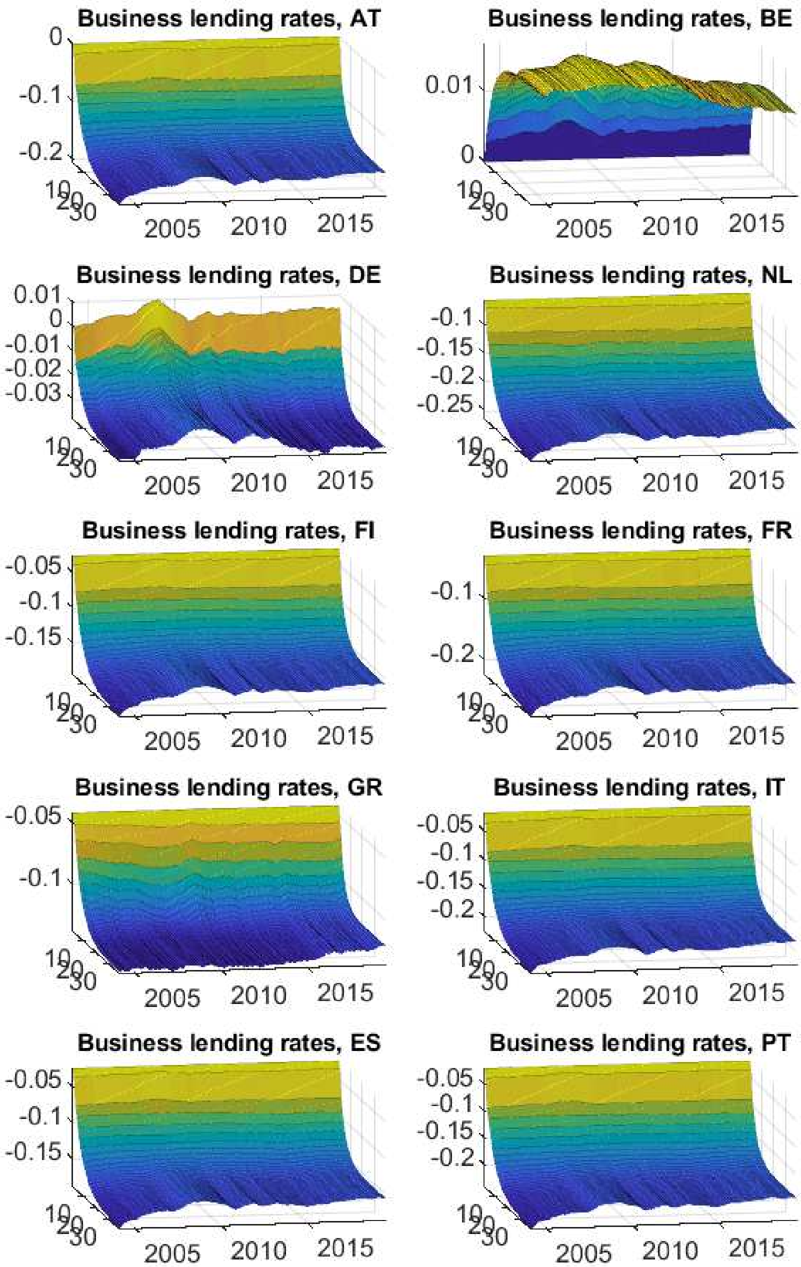

Figure A.18: Business lending rates: Accumulated responses from time-varying parameter FAVAR SV with the recursive identification.

Note: Time-varying median impulse response to a shock normalised to lower the EONIA by 1 percentage point on impact.

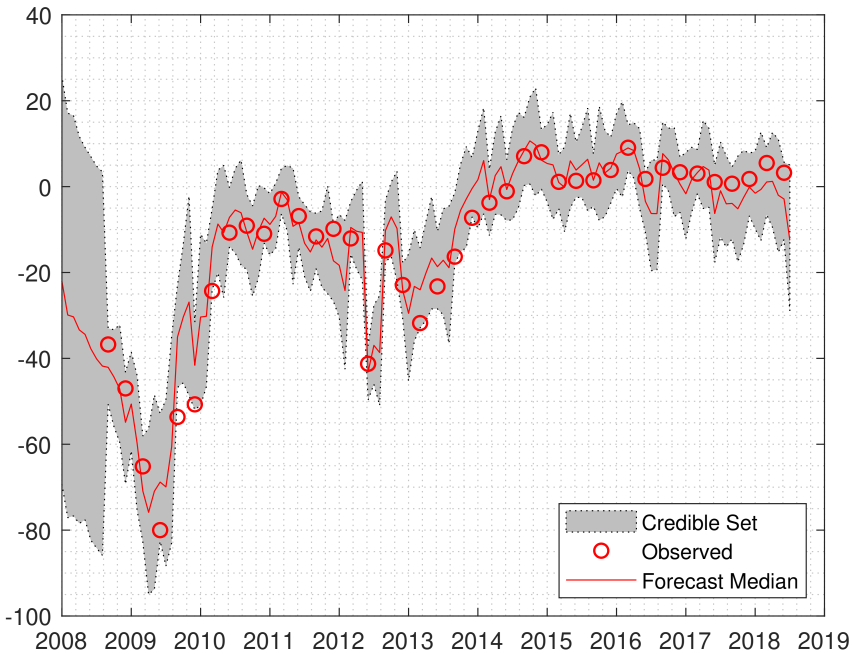

Figure A.19: Perceptions of economic activity, one-step ahead forecast. Multivariate MFVAR.

Note: The 'BLS' variable is the survey question on credit standards (eased=positive, tightened=negative). The credible set is 68%.

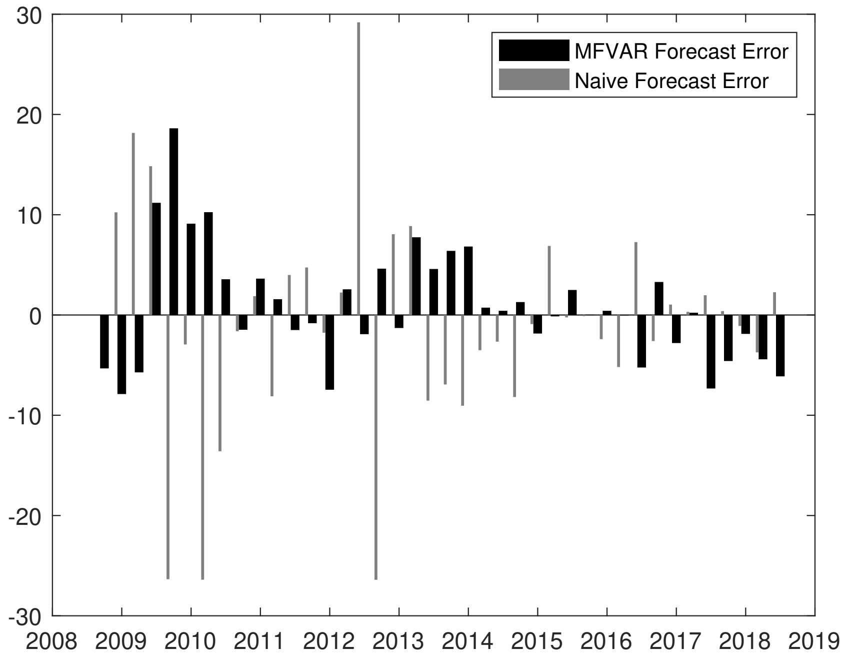

Figure A.20: Forecast error comparison: multivariate MFVAR and random walk
Note: Error is calculated as the difference between the realised value and median forecast produced by MFVAR using the pseudo sample. RMSE for multivariate MFVAR is 5.63 and for naive forecast 10.75.

Appendix B

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