# CROSS-COUNTRY HETEROGENEITY AND TIME VARIATION IN THE EURO-AREA ECONOMIES: INVESTIGATION USING VAR METHODS

by

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**Abstract**

This thesis investigates the monetary transmission mechanism in the Euro area, for countries taken individually and as an aggregate. The focus of the thesis is on the effects of monetary policy shocks on the area as a whole, across countries and over time during the period of single monetary policy by the Eurosystem. Using the most-recent empirical techniques such as factor-augmented vector autoregression (VAR), Bayesian Gibbs sampling, rolling windows, data pre-screening and panel VAR, the thesis investigates a novel (large) data set for the economies of the Euro area. According to our empirical analyses utilising these techniques, the thesis reaches the following main conclusions:

First, time variation in the impulse responses of area-wide consumer prices and monetary aggregates to monetary policy shocks is stronger than that of other key macroeconomic indicators. The contractionary impact of the monetary tightening on real activity is the strongest when it hits the economy during the global financial crisis period (Chapter 1). Second, although the effects of the policy shocks on national real activities and price levels are homogeneous across countries, the transmission mechanism displays important cross-country heterogeneity with the national monetary aggregates responding most heterogeneously to common monetary policy shocks (Chapter 2). Finally, despite the responses of the Eurosystem to the global financial crisis with unconventional monetary measures, country-specific factors such as defaults risks and bailouts played a significant role in disrupting the transmission of the policy actions to individual economic activities (Chapter 3).

*To my beloved wife Natiga.*
*This thesis would never exist without her.*

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| | |
|---|---|
| AIC | Akaike information criterion |
| AT | Austria |
| AU | Australia |
| AW | Area-wide |
| BBE | Bernanke et al. (2005) |
| BE | Belgium |
| BIC | Bayesian information criterion |
| BN | Boivin and Ng (2006) |
| BoE | Bank of England |
| CA | Canada |
| CBOE | Chicago Board Options Exchange |
| CL | Country-level |
| CPI | Consumer price index |
| CRB | Commodity Research Bureau |
| DE | Germany |
| DFM | Dynamic factor models |
| DSGE | Dynamic stochastic general equilibrium |
| EA | Euro area |
| ECB | European Central Bank |
| ECU | European Currency Unit |
| EM | Expectation-maximisation |
| EMI | European Monetary Institute |
| EMU | Economic and Monetary Union |
| ES | Spain |
| EU | European Union |
| FAVAR | Factor-augmented vector autoregression |
| Fed | Federal Reserve |
| FEVD | Forecast error variance decompositions |
| FI | Finland |
| FPE | Final prediction error |
| FR | France |
| GDP | Gross domestic product |
| GR | Greece |
| HICP | Harmonised index of consumer prices |
| HQ | Hannan-Quinn |
| IE | Ireland |
| IMF | International Monetary Fund |

| | |
|---|---|
| IP | Industrial production |
| IPN | Inflation Persistence Network |
| IRF | Impulse response function |
| IT | Italy |
| JP | Japan |
| LSAP | Large-scale asset purchases |
| LTRO | Longer-term refinancing operations |
| MA | Moving average |
| MFI | Monetary financial institutions |
| MIDAS | Mixed data sampling |
| NBER | National Bureau of Economic Research |
| NCB | National central bank |
| NL | Netherlands |
| OECD | Organisation for Economic Co-operation and Development |
| OLS | Ordinary least squares |
| PC | Principal components |
| PT | Portugal |
| RATS | Regression Analysis of Time Series |
| REFI | ECB official refinancing operation rate |
| SIC | Schwarz information criterion |
| SMP | Securities Markets Programme |
| SUR | Seemingly unrelated regression |
| TVP | Time-varying parameter |
| UK | United Kingdom |
| ULC | Unit labour cost |
| US | United States |
| VAR | Vector autoregression |
| VIX | CBOE Market Volatility Index |
| WDN | Wage Dynamics Network |
| WSJ | Wall Street Journal |

# INTRODUCTION

This thesis investigates the monetary transmission mechanism in countries of the Euro area (EA), taken individually and as an aggregate. Our attention in particular focuses on the impacts of monetary policy shocks on the area as a whole, across countries and over time during the period of single monetary policy by the Eurosystem. More specifically, in Chapter 1, we explore the area-wide and time-varying effects of the policy shocks in a data-rich environment of factor-augmented vector autoregression (FAVAR) techniques, proposed by Bernanke et al. (2005, henceforth BBE). In Chapter 2, we study the question of heterogeneity in the effects of common monetary policy shocks across the four largest Euro area economies using country-specific and panel FAVAR models. Finally, Chapter 3 applies the panel VAR approach of Gambacorta et al. (2012) to thirteen economies of the Euro area in order to investigate the cross-country effects of the Eurosystem's unconventional monetary policy actions during the global financial crisis period.

The first chapter of the thesis constructs a novel large data set for the Euro area as an aggregate, i.e. EA-17, spanning the period from January 1999 to December 2011. In order to investigate the transmission of monetary policy shocks to area-wide macroeconomic indicators and the question of time variation in the transmission mechanism, we employ two distinct estimation methods of a FAVAR model. The methods differ in terms of the estimation of "unobservable" components, i.e. factors, of the disaggregated data set under investigation. As described in Section 1.2.2, on the one hand, the two-step principal components (PC) approach provides a nonparametric way of estimating the factors (step 1) to be used in a VAR system (step 2) constructed of the factors and the monetary policy variable, i.e. the European Central Bank's (ECB) benchmark interest rate. On the other hand, the one-step Bayesian approach jointly estimates the factors and the VAR system using likelihood-based Gibbs sampling techniques. Both methods employ Bernanke et al.'s (2005) scheme for identifying the contractionary shocks to the policy variable in the system. Our essay contributes to the limited number of studies in the literature investigating the EA with the FAVAR approach by being the first, to our knowledge, to apply the Bayesian method to European data. Chapter 1 also employs the technique of rolling windows in order to capture time-varying impacts of the policy shocks, and the effects of the global financial crisis on the transmission mechanism in the EA as a whole. Finally, we contribute to the literature by investigating the Boivin and Ng (2006) pre-screening technique in a structural FAVAR context. In particular, we replicate our one- and two-step FAVAR estimations and the rolling analysis with a parsimonious data set pre-screened and minimised by the method. Technically, the approach is to examine the cross-section correlation in the idiosyncratic errors of the data, and eliminate those most correlated.

In Chapter 2, we construct identical and disaggregated large data sets for the four largest EA economies[1] spanning the period January 1999 - December 2011, as in the first chapter of the thesis. The main focus of the chapter is on the heterogeneity in the effects of common monetary policy shocks across the largest economies of the EA. In line with the contribution of the previous chapter, this essay pioneers the investigation

[1]See Table 0.0.2 below for the list of countries studied.

of the cross-country heterogeneity in the transmission of monetary policy shocks in the EA using the Bayesian FAVAR approach. In addition to country-level estimations, we construct a panel of the EA as an aggregate and the individual economies in order to test the robustness of the findings to the incorporation of area-wide factors into the system. We believe that our Bayesian panel approach contributes to the literature by providing alternative methodological investigation of the question of cross-country heterogeneity in the EA. The approach also links the first two chapters of the thesis where the total EA information is incorporated either by the use of an aggregate data set (Chapter 1) or a panel of individual data sets (Chapter 2). Similar to the structure of the previous chapter, the essay further explores time variation in, and the impact of the crisis on cross-country heterogeneity using the rolling windows approach. The impact of data size on the analysis is also investigated by applying the pre-screening technique of Boivin and Ng (2006) to country-specific data sets.

The last essay of the thesis (Chapter 3) focusses on the global financial crisis period and the question of cross-country effects of unconventional monetary policy in the EA using the panel VAR approach of Gambacorta et al. (2012). In particular, we estimate a (low-dimensional) panel VAR model for thirteen member states of the EA[2] for the crisis period from January 2008 to September 2012. To our knowledge, this paper is the first to investigate the effectiveness of unconventional monetary policy shocks across EA economies, and to do so using a structural panel VAR technique. Using a mix of zero and sign restrictions, we identify expansionary shocks to national central bank total assets and their possible impacts on the area-wide and country-level economic activities and price levels. Different from the previous chapters, here we investigate the area-wide effects

[2]See Table 0.0.2 below for the list of countries studied.

of the monetary policy shocks as the weighted average of the country-specific impulse response functions. The essay finally studies the transmission channels of (un)conventional monetary policies together with the developments in key macroeconomic indicators in core and peripheral economies of the EA in order to identify possible disruptions in the transmission of the policy actions across the regions of the area.

Table 0.0.2 presents a list of EA countries studied in each chapter of the thesis with the dates they adopted the euro as their currency.

Table 0.0.2: List of Countries Studied

| **Country** | **Year** | **Chapter 1** | **Chapter 2** | **Chapter 3** |
|---|---|---|---|---|
| Germany | 1 January 1999 | EA as an | Germany | All of the member |
| France | 1 January 1999 | aggregate | France | states which adopted |
| Italy | 1 January 1999 | | Italy | the euro before the |
| Spain | 1 January 1999 | | Spain | beginning of the esti- |
| Netherlands | 1 January 1999 | | | mation sample of the |
| Belgium | 1 January 1999 | | | chapter, i.e. Jan 2008. |
| Austria | 1 January 1999 | | | |
| Finland | 1 January 1999 | | | |
| Portugal | 1 January 1999 | | | |
| Ireland | 1 January 1999 | | | |
| Luxembourg | 1 January 1999 | | | |
| Greece | 1 January 2001 | | | |
| Slovenia | 1 January 2007 | | | |
| Cyprus | 1 January 2008 | | | |
| Malta | 1 January 2008 | | | |
| Slovakia | 1 January 2009 | | | |
| Estonia | 1 January 2011 | | | |

Source: ECB.

CHAPTER 1

# MONETARY TRANSMISSION MECHANISM AND TIME VARIATION IN THE EURO AREA

## 1.1 Introduction

One of the major focuses of modern monetary economics has been quantifying and analysing monetary disturbances in terms of their effects on various sectors of the economy. There is no doubt that measuring the interaction between monetary policy and the evolution of the entire economy is of crucial importance for good policy-making. Therefore, the study of monetary policy shocks has taken an important place in the modern macroeconomics literature.

In the applied macroeconomic literature, VAR models, pioneered by Sims (1972, 1980a,b), have become the most widely implemented method of identifying monetary policy shocks. We can attribute the popularity of these models to their ability to consider all the variables in the system as endogenous, to the dynamic structure of the models, to the practicality of impulse response and variance decomposition analyses, and last but not least, to the possibility of using simple techniques such as ordinary least squares (OLS) to estimate the models. Empirical results obtained from the early VAR models, however, were found to be misleading, and suggested puzzling dynamics in the behaviour of various macroeconomic variables, such as a rise in price levels in response to a monetary contraction, the so called price puzzle phenomenon.

To remedy these puzzles, a number of researchers have proposed various alternative methods such as (1) calculating monetary policy shocks as innovations to short-term interest rates instead of to "high-order" monetary aggregates (Bernanke and Blinder, 1992), (2) extension of the standard VARs by variables representing inflationary pressure, e.g. the commodity price index, (Sims, 1992), or (3) by variables capturing the foreign sector of the economy (Cushman and Zha, 1997).

Investigation of these explanations and solutions to the puzzles sheds light not only on the reasoning behind the puzzles but also on the crucial difficulty of the VAR models that they are commonly "low-dimensional".[1] The majority of VARs in the literature rarely employ more than five to eight variables due to the "curse of dimensionality", such that as the dimension of the system increases the number of parameters to be estimated grows quadratically and quickly exhausts the available degrees of freedom, even for large data sets.[2] Moreover, considering the large information sets used by central banks it is not possible to span these sets by low dimensional VAR systems.

According to BBE, two potential sets of problems emerge due to the use of the so called "sparse information sets" in VAR models. Firstly, since the capacity of the models employed by the econometricians and the span of information sets used by the policy makers are significantly different, "the measurement of policy innovations is likely to

[1]Here we refer to generally used standard VAR models. Throughout the literature, however, some studies, e.g. Leeper et al. (1996) and Bańbura et al. (2008) managed to employ 13-18 and up to 130 variables, respectively, using Bayesian techniques.

[2]Sims (1980b).

be contaminated".[3] As claimed by Mumtaz and Surico (2009, p.72), in this case "what appears to the econometrician to be a policy shock is, in fact, the response of the monetary authorities to the extra information not included in the VAR". Secondly, the impulse response functions (IRF) and forecast error variance decompositions can be obtained only for the variables included in the investigations. However, as emphasised above, these variables are known to "generally constitute only a small subset of the variables that the researcher and policymakers care about" (BBE, p.389).

As a solution to these drawbacks of the VAR models, BBE highlight the literature on dynamic factor models (DFM)[4] which suggests that comovements of a large number of macroeconomic time series can be summarised by a relatively small number of estimated "factors" or "indices". BBE claim that "if a small number of estimated factors effectively summarise large amounts of information about the economy, then a natural solution to the degrees-of-freedom problem in VAR analyses is to augment standard VARs with estimated factors".[5] Building on this idea, the authors develop the factor augmented VAR (FAVAR) model.

The key insight of the FAVAR approach is that, using the factors integrated into the model, it is possible to take almost all potentially relevant information for policymakers into account, and identify monetary policy shocks as simply as in standard VAR models. The FAVAR framework outperforms the standard VARs by making it possible to observe impulse responses for as many variables as we include in our large data sets.[6] It is an obvious fact that this feature of the model makes it possible to have a much more

[3]Bernanke et al. (2005, p.388).

[4]Introduced by Geweke (1977), and further studied by Sargent and Sims (1977), Stock and Watson (1998, 1999, 2002a,b), Giannone et al. (2004), among others.

[5]Bernanke et al. (2005, p.390).

[6]For technical details see the Methodology section of the chapter.

comprehensive picture of the effects of monetary policy shocks on the economy.

The FAVAR models have been widely implemented in the recent literature in the context of identifying the effects of monetary policy shocks on the economy. Table 1.1.1 presents some of these studies with their estimation and identification techniques, and countries studied.[7] From the table it is clearly noticeable that a majority of the studies apply the technique to United States (US) data, whereas only a few of them investigate the EA.

Further investigation of the literature suggests that the gap concerns not only the application of the approach for the EA in general, but also involves (i) the investigation of the post-1999 period using a common monetary policy variable controlled by the ECB only and (ii) the implementation of the Bayesian one-step estimation technique, details of which are described in Section 1.2.2. As we can see in the fourth column of the table, sample periods of the first three studies of the EA span both pre- and post-1999 periods. These studies either use some countries', e.g. Germany, short term interest rates as a proxy for the common policy variable, or aggregate country-specific series in order to obtain area-wide measures. As highlighted by McCallum and Smets (2007, p.10), however, "the identified monetary policy shock (in these FAVAR models) may not be completely homogenous across countries."

In addition to the lack of application of FAVARs and Bayesian techniques to the EA, we observe another important gap in the literature. As shown above, Boivin and Ng (2006, p.171) highlight the fact that "a new strand of research has made it possible to use information from a large number of variables while keeping the empirical framework small." Claiming that little is known in the literature about how data size and composition

[7] The details of the techniques employed in our study are described in Sections 1.2.2 and 1.2.3.

Table 1.1.1: The Monetary FAVAR Literature

| **Study** | **Estimation** | **Identification** | **Country** |
|---|---|---|---|
| BBE | Two-step PC<br>One-step Bayesian | Recursive ordering<br>$F_t^S$ vs $F_t^F$ | US<br>59:M1-01:M8 |
| Ahmadi (2005) | Bayesian | Sign Restrictions | US<br>59:M1-01:M08 |
| Stock and Watson (2005) | Two-step PC | Various Schemes | US<br>59:M1-03:M12 |
| Belviso and Milani (2006) | Bayesian | Cholesky Decomposition | US<br>60:M1-98:M12 |
| Ahmadi and Uhlig (2007) | Bayesian | Sign Restrictions | US<br>59:M1-01:M8 |
| Boivin and Giannoni (2007) | Two-step PC | BBE | US<br>84:M1-05:M2 |
| Boivin et al. (2009) | Two-step | BBE | US<br>76:M1-06:M6 |
| Bork (2009) | EM Algorithm | BBE | US<br>59:M1-01:M8 |
| Koop and Korobilis (2010) | Bayesian | BBE | US<br>53:Q1-06:Q3 |
| Mumtaz et al. (2011) | Bayesian | Sign Restrictions | UK<br>77:Q1-06:Q3 |
| McCallum and Smets (2007) | Two-step PC | BBE | EA[b]<br>86:Q1-05:Q4 |
| Boivin et al. (2008) | Two-step PC | Boivin et al.[a] (2009) | EA[c]<br>80:Q1-07:Q3 |
| Blaes (2009) | Two-step PC | BBE | EA[d]<br>86:Q4-06:Q4 |
| Soares (2011) | Two-step PC | BBE | EA[d]<br>99:M1-09:M3 |

[a] Boivin et al. (2009) approach is very close to but slightly different than the BBE scheme. For details see the original paper or Boivin et al. (2008). [b] Germany, France, Italy, Spain, the Netherlands, Belgium, Finland, Portugal, Greece, Ireland. [c] Belgium, France, Germany, Italy, the Netherlands, Spain. [d] EA as a whole.

affect the factor estimates, the authors ask whether it could be that increasing the number of observations in the cross-section “beyond a certain point is not even desirable.” By investigating the cross-section correlation in the idiosyncratic errors of the data, and eliminating those most correlated, Boivin and Ng find in a real time forecasting exercise that factors estimated from as few as 40 pre-screened series often yield equally well or even better forecasts than using all 147 series.[8] In other words, their analysis suggests that "expanding the sample size simply by adding data that bear little information about the factor components does not necessarily improve forecasts."[9]

There are similar approaches in the forecasting literature proposed by Grenouilleau (2004), Marcellino (2006), Banerjee et al. (2008), Bai and Ng (2008a), Bańbura and Rünstler (2011), among others, and surveyed by Eickmeier and Ziegler (2008) and Bai and Ng (2008b). However, to our knowledge, structural analysis with pre-screening is yet to be explored in the literature.

These observed gaps in the literature bring us to the key aims of this chapter which are fourfold. First, we gather a novel data set consisting of 120 disaggregated macroeconomic time series spanning the period 1999:M1 through 2011:M12, and identify the impacts of monetary policy shocks in the EA as an aggregate.[10] Second, in addition to the commonly used two-step PC FAVAR approach, we employ the Bayesian joint estimation technique and compare the results suggested by the two rather different methods, which produce distinct factor estimates. Third, given our sample includes the global financial crisis commencing in 2007-8, we use rolling windows to identify the changes created by the crisis on the impact of the shocks in the economy. Finally, we replicate the analyses in the first part of the chapter by using a rather parsimonious data set pre-screened and minimised by the Boivin and Ng (2006) approach, and try to identify the impact of screening from the perspective of structural analysis.

In brief, the main results of the chapter are as follow. Our FAVAR model suggests estimates for the responses of a wide variety macroeconomic variables to monetary policy

[8]See Section 1.4.3 for further details of the approach.
[9]Bai and Ng (2008a).
[10]See Appendix A for details of the data set.

shocks in the EA that are largely consistent with conventional wisdom. PC and Bayesian estimation techniques applied to our model suggest broadly similar findings, yet also provide distinct results such as smoother impulse responses with tighter confidence intervals from the latter technique. Our rolling windows approach shows that while a surprise monetary tightening has a consistently negative impact on the real activity measures, the global financial crisis leads to important variations in the responses of nominal variables such as the price level and money supply to the policy shock. Consistent with the real time forecasting exercise by Boivin and Ng (2006), finally, we find in a FAVAR context that factors extracted from as few as 67 series might do no worse, and as our Bayesian estimations suggest, better than ones extracted from 120 series.

The remainder of the chapter is organised as follows: Section 2 describes the methodology of the chapter which consists of the FAVAR framework, model estimation and identification, and Boivin and Ng pre-screening technique; preliminary analyses consisting of the data, number of factors and lags, and interpolation of quarterly series are contained in Section 3; Section 4 presents the empirical results of the chapter in three parts consisting of (a) study of the monetary transmission mechanism in the EA; (b) time variation and (c) Boivin and Ng analysis of impulse responses with screened data; Section 5 contains the robustness checks of the results; and Section 6 concludes the chapter.

## 1.2 Methodology

### 1.2.1 The FAVAR Model

Let $Y_t$ and $X_t$ be two vectors of economic variables with dimensions $M \times 1$ and $N \times 1$, respectively, and $t$ be a time index; $t = 1, 2, \ldots, T$, where $N$ can be larger than $T$. We can interpret $Y_t$ as a set of observable economic indicators, and $X_t$ as a large data set of economic indicators thought to be in central bank's information set. Bernanke et al. (2004a, pp.5-6) propose that the common dynamics of all variables in the economy, $X_t$, are driven by some "pervasive forces" and idiosyncratic components. These forces are assumed to consist of both "unobservable" and "observable" components. The unobservable ones are summarised by a $K \times 1$ vector of factors, $F_t$, while the policy variable, i.e. the ECB's benchmark interest rate, is assumed to be the only observable factor in the system. That is to say, $Y_t$ is a one-dimensional vector. It is additionally assumed that the joint dynamics of $Y_t$ and $F_t$ are described by a VAR system, providing the FAVAR model by BBE.

We can summarise the FAVAR model in state-space representation as follows:[11]

$$X_{it} = \Lambda_i^f F_t + \Lambda_i^y Y_t + e_t, \qquad E(e_t' e_t) = R \tag{1.2.1}$$

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + u_t, \quad E(u_t' u_t) = Q \tag{1.2.2}$$

where for $i = 1, \ldots, N$, $\Lambda^f$ is an $N \times K$ matrix of factor loadings, $\Lambda^y$ is $N \times M$, $e_t$ is an $N \times 1$ vector of error terms, which are mean zero and assumed to be either weakly correlated or uncorrelated depending on the method of estimation of the model,[12] $\Phi(L)$

[11]For further details see Kim and Nelson (1999), BBE, Stock and Watson (2005), among others.

[12]See Section 1.2.2 for details.

is a conformable lag polynomial of finite order $d$, and $u_t$ is a $(K + M) \times 1$ error vector that $u_t \sim i.i.d.N(0, Q)$. The error terms of equations (1.2.1) and (1.2.2) are assumed to be independent of each other, and $R$ is diagonal. Using state-space terminologies, (1.2.1) and (1.2.2) are the observation (or measurement) and the transition (or state) equations, respectively.

**Impulse Response Functions**

It has been noted earlier that one of the advantages of the FAVAR methodology over standard VARs is the possibility of conducting impulse response analysis on a larger scale. Here we follow Blaes (2009) and briefly explain how these functions are obtained.

According to the moving average (MA) representation of the transition equation (1.2.2), the impulse response functions of $\hat{F}_t$ and $Y_t$ are given by,

$$\begin{bmatrix} \hat{F}_t \\ Y_t \end{bmatrix} = \Psi(L) u_t \tag{1.2.3}$$

where $\Psi(L) = [I - \phi_1 L - \ldots - \phi_d L^d]^{-1} = [I - \Phi(L)]^{-1}$.

Combining equations (1.2.1) and (1.2.3) leads us to the following transformation:

$$X_{it}^{IRF} = \begin{bmatrix} \hat{\Lambda}^f & \hat{\Lambda}^y \end{bmatrix} \begin{bmatrix} \hat{F}_t \\ Y_t \end{bmatrix} = \begin{bmatrix} \hat{\Lambda}^f & \hat{\Lambda}^y \end{bmatrix} [\Psi(L) u_t] \tag{1.2.4}$$

which allows us to construct the impulse responses for any element $X_{it}$ of $X_t$.

It is important to note that equation (1.2.4) displays the impulse response functions to  shocks, i.e. innovations to $u_t$. The main focus of a structural analysis, however, is to investigate the responses of the variables of interest to structural, e.g. monetary policy, shocks. As we describe in subsection 1.2.3 later in the chapter, it is necessary to identify the relationship between the reduced form and structural shocks for this purpose.

Identification of the system allows us to calculate, in the same manner in equation (1.2.4), the responses of the variables in $X_{it}$ to structural shocks.[13]

### 1.2.2 Estimation

BBE propose two approaches to estimating the model. The first one is a two-step PC approach, "which provides a nonparametric way of uncovering the common space spanned by the factors of $X_t$".[14] The second is a joint estimation approach of (1.2.1) and (1.2.2) by likelihood-based Gibbs sampling techniques. BBE highlight that these approaches differ in various dimensions, and there are no clear a priori reasoning favouring one approach over the other. Therefore, as mentioned earlier, we employ both these approaches in this chapter. Details of the techniques are described in the following subsections.

**TWO-STEP PRINCIPAL COMPONENTS APPROACH**

The two-step PC procedure estimates (1.2.1) and (1.2.2) separately. In the first step, analogous to the forecasting exercises of Stock and Watson (2002b), PC analysis is applied to the observation equation (1.2.1) in order to estimate the space spanned by the factors using the first $K + M$ PC of $X_t$, denoted by $\hat{C}(F_t, Y_t)$. Notice that the estimation of this step does not impose the constraint that the observed factors, $Y_t$, are among the common components. That is to say, $Y_t$ is removed from the space covered by the PC "by performing a transformation of the PC exploiting the different behaviour of (so called) 'slow-moving' and 'fast-moving' variables, in the second step."[15,16] However, as

[13]See subsection 1.2.3, part 'Identification of the Monetary Policy Shocks' for details of the identification scheme employed in the chapter.

[14]Bernanke et al. (2005, p.398).

[15]Boivin et al. (2008, p.6).

[16]See Section 1.2.3 for the specific identifying assumption used in the second step.

highlighted by Bernanke et al. (2005, p.398), and shown in Stock and Watson (2002b), the PC consistently recover the space spanned by both $F_t$ and $Y_t$ in the case of $N$ being large and the number of PC used being at least as large as the true number of factors.

In other words, the first step of the approach employs the PC in order to estimate the factors $(\hat{F}_t^1, \hat{F}_t^2, \ldots, \hat{F}_t^K)$ from the measurement equation (1.2.1). Given the assumption that $R$ is diagonal in (1.2.1), the method estimates the model equation by equation using OLS in order to obtain the estimates of factor loadings, i.e. $(\hat{\Lambda}_1^f, \hat{\Lambda}_2^f, \ldots, \hat{\Lambda}_K^f)$.

In the second step, we replace the unobserved factors in the transition equation (1.2.2) by their PC estimates, and run a standard VAR

$$\begin{bmatrix} \hat{F}_t^1 \\ \hat{F}_t^2 \\ \vdots \\ \hat{F}_t^K \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} \hat{F}_{t-1}^1 \\ \hat{F}_{t-1}^2 \\ \vdots \\ \hat{F}_{t-1}^K \\ Y_{t-1} \end{bmatrix} + e_t$$

in order to obtain $\hat{\Phi}(L)$.

Computational simplicity, some degree of cross-correlation allowed in the idiosyncratic term $e_t$, and the fact that it imposes only few distributional assumptions are the main advantageous features of the two-step estimation method.[17] However, the approach implies the presence of “generated regressors” in the second step, which makes it necessary to implement a bootstrap procedure that accounts for the uncertainty in the factor estimation in order to obtain accurate confidence intervals on the impulse response functions.[18] Following BBE and the rest of the FAVAR literature, our analysis employs the bootstrapping procedure proposed by Kilian (1998) in order to obtain confidence intervals on the impulse response functions.

[17]See Stock and Watson (2005).

[18]See Bernanke et al. (2005, p.399).

Furthermore, as discussed by Eliasz (2005), the factors estimated in the two-step approach have unknown dynamic properties due to the fact that when the factors are constructed in the model only the measurement equation (1.2.1) is taken into account, and the dynamic structure of the model (1.2.2) is totally ignored.

### BAYESIAN JOINT ESTIMATION APPROACH

In contrast with the two-step method, the likelihood-based Bayesian, i.e. multi-move Gibbs sampling,[19] approach takes the observation and the transition equations into account jointly, and also "allows us to incorporate prior information into (the) estimation procedure and implies that (it is possible) to obtain relatively precise results."[20] The results obtained from this approach may be considered relatively more precise due to "an advantage of (the) approach that it facilitates the introduction of restrictions on the loadings, thus facilitating also the economic interpretation of the factors."[21]

Belviso and Milani (2006) evaluate the Bayesian estimation from a different perspective and state that the higher complexity of the approach is repaid with an easier and theoretically clearer assessment of the uncertainty of the estimates, due to simplicity of constructing and interpreting the error bands for those estimates.

Closely following BBE, we explain the details of the estimation procedure of the Bayesian approach in the subsequent sections.

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[19]Technique developed by Geman and Geman (1984), Gelman and Rubin (1992a), and Carter and Kohn (1994), and surveyed in Kim and Nelson (1999).

[20]Mumtaz and Surico (2007, p.12).

[21]Belviso and Milani (2006)

**Estimation Procedure**

In order to apply the likelihood methods to equations (1.2.1) and (1.2.2) jointly, let us transform the model into the following state-space form:

$$\begin{bmatrix} X_t \\ Y_t \end{bmatrix} = \begin{bmatrix} \Lambda^f & \Lambda^y \\ 0 & I \end{bmatrix} \begin{bmatrix} F_t \\ Y_t \end{bmatrix} + \begin{bmatrix} e_t \\ 0 \end{bmatrix} \tag{1.2.5}$$

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + u_t \tag{1.2.6}$$

As claimed by BBE, inclusion of the observable factor $Y_t$ in the measurement (1.2.5) and the transition (1.2.6) equations "does not change the model but allows for both notational and computational simplification."[22]

Our main aim in the procedure is to estimate the parameters of the model, $\theta = (\Lambda^f, \Lambda^y, R, vec(\Phi), Q)$, treated as random variables, and the factors $\{F_t\}_{t=1}^T$, where $vec(\Phi)$ is defined as a column vector of the elements of the stacked matrix $\Phi$ of the parameters of the lag operator $\Phi(L)$. As proposed by Carter and Kohn (1994), likelihood-based multi-move Gibbs sampling proceeds by alternately sampling the parameters $\theta$ and the unobserved factors $F_t$. Further details of the procedure are as follows:

First, let us rewrite the model in the following way:

$$\mathbf{X}_t = \mathbf{\Lambda}\mathbf{F}_t + \mathbf{e}_t \tag{1.2.7}$$

$$\mathbf{F}_t = \Phi(L)\mathbf{F}_{t-1} + u_t \tag{1.2.8}$$

where $\mathbf{X}_t = (X_t', Y_t')'$, $\mathbf{F}_t = (F_t', Y_t')'$, $\mathbf{\Lambda} = \begin{pmatrix} \Lambda^f & \Lambda^y \\ 0 & I \end{pmatrix}$, $\mathbf{e}_t = (e_t', 0 \ldots, 0)'$, $\mathbf{e}_t \sim$ *i.i.d.* $N(0, \mathbf{R})$, $\mathbf{R}$ is the covariance matrix of $\mathbf{e}_t$ augmented by zeros, and $\Phi(L)$ is a con-

[22] Bernanke et al. (2004a, pp.27-8).

formable lag polynomial with finite order $d$.

In order to rewrite the transition equation (1.2.8) as a first-order Markov process, we define $\bar{\mathbf{F}}_t = (\mathbf{F}'_t, \mathbf{F}'_{t-1}, \ldots, \mathbf{F}'_{t-d+1})'$, $\bar{u}_t = (u_t, 0, \ldots, 0)'$, and

$$\bar{\Phi} = \begin{bmatrix} \Phi_1 & \Phi_2 & \ldots & \Phi_{d-1} & \Phi_d \\ I_{(K+M)} & 0 & \ldots & 0 & 0 \\ 0 & I_{K+M} & \ddots & 0 & 0 \\ \vdots & \ldots & \ldots & \ddots & \vdots \\ 0 & 0 & \ldots & I_{(K+M)} & 0 \end{bmatrix} \quad (1.2.9)$$

Using these definitions, we obtain the following Markov process:

$$\bar{\mathbf{F}}_t = \bar{\Phi}\bar{\mathbf{F}}_{t-1} + \bar{u}_t$$

where $\bar{u}_t$ is with covariance matrix $\bar{Q}$ augmented by zeros.

By replacing $\mathbf{F}_t$ in the measurement equation (1.2.7) by newly defined $\bar{\mathbf{F}}_t$, we also obtain

$$\mathbf{X}_t = \bar{\mathbf{\Lambda}}\bar{\mathbf{F}}_t + \mathbf{e}_t \quad (1.2.10)$$

where $\bar{\mathbf{\Lambda}} = [\mathbf{\Lambda}\ 0\ \ldots\ 0]$.

Consideration of all the definitions above brings us to the following system which is to be estimated:

$$\mathbf{X}_t = \bar{\mathbf{\Lambda}}\bar{\mathbf{F}}_{\mathbf{t}} + \mathbf{e}_t \quad (1.2.11)$$

$$\bar{\mathbf{F}}_t = \bar{\Phi}\bar{\mathbf{F}}_{t-1} + \bar{u}_t \quad (1.2.12)$$

As highlighted in Bayesian theory section in Appendix B, the Bayesian approach requires the elements of the Bayes' rule to be random variables. As such, all the parameters and the factors of the system (1.2.11 - 1.2.12) are treated as random variables.

Furthermore, let us assume that $\tilde{\mathbf{X}}_\mathbf{T}$ and $\tilde{\mathbf{F}}_\mathbf{T}$ stand for the histories of $\mathbf{X}$ and $\bar{\mathbf{F}}$, respectively, from period 1 through period $T$. That is to say, $\tilde{\mathbf{X}}_T = (\mathbf{X}_1, \mathbf{X}_2, \ldots, \mathbf{X}_T)$, and $\tilde{\mathbf{F}}_T = (\bar{\mathbf{F}}_1, \bar{\mathbf{F}}_2, \ldots, \bar{\mathbf{F}}_T)$.[23]

**Inference**

In order to obtain the estimates of $\tilde{\mathbf{F}}_T$ and $\theta$, the Bayesian approach requires us to derive the posterior densities as

$$p(\tilde{\mathbf{F}}_T) = \int p(\tilde{\mathbf{F}}_T, \theta) d(\theta) \tag{1.2.13}$$

$$p(\theta) = \int p(\tilde{\mathbf{F}}_T, \theta) d(\tilde{\mathbf{F}}_T) \tag{1.2.14}$$

where $p(\tilde{\mathbf{F}}_T, \theta)$ is the joint posterior distribution and the integrals are taken with respect to the supports of $\theta$ and $\tilde{\mathbf{F}}_T$. Considering the posterior densities, the estimates of $\tilde{\mathbf{F}}_T$ and $\theta$ can be obtained as the means or the medians (quantiles) of the densities.

Since the true joint distribution is not known, multi-move Gibbs sampling is employed so as to obtain an empirical approximation of it. The details of the approximation procedure are the following:

- **Step 1 - Starting Values ($\theta^0$):** First of all, we choose an initial set of values for the parameter set $\theta$. As highlighted by BBE, it is advantageous to try a dispersed set of parameter values so as to check whether they generate similar empirical distributions. This is so due to proposal of Gelman and Rubin (1992a) that a single sequence from the Gibbs sampler, even if it has apparently converged, may give a "false sense of security".

According to BBE and Eliasz (2005), using parameter estimates obtained from PC

[23] For simplicity, the "bar" notation is omitted.

estimation of the observation equation (1.2.1) and vector autoregression of the transition equation (1.2.2) leads to a reasonable guess on the choice of $\theta^0$. Robustness of this choice is tested by BBE relative to some alternatives such as (i) $vec(\Phi) = 0$, (ii) $Q = I$, (iii) $\Lambda = 0$, (iv) OLS estimates of the factor loadings $\Lambda^y$ from the regression of $X$ on $Y$, and (v) $R =$ residual covariance matrix from the same regression.

In our empirical analysis, following the FAVAR literature, we stick to BBE's choice of PC and VAR estimates of the equations (1.2.1) and (1.2.2).

• **Step 2 - Conditional Density of the Factors:** The second step of the procedure is to draw a set of values for $\tilde{\mathbf{F}}_T$, say $\tilde{\mathbf{F}}_T^1$, from the conditional density of $\tilde{\mathbf{F}}_T$ given the initial values, $\theta^0$, and the data $\tilde{\mathbf{X}}_T$, i.e. $p(\tilde{\mathbf{F}}_T|\tilde{\mathbf{X}}_T, \theta)$.

It is possible to express the distribution of the whole factor history, $p(\tilde{\mathbf{F}}_T|\tilde{\mathbf{X}}_T, \theta)$, as the product of conditional distributions of factors at each date $t$, relying on the Markov property of state-space model that

$$p(\mathbf{F}_t|\mathbf{F}_{t+1}, \mathbf{F}_{t+2}, \ldots, \mathbf{F}_T, \mathbf{X}_T, \theta) = p(\mathbf{F}_t|\mathbf{F}_{t+1}, \mathbf{X}_t, \theta)$$

That is to say[24]:

$$p(\tilde{\mathbf{F}}_T|\tilde{\mathbf{X}}_T, \theta) = p(\mathbf{F}_T|\tilde{\mathbf{X}}_T, \theta) \prod_{t=1}^{T-1} p(\mathbf{F}_t|\mathbf{F}_{t+1}, \tilde{\mathbf{X}}_t, \theta)$$

where $\tilde{\mathbf{X}}_\mathbf{t} = (\mathbf{X}_1, \mathbf{X}_2, \ldots, \mathbf{X}_t)$.

Due to linearity and Gaussian properties of the state-space model under investigation, there are

$$\begin{aligned} &\mathbf{F}_T|\tilde{\mathbf{X}}_T, \theta \sim N(\mathbf{F}_{T|T}, \mathbf{P}_{T|T}) \\ &\mathbf{F}_t|\mathbf{F}_{t+1}, \tilde{\mathbf{X}}_t, \theta \sim N(\mathbf{F}_{t|t,\mathbf{F}_{t+1}}, \mathbf{P}_{t|t,\mathbf{F}_{t+1}}) \end{aligned} \tag{1.2.15}$$

[24]For details see Kim and Nelson (1999, p.191).

where the first holds for the Kalman filter for $t = 1, \ldots, T$, the second does so for the Kalman smoother for $t = T-1, T-2, \ldots, 1$[25], and

$$\begin{aligned}
\mathbf{F}_{T|T} &= E(\mathbf{F}_T|\tilde{\mathbf{X}}_T, \theta) \\
\mathbf{P}_{T|T} &= Cov(\mathbf{F}_T|\tilde{\mathbf{X}}_T, \theta) \\
\mathbf{F}_{t|t,\mathbf{F}_{t+1}} &= E(\mathbf{F}_t|\mathbf{F}_{t+1}, \tilde{\mathbf{X}}_t, \theta) = E(\mathbf{F}_t, \mathbf{F}_{t+1}, \mathbf{F}_{t|t}, \theta) \\
\mathbf{P}_{t|t,\mathbf{F}_{t+1}} &= Cov(\mathbf{F}_t|\mathbf{F}_{t+1}, \tilde{\mathbf{X}}_t, \theta) = Cov(\mathbf{F}_t|\mathbf{F}_{t+1}, \mathbf{F}_{t|t}, \theta)
\end{aligned}$$

- **Step 3 - Inference on the Parameters ($\theta$):** The final step of the Gibbs sampling procedure is to draw from $p(\theta|\tilde{\mathbf{X}}_T, \tilde{\mathbf{F}}_T)$. Given the data we observe and the factors generated in the previous step, it is possible to draw values for $\theta$. Since the factors are considered as known variables, it is possible to estimate the equations (1.2.7 - 1.2.8) separately as standard regression equations. By doing so we can specify the distributions of $\Lambda$ and $R$ with the measurement (1.2.7), and that of $vec(\Phi')$ and $Q$ with the transition (1.2.8) equations.

It is known that $\hat{R}_{ii} = \hat{e}'\hat{e}/(T - K_i)$ where $K_i$ is equal to the number of regressors in equation $i$, $R_{ij} = 0$ for $i \neq j$, and, like $vec(\hat{\Phi})$ and $\hat{Q}$, $\hat{R}$ and $\hat{e}$ are the estimates obtained from the standard regressions. At this point we can follow either Bernanke et al. (2005) and assume a "proper (conjugate) but diffuse Inverse-Gamma (3, 0.001)" prior for $R_{ii}$, or Belviso and Milani (2006) and assume an "uninformative prior" that

$$R_{ii}|\tilde{\mathbf{X}}_T, \tilde{\mathbf{F}}_T = (T - K_i)\frac{\hat{R}_{ii}}{x} \quad where \quad x \sim \chi^2(T - K_i)$$

If we follow the former, which we do in our empirical analysis, the prior is going to be;

$$R_{ii}|\tilde{\mathbf{X}}_T, \tilde{\mathbf{F}}_T \sim iG(\bar{R}_{ii}, T + 0.001)$$

[25]We skip the derivation of the Kalman filter and smoother. For these details see Eliasz (2005).

where $\bar{R}_{ii} = 3 + \hat{e}_i'\hat{e}_i + \hat{\Lambda}_i'[M_0^{-1} + (\tilde{\mathbf{F}}_T^{(i)'}\tilde{\mathbf{F}}_T^{(i)})^{-1}\hat{\Lambda}_i]$ and $M_0^{-1}$ is the variance parameter in the prior on the coefficients of the $i^{th}$ equation, $\Lambda_i$. Similarly, Mumtaz (2005) uses the prior specification $R_{ii} \sim IG(5, 0.001)$ in order "to reflect the high volatility of some of the series in (his) panel" (p.17).[26]

According to BBE, we should draw values for $\Lambda_i$, given draws of $R_{ii}$, from the posterior $N(\bar{\Lambda}, R_{ii}\bar{M}_i^{-1})$ where $\bar{\Lambda}_i = \bar{M}_i^{-1}(\tilde{\mathbf{F}}_T^{(i)'}\tilde{\mathbf{F}}_T^{(i)})\hat{\Lambda}_i$ and $\bar{M}_i = M_0 + \tilde{\mathbf{F}}_T^{(i)'}\tilde{\mathbf{F}}_T^{(i)}$.

After obtaining all the elements of $\theta$ explained above, the final draw is for $Q$ and $vec(\Phi)$. The way of obtaining $Q$ and $vec(\Phi)$ suggested by Bernanke et al. (2005) is to, first, impose a diffuse conjugate Normal-Wishart prior that

$$vec(\Phi)|Q \sim N(0, Q \otimes \Omega_0), \qquad Q \sim iW(Q_0, K + M + 2)$$

where $vec(\Phi)$ is as described above.

Then we can draw $Q$ from $iW(\bar{Q}, T + K + M + 2)$, where $\bar{Q} = Q_0 + \hat{V}'\hat{V} + \hat{\Phi}'[\Omega_0 + (\tilde{\mathbf{F}}_{T-1}'\tilde{\mathbf{F}}_{T-1})^{-1}]\hat{\Phi}$, and $\hat{V}$ is the matrix containing OLS residuals.

Finally, conditional on the obtained $Q$, $\{\Phi^{ijt}\}$ can be drawn from

$$vec(\Phi) \sim N\left(vec(\bar{\Phi}), Q \otimes \bar{\Omega}\right)$$

where $\bar{\Phi} = \bar{\Omega}(\tilde{\mathbf{F}}_{T-1}'\tilde{\mathbf{F}}_{T-1})\hat{\Phi}$ and $\bar{\Omega} = (\Omega_0^{-1} + \tilde{\mathbf{F}}_{T-1}'\tilde{\mathbf{F}}_{T-1})^{-1}$.

In the Gibbs sampling procedure steps 2 and 3 explained above constitute one iteration and are repeated for each iteration $s$. Then, inference obtained from the sampling of the parameters $\theta$ is based on the distribution of $(\tilde{\mathbf{F}}_T^s, \theta^s)$, for $s \geq B$ with large $B$ proportion of initial draws discarded so as to guarantee convergence of the algorithm. As shown by Geman and Geman (1984), as the number of iterations approaches to infinity, i.e.

[26] We find that our empirical results are robust to this slightly higher specification.

$s \to \infty$, the marginal and joint distributions of the values obtained from iterations, $\tilde{\mathbf{F}}_T^s$ and $\theta^s$, converge to the true distributions $(\mathbf{F}_T, \theta)$ at an exponential rate. Depending on the inference, estimates of factors, model parameters and the associated confidence intervals are calculated as medians and percentiles[27] of $(\tilde{\mathbf{F}}_T^s, \theta^s)$ for $s = B+1, \ldots, S$. The procedure, finally, allows us to evaluate the impulse response functions for each draw with their medians.

### 1.2.3 Identification

Along with the estimation of the system, another important aspect of the FAVAR model is model identification. Contrary to the standard (structural) VAR literature, in a FAVAR framework, the procedure requires not only identification of the structural shocks, but also that of the factor space in the model. We describe these steps in the following parts.

**IDENTIFICATION OF THE FACTORS**

Options available for factor identification in FAVARs are to restrict either the observation or the transition equations. BBE prefer not to restrict the VAR dynamics, and propose that sufficient factor identification conditions for the two-step method is to restrict the loadings by $\Lambda^{f\prime}\Lambda^f/N = I$ or to restrict the factors by $F'F/T = I$. For joint estimation, BBE suggest setting the upper $K \times K$ block of $\Lambda^f$ to an identity matrix and the top $K \times M$ block of $\Lambda^y$ to zero. In other words, BBE propose these restrictions for the purpose of normalising or re-basing the factor space. In our empirical analysis we follow BBE and identify the factors in the same way.

[27]Different from the two-step method, confidence intervals of the median impulse responses are constructed in the one-step approach from the quantiles of the Gibbs draws.

**IDENTIFICATION OF THE MONETARY POLICY SHOCKS**

Here we explain the problem of identification in (FA)VAR context first, then summarise the BBE identification schemes we employ in the chapter.[28]

Broadly speaking, the problem of identification arises "since there is more than one structure of economic interest which can give rise to the same statistical model for (a) vector of variables."[29] In other words, we can draw no conclusions about the structural, i.e. 'true' model, parameters from the data as it is possible to obtain the same reduced-form from different structural models.

The solution to the problem comes by imposing identifying restrictions on the structure where the number of parameters is greater than that in the reduced form. How these restrictions are imposed in the BBE approach is explained in the following subparts.

Before these details, let us consider the reduced-form FAVAR in equation (1.2.2):

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + u_t, \quad E(u_t' u_t) = Q$$

Suppose an orthogonal and invertible matrix of dimension $(K+M) \times (K+M)$, called $A$, represents the contemporaneous relationships between the variables in the FAVAR. Therefore, the structural model can be obtained by premultiplying the reduced form with the rotation matrix $A$. This gives us the following linear relationship between the structural shocks ($\varepsilon_t$) and the reduced-form innovations ($u_t$):

$$\varepsilon_t = A u_t \quad \text{or} \quad u_t = A^{-1} \varepsilon_t \tag{1.2.16}$$

Parallel to equation (1.2.3), the MA representation of the structural form is:

[28] For further details on the issue of identification in general see Favero (2001, Chapters 3 and 6) and Enders (2004, Chapter 5), among others.

[29] Favero (2001, p.85)

$$\begin{bmatrix} \hat{F}_t \\ Y_t \end{bmatrix} = \Psi^*(L)u_t \tag{1.2.17}$$

where $\Psi^*(L) = \Psi(L)A^{-1}$.

In these notations, the task of identification is to identify $A$ or, if one is interested in just one economic shock, like the monetary policy shock as in our case, only a row of $A$. As Kilian (2012) highlights, without proper identification of the system, studying the responses of the variables in the (FA)VAR to reduced-form innovations will tell us nothing about that of the variables to the structural shocks. "It is the latter responses that are of interest if we want to learn about the structure of the economy."[30]

According to BBE and Kilian (2012), we can categorise the structural (FA)VAR models in the literature as identified by (i) short-run restrictions (e.g. recursive, non-recursive, and contemporaneous frameworks); (ii) long-run restrictions; (iii) sign restrictions; (iv) alternative approaches based on heteroskedasticity of the structural shocks, or high-frequency financial markets data, and (v) mixture of contemporaneous and long-run (or sign) restrictions.[31,32]

We mentioned earlier that the identification of the monetary policy shocks in our empirical analysis depends on a scheme proposed by BBE. As shown by Stock and Watson (2005), it is possible to categorise the BBE identification scheme, explained on p.27, into the category of contemporaneous timing restrictions. Hence, in the following subpart we

[30] Kilian (2012, p.3).

[31] Among others, see Bernanke and Blinder (1992); Sims (1992); Strongin (1995); Christiano et al. (1999) for recursive frameworks, Gordon and Leeper (1994); Leeper et al. (1996); Bernanke and Mihov (1998) for contemporaneous, non-recursive restrictions, Blanchard and Quah (1989); Faust and Leeper (1997); Pagan and Robertson (1998); Giannone et al. (2002) for long-run restrictions, Faust (1998); Canova and de Nicoló (2002); Uhlig (2005); Mumtaz and Surico (2009); Kilian and Murphy (2012) for sign restrictions, Rigobon (2003); Faust et al. (2004) for the alternative financial market approaches, and Gali (1992); Bernanke and Mihov (1998) for the mixture approaches.

[32] In Chapter 3 of the thesis, we employ the mixture of zero and sign restrictions in order to identify the unconventional monetary policy shocks in the EA. For details of the approach see Chapter 3, Section 3.3.3.

briefly explain these restrictions according to Stock and Watson (2005) and Favero (2001, Chapter 6).

**Contemporaneous Timing Restrictions**

The contemporaneous restrictions are exclusion restrictions stating that certain structural shocks, e.g. monetary policy shocks, do not affect certain variables, e.g. prices or output, contemporaneously, i.e. within the month or quarter depending on the frequency of the data. As the pioneering study of identification of VAR systems using this type of restrictions, Sims (1980b) proposed the following identification strategy, based on Wold causal ordering of variables and Cholesky decomposition of the reduced form covariance matrix, i.e. $Q$ in equation (1.2.2). It is assumed by Sims (1980b) that $A$, i.e. the invertible matrix in (1.2.16), is lower triangular as follows:

$$A = \begin{bmatrix} 1 & 0 & \dots & 0 \\ a_{21} & 1 & \ddots & 0 \\ \vdots & \ddots & \ddots & 0 \\ a_{N1} & \dots & a_{NN-1} & 1 \end{bmatrix} \tag{1.2.18}$$

where $a$'s denote an unrestricted non-zero element. The lower triangular structure of the matrix "corresponds to a recursive economic structure, with the most endogenous variable ordered last."[33] If we assume a (FA)VAR with $N$ variables, the lower triangular structure leads to $N(N-1)/2$ exclusion restrictions in (1.2.18), which therefore means that $A$ is exactly identified.

Following Bernanke (1986), it is common in the literature to assume that the structural shocks are orthogonal to each other[34] and normalised to have a unit variance, i.e. $E[\varepsilon_t \varepsilon_t'] =$

[33]Favero (2001, p.165)

[34]According to Favero (2001, Chapter 6), this is the main assumption separating the traditional Cowles

$I$. Considering the relationship between the reduce-form innovations and the structural shocks in (1.2.16), we obtain the covariance matrix of the former as follows:

$$Q_u = E[u_t u_t'] = A^{-1} E[\varepsilon_t \varepsilon_t'] A^{-1\prime} = A^{-1} A^{-1\prime} \tag{1.2.19}$$

Given (1.2.19), Stock and Watson (2005) and Kilian (2012), among others, show that one possible solution for recovering $\varepsilon_t$ is $A^{-1} = S$ where $S$ is the Cholesky decomposition of the covariance matrix $Q_u$ such that $SS' = Q_u$. Because the lower triangular structure of $S$ provides $N(N-1)/2$ free parameters, as in (1.2.16), the Cholesky approach exactly identifies the system.

As a second example to contemporaneous timing restrictions, Stock and Watson (2005) highlight the BBE scheme as "partial identification via block lower-triangular exclusion restrictions" (p.18). We next describe this identification scheme which we employ in our essay.

### BBE Identification Scheme

In order to identify a single shock in a structural FAVAR, BBE introduced a scheme which partitions the structural shocks and variables $X_{it}$ into three groups as "slow-moving" variables, the monetary policy variable and "fast-moving" variables. As the authors explain, whereas the slow-moving variables are assumed to be "largely predetermined as of the current period", e.g. output, employment, and prices, the "fast-moving" ones are those known to be "highly sensitive to contemporaneous economic news or shocks", e.g. interest and exchange rates, share prices and monetary aggregates.

Commission and the VAR models as identification in the former models is obtained without assuming orthogonality of the structural disturbances.

Following the Cholesky decomposition explained above, BBE assume a recursive structure for the transition equation (1.2.2) ordering the policy instrument last after the slow-moving factors. The main assumption here is that the slow-moving factors do not respond contemporaneously to the innovations in the policy variable, which are treated as the monetary policy shocks. BBE also assume that the "fast-moving" factors follow the movements in the policy instrument very closely, and, in order to prevent collinearity in the system, they exclude these factors from their recursive structure.

In order to briefly show the scheme algebraically,[35] let $\Psi_0^*$ be the coefficient matrix that is the leading (zero-lag) term of $\Psi^*(L)$ in equation (1.2.17). Additionally suppose that the structural shocks are $\zeta_t = (\zeta_t^{S\prime}, \zeta_t^R)'$, where $S$ stands for slow-moving, $R$ is the policy variable, $\zeta_t^S$ is $K_S \times 1$, and $\zeta_t^R$ is a scalar.

The contemporaneous timing restrictions of the identification explained above lead to the following block lower triangular structure for $\Psi_0^*$:[36]

$$\Psi_0^* = \begin{bmatrix} \Psi_{0,SS}^* & 0 \\ \Psi_{0,RS}^* & \Psi_{0,RR}^* \end{bmatrix} \tag{1.2.20}$$

where $\Psi_{0,SS}^*$ is $K_S \times q_S$, $\Psi_{0,RS}$ is $1 \times q_S$, and $\Psi_{0,RR}^*$ is a scalar.

Following Stock and Watson (2005), finally, the block triangular restrictions in (1.2.20) identify $\zeta_t^R$ (the shock of interest), and the space spanned by the $\zeta_t^S$. Identification of $\zeta_t^R$ means that "the column of $[\Psi^*(L)]$ associated with $\zeta_t^R$ is [also] identified and thus the structural impulse responses of $X_t$ with respect to $\zeta_t^R$ is identified" (p.18).

[35] See Stock and Watson (2005, pp.18-20) for further details of this part.

[36] Stock and Watson (2005) include the "fast" variables in this expression. However, due to our explanation of the scheme above, these variables are excluded here.

**One-step FAVAR:** Regarding the implementation of this scheme in the Bayesian joint estimation methodology, BBE propose that the only requirement is that we select the first $K$ variables in the data from the set of slow-moving variables and then impose the recursive structure between the (slow-moving) factors and the policy variable in the transition equation accordingly.

**Two-step FAVAR:** Implementation of the scheme in the two-step FAVAR model, however, requires further adjustments such as controlling for the part of the space spanned by the factors, i.e. $\hat{C}(F_t, Y_t)$, that corresponds to the monetary policy variable, $Y_t$. BBE suggest the following way in order to achieve this:

First, we estimate slow-moving factors, $F_t^s$, as the first $K$ PC of the slow-moving variables in $X_t$. Second, estimating the following regression,

$$\hat{C}_t = \beta_{F^s}\hat{F}_t^s + \beta_Y Y_t + e_t \tag{1.2.21}$$

we construct $\hat{F}_t$ from $\hat{C}_t - \hat{\beta}_Y Y_t$. Notice that as $\hat{F}_t^s$ and $Y_t$ are correlated, so are $\hat{F}_t$ and $Y_t$. Finally, we estimate the FAVAR in $\hat{F}_t$ and $Y_t$, and, as explained above, identify the monetary policy shocks recursively using this ordering.

### Monetary Policy Shocks in the Euro Area

Monetary policy shocks are considered as "unanticipated/surprise" changes in the monetary policy. In other words, we may say that they "arise as errors of assessment of the economic situation"[37] by the central banks.

On the one hand, identification and investigation of the impact of the shocks take a considerable part in the literature. It is important to note, on the other hand, that this

[37] Uhlig (2005, p.398)

is not because, as Boivin et al. (2008, p.2) point out, "we believe that monetary policy shocks constitute an important source of business cycle fluctuations that we are interested in documenting the effects of such shocks." On the contrary, there is a consensus in the literature that contribution of the monetary policy shocks to business cycle fluctuations is relatively small[38], and monetary policy mainly affects the economy through its systematic reaction to changes in economic conditions. The main reason is that, as Boivin et al. (2008) highlighted:

> The impulse response functions to monetary policy shocks provide a useful description of the effects of a systematic monetary policy rule, by tracing out the responses of various macroeconomic variables following a surprise interest-change, and assuming that policy is conducted subsequently according to that particular policy rule. (p.2)

Although the investigation of unanticipated monetary policy shocks is predominant in the literature, the distinction between unanticipated and anticipated shocks is also important.[39] In line with Cochrane (1998); Hoover and Jordá (2001); Romer and Romer (2004); Matsumoto and Rebucci (2008), Milani and Treadwell (2012) incorporate news about future monetary policy actions of the Federal Reserve in order to disentangle the anticipated and unanticipated components of policy shocks. Milani and Treadwell conclude that "credible policy announcements by policymakers are likely to yield larger effects than attempts to surprise the markets through unexpected monetary policy decisions" (p.1682).

We do not deal here with the issue of anticipated policy shocks. Instead, as we highlighted earlier, one of the main contributions of the chapter is the application of the Bayesian FAVAR method to the EA to study unanticipated monetary policy shocks.

[38] See Uhlig (2005) and Sims and Zha (2006).
[39] See Milani and Treadwell (2012, p.1670).

In particular, we use the BBE scheme described above and identify the impacts of contractionary unanticipated monetary policy shocks in the EA. The shock is standardised to correspond to a 25-basis-point increase in the ECB official refinancing operation rate (REFI). Unless otherwise stated, all the results presented below are the impulse response functions of the variables to a one-off policy shock in the economy.

### 1.2.4 Pre-screening Analysis

We highlighted in the Introduction of the chapter that there is a gap in the literature to implement the Boivin and Ng (2006) pre-screening technique in a structural context. We believe that the technique is of importance for our thesis in the sense that it not only fills the aforementioned gap in the literature but also it provides the chapter with robustness checks for the main empirical findings. This subsection describes details of the technique relevant to our structural FAVAR analysis.[40]

Boivin and Ng (2006, p.171) argue that "using more data to estimate the factors might not be desirable." There are two assumptions in the asymptotic theory, which the method of PC depends on, that (i) the cross-correlation in the errors is not too large, and (ii) the variability of the common component is not too small. As suggested by the variables investigated above and summarised in the literature, we typically draw our data from a small number of broad categories such as industrial production (IP), prices, interest rates and monetary aggregates. Think of a data set consisting of some series chosen from each category according to rank of importance of their common components. Then let us expand the data set by adding the lower ranked, or 'noisy' series. As Boivin and Ng clearly highlight, two things will happen:

[40]See the original paper for further details beyond the scope of our thesis.

> The average size of the common component will fall as more series are added, and the possibility of correlated errors will increase as more series from the same category are included. When enough of the 'noisy' series are added, the average common component will be smaller, and/or the residual cross-correlation will eventually be larger than that warranted by theory, creating a situation where more data might not be desirable. (p.171)

Therefore, the authors propose the following procedure for pre-screening the data for these 'noisy' series: First, we fit a standard factor model to our complete data set in order to obtain $\hat{\tau}_{ij}$, i.e. the correlation coefficient between the residuals for series $i$ and $j$. For each series $i$, we then identify

$$\hat{\tau}_1^*(i) = \max_j |\hat{\tau}_{ij}| = \hat{\tau}_{ij_i^1}.$$

where $j_i^1$ is the series whose idiosyncratic error is most correlated with series $i$, and the correlation between series $i$ and $j_i^1$ is $\hat{\tau}_1^*(i)$.

We construct a set of series, $j^* = j_i^1, j_i^2, \ldots$, whose error is most correlated with some other series, and following the Rule 1 in Boivin and Ng (2006, p.185), we drop all the series in $j^*$. This way, finally, we obtain a parsimonious version of our data set used to identify the impact of BN in a structural context.[41]

## 1.3 Preliminary Analyses

Having explained the methodological details, this section of the chapter lists the preliminary analyses conducted prior to estimating the empirical results, which we present in Section 1.4. We first explain the data, then report how the number of factors and lags in the FAVAR are determined. Following these, we discuss the reasons and techniques

[41]Note that Boivin and Ng also suggest Rule 2 where the second most correlated series are dropped, leading to even smaller data sets.

for interpolation of some of the quarterly series. Finally, the details of Boivin and Ng pre-screening technique and the results it suggests for our data conclude the section.

### 1.3.1 Data

The data set analysed in the chapter is a balanced panel of 120 monthly macroeconomic time series for the EA as an aggregate, and spans the period from 1999:1 through 2011:12.

Following the FAVAR literature, the series are chosen from the following categories: real output and income, industrial new orders and turnover, retail sales and turnover, building permits, employment, consumption, price indices, exchange rates, short- and long-term interest rates, share price indices, money and credit quantity aggregates, balance of payments and external trade, confidence indicators, and some foreign variables such as output, prices, interest rates, and stock markets for the US, UK and Japan used as proxies for external real, nominal and monetary influences. For detailed description of the series and data sources see Appendix A. We process the data as follows:

Firstly, we correct the series for missing observations and outliers using the Demetra+ package developed by the Eurostat.[42,43] Using the same package, secondly, we seasonally adjust the data by the method of TramoSeats with the proper type of additive or log-additive models being automatically chosen by the software.

Although the majority of the series in our data set are in monthly frequency, some series are not available in this frequency for the EA, i.e. capacity utilisation, consumption expenditures, employment and unit labour cost indicators. In order to maximise the

[42]See Depoutot et al. (1998) for details of the software.

[43]When either the first or the last observation of a series is missing Demetra+ does not provide any estimations. For this kind of occasional observations, using a MATLAB code obtained from Bańbura and Modugno (2010), we replaced the missing values by the median of the series and then applied a centred MA(3) to the replaced observations. We thank the authors for kindly sharing the replication files of their paper.

information used in our FAVAR analysis, we, thirdly, apply the most commonly used interpolation technique, i.e. Chow and Lin (1971), to the quarterly observations of these series in order to obtain their monthly estimates.[44,45]

Finally, as explained in Appendix A, we transform the data in order to induce stationarity. Those series of which first difference of natural logarithms is taken are multiplied by 100 in order to have the same scale between the transformed and other series which are already in percentages. We observed that this scaling is important to have readable impulse responses when the model is estimated with the Bayesian joint estimation technique whilst it does not make any difference with the two-step approach.[46]

### 1.3.2 Number of Factors

Determining the number of factors for large dimensional factor models takes a considerable place in the literature.[47] It is possible to highlight studies by Lewbel (1991) and Donald (1997) who tested the number of factors using the rank of a matrix; Cragg and Donald (1997) where the use of information criteria is considered for the models with factors being functions of a set of observable explanatory variables; Connor and Korajczyk (1993) who developed a test for determining the number of factors for large dimensional panels of asset returns; Forni and Reichlin (1998) suggesting a graphical approach to the problem; Stock and Watson (1998) who showed that we can use a modification to the Bayesian information criterion (BIC) to determine the number of factors optimal for forecasting a

[44]For comparison of the empirical results with and without these interpolated series see Section 1.3.4, and for details of the Chow and Lin (1971) technique see Appendix C.

[45]Alternatively, mixed data sampling (MIDAS) models, mixed-frequency VARs, and approaches employing EM algorithms are available in the literature to deal with mixed frequencies. Among others, see Stock and Watson (2002b); Ghysels et al. (2004); Kuzin et al. (2011).

[46]We thank Fabio Canova for suggesting this scaling during the presentation of the paper at 2011 Royal Economic Society Easter School held at the University of Birmingham.

[47]See Appendix D for details of the factor models and the determination of their number of factors.

single series; and Forni et al. (2000) where a multivariate variant of the Akaike information criterion (AIC) is suggested. Following these studies, the seminal paper by Bai and Ng (2002) transformed the task of determining the number of (static) factors into a problem of model selection. Bai and Ng (2007) also adapted their work to the restricted dynamic framework. We can finally highlight a more recent work by Kapetanios (2010) which proposes an alternative method to information criteria based on random matrix theory.

When it comes to FAVAR models in practice, however, a different picture emerges. As claimed by BBE, the most commonly used criterion by Bai and Ng (2002) "does not necessarily address the question of how many factors should be included in the VAR" (p.407). Given their main results with 3 (static) factors, therefore, BBE explore the sensitivity of the results to the use of 5 factors and observe that "the qualitative conclusions on the effect of monetary policy are not altered by the use of five (static) factors" (pp.408-9).

It is worth highlighting here that the discussion above and our tests as follow focus on static factors only. Following Sargent and Sims (1977); Forni et al. (2000); Forni and Lippi (2001), dynamic factors have also taken an important place in the literature on the so called generalised dynamic factor models, also known as dynamic PCs. BBE, on the other hand, note Stock and Watson (1998) and claim that we can interpret the (static) factors, i.e. $F_t$ in the measurement equation (1.2.1), as including arbitrary lags of the fundamental factors. Therefore, although our focus is on static factors, we can consider the model as (indirectly) allowing for dynamic factors. In particular, we think, in the one-step method where the dynamic structure of the state-space model is taken into account explicitly.

We follow the following procedure in order to determine the number of (static) factors to be used in our empirical analysis. First, we test the number of static factors in our data using (i) all the panel and information criteria proposed by Bai and Ng (2002), and (ii) BIC.[48] According to our tests with the criteria, whereas all Bai and Ng (2002) criteria suggest 9-10 factors when we allow maximum of 10 factors in the estimations, BIC estimates a more parsimonious specification, i.e. 4 factors.

Second, we calculate the $R^2$ statistics which measures the proportion of the total variation in the variables explained by that in the common components of the model. In other words, $R^2$ stands for the explanatory power of $\hat{\Lambda}^f \hat{F}_t + \hat{\Lambda}^y Y_t$ in the observation equation (1.2.1) of the FAVAR system. We compute the $R^2$ statistics for two sets of variables: $(i)$ all 120 variables in the data set, $(ii)$ 20 main variables which our empirical findings will be based on. Figures 1.3.1 and 1.3.2 present, respectively, the statistics for the sets $i$ and $ii$. We find that marginal gain of having 9 factors (Bai and Ng (2002), $IC_2$) instead of 4 (BIC) is less then 20% for both sets of variables.

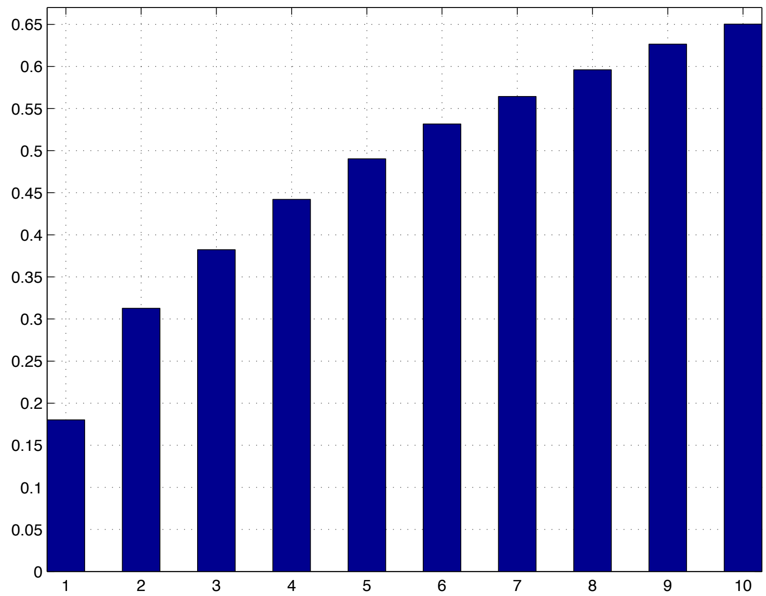



Figure 1.3.1: Number of Factors: $R^2$ Statistics - All Variables

[48]We thank Schumacher and Breitung (2008) for making the replication files of their paper publicly available, and also thank Christian Schumacher for sharing the files and his comments with us. Our tests are based on the replication files of the paper.

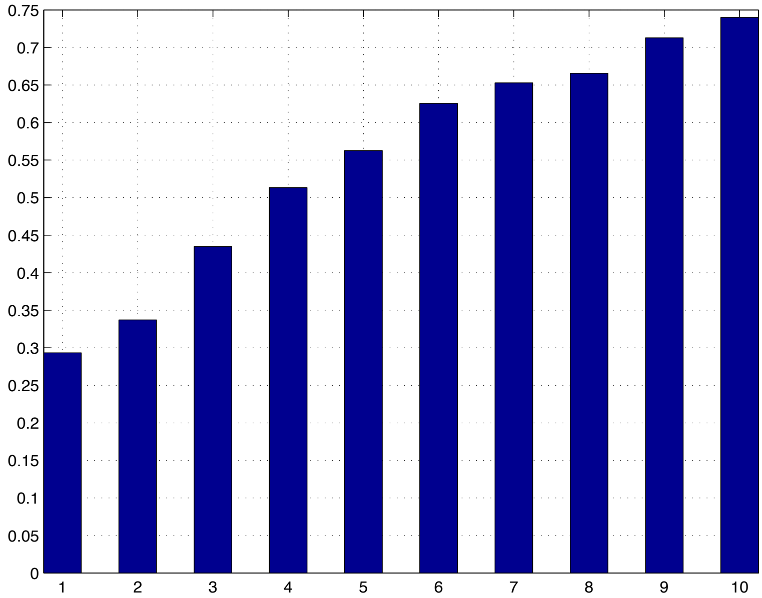



Figure 1.3.2: Number of Factors: $R^2$ Statistics - Main Variables

Given that (a) BIC criterion estimates 4 factors in our data set; and (b) 4 factors account for more than 50% of the variations of the main variables and almost 45% of that of the whole data set, we prefer to use 4 factors in our empirical analyses. Our choice is supported by the literature which suggests "that four to six static factors explain between 37% and 55% of the total variance in euro area macroeconomic [data sets]."[49] We also test the robustness of our empirical results to the factor specification in Section 1.5.1.

### 1.3.3 Lag Length

Similar to the issue of the choice of the number of factors, the lag length of the transition equation (1.2.2) is another specification which needs to be determined. The importance of the specification is demonstrated by Braun and Mittnik (1993) who show that estimates of and impulse response functions and variance decompositions obtained from a VAR are inconsistent when lag length used in the model is different from the true lag length.

[49] Eickmeier (2009, p.939). See also Marcellino et al. (2000); Altissimo et al. (2001); Eickmeier and Breitung (2006); Altissimo et al. (2011).

Lütkepohl (2005) also indicates that whereas over-fitting a VAR causes an increase in the mean-square-forecast errors, under-fitting the lag length often generates autocorrelated errors.

The lag lengths are frequently selected in the VAR literature using a statistical criterion such as AIC, BIC, final prediction error (FPE) and Hannan-Quinn (HQ). In the FAVAR literature, however, no specific criterion is used, to our knowledge. To illustrate, on the one hand, BBE and Belviso and Milani (2006) use 13 lags in order to "allow sufficient dynamics"[50] in their models analysing similar monthly data sets. Stock and Watson (2005), on the other hand, fit a 2-lag FAVAR model to an updated version of also monthly Stock and Watson (2002b) data set.

In order to select lag length of our model, we replicate a FAVAR by extracting four "slow-moving" static factors from our data set and having the ECB's benchmark interest rate as the only observable factor in the model. Then, using JMulti v-4.24[51] we test the lag length in this FAVAR with all the selection criteria listed above. We find that only a few lags, i.e. 1 or 2, are enough to account for the variations in our data set.

Given the results above, and the fact that we have only 13 years of data and a number of parameters being estimated in the models, we prefer to be as parsimonious as possible and use 2 lags in our empirical analyses. The sensitivity of our empirical findings to the lag length of the system is tested in Section 1.5.1.

[50]Belviso and Milani (2006, p.8).

[51]For software details see Lütkepohl and Krätzig (2004).

### 1.3.4 Interpolation

We reported in Section 1.3.1 that the Chow and Lin (1971) interpolation technique is employed in our study in order to obtain monthly observations of some series available only in quarterly and annual frequencies. These interpolated indicators are from important areas of the economy such as real activity,[52] labour market,[53] earnings[54] and balance of payments.[55] Appendix E presents preliminary impulse response functions of selective variables with and without the interpolated series.

We find that inclusion of extra information into the data set not only keeps the majority of the responses unchanged but also eliminates some puzzles such as increase in IP, construction, exports, imports, and monetary aggregates following a contractionary monetary policy shock. Considering the interpolated variables and the importance of the information they have brought into the model, our results support the idea of "condition(ing) VAR analyses of monetary policy on richer information sets."[56][57]

As we reported in Section 1.2.4, following Boivin and Ng (2006), we might need to be cautious about whether or not the extra information brought into the factor models are "noisy". However, because the interpolated variables in our analysis bring information from the areas of the economy which would otherwise be missing in the model, e.g. labour market and investment, we believe that our interpolation exercise as a whole is important and necessary. This is also supported by the results of our Boivin and Ng analysis which

[52] Capacity utilisation rate, gross domestic product, final consumption expenditure, gross fixed capital formation.

[53] Total employment, total employees, total self-employed, real labour productivity per person employed, real unit labour cost.

[54] Earnings per employee, wages and salaries.

[55] Current, capital and financial accounts.

[56] Bernanke et al. (2005, p.389).

[57] A similar approach has been used by Soares (2011) for the EA in order to have a panel of monthly macroeconomic time series consisting of the variables we have interpolated for our own data set.

eliminates only a few of these interpolated variables.[58]

## 1.4 Results

In three parts, this section presents the empirical findings of the chapter. First, we estimate a FAVAR model by one- (Bayesian) and two-step (PC) methods, and compare the monetary transmission mechanisms estimated by these methods. The comparison is based on the impulse response functions of 20 macroeconomic variables to a 25-basis-point contractionary monetary policy shock. Second, we investigate variations in the transmission of the shock over time using the approach of rolling windows. In this part, we specifically examine the changes, if there are any, in the impact of the policy shocks due to the 2007-8 global financial crisis. Finally, we replicate these analyses with a smaller data set obtained by Boivin and Ng (2006) pre-screening technique applied to the original 120-variable data set.

### 1.4.1 Baseline Results

Our main results obtained from the estimation of the one- and two-step FAVAR models are shown, respectively, in Figures 1.4.1 and 1.4.2 below. The impulse responses of a set of key macroeconomic variables to a monetary policy shock are displayed in the figures for a horizon of up to four years with 68% confidence intervals (dashed lines) based on 8,000 Gibbs samplings (Figure 1.4.1) and 1,000 bootstraps (Figure 1.4.2). As explained above, the FAVAR models are estimated with 4 factors and 2 lags. Bayesian estimates in Figure 1.4.1 employ 10,000 Gibbs sampling iterations, of which the first 2,000 were

[58]Earnings per employee, total employees, GDP, real labour productivity per person employed. See Appendix A for further details.

discarded in order to minimise the impact of initial conditions, i.e. the starting values in Section 1.2.2.[59] All results are reported in standard deviation ($SD$) units.

First of all, the estimated monetary transmission mechanisms in Figures 1.4.1 and 1.4.2 are largely consistent with conventional wisdom: following a contractionary monetary policy shock, real activity measures such as IP, consumption, employment etc. all decline, prices eventually go down, despite some liquidity puzzles in M1, monetary aggregates decline, and the real effective exchange rate (REER) appreciates.

One clear distinction between the one- and two-step model estimates is that the latter method suggests impulse responses with much wider confidence intervals, e.g. real unit labour cost (ULC), consumer price index (CPI), REER, and monetary aggregates. Another difference is that the impact of the shock is estimated to be more transitory by the one-step method. To illustrate, whereas, despite being relatively persistent, the response of IP estimated with one-step method returns towards zero after reaching its minimum of -0.55 $SD$ in period 25 following the shock, that with the two-step is considerably more persistent. The same difference between the methods is also present in responses of consumption, employment, real ULC, wages, CPI, and trade variables.

Our FAVAR methods suggest the following common findings. Regarding real activity, we find that the most affected indicators are real investment, in line with Smets and Wouters (2003); McCallum and Smets (2007), and total employment. Both methods capture the medium and long-term statistically significant decline in these variables. Despite a statistically significant decrease in nominal wages in the economy, decreases in the (real) output and prices lead the real ULC to increase, statistically significantly in only one-step

[59]See Section 1.5 for robustness check for the Gibbs iterations.

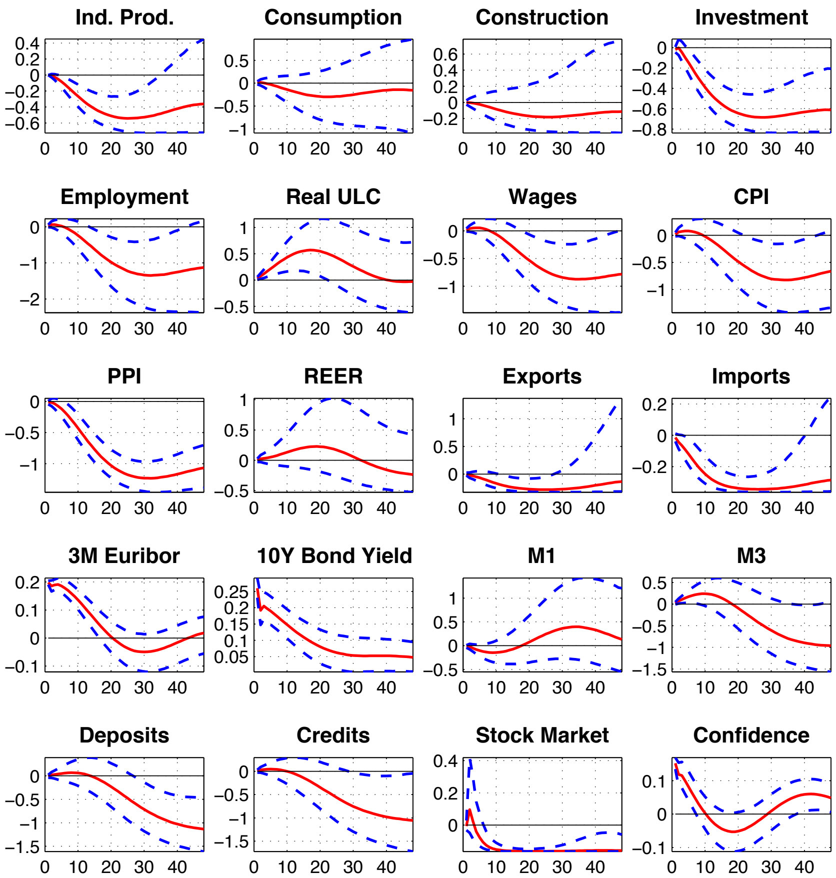



Figure 1.4.1: Baseline Results - One-step FAVAR

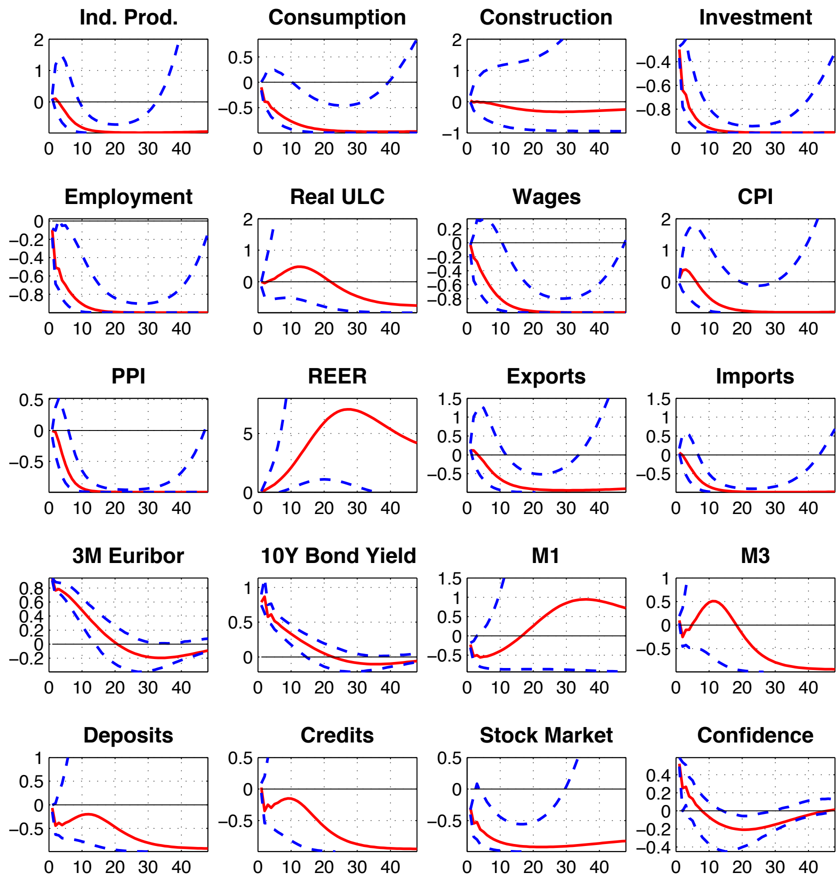



Figure 1.4.2: Baseline Results - Two-step FAVAR

Notes: - Consumption: Final Consumption Expenditure; Construction: Construction Production Index; Investment: Gross Fixed Capital Formation; Euribor: The Euro Interbank Offered Rate; Deposits: Total Deposits of Residents Held at Monetary Financial Institutions (MFI); Credits: Credits to Total Residents Granted by MFI; Confidence: Consumer Confidence Indicator. - The dashed lines indicate 68% confidence intervals based on 8,000 Gibbs samplings (one-step) and 1,000 bootstraps (two-step).

FAVAR model.[60]

While there are slightly positive responses of prices in the first five (two-step) and ten (one-step) months following the shock, our results[61] suggest that our data set and the model properly capture the information that Sims (1992) argued could be missing from the standard VARs. It is also important to note the similarity between the shape and statistical significance of our, especially, one-step and BBE's two-step CPI results. That is to say, our findings support BBE that even with the FAVAR approach, it is possible to observe the price level initially increasing, statistically insignificantly though, following a contractionary monetary policy shock, before it decreases statistically significantly. Another similarity is that the two-step method tends to estimate the impact of the shock on prices to be persistent. Our one-step method, however, suggests more transitory responses of prices, turning towards zero after reaching the minimum in year 3 following the shock.

Comparing our results with those obtained by Boivin et al. (2008), where the impact of the creation of the EA is studied using a two-step FAVAR approach, the following remarks may be made. One of the findings of the Boivin et al. paper, for the period from 1999 to 2007, is strong responses of trade and the effective real exchange rate to a 100 basis-point contractionary monetary policy shock in the EA. Whereas the strong REER results suggested by our two-step approach are qualitatively quite consistent with Boivin et al.'s, our one-step approach highlights that this finding might be an approach-dependent one. That is to say, as our one-step estimation results also suggest an appreciation in the euro[62] for 30 months following the shock, the impulse responses are not as strong as suggested

[60]Here we consider the definitions of nominal and real ULC which are, respectively, the ratio of total labour cost to real output, and that of nominal ULC to a price index, e.g. GDP deflator according to OECD glossary.

[61]i.e. CPI and statistically significantly PPI.

[62]According to the definition of the real effective exchange rate series, a rise in the index means loss of competitiveness of the home country (EA).

by our and Boivin et al.'s two-step approaches. Given the decline in prices reaching its minimum in period 30, our one-step approach even suggests, statistically insignificantly though, depreciation in the currency from period 30 onwards. We observe from the two-step approach that during the same period euro continues to appreciate but at a decreasing rate. Also consistent with Boivin et al. (2008), we observe that given the appreciation in euro and decline in real activity and consumption in the economy, trade also responds negatively to the monetary tightening. Similar to the REER case above, however, our one-step Bayesian approach estimates a smaller impact than the two-step.

In line with the decline in real activity and investment, both short- and long-term interest rates are found to respond statistically significantly and positively to the contractionary monetary policy shock in the economy for 10-20 months following the shock.[63] As of period 20, we observe the short-term interest rates turn negative, i.e. decrease below the pre-shock level.[64] We explain below that a qualitatively similar behaviour is also observed from the responses of the benchmark monetary policy rate in Figure 1.4.3, estimated by the one- and two-step approaches.[65] Considering the interaction between the interest rates and the benchmark policy rates, we believe that our explanation below for the negative responses of the later applies to that of the former as well.

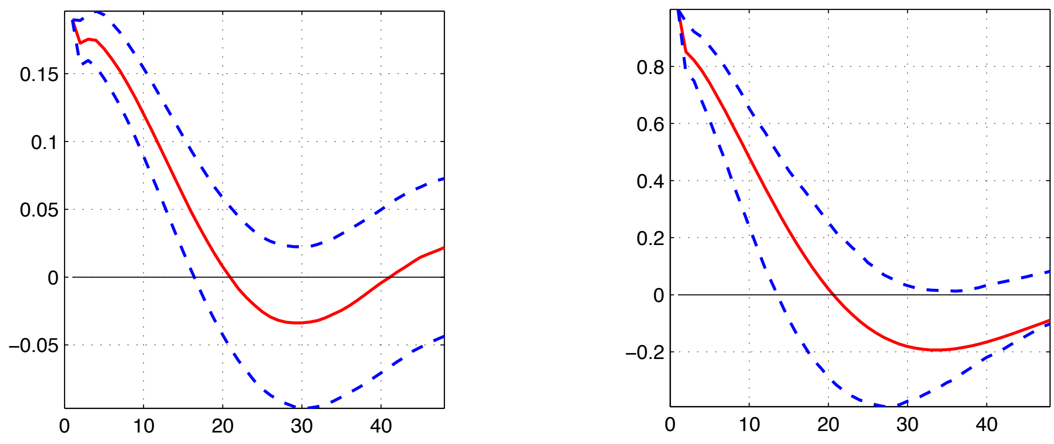
There is a common finding in the (FA)VAR literature that after the initial jump for 1-2 years, the monetary policy variables respond negatively to their own shocks.[66] Given the fact that the "impulse responses contain the endogenous reaction of monetary policy

[63]Surprisingly, the positive response of the 10-year bond yield is estimated by the one-step approach to last more than 4 years.

[64]Long-term interest rate too by the two-step approach.

[65]If we recall, the policy variable is the only observable factor in the transition equation (1.2.2), and its impulse responses can also be calculated in standard ways.

[66]To illustrate, see BBE, Uhlig (2005), Belviso and Milani (2006), McCallum and Smets (2007), Ahmadi and Uhlig (2007), Boivin et al. (2008), Blaes (2009), Bork (2009), among others.




**One-step** **Two-step**

Figure 1.4.3: Impulse Responses of the Monetary Policy Variable i.e. ECB Official Refinancing Operation Rate

The dashed lines indicate one-$SD$ confidence intervals.

to its own shocks", Uhlig (2005) explains the negative responses of the policy variables by proposing two possible reasons:

> First, this may reflect that monetary policy shocks really arise as errors of assessment of the economic situation by the (central bank). (The bank) may typically try to keep the steering wheel steady: should they accidentally make an error and shock the economy, they will try to reverse course soon afterwards. Second, this may reflect a reversal from a liquidity effect to a Fisherian effect: with inflation declining, a decline in the nominal rate may nonetheless indicate a rise in the real rate. (pp.397-8)

Regarding the impact of the shock on monetary aggregates, furthermore, we obtain the following findings: First of all, consistent with BBE for the US, and Boivin et al. (2008) and Blaes (2009) for the EA, we observe the responses of narrow (M1) and broad (M3) money stocks to be statistically insignificant. To our knowledge, there is no clear explanation on the issue of statistical insignificance in the FAVAR literature. Our point estimates suggest, on the one hand, that where there is hike in the interest rates due to the shock (period 0-20), M1 unsurprisingly responds negatively before showing positive responses during the decline in the interest rates (period 20 onwards). On the other hand, broader monetary aggregates display some liquidity puzzles.[67] In Blaes (2009), where similar puzzling M3 responses are observed for the EA as an aggregate, 'temporary portfolio shifts' are proposed as a possible explanation to the findings. Blaes claims that "higher short-term interest rates at first render the short-term assets contained in M3 more attractive than longer-term investments, leading to a temporary increase in money stock M3" (p.11).

Furthermore, we find that the contractionary shock leads to decreases in the total deposits held at monetary financial institutions (MFI), while total credits granted by them also decline as a result of the shock. These responses except the deposits, in periods 25 onwards, estimated by the one-step approach, are found to be statistically insignificant. Similar to Boivin et al. (2008), our estimations suggest that except for the contemporaneous response, stock markets fall persistently due to the monetary tightening. Surprisingly, despite the negative impacts of the shock on real activity, mainly employment, consumer confidence is found to display statistically significantly positive responses for 8-10 months following the shock. Whereas, according to one-step estimation, the confidence indicator first declines and then increases again, similar to BBE this variable always declines according to the results of the estimations by the two-step method.

As a final remark on the impulse responses above, we observe that the impact of a 'surprise' change in the monetary policy on the economy is estimated by both methods to reach its maximum between one and two years.[68]

[67] The failure of the negative correlations between nominal interest rates and the money stock expected to be created by monetary policy disturbances. See Kelly et al. (2011).

[68] Consistent with ECB (2010).

**Forecast Error Variance Decomposition and $\mathbf{R^2}$ Statistics**

Apart from impulse response functions, it is a common exercise in the (FA)VAR context to report forecast error variance decompositions (FEVD). In other words, "the fraction of the forecasting error of a variable, at a given horizon, that is attributable to a particular shock."[69,70] Specific to the FAVAR approach, additionally, $R^2$ statistics are another tool used to analyse the estimation results. The statistics are calculated as the fraction of the variance of a variable accounted for by the common components of the FAVAR system, i.e. $\hat{\Lambda}^f \hat{F}_t + \hat{\Lambda}^y Y_t$ in the observation equation (1.2.1).

We report in Table 1.4.1 below the variance decomposition and $R^2$ results for the same twenty macroeconomic indicators analysed in the previous figures. Following BBE, and the FAVAR literature in general, the results are based only on the two-step estimation method.

First of all, although it is expected for the monetary policy shock to explain "a relatively small fraction of the forecast error of real activity measures or inflation"[71], our results show that the policy shock accounts for very little of even the variations in the monetary aggregates, 1.05% of M1 and 0.74% of M3.[72] As we can see from the table, apart from the interest rates, the contribution of the policy shock varies from 0.07%, construction, to 1.76%, investment. According to our estimations, respectively, 17.5% and 13.07% of the variations in 3-month Euribor and 10-year government bond yield are accounted for by that in the policy shock at the horizon of 5 years. Although the FEVD results here and in the literature suggest that the shock has little effect on the economy in the horizon

[69]Bernanke et al. (2005, p.413).

[70]For technical details see Appendix F.

[71]Bernanke et al. (2005, p.413)

[72]In BBE, these rates are 0.5% for the US monetary base and M2 aggregates.

Table 1.4.1: Variance Decomposition and $R^2$ Statistics (%)

| Variables | FEVD | $R^2$ |
|---|---|---|
| IP | 0.31 | 71.0 |
| Consumption | 1.19 | 23.0 |
| Construction | 0.07 | 10 .2 |
| Investment | 1.76 | 56.4 |
| Employment | 1.21 | 73.7 |
| Real ULC | 0.05 | 42 .1 |
| Wages | 0.73 | 44.6 |
| CPI | 0.35 | 51.6 |
| PPI | 0.95 | 70.3 |
| REER | 0.57 | 15.0 |
| Exports | 0.24 | 41.8 |
| Imports | 0.57 | 46.5 |
| 3M Euribor | 17.50 | 98.7 |
| 10Y Yield | 13.07 | 45.8 |
| M1 | 1.05 | 35.4 |
| M3 | 0.74 | 57.1 |
| Deposits | 0.91 | 48.4 |
| Credits | 0.72 | 51.6 |
| Stock Market | 0.61 | 66.8 |
| Confidence | 1.43 | 76.6 |

At the horizon of 5 years.

of 5 years, as we discussed in Section 1.2.3[73], we still believe in the practical aspects of the identification of monetary policy shocks in terms of providing a useful description of the effects of a systematic monetary policy rule on various macroeconomic variables.

Looking at the $R^2$ decompositions, we note the following. A sizeable fraction of the variables is explained by the factors in the model. To illustrate from real activity measures: IP (71%), gross fixed capital formation (56.4%), employment (73.7%). Moreover, the variation in the factors explain 51.6% of the consumer and 70.3% of the producer prices. Regarding the monetary aggregates, on average almost 50% of the variations of the indicators are accounted for by the factors: M1 (35.4%), M3 (57.1%), deposits (48.4%), and credits (51.6%). Interestingly, whereas almost entire variations in the short-

[73]Part: Monetary Policy Shocks in the Euro Area.

term interest rates are explained by the common components (98.7%), only less than 50% of the long-term interest rates (45.8%) can be explained in the model. Bernanke et al. (2005, p.414), present low levels of their $R^2$ estimations for the monetary base (10.3%) and M2 (5.2%), and highlight the necessity of being less confident in the impulse response estimates for those variables. In light of this conclusion of BBE, finally, we consider our impulse responses as relatively reliable point estimates.

### 1.4.2 Time Variation

Here in the second part of our empirical results, we investigate the impact of the global financial crisis of 2007-8 on the monetary policy transmission mechanism in the EA. As mentioned before, a simple technique of rolling windows is employed in this analysis. This approach will "allow us to use relatively standard techniques to study the nature of the time variations ... while keeping computational costs manageable."[74]

Given the fact that our study employs the highly computational intensive Bayesian FAVAR approach, relative to some alternatives such as time-varying parameter (TVP) FAVAR models, the method of rolling windows is an effective option for the purpose of investigation of time variations in our data set. Additionally, and more importantly, given the short history of the EA and the number of parameters to be estimated in a standard TVP-FAVAR model, we were not able to work with too many detailed restrictions on the model, e.g. the form of covariance matrix.[75,76] We believe that this is the main reason why

[74]Canova et al. (2012, p.48)

[75]We thank Gary Koop for valuable discussions and comments during the presentation of the paper in 2011 at the 6th annual Bayesian econometrics workshop organised by the Rimini Centre for Economic Analysis in Italy.

[76]Additionally, despite many and quite long trials with the replication files of Koop and Korobilis (2009) to fit both one- and two-step TVP-FAVAR models to our relatively short data set, we could not obtain any reasonable results. We anyway thank the authors for making the files available to the public.

TVP-FAVAR models are yet to be applied to the EA whilst there are already a number of studies employing the technique to investigate the issue of time variation in the monetary transmission mechanisms in the US and the UK.[77]

Basically, the rolling windows approach estimates the same model over samples of fixed length in order to assess its stability over time. As explained by Zivot and Wang (2006, Chapter 9), if the parameters of the model are truly constant over the entire sample, then one should expect the estimates over the rolling windows not to be too different. "If the parameters change at some point during the sample, then the rolling estimates should capture this instability" (p.313).

We estimate our FAVAR model[78] by the one-step and two-step estimation methods over fixed length samples rolled by twelve, six and three months.[79] The estimation results are then compared by plotting together the impulse response functions of the main twenty macroeconomic indicators calculated in each sample.

### Initial Rolling Window

There is no doubt that the growing turmoil in the global financial markets in late 2007 turned into a global financial crisis following the collapse of Lehman Brothers in September 2008. As such, we should separate our rolling windows as pre- and post-Sep08 referring to before and after the crisis periods. Instead of setting Sep08 as the end of the initial window, which will provide us with only one impulse response function for the pre-crisis period, we determine the initial window according to the peaks of the financial markets and real activity in the EA before the crisis period. In other words, as we can see from

[77] See Korobilis (2012), Barnett et al. (2012), and references therein.
[78] Still with 4 factors and 2 lags.
[79] Only six-month rolling is estimated by the one-step method. For details see below.

Figure 1.4.4, the European financial markets peak in June 2007 prior to the turmoil and beginning of the crisis.

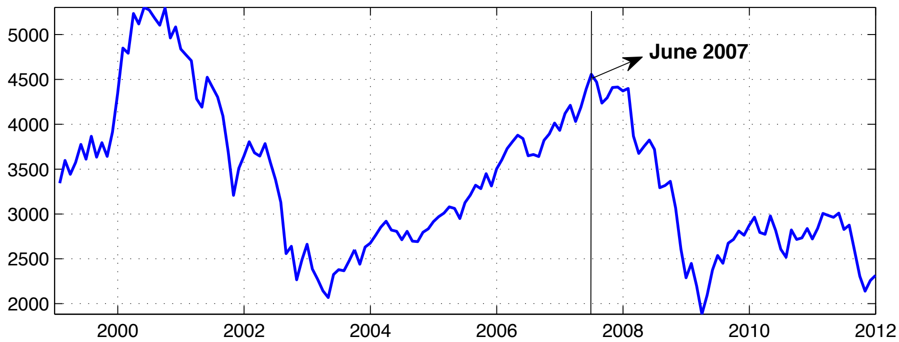



Figure 1.4.4: Initial Rolling Window: Financial Markets

Euro Stoxx 50 (Points, SA)

Therefore, we set the initial window as March 1999 - June 2007, inclusive.[80] This approach provides us with multiple impulse response functions for the pre- and post-crisis periods depending on the frequency of rolling augmentations, i.e. twelve, six, three months. As we explain in Section 1.5.4, we test the robustness of our estimations to an alternative initial window specification.

**Crisis in the Euro Area Economies**

Before the findings of the chapter, it is important to note the following. There is no doubt that the EA economies are still struggling with the aftermaths of the global financial and the European sovereign debt crises even when this thesis is being written in 2012-3. Therefore, when we discuss our empirical results in the following parts of the section, we refer all the years following September 2008 until the end of our whole sample, i.e. December 2011, as the crisis period for the EA.

[80]First three observations are lost due to data transformations explained above in Section 1.3.1.

**Two-step Rolling Estimations**

Due to its computational simplicity, we start the analysis with the two-step estimation method. We do so in order to be able to investigate the question of time variation in as detailed a way as possible, i.e. alternative rolling augmentations. Following the set of results with the two-step method, we then replicate on p.59 below the limited version of the exercise with the one-step estimation method. Due to computational intensity of the one-step method and given the two-step results, we estimate the former method according to 6-month rollings only. We summarise the details of the results obtained with the two-step method as follows.

Our rolling estimation results are presented in Figures 1.4.5 - 1.4.7, with windows reported below the figure. For the sake of comparability across windows, the impulse responses are plotted without their confidence intervals. Due to having a number of variables and windows, we present statistical significance of the four main variables such as IP, CPI, M1 and M3 in Appendix G.1.

Looking at the results, we note the following points which turn out to be robust to the rolling augmentations. First of all, there is little sign of any variation in some of the real variables such as consumption, investment and employment. That is to say, the monetary policy shocks hitting the economy either before or after the crisis periods have almost identical contractionary impacts on these measures of the real economy.[81] Regarding IP, we observe from the results that there are differences in the speed of the impact of the monetary policy shock pre- and post-Sep08. Whereas the contemporaneous impact of the shock is mixed across windows, it is clear from the results that IP declines, unsurprisingly,

[81]Estimating our FAVAR model window by window means identification of a new 25 basis-point shock specific to that particular sample.

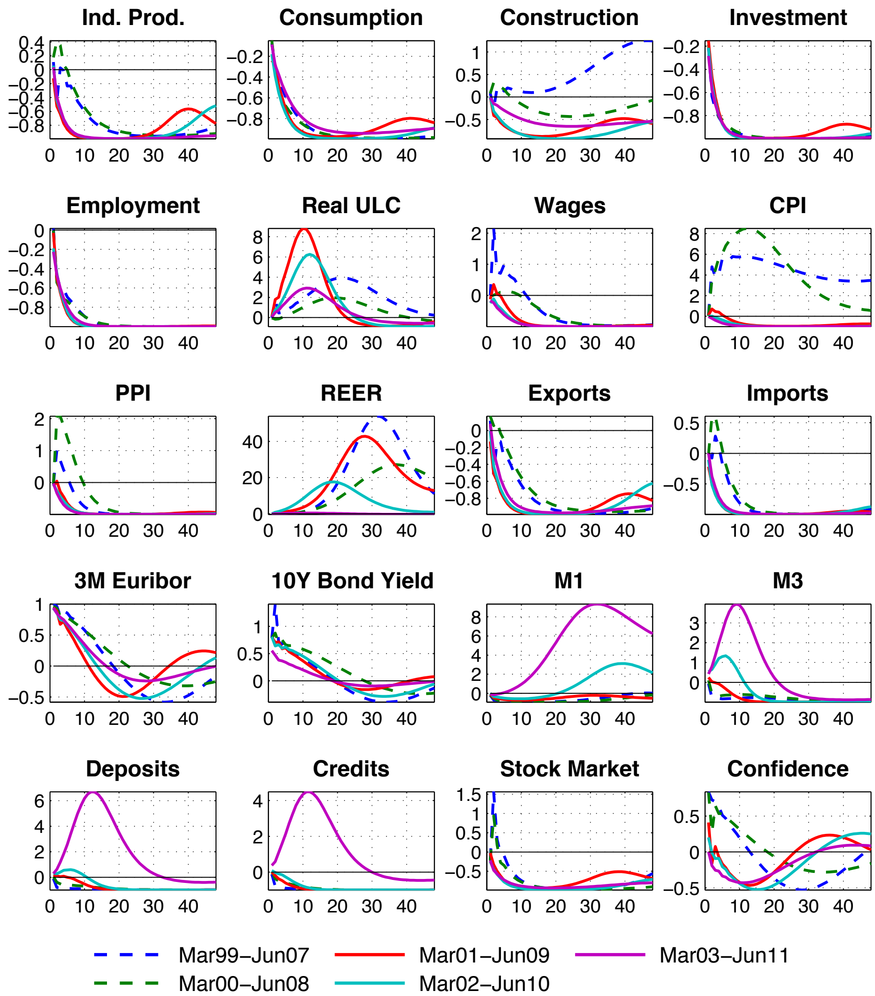



Figure 1.4.5: Rolling Windows, Two-step, 12M

much faster when hit by a contractionary monetary policy shock during the crisis period. For some of the windows spanning the period 1999 - June 2008, we find that it takes IP 20 or more periods to reach its minimum point. By contrast this is reached within half this time, i.e. by 10 months, when the economy is hit by a shock during the crisis period. Similar results are also obtained for construction, wages, trade, stock markets, and producer prices.[82]

Furthermore, we do not observe much variation in the impulse responses of the interest rates. With some signs of time variation, REER also does not show clear-cut time vari-

[82]Despite not being as clear for construction and trade indicators estimated with 3M and 6M rollings, respectively.

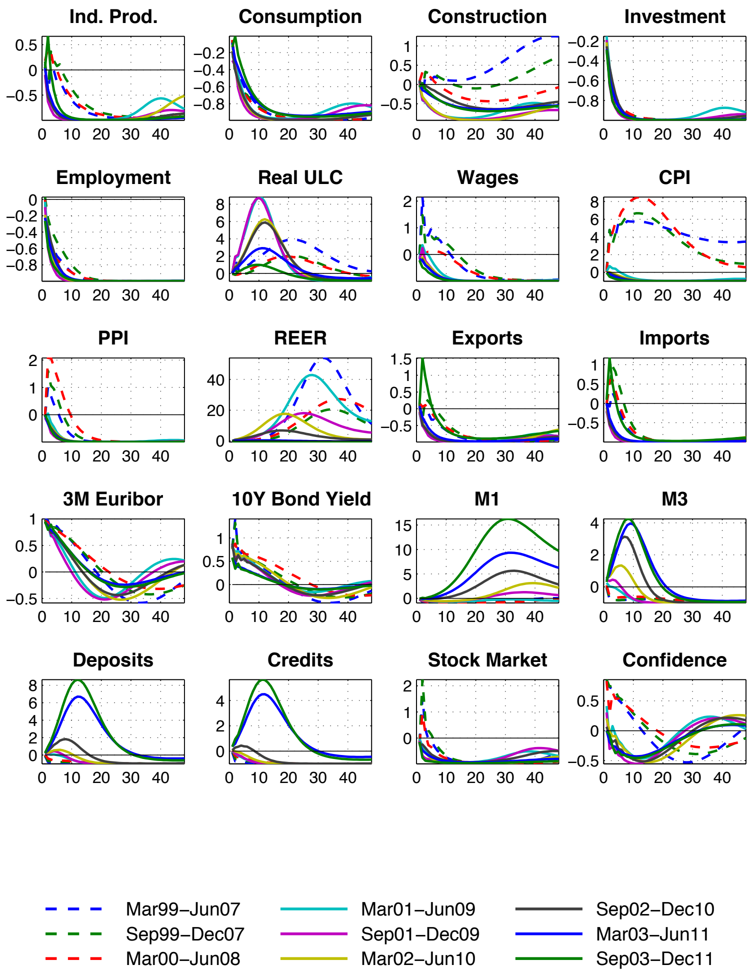



Figure 1.4.6: Rolling Windows, Two-step, 6M

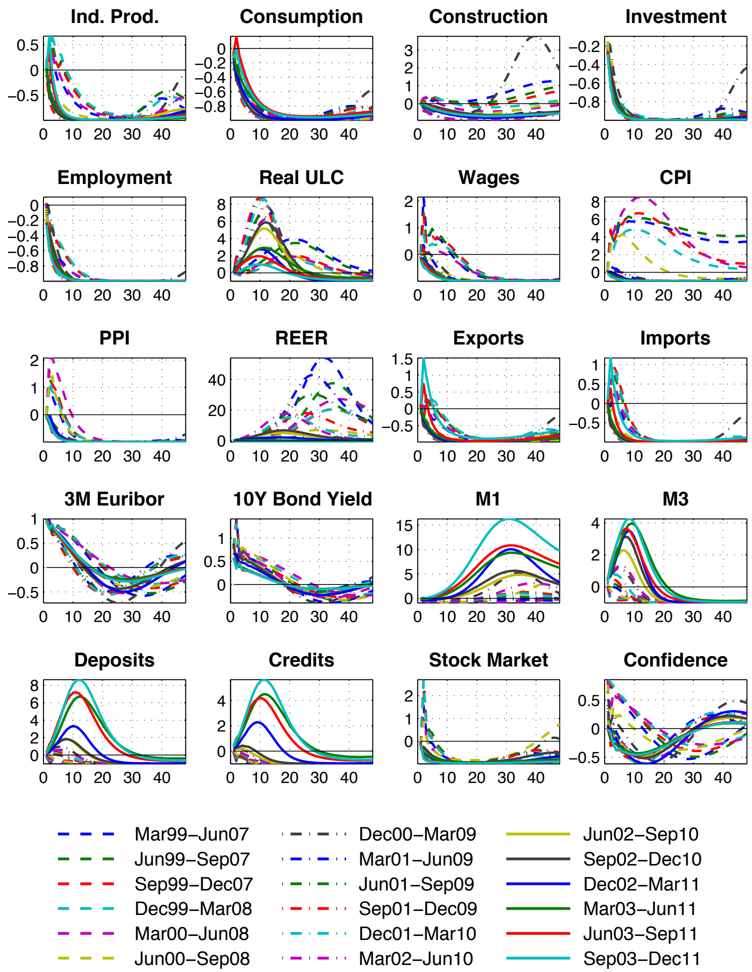



Figure 1.4.7: Rolling Windows, Two-step, 3M

Note: In order to be able to present other windows clearly, sample Sep00-Dec08 is eliminated from the figures due to very strange impact of Sep-Dec 2008, we believe, on the impulse responses. Some of the results from this window can be observed from Appendix G.1.

ation pre- and post-crisis periods. Consumer confidence, however, is observed to display quite opposite responses. Whereas the confidence indicator responds first positively then negatively to the shock in the rolling sample between 1999 and June 2008, its responses are the other way around for the samples onwards. Another interesting result is obtained with the measure for real ULC. Consistent with the sudden drops in the output explained above, the cost of labour seems to increase faster and higher when there is a contractionary shock in the post-crisis period. Prior to the crisis, we still observe increases in the cost, but the contractions are more gradual and less steep.

In addition to the results above, our two-step FAVAR rolling analysis suggests two sets of very interesting findings about the variations in the impact of monetary tightening on the monetary aggregates and consumer prices. Again similar to the other results above, these observations are also robust to different rolling frequencies:

Starting with the monetary aggregates, our rolling estimations repeatedly suggest that the more observations from the post-crisis period, i.e. September 2008 onwards, are included in the samples, the stronger a liquidity puzzle is observed as a result of the contractionary policy shock. When there is a shock prior to the crisis, however, the indicators respond negatively in almost all windows. We investigate in Chapter 3 of the thesis the response of the Eurosystem[83] to the global financial crisis with "extreme" unconventional monetary measures. Given the unprecedented amount of liquidity injected to the financial markets of the EA, we believe that our findings of the liquidity puzzles for the post-crisis period might be related to the unconventional policy actions.

We believe that a cautious approach to the findings on the monetary aggregates is of

[83] i.e. the monetary authority of the EA which consists of the ECB and national central banks of the countries in the monetary union.

importance due to potential issues of endogeneity, state contingency, and contamination in these variables caused by the portfolio shifts and cross-border movements in the EA, especially from 2008.[84] This also suggests the importance of incorporating more detailed unconventional monetary measures into data sets investigated with the FAVAR approach. Regarding this, it is also important to consider the differences in the composition of the central banks' balance sheet policies, which we discuss in the Introduction of Chapter 3. We believe that this practice is of importance for our analysis in order to test whether the liquidity puzzles would disappear should we were to include more information in our data set on the central bank and/or financial institutions' balance sheets and cross-border movements in the EA.

Secondly, our rolling analysis raises an important point about puzzling CPI responses in the literature. We summarised in the Introduction of the chapter that solving the issue of price puzzles has largely been the main focus of the (FA)VAR literature. As our results in Section 1.4.1 and that of other studies frequently cited throughout the chapter suggest, despite the issue of statistical significance we highlighted before, the FAVAR approach does capture important dimensions of the business cycle movements. Given this merit of the approach, therefore, it estimates negative responses of prices to a contractionary monetary policy shock in the economy. Our rolling estimations with the same FAVAR approach, however, propose that it might not be the case that prices must always respond negatively following a monetary tightening. As we can clearly see from Figures 1.4.5 - 1.4.7, our FAVAR model, estimated with constant specifications among the windows, suggests that whilst prices respond persistently negatively to the shocks in the post-crisis

[84] See Chapter 3 for details of the global financial crisis period and unconventional monetary actions of the Eurosystem.

period, they strongly puzzle when the shock occurs prior to the crisis. That is to say, as the dashed-line impulse responses in Figures 1.4.5 - 1.4.7 report, the prices increase strongly following a contractionary monetary policy shock during the pre-crisis period. We also find the puzzling responses to be transitory but most of the time lasting for almost four years following the shock. We consider this finding another type of a price puzzle for the (FA)VAR literature.

**Interpolation of the Crisis Period (2008Q4)**

Before moving to the one-step rolling estimation results, we further analyse the impact of the crisis on the overall time variation results summarised above. We observed from the rolling estimations that there are considerable changes in the impact of the shocks on mainly prices and monetary aggregates prior to and after September 2008. We also highlighted on p.54 that window Sep00-Dec08 is eliminated from Figures 1.4.6 - 1.4.7 due to very strange impact of the period September - December 2008 on the impulse responses. According to these findings, we believe that the fourth quarter of 2008 is the period when the economy is most severely hit by the crisis. Therefore, we want to test possible changes in the results had all the series in our data set continued in their normal trends during this period.

Using the replication files of the study by Bańbura and Modugno (2010) cited previously, we replace all of the 360 observations, i.e. 3*120, of the data spanning the fourth quarter of 2008 with their estimates calculated according to their "relatively normal" trending.[85] Then we replicate the rolling analysis in Figure 1.4.6.[86] The results of the

[85] We still prefer to be cautious about the estimates being normal trend of the series due to the fact that both financial markets and the real economy are to some extent hit by the crisis until the fourth quarter of 2008.

[86] We limit the exercise to 6M-rollings for the sake of simplicity.

short exercise are displayed in Figure 1.4.8.

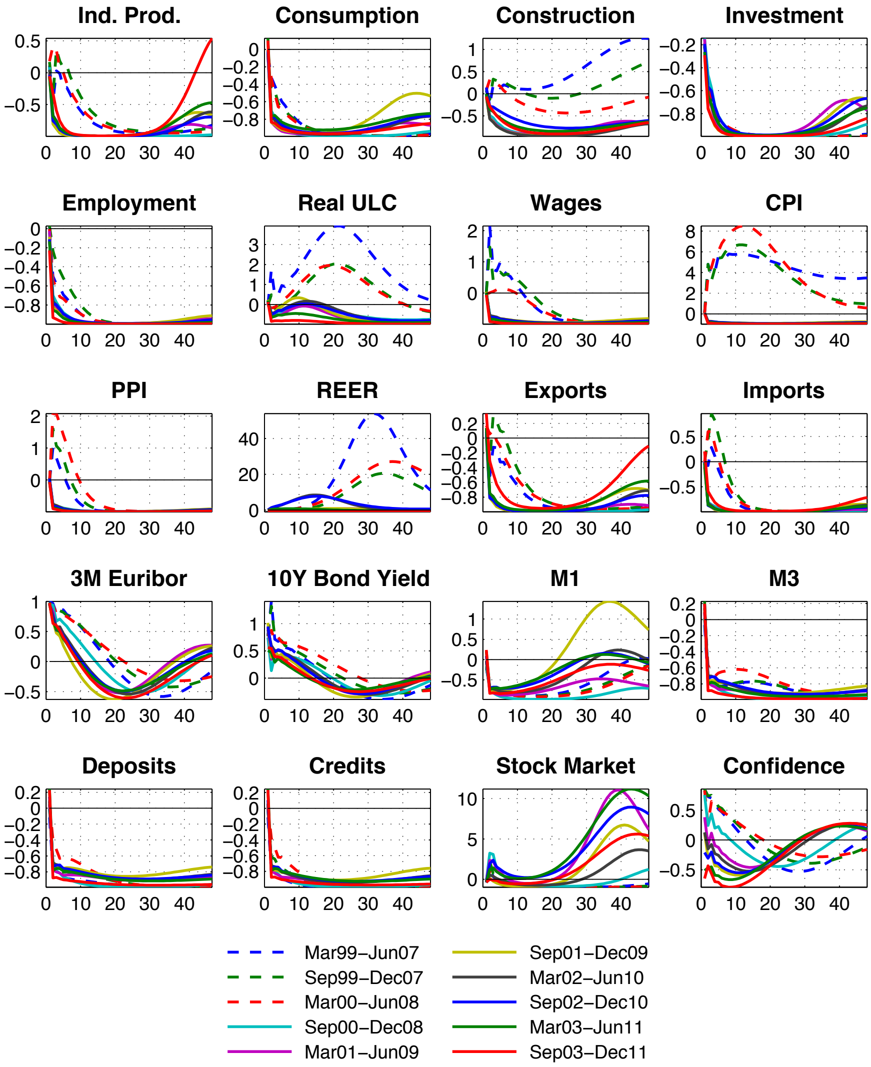



Figure 1.4.8: Interpolation of the Crisis Period

First, given the financial nature of the crisis, unsurprisingly the estimations for the impulse responses of monetary aggregates and stock markets change significantly. To illustrate, we observe, on the one hand, that almost all the strong increases in M1, M3, deposits, and credits in Figure 1.4.6 disappear in rolling estimations with the interpolated data in Figure 1.4.8. On the other hand, instead of permanent decrease in stock markets following a contractionary shock (Figure 1.4.6), interpolated data suggest that a shock hitting the economy in the post-crisis period might strongly increase the markets after 20 months (Figure 1.4.8). These findings suggest that (strong) liquidity puzzles in the whole (Figure 1.4.2) or rolling samples (Figure 1.4.6) are quite likely due to occurrence of the crisis in the sample period investigated. In addition, significant increases in real ULC and REER during the crisis period seem to disappear, making a clearer distinction between the results pre- and post-crisis periods. Finally, and more importantly, the results on the impact of the shock on prices explained in the subsection above are found to be robust to the inclusion and exclusion of the severe crisis observations in the data. In other words, the persistent and negative responses of prices in Figure 1.4.6 are not because of the severe impact of the crisis in the fourth quarter of 2008. Similar to the prices, the time variation in real activity measures are also found to be robust to the interpolation of the observations of the fourth quarter of 2008.

**One-step Rolling Estimations**

Consistent with the Section 1.4.1, we carry out the rolling analysis not only with the two-step method but also the one-step Bayesian approach.[87] However, due to the computational intensity of the method, and the previous finding that the general findings of the two-step estimations are robust to rolling augmentations, we apply the Bayesian rolling analysis to the initial window of 1999 - June 2007 with 6-month rollings only. We present the estimation results in Figure 1.4.9. Comparison of the methods in the rolling analysis context highlights the following points.

We firstly observe that the Bayesian approach is not affected by the severe observations of the crisis period. As we can see from the plot labels below, the estimations results for

[87]Slightly differently, due to the computational intensity of the approach, and given the robustness results in Section 1.5, we base the estimation results here on 5,000 iterations, first 2,000 of which are discarded.

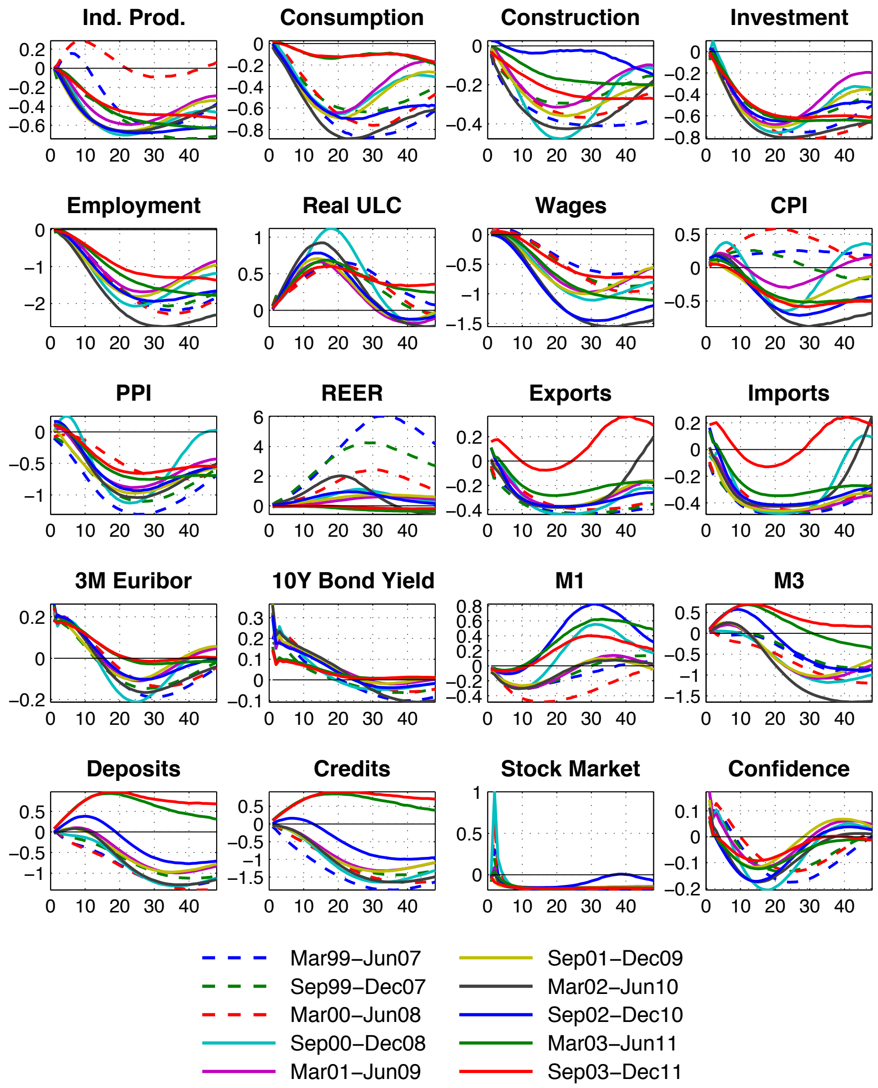



Figure 1.4.9: Rolling Windows, One-step, 6M

the window Sep00-Dec08 are obtained normally by the one-step method. Additionally, the Bayesian rolling approach presents smoother impulse responses for the post-crisis period.[88]

Besides these general differences between the approaches, one-step rolling analysis qualitatively supports almost all the findings we explained above. To name a few, we still observe (i) few or no variations in the impact of the shock on the real variables relative to the nominal ones, (ii) no serious variations in the impact of the monetary tightening

[88]The only exception is the stock markets, impulse responses of which are quite identical across the methods.

on the interest rates, and (iii) relative to the period before crisis, greater increases in the real ULC when the economy is hit by the shock during the crisis period. Furthermore, all the main findings of the two-step analysis are present in the results by the one-step: i.e. liquidity and price puzzles. In other words, our Bayesian rolling analysis also suggests that while the impulse responses of the prices puzzle prior to the crisis period, the puzzles in the monetary aggregates take place only in the post-crisis period in line with our hypothesis of the liquidity effects of the unconventional monetary measures during the global financial crisis period.

Regarding the statistical significance of the findings summarised in this section, it is important to note the following. We discussed in Section 1.4.1 the difference in the estimation of confidence intervals by the one- and two-step methods. The main reason why statistical (in)significance of the results has not been mentioned previously in the section is due to bad performance of the two-step method in terms of estimating reliable error bands. As we can see in Section G.1, however, our one-step approach performs relatively very well in terms of estimating statistically significant impulse responses. On the one hand, Figure G.1.5 shows that the Bayesian technique estimates the sharper output responses during the crisis period to be statistically significant. On the other hand, the estimations in Figure G.1.1 clearly show that the more the rolling samples encompass the crisis period, the more explosive estimations the two-step PC method suggests for the same findings.

Finally, in light of (i) the (in)sensitivity of the two-step (one-step) method to the observations from the crisis period, and (ii) the superiority of the one-step method over the two-step in terms of statistical significance of the estimations, our empirical analysis concludes that the one-step FAVAR approach turns out to be the more-credible methodology of the chapter. This finding therefore highlights the importance of our study for the limited FAVAR literature applied to the EA.

### 1.4.3 Pre-screening Analysis

Having explained the main and time-varying estimation results, we now move to investigation of a limited version of our data set constructed using the Boivin and Ng (2006) pre-screening analysis (henceforth BN), described in Section 1.2.4.

According to our BN analysis, we find the idiosyncratic errors of 57 series to be most correlated with other series in our data set. These variables dropped from the data set are listed in Appendix A. For example, total IP and IP - intermediate goods errors are both most correlated with IP - manufacturing, with correlation coefficients of 0.91 and 0.64, respectively. Note that when any of our main twenty macroeconomic variables are suggested by the analysis to be dropped from the data set, instead of these variables we eliminated the ones their error is most correlated with our main variables. In case of two main series being most correlated with each other, we make no eliminations. Table 1.4.2 displays the variables eliminated instead of the main ones.

Similar to the previous subsections, we present the empirical results of our BN analysis in two parts as the baseline and time variation.

#### Post-BN Baseline Results

The transmission mechanism of a 25-basis-point contractionary monetary policy shock estimated with one- and two-step FAVAR methods using the new data set is presented

Table 1.4.2: Pre-screening Exclusions Instead of the Main Variables

| Variables | Most Correlated |
|---|---|
| IP | IP-Manufacturing |
| Consumption | - |
| Construction | - |
| Investment | - |
| Employment | Total Employees |
| Real ULC | - |
| Wages | Earnings per Employee |
| CPI | HICP-Goods |
| PPI | PPI-Manufacturing |
| REER | US Dollar-Euro |
| Exports | * |
| Imports | * |
| 3M Euribor | 6M Euribor |
| 10Y Yield | 5Y Gov. Bond Yield |
| M1 | Overnight Deposits |
| M3 | M2 |
| Deposits | 10Y Bond Yield USA |
| Credits | - |
| Stock Market | Stock Market-Industrials |
| Confidence | Economic Sentiment Indicator |

- Not suggested, * No elimination.

in Figures 1.4.10 and 1.4.11, with 68% confidence intervals based on, respectively, 8,000 Gibbs samplings and 1,000 bootstraps. Comparing these results to those in Figures 1.4.1 and 1.4.2 suggests the following findings.

First of all, and of significant importance, exclusion of the information carried by the variables dropped from the data set does not change the estimated impact of the shock on the real activity measures,[89] prices, trade, and stock markets. The results obtained with the one-step method are even better in terms of statistical significance. To illustrate, despite being statistically marginally significant in the full data set case, the eventual negative impact of the shock on prices, i.e. period 20 onwards, is estimated

[89]Except employment responses estimated by two-step method.

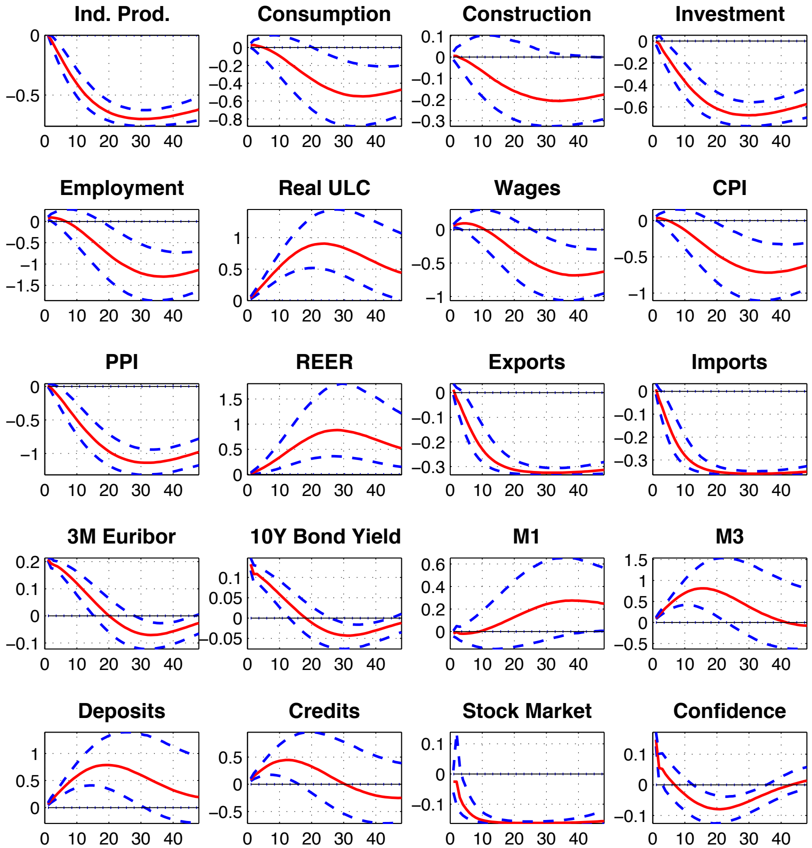



Figure 1.4.10: Post-BN - Baseline Results - One-step

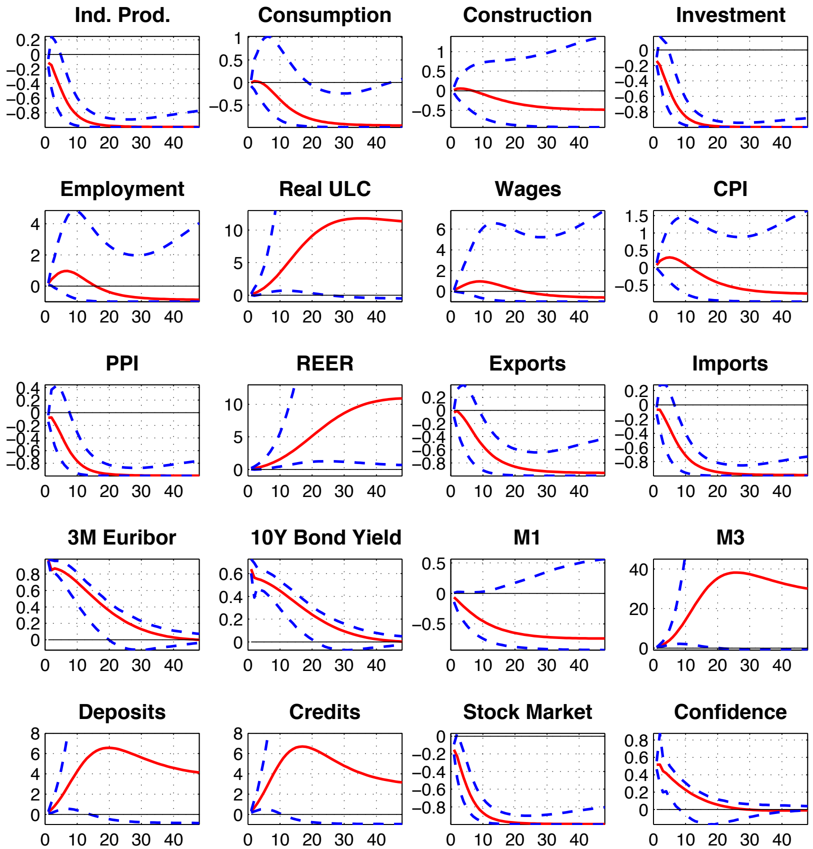



Figure 1.4.11: Post-BN - Baseline Results - Two-step

to be statistically significant with the new data set. Similar findings are present for consumption, real ULC, and REER. As in the pre-BN case, on the other hand, statistical significance of the impulse responses estimated by the two-method is still quite weak, e.g. CPI, employment, among others.

We observe the only significant change in the results to be with the impulse responses of deposits and credits. Instead of persistent negative responses as in Figures 1.4.1 and 1.4.2, both methods estimate that these indicators respond positively and statistically significantly, according to the one-step only, following the monetary tightening.

Regarding the monetary aggregates, our results suggest almost no change in M1 responses pre- and post-BN (one-step), full horizon increase in M3 first 20 periods of which are statistically significant (one-step)[90], no puzzle in M1 but a stronger one in M3 (two-step).

Consistent with long-lasting interest rate responses, we observe that two-step estimates with BN are almost always stronger than those reported in the pre-BN case previously. For example, output, REER, stock markets, and other monetary aggregates show such stronger impulse responses to contractionary monetary policy shocks.

### Post-BN Time Variation

Following the whole sample BN results above, here we test the impact of the analysis on time variation findings previously reported in Figures 1.4.6 and 1.4.9. Our BN rolling estimation results are presented in Figures 1.4.12 - 1.4.13.

Briefly, and very importantly, according to our BN analysis, the very same rolling estimation results 1.4.6 and 1.4.9 are obtainable with a more parsimonious data set.

[90] Note M3 in Figure 1.4.1 which responds negatively to the shock between periods 20-48.

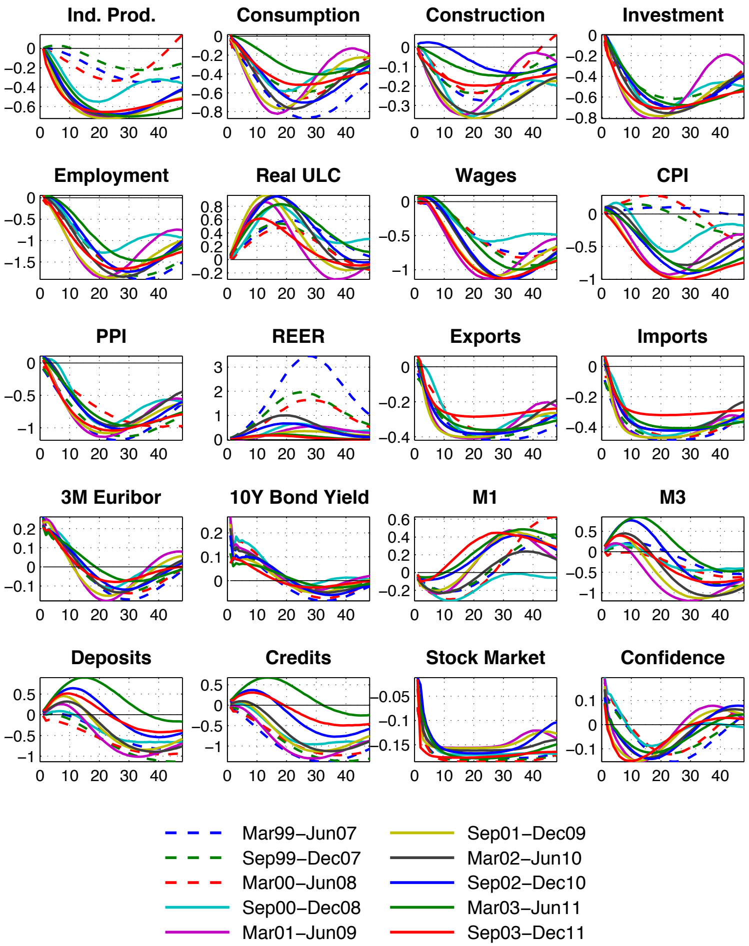



Figure 1.4.12: Post-BN - Rolling Windows, One-step, 6M

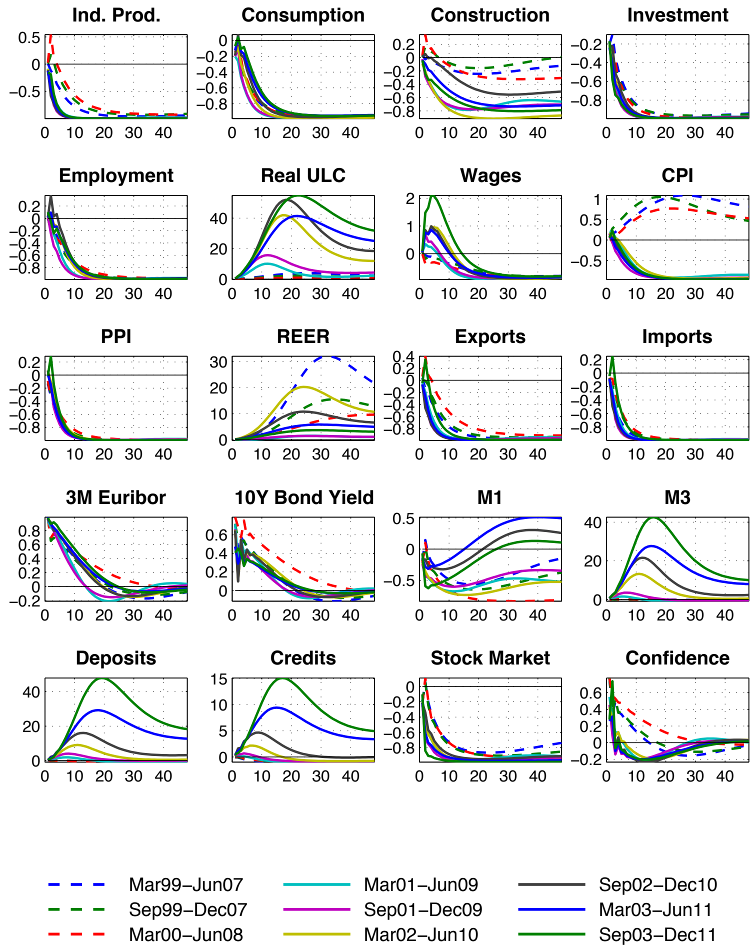



Figure 1.4.13: Post-BN - Rolling Windows, Two-step, 6M

The main advantage of this finding is, of course, with the computer intensive Bayesian approach as the pre-screening reduces its estimation time.

## 1.5 Robustness

This section contains the robustness checks of the chapter. First, following from the preferred specifications explained in Section 1.3, we test the sensitivity of our estimations to model specifications in two parts as the number of factors and lag length. Second, we test the robustness of our Bayesian estimation results by looking at convergence and Gibbs iterations.

### 1.5.1 Model Specifications

**Number of Factors:** We determined the preferred factor specification in Section 1.3.2 according to the information criteria and the explanatory power of the factors. In addition to these tests, we investigated our FAVAR model with number of factors varying from 1 to 9, and tested how the choice of number of factors in the model affects the impulse response functions. We present these robustness estimations in Appendix H.1.

We notice from the robustness estimations that with some exceptions the results are qualitatively robust to the choice of the number of factors. Some variables, however, display divergence from the general behaviour of the responses when either very few (1-2) or a large number of (7-9) factors are used in the model. To illustrate real ULC, monetary aggregates, and stock market are some of these variables. When we vary the number of factors within the middle range, however, our results turn out to be robust to factor specification.

**Lag Length:** Similar to the factor specification, we estimate our FAVAR model with the preferred number of factors (4) and different lag lengths of 1, 2, 4, 7, and 13. In addition to those suggested by the information criteria in Section 1.3.3, we also consider other lag lengths intentionally in order to test whether having more interaction between quarters, semi-years, and years provides us with "better" results. Figure H.2.1 displays the test results.

It is clear from the results that, on the one hand, having 1 lag or increasing the lag length beyond 4 in the model creates extra volatility and makes the results explosive. On the other hand, our preferred specification, i.e. FAVAR(2), suggests the smoothest impulse responses.

### 1.5.2 Convergence

Convergence of Gibbs sampling is an important issue in Bayesian analyses. As such, here we test whether the single factor chains of the Gibbs iterations converge in our pre- and post-BN main and rolling estimations.

In order to test the convergence of the algorithm there are a number of criteria that could be employed. To illustrate, Gelman and Rubin (1992b), Raftery and Lewis (1992, 1996), and McCulloch and Rossi (1994) are some of the widely used ones in the literature. Instead of going with formal and relatively more difficult implementation of convergence diagnostics, we prefer to choose a less formal and easy-to-implement method. Following Ahmadi (2005), we basically take last 8000 of the total Gibbs sampling draws[91] of each factor, and plot the first half of the median of the draws against the second half. The

[91]Remember first 2,000 iterations are discarded in order to eliminate the influence of our choice of starting values.

idea is that if there is no significant deviation between the first and the second halves of the draws, we conclude that this single chain of the factor has converged.

Appendix I presents the results of the convergence tests for the main and rolling estimations results with and without the BN analysis. Overall the results suggest that our Gibbs algorithms do converge in all one-step estimations. In Figures I.1.2 - I.1.3 and I.2.2 - I.2.3, convergence test results are presented for only the first and the last rolling samples. The results not reported are qualitatively very similar to the ones in these figures, and convergence is also obtained in these estimations.

### 1.5.3 Gibbs Iterations

In addition to convergence of the Gibbs algorithms, we also test the robustness of our main estimation results to the number of Gibbs iterations. As we can see from Figure J.0.1 in Appendix J, using either 10,000 or 20,000 iterations[92] essentially give the same results. Bayesian time variation (pre- and post-BN) and post-BN main estimation results are also robust to the number of Gibbs iterations.[93]

### 1.5.4 Initial Rolling Window

We based our time variation analysis in Section 1.4.2 on the initial window with the upper bound June 2007, when the European stock markets peaked before the turmoil in the global financial markets. In order to test the robustness of our findings to this specification, we replicate our rolling estimations with the initial window 1999 - March 2008. Similar to the main rolling analysis, March 2008 is determined according to the

[92]First 20% of which are discarded to minimise the effects of starting values.

[93]The test results are not reported due to being very similar to those in Figure J.0.1.

date when real activity in the EA peaked before the global crisis.

Our robustness estimations are displayed in Appendix G.2. Figures G.2.1 - G.2.3 clearly suggest that our empirical findings summarised in Section 1.4.2 are robust to the initial window specification.

## 1.6 Conclusion

In this chapter, we have provided a broad empirical analysis of the monetary transmission mechanism in the EA as an aggregate. Whilst the FAVAR models have been the main methodology, the analyses based on rolling windows and Boivin and Ng (2006) pre-screening technique have also been used in the chapter in order to examine the issues of time variation and data size.

Analysing a novel data set of 120 macroeconomic time series, spanning the period 1999-2011, we estimate a transmission mechanism of a contractionary monetary policy shock in the EA largely consistent with conventional wisdom. In addition to the two-step principal component method, i.e. the only FAVAR method used for the EA, we have employed a computationally burdensome Bayesian joint estimation technique. Comparison of the results estimated by these two distinct methods suggests that despite qualitative similarities between the results, there are considerable gains from implementation of the one-step technique such as smoother impulse responses and statistical significance of the estimates. Our findings highlight the fact that there is room for future research on the EA implementing not only the PC but also the Bayesian FAVAR technique. For example, alternative identification schemes, e.g. sign restrictions, may help us to test robustness of the results to identification of monetary policy shocks in the EA. Investigation of cross-country heterogeneity in the EA with a FAVAR model estimated with the Bayesian methodology, i.e. the main focus of the following chapter, is another interesting direction.

We highlighted that, according to the rolling estimations, the main time-varying responses to monetary policy shocks are for consumer prices and monetary aggregates. As our exercise of interpolation of the fourth quarter of 2008 suggests, whereas the puzzling responses of monetary aggregates might have something to do with the most severe impact of the global financial crisis in this period, the finding that prices puzzle prior to but decrease during the crisis period following a contractionary monetary policy shock seems to be what we have in the data itself. Regarding future research, as more data become available for the EA, we believe that application of time-varying parameter FAVAR models will be possible and bring good source of comparison to our simple time variation analysis.

Looking at a new set of impulse responses and rolling windows obtained with a limited data set determined by the pre-screening technique of Boivin and Ng (2006), we tried to contribute to the question of whether more data are always better for factor analysis as well as the estimation of structural FAVAR models. Consistent with the real time forecasting exercise by Boivin and Ng, we observed in a FAVAR context that when factors in a FAVAR are extracted from as few as 67 series, they might do no worse, and as our Bayesian estimations suggest, better than ones extracted from 120 series. Given that almost half of the data set is eliminated in our case, and significant gains obtained accordingly in terms of speed of estimation of the Bayesian approach in a structural context, we believe that not only the PC aspects of the pre-screening technique must be studied, but also the Bayesian properties and extensions should be investigated. It would also be interesting to analyse the impact of the technique in a different structural context such as cross-country heterogeneity in the EA. This is the topic we turn to next in the second chapter of the thesis.

# APPENDIX A

# DATA DESCRIPTION

Details of our EA data set are as below. The transformation (Tr.) codes are 1 - no transformation; 2 - first difference; 5 - first difference of logarithm. The variables denoted as "1" ("0") in column 4 are assumed to be slow- (fast-) moving. Data details in brackets apply to the following same category series unless otherwise stated. Following our BN pre-screening analysis, column $\hat{\tau}_1^*$ presents the correlation coefficients between the residuals of the series and the ones listed in column $j_1$.

| No. | Description | Tr. | S/F | Source | $\hat{\tau}_1^*$ | $j_1$ |
|---|---|---|---|---|---|---|
| 1 | IP Total (2005=100) | 5 | 1 | OECD | 0.91 | 8 |
| 2 | IP-Intermediate Goods | 5 | 1 | Eurostat | 0.64 | 8 |
| 3 | IP-Energy | 5 | 1 | Eurostat | 0.54 | 7 |
| 4 | IP-Capital Goods | 5 | 1 | Eurostat | 0.70 | 8 |
| 5 | IP-Durable Consumer Goods | 5 | 1 | Eurostat | 0.43 | 8 |
| 6 | IP-Non-Durable Consumer Goods | 5 | 1 | Eurostat | 0.32 | 5 |
| 7 | IP-Mining And Quarrying | 5 | 1 | Eurostat | 0.54 | 3 |
| 8 | IP-Manufacturing | 5 | 1 | Eurostat | 0.91 | 1 |
| 9 | IP-New Orders | 5 | 1 | Eurostat | 0.77 | 8 |
| 10 | Construction Production Index | 5 | 1 | Eurostat | 0.29 | 2 |
| 11 | Unemployment Rate (%) | 1 | 1 | Eurostat | 0.79 | 12 |
| 12 | Youth Unemployment Rate | 1 | 1 | Eurostat | 0.79 | 11 |
| 13 | Unemployment Total (1000 persons) | 5 | 1 | Eurostat | 0.41 | 39 |
| 14 | Retail Sale of Food, Bev. & Tobacco [a] | 5 | 1 | Eurostat | 0.52 | 17 |
| 15 | Retail Sale of Non-Food Products | 5 | 1 | Eurostat | 0.72 | 17 |
| 16 | Retail Sale of Textiles | 5 | 1 | Eurostat | 0.68 | 15 |
| 17 | Retail Trade | 5 | 1 | Eurostat | 0.72 | 15 |
| 18 | Passenger Car Registration (2005=100) | 5 | 1 | OECD | 0.24 | 113 |
| 19 | Exports Total[b] | 5 | 1 | Eurostat | 0.67 | 20 |
| 20 | Imports Total | 5 | 1 | Eurostat | 0.67 | 19 |
| 21 | Total Reserves inc. Gold (Mil. Euro) | 5 | 1 | ECB | 0.56 | 60 |
| 22 | HICP All-Items (2005=100) | 5 | 1 | Eurostat | 0.83 | 26 |
| 23 | Overall exc. Energy & Unp. Food | 5 | 1 | Eurostat | 0.53 | 27 |

| No. | Description | Tr. | S/F | Source | $\hat{\tau}_1^*$ | $j_1$ |
|---|---|---|---|---|---|---|
| 24 | HICP-Energy And Unprocessed Food | 5 | 1 | Eurostat | 0.89 | 25 |
| 25 | HICP-Liquid Fuels | 5 | 1 | Eurostat | 0.89 | 24 |
| 26 | HICP-Goods | 5 | 1 | Eurostat | 0.83 | 22 |
| 27 | HICP-Services | 5 | 1 | Eurostat | 0.53 | 23 |
| 28 | HICP-Non-Energy Ind. Goods, Durable | 5 | 1 | Eurostat | 0.25 | 85 |
| 29 | HICP-Non-Energy Ind. G., Non-durable | 5 | 1 | Eurostat | 0.22 | 22 |
| 30 | PPI-Industry | 5 | 1 | Eurostat | 0.79 | 35 |
| 31 | PPI-Intermediate and Capital Goods | 5 | 1 | Eurostat | 0.37 | 83 |
| 32 | PPI-Durable Consumer Goods | 5 | 1 | Eurostat | 0.40 | 95 |
| 33 | PPI-Non-Durable Consumer Goods | 5 | 1 | Eurostat | 0.35 | 25 |
| 34 | PPI-Mining and Quarrying | 5 | 1 | Eurostat | 0.29 | 31 |
| 35 | PPI-Manufacturing | 5 | 1 | Eurostat | 0.79 | 30 |
| 36 | Crude Oil (West Texas Int., $/BBL) | 5 | 0 | WSJ | 0.53 | 25 |
| 37 | CRB[c] Spot Index (1967=100) | 5 | 0 | CRB | 0.34 | 49 |
| 38 | ECB Commodity Price Ind. (2000=100) | 5 | 0 | ECB | 0.57 | 105 |
| 39 | 3M Euribor (%) | 1 | 0 | Datastream | 0.98 | 40 |
| 40 | 6M Euribor | 1 | 0 | Datastream | 0.98 | 39 |
| 41 | 1Y Euribor | 1 | 0 | Datastream | 0.96 | 40 |
| 42 | 5Y Government Bond Yield | 1 | 0 | Datastream | 0.83 | 43 |
| 43 | 10Y Government Bond Yield | 1 | 0 | OECD | 0.83 | 42 |
| 44 | Spread 3M-REFI | 1 | 0 | Calculated | 0.91 | 45 |
| 45 | Spread 6M-REFI | 1 | 0 | Calculated | 0.95 | 46 |
| 46 | Spread 1Y-REFI | 1 | 0 | Calculated | 0.95 | 45 |
| 47 | Spread 5Y-REFI | 1 | 0 | Calculated | 0.82 | 48 |
| 48 | Spread 10Y-REFI | 1 | 0 | Calculated | 0.82 | 47 |
| 49 | Euro Stoxx 50 (Points) | 5 | 0 | Eurostat | 0.58 | 51 |
| 50 | Share Price Index-Basic Materials | 5 | 0 | Datastream | 0.44 | 56 |
| 51 | Share Price Index-Industrials | 5 | 0 | Datastream | 0.71 | 54 |
| 52 | Share Price Index-Consumer Goods | 5 | 0 | Datastream | 0.42 | 50 |
| 53 | Share Price Index-Health Care | 5 | 0 | Datastream | 0.33 | 56 |
| 54 | Share Price Index-Consumer Services | 5 | 0 | Datastream | 0.71 | 51 |
| 55 | Share Price Index-Telecommunication | 5 | 0 | Datastream | 0.51 | 54 |
| 56 | Share Price Index-Financials | 5 | 0 | Datastream | 0.52 | 51 |
| 57 | Share Price Index-Technology | 5 | 0 | Datastream | 0.54 | 49 |
| 58 | Share Price Index-Utilities | 5 | 0 | Datastream | 0.57 | 49 |
| 59 | Currency in Circulation (Mil. Euro) | 5 | 0 | Eurostat | 0.41 | 85 |
| 60 | Capital And Reserves | 5 | 0 | Eurostat | 0.56 | 21 |
| 61 | Money Stock: M1 | 5 | 0 | ECB | 0.72 | 68 |
| 62 | Money Stock: M2 | 5 | 0 | ECB | 0.82 | 63 |
| 63 | Money Stock: M3 | 5 | 0 | ECB | 0.82 | 62 |
| 64 | Deposits with Agreed Mat. up to 2Y | 5 | 0 | Eurostat | 0.54 | 95 |
| 65 | External Assets | 5 | 0 | Eurostat | 0.83 | 66 |
| 66 | External Liabilities | 5 | 0 | Eurostat | 0.83 | 65 |
| 67 | Total Deposits of Residents Held at MFI | 5 | 0 | Eurostat | 0.55 | 95 |

| No. | Description | Tr. | S/F | Source | $\hat{\tau}_1^*$ | $j_1$ |
|---|---|---|---|---|---|---|
| 68 | Overnight Deposits | 5 | 0 | Eurostat | 0.72 | 61 |
| 69 | Repurchase Agreements | 5 | 0 | Eurostat | 0.37 | 93 |
| 70 | Credit to Total Residents g.by MFI | 5 | 0 | Eurostat | 0.49 | 71 |
| 71 | Loans to General Gov. Gran. by MFI | 5 | 0 | Eurostat | 0.54 | 67 |
| 72 | Loans to Other Residents Granted MFI | 5 | 0 | Eurostat | 0.50 | 120 |
| 73 | Debt Securities of EA Residents | 5 | 0 | Eurostat | 0.66 | 20 |
| 74 | Central Bank Claims on Banking Ins. | 5 | 0 | Eurostat | 0.35 | 66 |
| 75 | Economic Sentiment Indicator (Index) | 5 | 0 | Eurostat | 0.83 | 80 |
| 76 | Construction Confidence Indicator (%) | 1 | 0 | Eurostat | 0.94 | 84 |
| 77 | Industrial Confidence Indicator | 1 | 0 | Eurostat | 0.82 | 82 |
| 78 | Retail Confidence Indicator | 1 | 0 | Eurostat | 0.60 | 93 |
| 79 | Consumer Confidence Ind. (2005=100) | 5 | 0 | OECD | 0.70 | 75 |
| 80 | Services Confidence Indicator | 1 | 0 | Eurostat | 0.83 | 75 |
| 81 | Employment Expec., Months Ahead | 1 | 0 | Eurostat | 0.78 | 77 |
| 82 | Production Expec. Months Ahead | 1 | 0 | Eurostat | 0.82 | 77 |
| 83 | Selling Price Expec. Months Ahead | 1 | 0 | Eurostat | 0.78 | 77 |
| 84 | Assessment of Order Books | 1 | 0 | Eurostat | 0.94 | 76 |
| 85 | Price Trends Over The Next 12 Months | 1 | 0 | Eurostat | 0.52 | 81 |
| 86 | IP-USA (2005=100) | 5 | 1 | OECD | 0.26 | 40 |
| 87 | IP-UK | 5 | 1 | OECD | 0.24 | 69 |
| 88 | IP-JP | 5 | 1 | OECD | 0.33 | 23 |
| 89 | CPI-USA | 5 | 1 | OECD | 0.54 | 25 |
| 90 | CPI-UK | 5 | 1 | OECD | 0.38 | 79 |
| 91 | CPI-JP | 5 | 1 | OECD | 0.26 | 79 |
| 92 | US Federal Funds Target Rate % | 1 | 0 | FED | 0.54 | 80 |
| 93 | UK Bank Of England Base Rate | 1 | 0 | BoE | 0.68 | 76 |
| 94 | JP Overnight Call Money Rate | 1 | 0 | BoJ | 0.50 | 95 |
| 95 | 10Y Bond Yield USA | 1 | 0 | OECD | 0.78 | 96 |
| 96 | 10Y Bond Yield UK | 1 | 0 | OECD | 0.78 | 95 |
| 97 | 10Y Bond Yield JP | 1 | 0 | OECD | 0.48 | 46 |
| 98 | Share Price Ind.-USA (Dow 30, Points) | 5 | 0 | Reuters | 0.86 | 99 |
| 99 | Share Price Ind.-UK (FTSE 100) | 5 | 0 | Reuters | 0.86 | 98 |
| 100 | Share Price Ind.-JP (Nikkei 225) | 5 | 0 | Reuters | 0.56 | 98 |
| 101 | US Dollar-Euro (Monthly average) | 5 | 0 | Eurostat | 0.93 | 105 |
| 102 | Pound Sterling-Euro | 5 | 0 | Eurostat | 0.64 | 105 |
| 103 | Swiss Franc-Euro | 5 | 0 | Eurostat | 0.32 | 99 |
| 104 | Japanese Yen-Euro | 5 | 0 | Eurostat | 0.66 | 105 |
| 105 | REER (1999=100) | 5 | 0 | Eurostat | 0.93 | 101 |
| 106 | Capacity Utilisation Rate%* | 1 | 1 | ECB | 0.50 | 77 |
| 107 | GDP at Market Prices$^{d*}$ | 5 | 1 | Eurostat | 0.91 | 113 |
| 108 | Final Consumption Expenditure* | 5 | 1 | Eurostat | 0.79 | 107 |
| 109 | Gross Fixed Capital Formation* | 5 | 1 | Eurostat | 0.70 | 107 |
| 110 | Employment Total (1000 persons)* | 5 | 1 | Eurostat | 0.97 | 111 |
| 111 | Employees Total* | 5 | 1 | Eurostat | 0.97 | 110 |

| No. | Description | Tr. | S/F | Source | $\hat{\tau}_1^*$ | $j_1$ |
|---|---|---|---|---|---|---|
| 112 | Self Employed Total* | 5 | 1 | Eurostat | 0.45 | 110 |
| 113 | Real Labour Prod./Person Emplyd[e]* | 5 | 1 | ECB | 0.91 | 107 |
| 114 | Real Unit Labour Cost* | 5 | 1 | Eurostat | 0.69 | 116 |
| 115 | Earnings/Employee (Current, Euro)* | 5 | 1 | Oxford Econ. | 0.91 | 116 |
| 116 | Wages & Salaries (Current, Bil. Euro)* | 5 | 1 | Oxford Econ. | 0.91 | 115 |
| 117 | Current Account (Net,Mil.Euro,World)* | 2 | 1 | OECD | 0.39 | 116 |
| 118 | Capital Account* | 2 | 1 | OECD | 0.44 | 51 |
| 119 | Financial Account* | 2 | 1 | OECD | 0.52 | 21 |
| 120 | ECB Official Refi. Operation Rate (%) | 1 | 0 | Eurostat | 0.90 | 39 |

[a] (2005=100), [b] (vis-a-vis World, Trade value, Mil. Euro), [c] Commodity Research Bureau, [d] (Chained at Market Prices, Mil. 2000 Euro), [e] (2000=100). An asterisk (*) denotes the variable is originally available in quarterly frequency.

APPENDIX B

# BAYESIAN THEORY

In order to provide some basic details related to likelihood-based joint estimation techniques, here we briefly explain the Bayesian theory.

First of all, the theory is fundamentally follows the simple probability rule that

$$p(A, B) = p(A|B)\ p(B)$$

where $A$ and $B$ are considered to be two random variables, $p(A, B)$ is the joint probability[1] of the occurring of $A$ and $B$, $p(A|B)$ is the probability of $A$ occurring on the condition of $B$ having occurred, and $p(B)$ is the marginal probability of $B$. By reversing the roles of $A$ and $B$, the joint probability can also be expressed as

$$p(A, B) = p(B|A)\ p(B)$$

Rearranging these two expressions brings us to the Bayes' rule that

$$p(B|A) = \frac{p(A|B)\ p(B)}{p(A)}$$

Considering the Bayes' rule, assume that we are interested in estimating a parameter

[1]As highlighted by Koop (2003), "probability density" and "probability function" terminologies should be used if the random variable is continuous and discrete, respectively.

matrix $\theta$ based on the information we obtain from the data $y$. As such, Bayes' rule is modified as follows:

$$p(\theta|y) = \frac{p(y|\theta)\ p(\theta)}{p(y)}$$

Since our fundamental interest is learning about $\theta$, in other words "because $[p(y)]$ has no operational significance"[2], $p(y)$ can be ignored from the rule above. Hence, it could be written that

$$p(\theta|y) \propto p(y|\theta)\ p(\theta) \tag{B.0.1}$$

where $p(\theta|y)$, $p(y|\theta)$ and $p(\theta)$ are respectively referred to as the posterior density, the likelihood function, and the prior density. According to Koop (2003), this relationship is often stated as "posterior is proportional to likelihood times prior".

In order to briefly explain these terms technically the following are worth mentioning. The prior density, $p(\theta)$, contains what we know about the parameters prior to seeing the data. That is to say it summarises the non-data information available to the researcher about the parameters. The likelihood function, $p(y|\theta)$ is the data generating process considered as the density of the data conditional on the model parameters. If we imagine, for example, a linear regression model with the errors normally distributed, $p(y|\theta)$ is a Normal density depending upon the regression coefficients and the error variance. Finally, the posterior, $p(\theta|y)$, is the summary of all we have learned about the parameters after (posterior to) observing the data. In light of these, the equation (B.0.1) is named by Koop (2003) as the "updating rule" as "the data allows us to update our prior views about $\theta$". The result obtained from the Bayes' rule is then the posterior which combines both the data and non-data information.

[2] Kim and Nelson (1999, p.179)

# APPENDIX C

# CHOW-LIN INTERPOLATION TECHNIQUE

As mentioned in text, because some series commonly used in the FAVAR literature are available only in quarterly frequency for the eurozone countries, monthly observations are estimated for these series using Chow and Lin (1971). Here we summarise the details of the technique.

In this process we apply "interpolation" to the stock variables and "distribution" (or temporal disaggregation) to the flows aggregates and time averages of stock variables (indices). The terminologies differ such that the monthly estimates corresponding to the observed quarters (i.e. months 3, 6, 9, 12) are equal to these observations in interpolation while the sum of the three monthly estimates for each quarter ought to equal the observed value for the quarter in the process of distribution.

The main assumption of the Chow and Lin (1971) technique is that the "monthly observations . . . of the series to be estimated satisfy a multiple regression relationship with some related series. In our analysis we follow Angelini et al. (2006) and use the static factors extracted from the monthly data sets as related series. Angelini et al. (2006) concludes that the this type of factor model disaggregation outperforms more standard methods when there is (1) a large number of explanatory variables for the variable to be interpolated or backdated, (2) a limited idiosyncratic component for the set of variables to be used for factor extraction, (3) a limited measurement error for both the variable to be interpolated and the set of factor extraction variables.

Once the related series (factors) are constructed the Chow and Lin (1971) procedure proceed as follows:[1]

First, depending on whether the series are being interpolated or distributed an $n \times 3n$ matrix is constructed to convert the $3n$ monthly observations into $n$ quarterly observations. For interpolation, with end of period values, the matrix takes the form:

$$C_I = \begin{bmatrix} 0 & 0 & \dots & 1 & 0 & 0 & \dots & 1 & \dots & 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 & 0 & 0 & \dots & 1 & \dots & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & \dots & 0 & 0 & \dots & 1 \end{bmatrix} \tag{C.0.1}$$

and in the case of distribution we have:

$$C_D = \frac{1}{3} \begin{bmatrix} 1 & 1 & \dots & 1 & 0 & 0 & \dots & 0 & \dots & 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 & 1 & 1 & \dots & 1 & \dots & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 & \dots & 1 & 1 & \dots & 1 \end{bmatrix} \tag{C.0.2}$$

Then it is assumed that the vector of $n$ quarterly observations of the series to be disaggregated will satisfy the regression model

$$y. = Cy = CX\beta + Cu = X.\beta + u., \quad Eu.u.' = V.CVC' \tag{C.0.3}$$

[1] Here we follow Chow and Lin (1971).

where $y$ is the vector of monthly observations of the series to be estimated, $X$ is the vector of related series, and dots refer to the series' being quarterly.

Chow and Lin (1971) explain the problem as to estimate a vector $z$ of $m$ observations on the dependent variables, where $z$ would be identical with $y$, and propose that a linear unbiased estimator $\hat{z}$ of $z$ satisfies, for some $m \times n$ matrix $A$,

$$\hat{z} = Ay. = A(X.\beta + u.) \tag{C.0.4}$$

In order to find the best linear unbiased estimator of $\hat{z}$, the trace of the covariance matrix of $(\hat{z} - z)$ is minimised w.r.t. $A$, and subject to the $m \times p$ matrix equation $AX - X_z = 0$. The solution for $A$ and the resulting estimator are, respectively,

$$A = X_z(X.'V.^{-1}X.)^{-1}X.'V.^{-1} + V_z.V.^{-1}[I - X.(X.'V.^{-1}X.)^{-1}X.'V.^{-1}]$$

$$\hat{z} = Ay. = X_z\hat{\beta} + (V_z.V.^{-1})\hat{u}. \tag{C.0.5}$$

where, $X_z$ and $V_z$ denote variables in the regression model for $z$ (equation C.0.4),[2] and

$$\beta = (X.'V.^{-1}X.)^{-1}X.'V.^{-1}y \tag{C.0.6}$$

Finally, regarding the knowledge of the covariance matrix $V$, Chow and Lin (1971) suggest (1) the simple case where the monthly regression residuals are assumed to be serially uncorrelated, each with variance $\sigma^2$, (2) to assume that the monthly residuals follow a first order autoregression[3], and (3) the assumption that the monthly residuals are serially uncorrelated, but have variances proportional to a known function of an explanatory variable or a certain linear combination (possibly the PC) of the explanatory variables.

[2]It is highlighted by Chow and Lin (1971) that $X_z$ is identical with $X$ in the case of interpolation and distribution, relative to extrapolation.

[3]The case implemented in our analysis.

# APPENDIX D

# FACTOR ANALYSIS

As highlighted by Bai and Ng (2002), "central to both the theoretical and the empirical validity of factor models is the correct specification of the number of factors". Here we first describe a factor model and its estimation,[1] then summarise the procedure proposed by Bai and Ng (2002) to determine the number of factors in these models.[2]

## Factor Model

Consider the following model:

$$X_{it} = \lambda_i' F_t + e_{it} \tag{D.0.1}$$

where, for $i = 1, \ldots, N$, and $t = 1, \ldots, T$, $X_{it}$ is a vector of the observed data for the $i$th cross-section unit at a time $t$, $F_t$ is a vector of common factors, $\lambda_i$ consists of the factor loadings associated with $F_t$, and $e_{it}$ is the idiosyncratic component of $X_{it}$. The product $\lambda_i' F_t$ is called the common component of the data.

One of the superiorities of the Bai-Ng method is the fact that their estimation results

[1] Further details of these models and their estimation could be obtained from Stock and Watson (1998, 1999, 2002a,b), among others.

[2] Here we closely follow the original paper.

hold under weak serial and cross-section dependence in the idiosyncratic components. Therefore, we could consider the model in equation (D.0.1) to have an *approximate factor structure*.

In order to estimate common factors in large panels like equation (D.0.1), Bai and Ng (2002) use the method of asymptotic PC. They claim that the number of factors that can be estimated by this non-parametric method is $min\{N, T\}$, much larger than permitted by estimation of state space models. In order to determine which of these factors are statistically important, Bai and Ng (2002) highlight the necessity to first establish consistency of all the estimated factors when both $N$ and $T$ are large, and consider an arbitrary number $k$, $k < min\{N, T\}$, to start with.

Estimates of $\lambda^k$ and $F^k$ are obtained by solving the following optimisation problem:

$$V(k) = \min_{\Lambda, F^k} \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} (X_{it} - \lambda_i^{k'} F_i^k)^2 \tag{D.0.2}$$

subject to the normalisation of either $\Lambda^{k'}\Lambda^k/N = I_k$ or $F^{k'}F^k/T = I_k$.

Concentrating $\Lambda^k$ out and using the latter normalisation leads the optimisation problem to be identical to maximising $tr(F^{k'}(XX')F^k)$. Bai and Ng list two solutions to the minimisation problem above as (1) where the estimated factor matrix, $\tilde{F}^k$, is $\sqrt{T}$ times the eigenvectors corresponding to the $k$ largest eigenvalues of the $T \times T$ matrix $XX'$, and given $\tilde{F}^k$, the corresponding matrix of factor loadings is $\tilde{\Lambda}^{k'} = (\tilde{F}^{k'}\tilde{F}^k)^{-1}\tilde{F}^{k'}X = \tilde{F}^{k'}X/T$, (2) by $(\bar{F}^k, \bar{\Lambda}^k)$, where $\bar{\Lambda}^k$ is constructed as $\sqrt{N}$ times the eigenvectors corresponding to the $k$ largest eigenvalues of the $N \times N$ matrix $X'X$. The normalisation that $\Lambda^{k'}\Lambda^k/N = I_k$, employed in the second solution, implies $\bar{F}^k = X\bar{\Lambda}^k/N$. It is important to note here that adding the second solution is crucial due to the fact that "the (former) solution ... is not unique, even though the sum of squared residuals $V(k)$ is unique". Regarding computational intensity of the solutions, finally, we could say the second set of calculations is less costly when $T > N$, while the first is less intensive when $T < N$.

## Estimating the Number of Factors

Having the model and its estimation described, we move to determining the number of static factors in the model.

Thanks to linearity of the model and the factors being observable, $\lambda_i$ can be estimated by applying OLS to each equation. Therefore, Bai and Ng describe the case as a classical model selection problem.

If we assume $F^k$ to be a matrix of $k$ factors, then we can show the sum of squared residuals (divided by $NT$) from time-series regressions of $\underline{X}_i$ [3] on the $k$ factor for all $i$ as

$$V(k, F^k) = \min_{\Lambda} \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} (X_{it} - \lambda_i^{k\prime} F_i^k)^2 \tag{D.0.3}$$

Then the purpose is to find penalty functions, $g(N, T)$, such that criteria of the form

$$PC(k) = V(k, \hat{F}^k) + kg(N, T) \tag{D.0.4}$$

can consistently estimate the true common factors $(r)$.[4]

Following Theorem 2[5] of the paper, Bai and Ng propose another class of criteria defined by

$$IC(k) = ln(V(k, \hat{F}^k)) + kg(N, T) \tag{D.0.5}$$

[3] A $T$ vector of time-series observations for the $i$th cross-section unit.

[4] Note that $V(k, \tilde{F}^k) = V(k, \bar{F}^k) = V(k, \hat{F}^k)$ as $F$ span the same vector space.

[5] See (Bai and Ng, 2002, p.199).

which also estimate $r$ consistently.

Under the assumption that the factors are estimated by the method of PC, the authors propose the following formulations of $g(N,T)$ in $PC(k)$ and $IC(k)$:

$$PC_{p1}(k) = V(k,\hat{F}^k) + k\hat{\sigma}^2 \left(\frac{N+T}{NT}\right) \ln \left(\frac{NT}{N+T}\right) \tag{D.0.6}$$

$$PC_{p2}(k) = V(k,\hat{F}^k) + k\hat{\sigma}^2 \left(\frac{N+T}{NT}\right) \ln C_{NT}^2 \tag{D.0.7}$$

$$PC_{p3}(k) = V(k,\hat{F}^k) + k\hat{\sigma}^2 \left(\frac{\ln C_{NT}^2}{C_{NT}^2}\right) \tag{D.0.8}$$

$$IC_{p1}(k) = ln(V(k,\hat{F}^k)) + k \left(\frac{N+T}{NT}\right) \ln \left(\frac{NT}{N+T}\right) \tag{D.0.9}$$

$$IC_{p2}(k) = ln(V(k,\hat{F}^k)) + k \left(\frac{N+T}{NT}\right) \ln C_{NT}^2 \tag{D.0.10}$$

$$IC_{p3}(k) = ln(V(k,\hat{F}^k)) + k \left(\frac{\ln C_{NT}^2}{C_{NT}^2}\right) \tag{D.0.11}$$

In addition to being a superior theory in the literature due to allowing weak serial and cross-section dependence, the technique is also advantageous due to the fact that (1) it does not rely on sequential limits, (2) it does not impose any restrictions between $N$ and $T$, (3) the results hold under heteroskedasticity in both the time and the cross-section dimensions, and (4) simulations run by the authors show that the criteria have good finite sample properties. Finally, regarding the information criterion used in our analysis Bai and Ng claim that the main advantage of it and other panel information criteria ($IC_p$) is that they do not depend on the choice of $kmax$ through $\sigma^2$, where $V(k,\hat{F}^k) = N^{-1}\sum_{i=1}^{N}\hat{\sigma}_i^2$, and $\hat{\sigma}_i^2 = \hat{e}_i'\hat{e}_i/T$ from equation (D.0.1).

# APPENDIX E

# INTERPOLATION

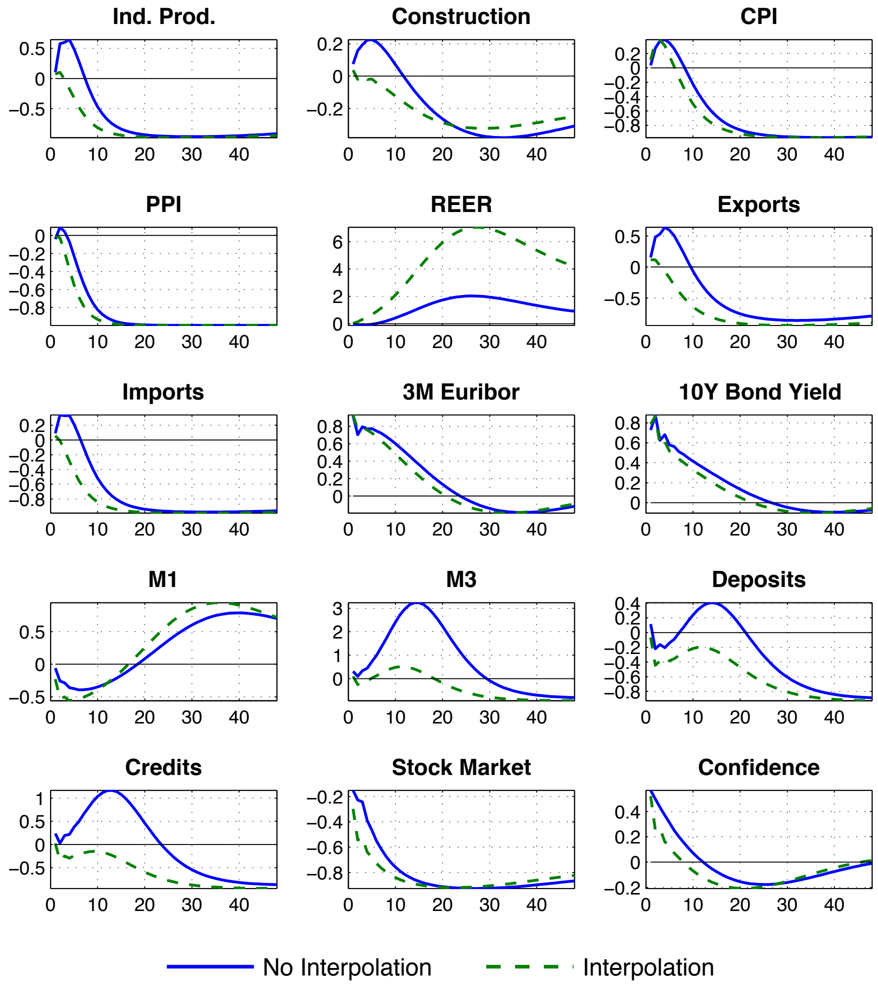



Figure E.0.1: Interpolation of the Quarterly Series

Note: The impulse responses are obtained with a FAVAR(2) with 4 factors estimated for the full sample with the two-step method.

# APPENDIX F

# FORECAST ERROR VARIANCE DECOMPOSITION

In addition to the IR function analysis, that of FEVD is another useful tool widely used in S(FA)VAR literature in order to uncover interrelationships among the variables in the system. According to Enders (2004, p.278), the variance decomposition of a sequence $\{y_t\}$ can be summarised as follows:

First, if we assume that the $\{y_t\}$ sequence is affected by, for simplicity, only two shocks ($e_y$ and $e_x$), the $n$-step-ahead forecast error of the sequence is

$$\begin{aligned} y_{t+n} - E_t y_{y+n} &= \psi_{11}(0)e_{y,t+n} + \psi_{11}(1)e_{y,t+n-1} + \ldots + \psi_{11}(n-1)e_{y,t+1} \\ &+ \psi_{12}(0)e_{x,t+n} + \psi_{12}(1)e_{x,t+n-1} + \ldots + \psi_{12}(n-1)e_{x,t+1} \end{aligned} \tag{F.0.1}$$

If we denote the $n$-step-ahead forecast error variance of sequence as $\sigma_y(n)^2$, (F.0.1) can be written as

$$\begin{aligned} \sigma_y(n)^2 &= \sigma_y^2[\psi_{11}(0)^2 + \psi_{11}(1)^2 + \ldots + \psi_{11}(n-1)^2] \\ &+ \sigma_x^2[\psi_{12}(0)^2 + \psi_{12}(1)^2 + \ldots + \psi_{12}(n-1)^2] \end{aligned}$$

It is important to note that it is possible to decompose the $n$-step-ahead forecast error variance into the proportions due to each shock. As such, this decomposition of $\sigma_y(n)^2$ for the shocks in $\{e_{y,t}\}$ and $\{e_{x,t}\}$ can be represented as follows:

$$\{e_{y,t}\} \quad \Rightarrow \quad \frac{\sigma_y^2[\psi_{11}(0)^2 + \psi_{11}(1)^2 + \ldots + \psi_{11}(n-1)^2]}{\sigma_y(n)^2}$$

$$\{e_{x,t}\} \quad \Rightarrow \quad \frac{\sigma_x^2[\psi_{12}(0)^2 + \psi_{12}(1)^2 + \ldots + \psi_{12}(n-1)^2]}{\sigma_y(n)^2}$$

> The forecast error variance decomposition tells us the proportion of the movements in a sequence due to its "own" shocks versus shocks to the other variable. If $e_{x,t}$ shocks explain none of the forecast error variance of $\{y_t\}$ at all forecast horizons, we can say that the $\{y_t\}$ sequence is exogenous. ... At the other extreme, $e_{x,t}$ shocks could explain all of the forecast error variance in the $\{y_t\}$ sequence at all forecast horizons, so that $\{y_t\}$ would be entirely endogenous.[1]

[1] Enders (2004, p.280)

APPENDIX G

# ROLLING WINDOWS ANALYSIS

## G.1 Confidence Intervals

### G.1.1 Two-step Estimations

#### 6M Rollings

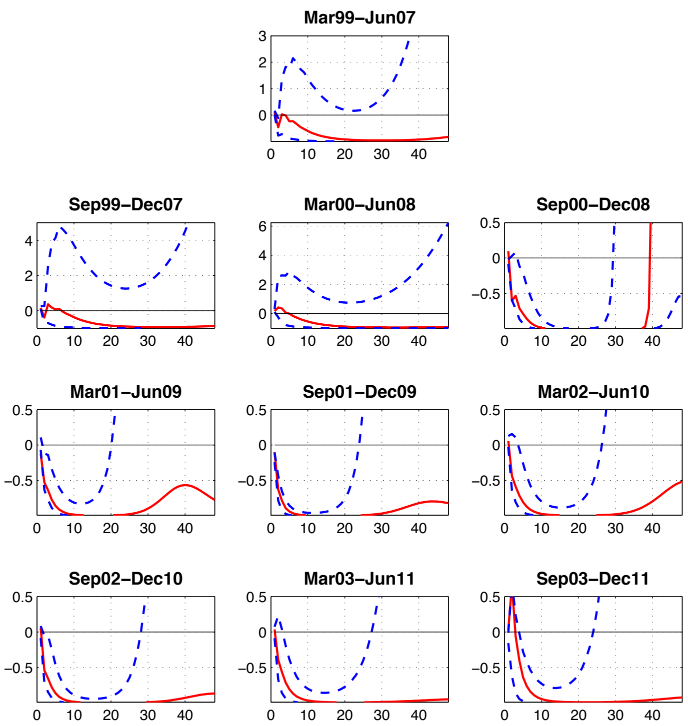



Figure G.1.1: Rolling Windows, Two-step: IP

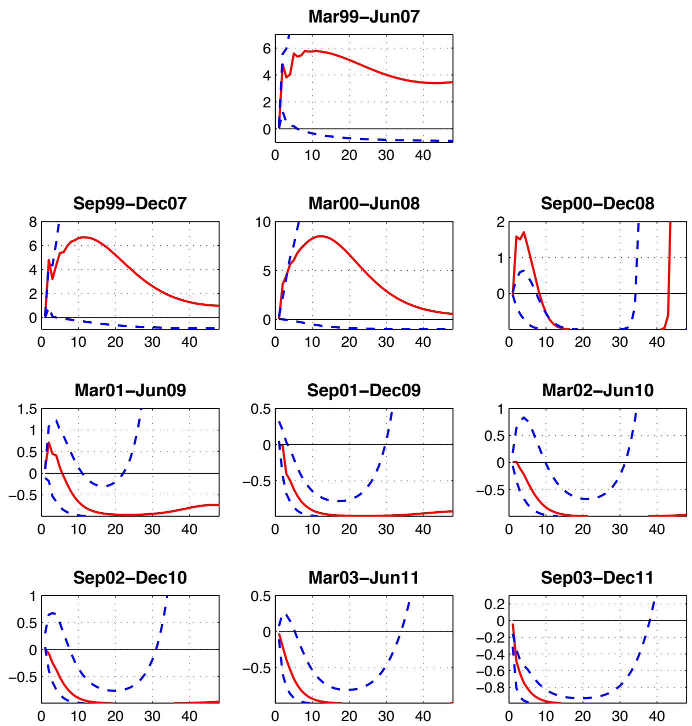



Figure G.1.2: Rolling Windows, Two-step: CPI

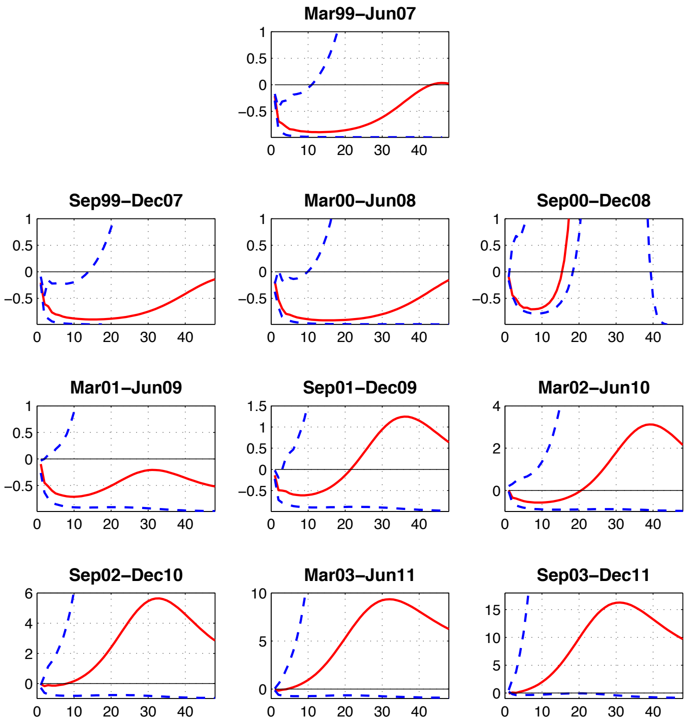


Figure G.1.3: Rolling Windows, Two-step: M1

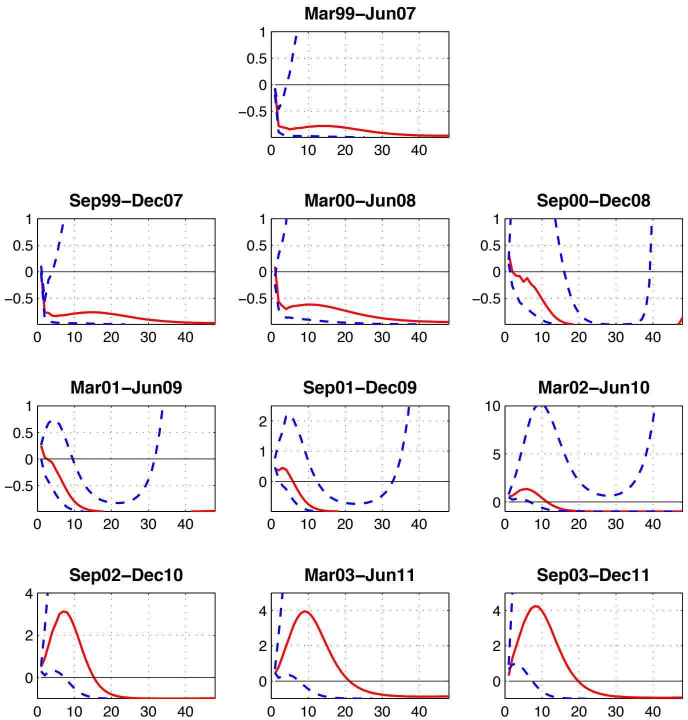


Figure G.1.4: Rolling Windows, Two-step: M3

## G.1.2 One-step Estimations

### 6M Rollings

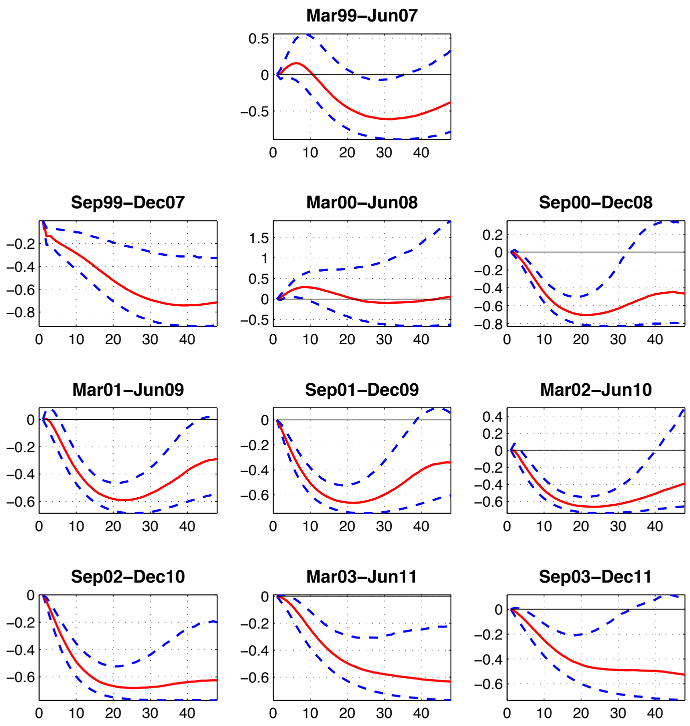



Figure G.1.5: Rolling Windows, One-step: IP

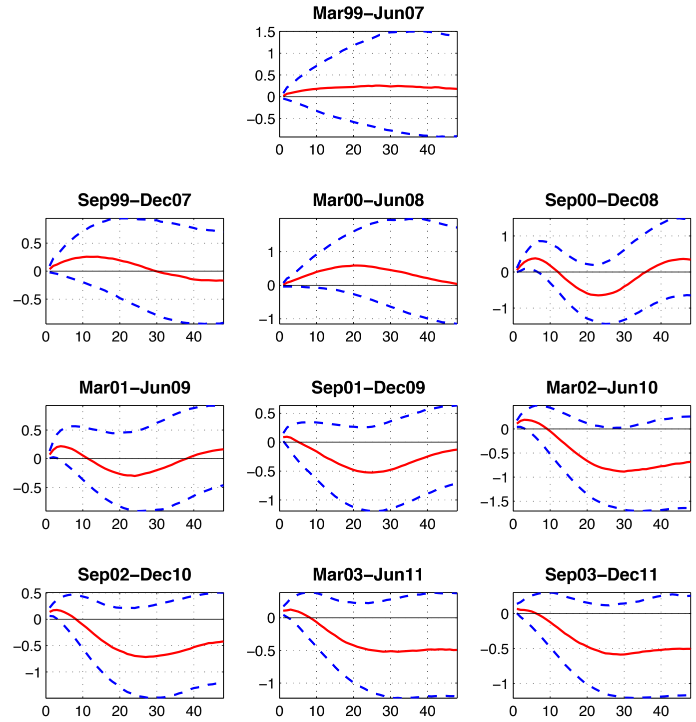



Figure G.1.6: Rolling Windows, One-step: CPI

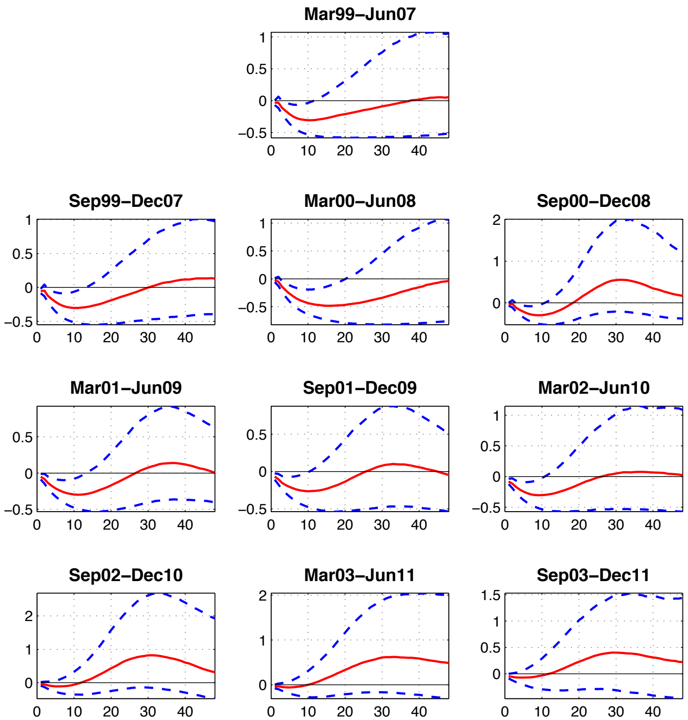



Figure G.1.7: Rolling Windows, One-step: M1

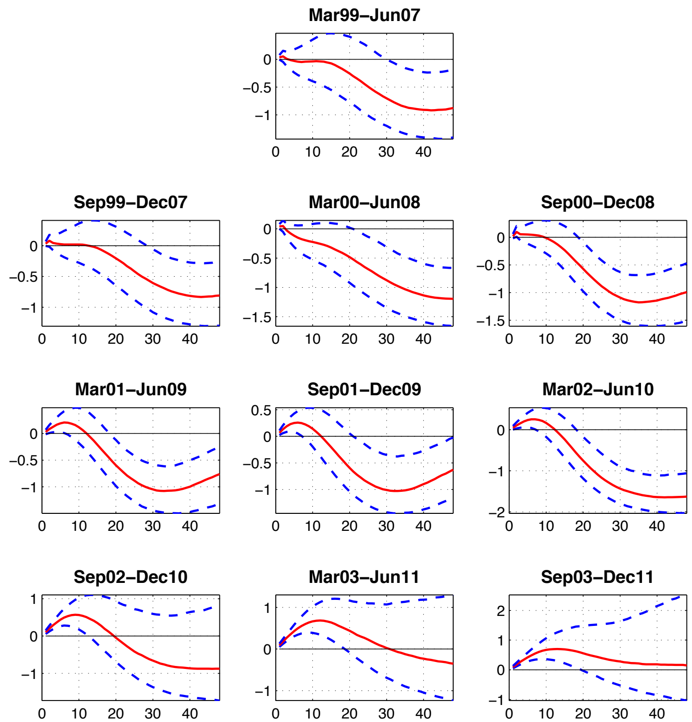



Figure G.1.8: Rolling Windows, One-step: M3

## G.1.3 Post-BN - Two-step Estimations

### 6M Rollings

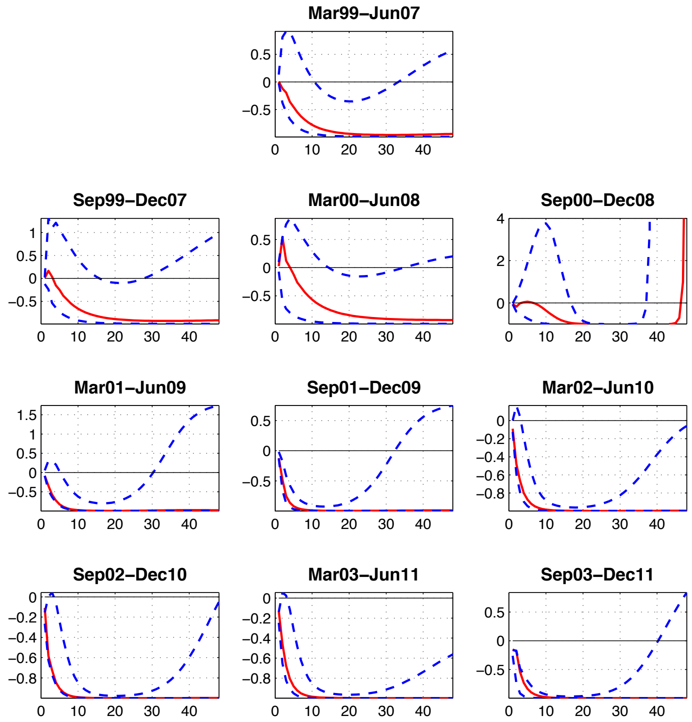



Figure G.1.9: Post-BN Rollings, Two-step: IP

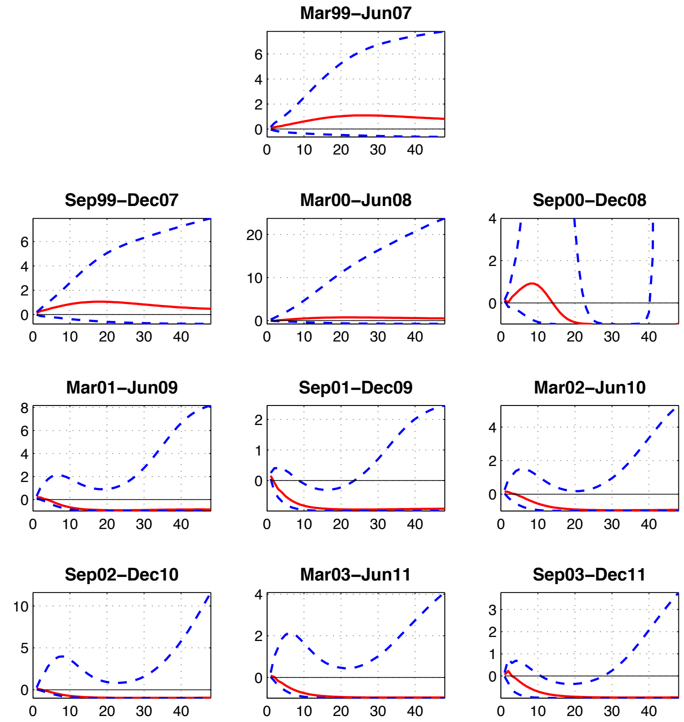



Figure G.1.10: Post-BN Rollings, Two-step: CPI

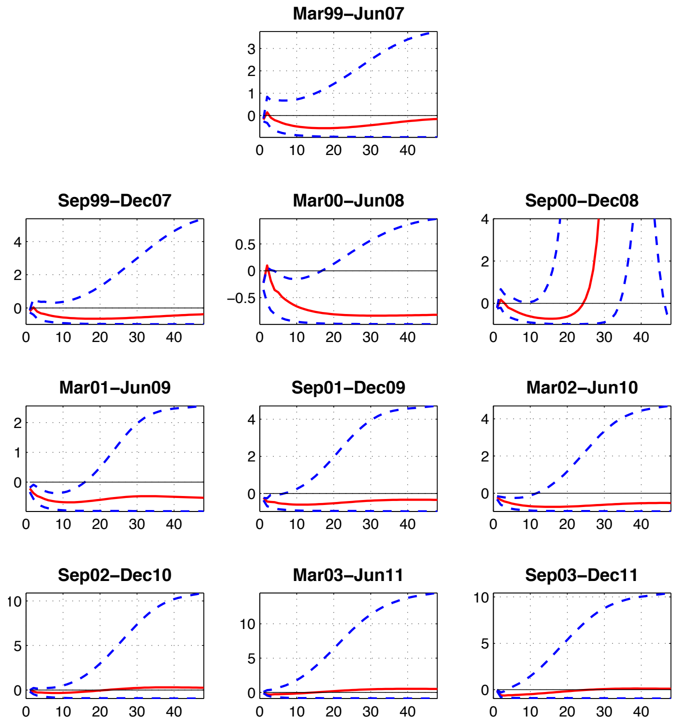



Figure G.1.11: Post-BN Rollings, Two-step: M1

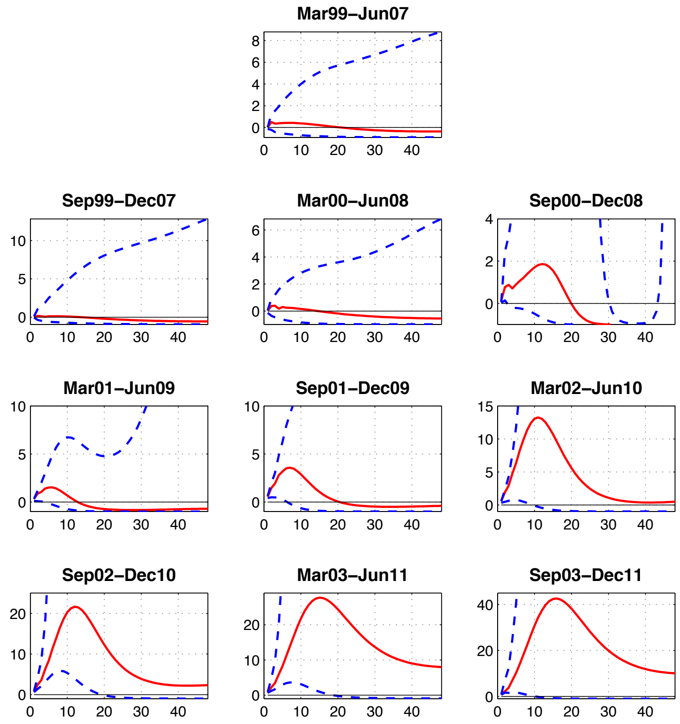



Figure G.1.12: Post-BN Rollings, Two-step: M3

## G.1.4 Post-BN - One-step Estimations

### 6M Rollings

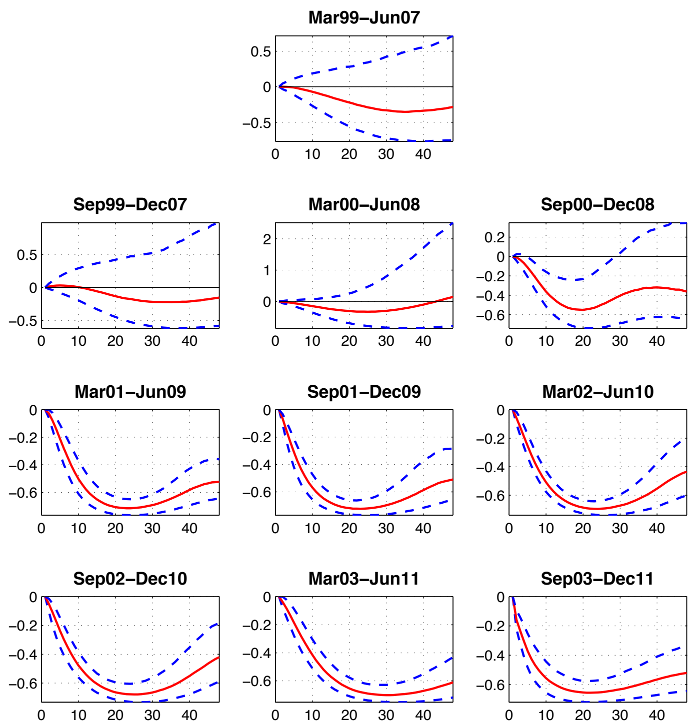



Figure G.1.13: Post-BN Rollings, One-step: IP

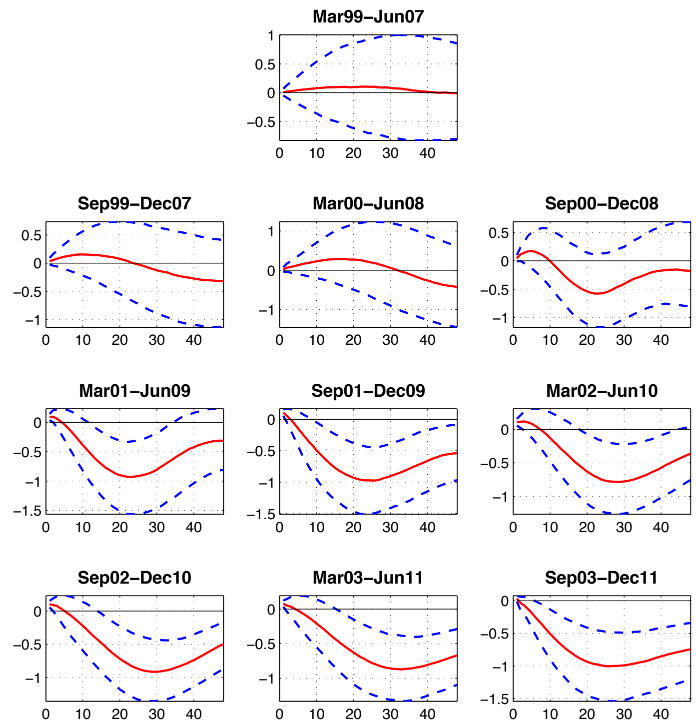



Figure G.1.14: Post-BN Rollings, One-step: CPI

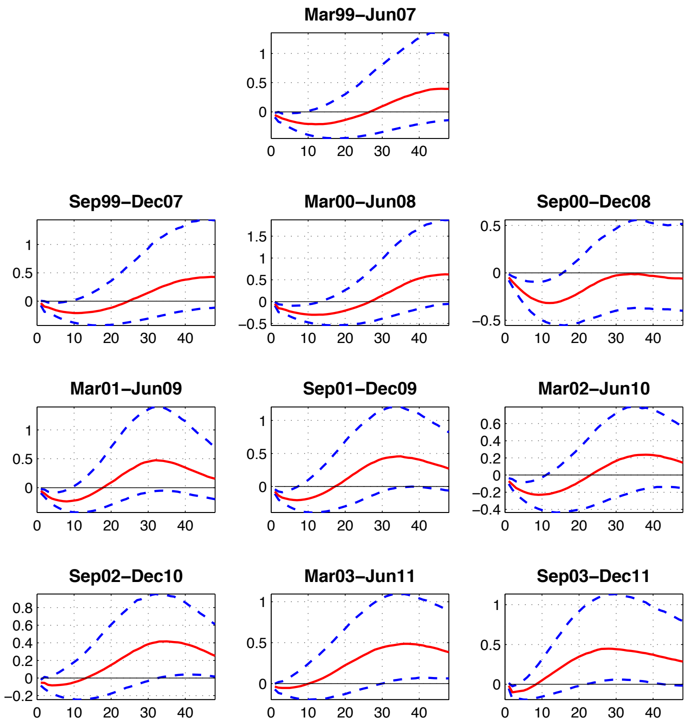



Figure G.1.15: Post-BN Rollings, One-step: M1

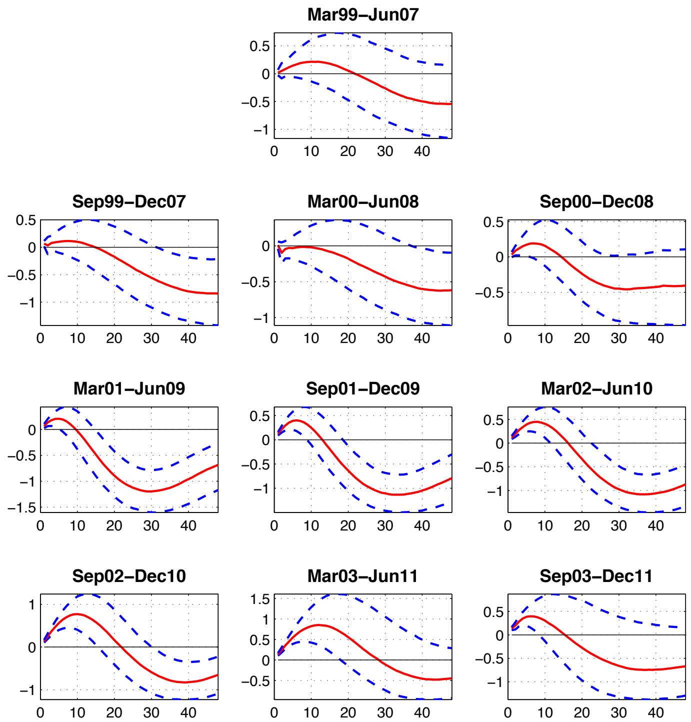



Figure G.1.16: Post-BN Rollings, One-step: M3

## G.2 Robustness to the Initial Window

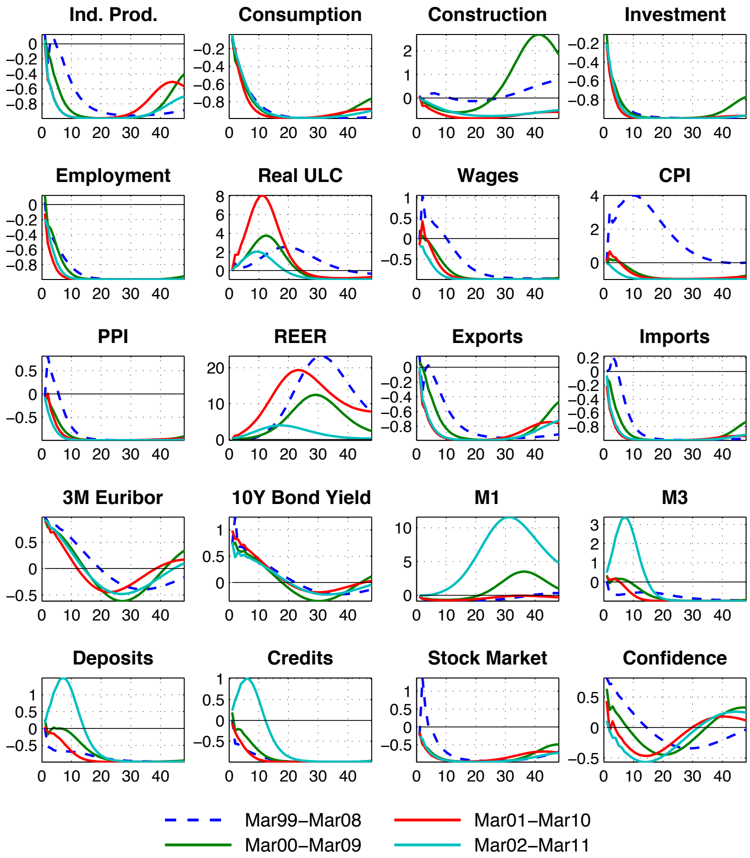



Figure G.2.1: Rolling Windows, Two-step, Robustness, 12M

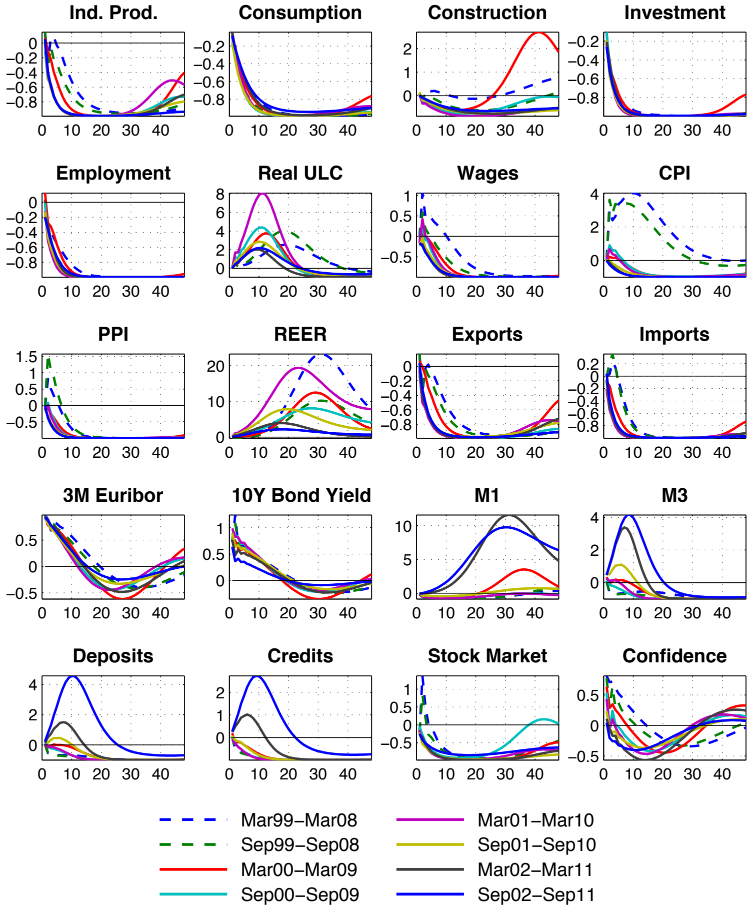



Figure G.2.2: Rolling Windows, Two-step, 1999-Mar2008, 6M

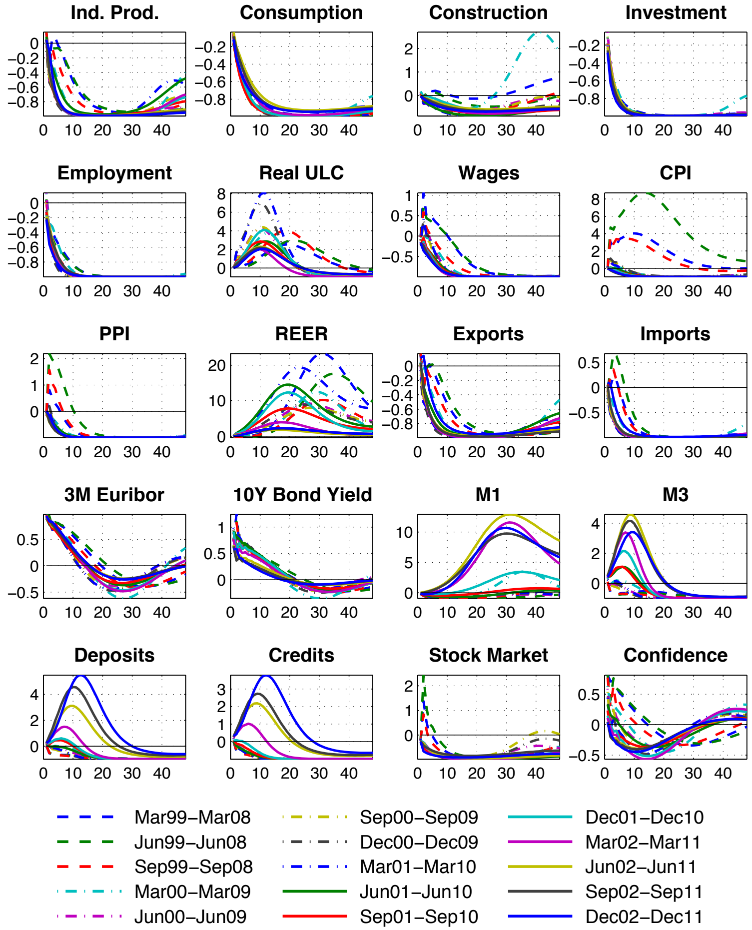



Figure G.2.3: Rolling Windows, Two-step, 1999-Mar2008, 3M

# APPENDIX H

# ALTERNATIVE MODEL SPECIFICATIONS

## H.1 Number of Factors

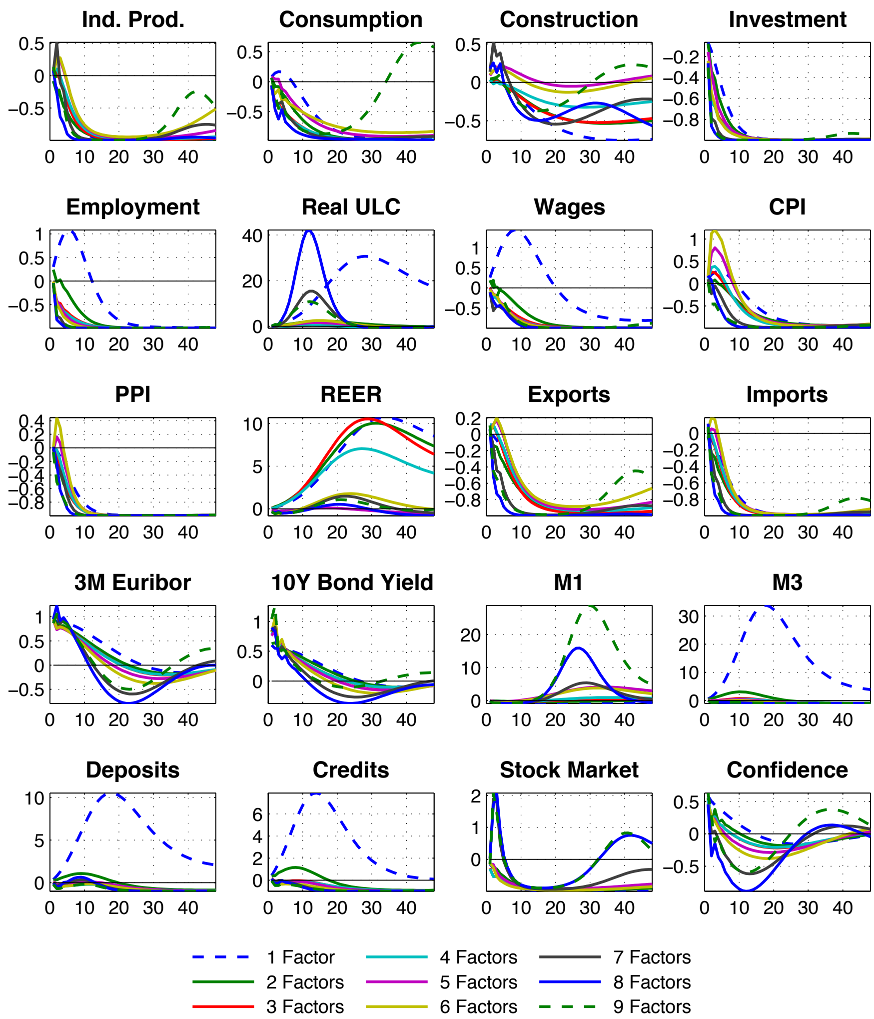



Figure H.1.1: Alternative Model Specifications: Number of Factors

Note: The impulse responses are obtained with the two-step method estimated with two lags. Two-step approach is chosen here only because of its computational simplicity.

## H.2 Lag Length

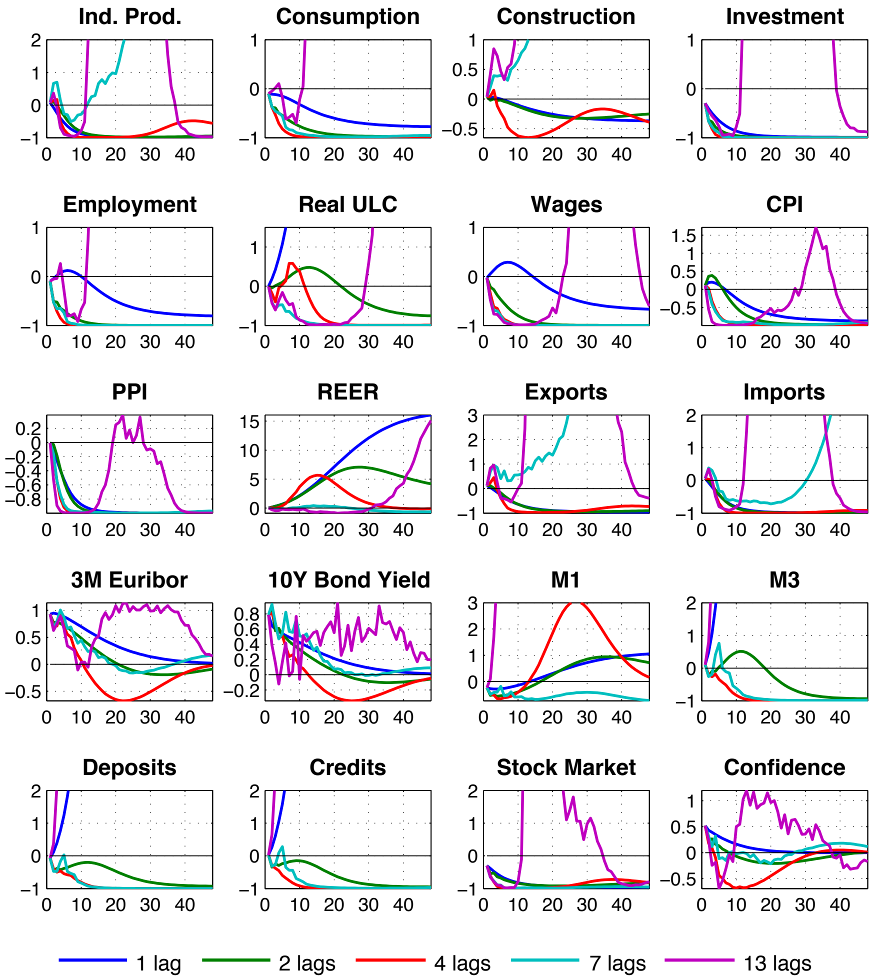



Figure H.2.1: Alternative Model Specifications: Lag Length

Note: The impulse responses are obtained with the two-step method estimated with four factors.

# APPENDIX I

# CONVERGENCE OF GIBBS SAMPLINGS

## I.1 Pre-BN Analysis

### I.1.1 Baseline Results

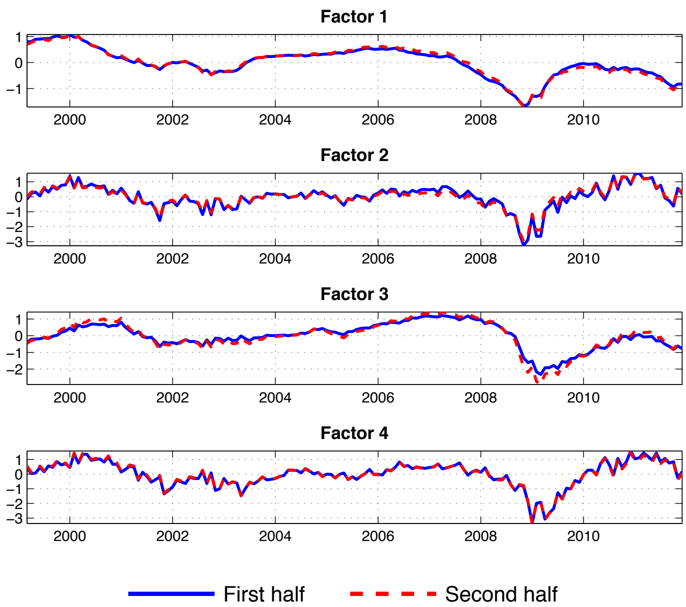



Figure I.1.1: Convergence - Baseline Results

## I.1.2 Time Variation

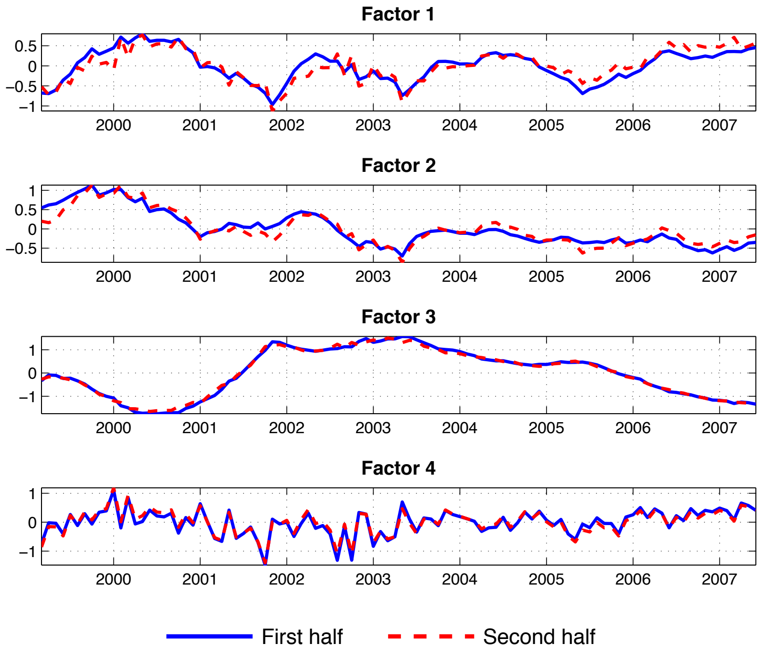



Figure I.1.2: Rolling Windows, 6M, Window:1

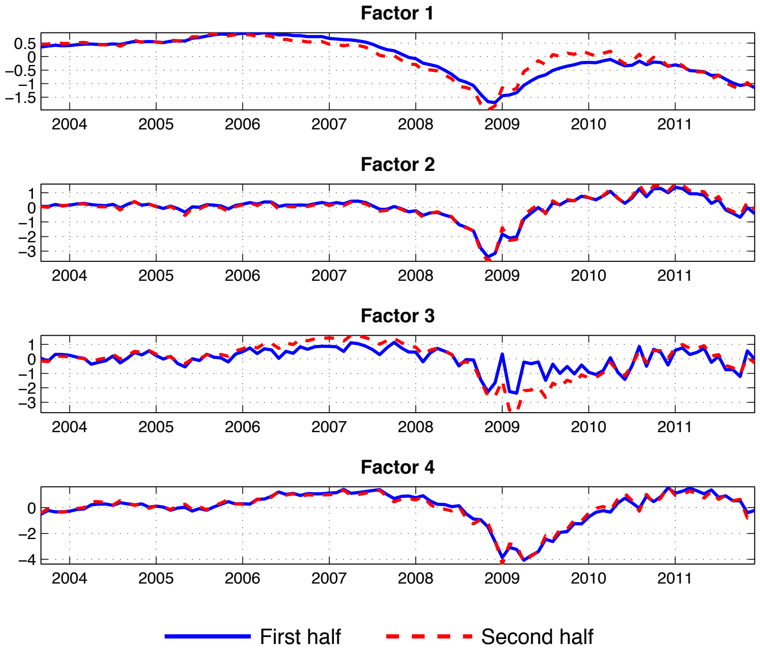



Figure I.1.3: Rolling Windows, 6M, Window:10

## I.2 Post-BN Analysis

### I.2.1 Baseline Results

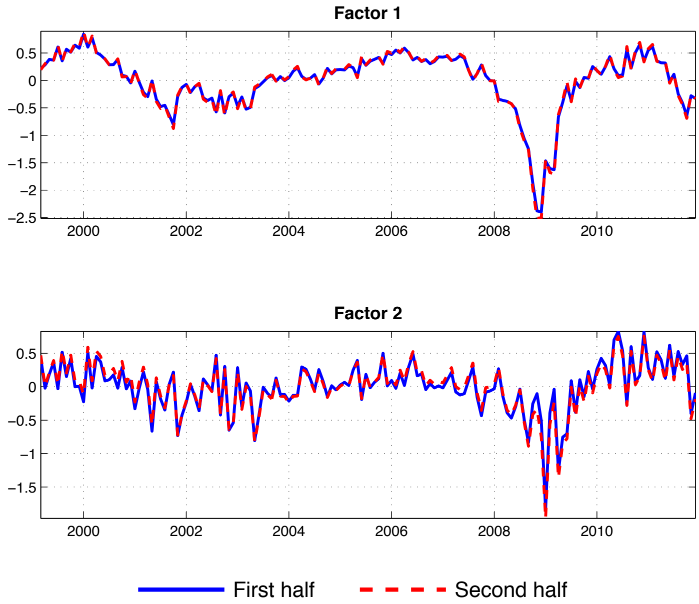



Figure I.2.1: Baseline Results, Post-BN

## I.2.2 Time Variation

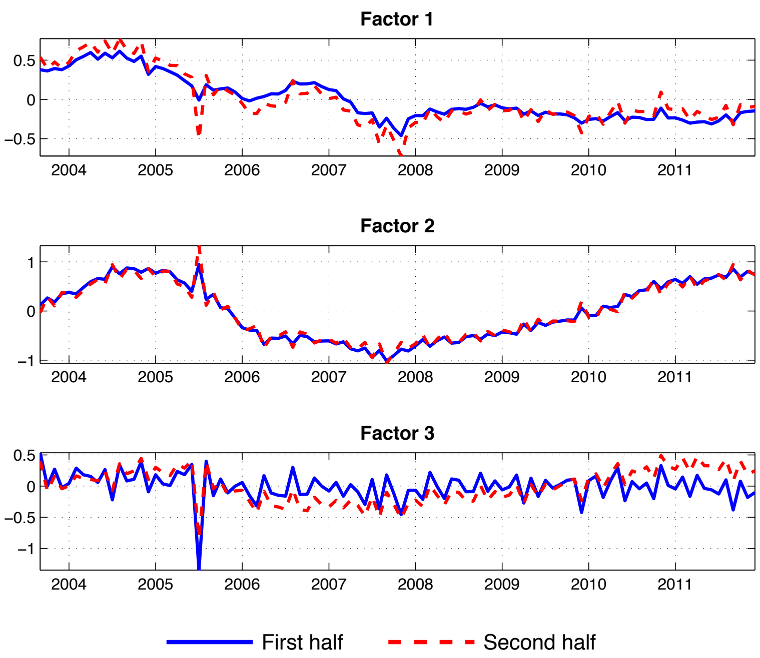



Figure I.2.2: Rolling Windows, Post-BN, 6M, Window:1

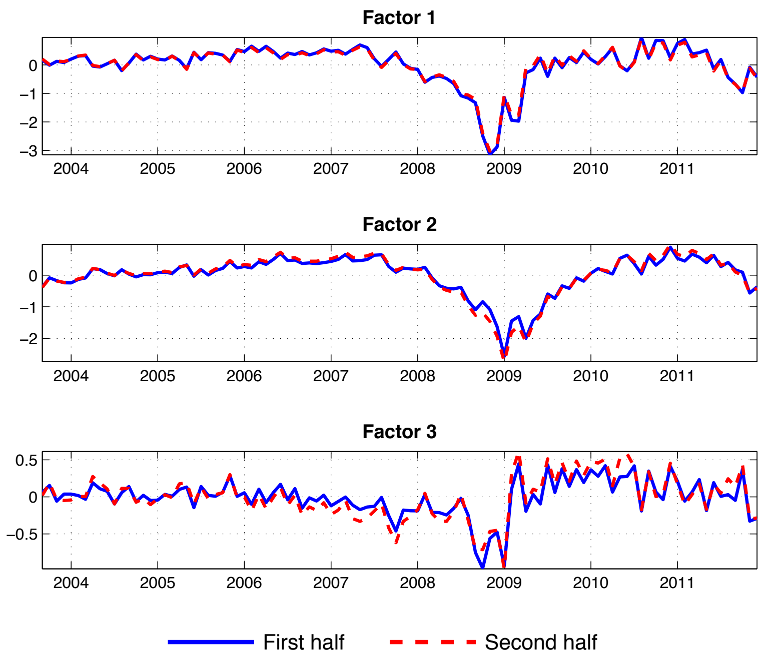



Figure I.2.3: Rolling Windows, Post-BN, 6M, Window:10

# APPENDIX J

# GIBBS ITERATIONS

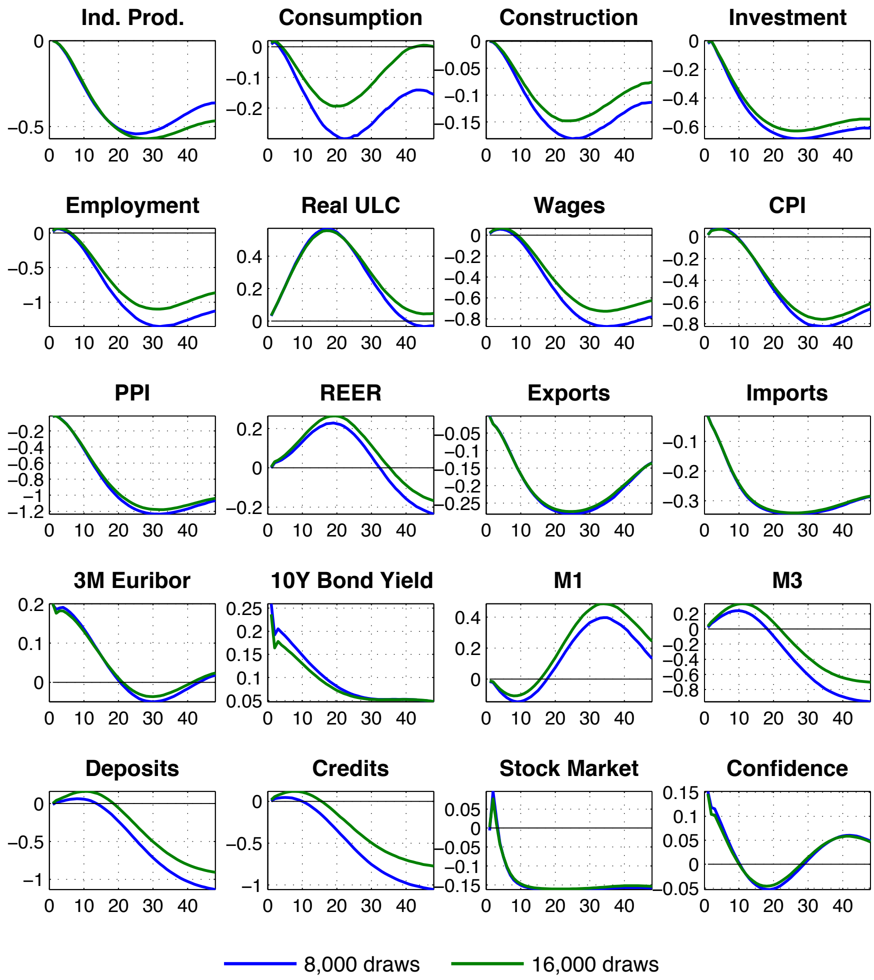



Figure J.0.1: Gibbs Iterations

# CHAPTER 2

# MONETARY POLICY SHOCKS AND CROSS-COUNTRY HETEROGENEITY IN THE EURO AREA

## 2.1 Introduction

In June 1988, the European Council confirmed the objective of the three-stage progressive realisation of Economic and Monetary Union (EMU).[1] Stage one, beginning on 1 July 1990, brought Europe 'complete freedom for capital transactions', 'increased co-operation between central banks', 'free use of the ECU (European Currency Unit, forerunner of the euro)', and 'improvement of economic convergence'.[2] The establishment of the European Monetary Institute (EMI) on 1 January 1994 marked the start of the second stage of EMU. It was aimed in this stage to ban 'the granting of central bank credit to the public sector'; to increase 'co-ordination of monetary policies'; to strengthen 'economic convergence'; and to complete the process of the independence of the national central banks 'latest by the date of establishment of the European Systems of Central Banks' in 1998. On January

[1] See ECB (2012b).

[2] With the recent Cypriot banking crisis as of March 2013, however, 'complete freedom for capital transactions' has been violated in the Union.

1st, 1999, the third and final stage of EMU commenced with the euro officially becoming the common currency for 11 Member States initially participating in Monetary Union, and with the conduct of a single monetary policy under the authority of the ECB.

In the period summarised above, Europe experienced the theoretical steps of economic integration and convergence. In practice, however, as Giovannetti and Marimon (1998) highlighted very importantly just before the beginning of the third stage:

> Despite the implementation of the single market from 1992, despite all the changes brought about by deregulation, capital liberalisation and technological innovation in the last two decades, the financial systems of European countries are still characterised by a high degree of heterogeneity. Furthermore, their convergence over time has been quite limited and some of the fundamental differences existing in the 1980s have survived all the changes. (p.5)

That is mainly why there has been extensive empirical work in the literature, since the creation of the EA, on cross-country asymmetries and time variation in the transmission mechanism of the single monetary policy. Table 2.1.1 provides a selective overview of this literature.[3]

The overall conclusion of the empirical evidence obtained in the literature on cross-country heterogeneity and time variation in the monetary policy transmission mechanism is quite mixed. To illustrate, if we consider Barran et al. (1996) and Ramaswamy and Sloek (1998), i.e. two studies investigating the same countries for very similar periods using the same estimation technique, while we observe, on the one hand, European Union (EU) countries being "similar in the sense of responses and lags"[4] to a monetary policy shock, on the other hand, "there appear to be marked differences in the real effects of monetary policy among (the same) EU countries."[5] In particular, Ramaswamy and Sloek

[3]The table is based on the overview by Georgiadis (2012, p.47) in addition to our own literature review.

[4]Barran et al. (1996, p.21).

[5]Ramaswamy and Sloek (1998, p.383).

Table 2.1.1: The Literature on Cross-Country Heterogeneity and Time Variation in Monetary Transmission

| **Study** | **Approach** | **Country/Sample** |
|---|---|---|
| Gerlach and Smets (1995) | Country-specific VAR models with long- and short-term identification restrictions | DE, CA, FR, IT, JP, UK, US 1979Q1-1993Q4 |
| Barran et al. (1996) | Identical, country-specific VAR models with recursive identification | AT, DE, DK, ES, FI, IT, NL, UK 1976Q1-1994Q4 |
| Dornbusch et al. (1998) | Country-specific monetary policy reaction functions and dynamic output equations | DE, ES, FR, IT, SE, UK 1985M5-1996M7 |
| Giovannetti and Marimon (1998) | Dynamic equilibrium and VAR models | DE, FR, IT, UK - 1973Q1-1997Q4 |
| Kieler and Saarenheimo (1998) | Identical, country-specific VAR models | DE, FR, UK - 1970Q1-1997Q3 |
| Ramaswamy and Sloek (1998) | Country-specific VAR models with recursive identification | AT, DE, BE, DK, ES, FI, FR, IT, NL, PT, SE, UK - 1972Q1-1995Q4 |
| Kim (1999) | Identical, country-specific structural VAR models | DE, CA, FR, IT, JP, UK, US 1961M3-1997M5 |
| Ehrmann (2000) | Country-specific and varying VAR models | AT, DE, BE, DK, ES, FI, FR, IE, IT, NL, PT, SE, UK - 1984Q1-1997Q4 |
| Clements et al. (2001) | Country-specific VAR models with recursive identification | AT, DE, BE, FI, FR, ES, IE, IT, NL, PT - 1983Q1-1998Q4 |
| Mihov (2001) | Country-specific VAR models with recursive identification | AU, AT, DE, CA, FR, IT, JP, NL, UK, US - 1979Q3-1998Q4 |
| Mojon and Peersman (2001) | Country-specific, structural VAR models | AT, DE, BE, FI, FR, GR, ES, IE, IT, NL - 1970Q1-1998Q4 |

| Study | Approach | Country/Sample |
|---|---|---|
| Hughes Hallett and Piscitelli (2002) | IMF MULTIMOD MARK III model (MULTI-region econometric MODel) | DE, FR, UK, IT + (CA, JP, US) Simulation for the period 1999-2020 |
| Sala (2002) | Dynamic factor model | AU, DE, BE, ES, FR, IT, NL, PT 1985M1-1998M12 |
| Dedola and Lippi (2005) | Country-specific VAR models with recursive identification | DE, FR, IT, UK, US 1975M1-1997M3 |
| Ciccarelli and Rebucci (2006) | Approach similar to Dornbusch et al. (1998) with time-varying coefficients | DE, ES, FR, IT 1980M1-1998M12 |
| Hofmann (2006) | Equations of lending rates in error correction form | DE, FR, IT, ES 1984M1-1998M12 |
| McCallum and Smets (2007) | Two-step FAVAR model with BBE identification scheme | BE, DE, ES, FI, FR, IT, NL PT, GR, IE, US - 1986Q1-2005Q4 |
| Boivin et al. (2008) | Two-step FAVAR model with Boivin et al. (2009) identification scheme | DE, BE, ES, FR, IT, NL, EA as an aggregate - 1980Q1-2007Q3 |
| Setzer et al. (2010) | Money demand equation specified in a panel model | AT, DE, BE, EA, ES, FI, FR, IE, IT, NL, PT - 1999Q1-2008Q4 |
| Cecioni and Neri (2011) | Bayesian structural VAR and dynamic stochastic general equilibrium (DSGE) models | EA 1989Q1-2009Q2 / 1994M1-2009M9 |
| Weber et al. (2011) | VAR model with recursive identification | EA - 1980Q1-2006Q4 |
| Darvas (2012) | Time-varying coefficient VAR model | CZ, HU, PL - 1993Q1-2011Q4 |

Abbreviations: AT-Austria, AU-Australia, BE-Belgium, CA-Canada, CZ-Czech Republic, DE-Germany, DK-Denmark, GR-Greece, ES-Spain, FI-Finland FR-France, HU-Hungary, IE-Ireland, IT-Italy, JP-Japan, NL-Netherlands, PL - Poland, PT-Portugal, SE-Sweden, UK-United Kingdom, US-United States.

(1998) state, according to their three-variable VAR[6] estimations, that EU countries fall into two broad groups. Whereas the response of output to monetary policy shocks in one group[7] is stronger, more persistent and "typically bottoms out (relative to baseline) about 11 to 12 quarters"[8] following a contractionary shock, the impact of the shock on output in the other group[9] is less, transitory and "typically bottoms out about 5 to 6 quarters after a contractionary monetary policy shock".[10]

Furthermore, the estimates of the effects of monetary policy obtained by Gerlach and Smets (1995) and Dornbusch et al. (1998) (a) "provide little evidence of large differences in the monetary transmission between (G-7) countries, particularly not when estimated confidence bands are taken into account" (the former, p.39); (b) suggest that "the impact effect on output is always significant, but different across countries" (the latter, p.40). Using structural VAR models, however, Kim (1999) finds for almost the same set of countries studied by Dornbusch et al. (1998)[11] that "the output responses (to a monetary policy shock) are very similar across (the) countries" (p.399). Moreover, whereas we have Kieler and Saarenheimo (1998), Mojon and Peersman (2001), Dedola and Lippi (2005), and Hofmann (2006) on the "homogeneity" side of the literature, Ehrmann (2000), Clements et al. (2001), Mihov (2001), and Sala (2002) are among those suggesting heterogeneous monetary transmission mechanism in Europe.

Ciccarelli and Rebucci (2006) highlight "the presence of significant differences across countries in the transmission mechanism of monetary policy in Europe" (p.738), and claim that "cross-country heterogeneity ... have not decreased over time" (p.739) among the

[6]i.e. output, prices and short-term interest rate.
[7]Austria, Belgium, Finland, Germany, the Netherlands, and the United Kingdom.
[8]Ramaswamy and Sloek (1998, p.380).
[9]Denmark, France, Italy, Portugal, Spain, and Sweden.
[10]Ramaswamy and Sloek (1998, p.380).
[11]The only exclusion from the sample of Dornbusch et al. (1998) is Sweden.

largest four EA economies[12] during the period of their supposed 'economic convergence' in the process of EMU. By estimating a fixed-parameter VAR model and endogenously searching for breaks in the data, Weber et al. (2011) conclude that dynamics of the EA monetary transmission are statistically indistinguishable in the split samples, i.e. 1980-1996 and 1999-2006. The authors argue that this interim period could be responsible for the conflicting findings on time variation in the monetary transmission in the EA.

According to a FAVAR model estimated by Boivin et al. (2008) for the EA as an aggregate and for the six largest economies of the area,[13] the creation of the euro in the final stage of EMU has brought some changes to the transmission mechanism of common monetary policy shocks. In particular, Boivin et al. find that the third-stage of EMU has led to a widespread reduction in the effect of the shocks on output, inflation and long-term interest rates, and an increase in the effects on the exchange rate. Using a structural open-economy model, the authors also argue that these empirical findings observed in the data can be attributed to the combination of the elimination of an exchange-rate risk through the monetary union, and having "a central bank more decisively focused on inflation and output stabilisation" (p.118). Despite these changes, however, Boivin et al. (2008) highlight the responses of several macroeconomic variables, especially the monetary aggregates, which remain heterogeneous across the EA economies in the post-1999 period.

Cecioni and Neri (2011) obtain two conclusions from their estimations of Bayesian VAR and DSGE models for the pre- and post-1999 periods. First, the monetary transmission in the EA has not significantly changed over time according to the empirical evidence from their VAR analysis. "If anything, (the authors claim,) monetary policy has become slightly

[12] Germany, France, Italy, Spain.
[13] Germany, France, Italy, Spain, Belgium and the Netherlands.

more effective in stabilising the economy" (p.8). Cecioni and Neri mean by effectiveness of the monetary policy that "both output and prices are more responsive to an exogenous change of the nominal interest rate" (Ibid.).[14] Second, according to their DSGE model estimations, they observe more clear differences across the two samples as a result of "a reduction in the degree of nominal rigidities and to an increase in the strength of the systematic reaction of monetary policy to inflation" (Ibid.).

Overall, investigation of Table 2.1.1 and the findings of the studies reported therein, suggests the following important points. First, a significant number of the reported studies deals with the period before the start of the third-stage of EMU, at which time there was no single monetary policy. As a result, "the identified (common) monetary policy shock may not be completely homogeneous across countries."[15]

This, therefore, raises the question of whether what we observe in the literature is "that the euro area monetary transmission process is (genuinely) uneven across countries",[16] or a reflection of the fact that the shocks considered to be common are heterogeneous in nature, and, therefore, they have different effects across European economies. There is no doubt that the former could complicate the conduct of the single monetary policy in the area.

Second, with the passage of time, the impact of common monetary policy across countries is likely to get less heterogeneous due to forces of convergence. However, as summarised above, the empirical literature is also inconclusive on whether or not the EA monetary transmission mechanism and its impact across countries have changed over

[14]Note the contradiction between the conclusions of Boivin et al. (2008) and Cecioni and Neri (2011) on the changes in the effectiveness of the monetary policy in the EA.

[15]McCallum and Smets (2007, p.10).

[16]Angeloni and Ehrmann (2003, p.6).

time.

Third, as shown by Kieler and Saarenheimo (1998), Guiso et al. (1999) and Angeloni and Mojon (2003), the findings are not robust to changes in empirical methodology and data. Guiso et al. (1999) claim that, for example, "models with a similar structure tend to yield small differences in the transmission mechanism, whereas models with a more idiosyncratic structure tend to show larger differences" (p.61).

Fourth, there are a few studies employing the FAVAR approach in the context of cross-country heterogeneity in the transmission of the EA monetary policy shocks. We highlighted in Chapter 1 the merits of the FAVAR models in terms of covering the information set of the central banks, identifying the exogenous monetary policy shocks, and estimating their effects on various macroeconomic indicators. Therefore, we believe that more and detailed investigation of the effects of monetary policy shocks across the EA countries with the FAVAR approach is of significant importance.

Finally, these few FAVAR studies on the EA methodologically focus only on the two-step estimation technique, which makes the Bayesian joint estimation, i.e. one-step FAVAR, yet to be explored. Given our conclusion in Chapter 1 that there are considerable gains from implementation of the one-step technique such as smoother impulse responses and statistical significance of the estimates, we believe that this is an important gap in the literature.

In light of the points highlighted above and the fact that there are now "sufficient data to potentially observe effects of the monetary union on business cycle dynamics"[17] in the EA, the key aims of this chapter are fourfold. First, we follow the recent literature and use the FAVAR approach in order to investigate the cross-country heterogeneity in

[17]Boivin et al. (2008, p.77).

the transmission of common monetary policy shocks in the EA. In order to contribute to the literature, contrary to McCallum and Smets (2007) and Boivin et al. (2008),[18] we estimate our FAVAR model with the one-step Bayesian approach.[19] Second, we expand the data set used in the previous chapter for the four largest EA economies, i.e. Germany, France, Italy, Spain. Our novel data set spans the post-launch-of-euro period only, i.e. 1999:M1 through 2011:M12, and consists of $5 \times 120$ disaggregated monthly macroeconomic time series for the individual countries and the EA as an aggregate. Different from the previously summarised studies, our common monetary policy shocks are identified for each country from the same benchmark policy variable of the ECB. Third, similar to the previous chapter, we employ rolling windows analysis in order to empirically investigate the expected convergence of the responses and the impact of the 2007-8 global financial crisis on the transmission of the common policy shocks across countries. Finally, given the gains obtained from Boivin and Ng (2006) pre-screening technique (BN) in the previous chapter, we investigate the impact of the size of the data on our conclusions on cross-country heterogeneity.

In summary, the main findings of the study are the following. First and foremost, although the effects of single monetary policy shocks on national real activities and price levels are homogeneous across the four largest EA economies, the transmission mechanism displays important cross-country heterogeneity with the national monetary aggregates responding more heterogeneously to the shocks relative to most other macroeconomic indicators. Second, according to our analysis based on rolling windows, the monetary

[18] Which are the only studies, to our knowledge, applying the technique to the question of cross-country heterogeneity in the EA.

[19] As in Chapter 1, we also estimate the model with two-step method. However, given the focus of the chapter on the cross-country heterogeneity, instead of the differences between the estimation methods, two-step estimation results are omitted from the chapter. The results are available upon request.

aggregates turn out to be most heterogeneous not only across countries but also over time in the era of single monetary policy of the EMU. In Chapter 3 of the thesis, we investigate the cross-country effects of the unconventional monetary actions in the EA during the global financial crisis period. In light of that analysis, the first two main findings of the present chapter importantly highlight the possibility of heterogeneous transmission of the unconventional policy actions across the EA economies through (heterogeneous) channels. Finally, in addition to our contribution in Chapter 1, our cross-country pre-screening analysis also shows that this technique provides the same full-data results with reduced computational burden of the one-step Bayesian FAVAR approach.

The remainder of the chapter is organised as follows. In Section 2, we summarise the empirical methodologies of the chapter which consists of the estimation of one-step FAVAR models with country-level and area-wide factors, rolling windows, and the BN technique; Section 3 contains the results of a preliminary analysis of the data and the estimation of the number of factors and lags; Section 4 presents the empirical results of the chapter on (a) cross-country heterogeneity in the transmission of common monetary policy shocks; (b) time variation and (c) BN analysis; in Section 5 we test robustness of the results by looking at convergence and confidence intervals; Section 6 summarises and concludes the chapter.

## 2.2 Empirical Methodologies

The FAVAR framework, model estimation and identification are described in the previous chapter.[20] Because the same methodology is used in the present chapter, we summarise

[20]For technical details of the FAVAR approach, see Section 1.2.

in this section how the question of cross-country heterogeneity is analysed.

### 2.2.1 Country-Level and Panel Approaches

As mentioned earlier, we estimate our FAVAR model with the one-step Bayesian method, and, specific to this chapter, with country-level and area-wide factors. That is to say, we construct country-level ($X_t^{CL}$) and area-wide ($X_t^{AW}$) data sets, from which the factors are extracted to be used in the transition equation of our FAVAR model.[21,22] In this approach, while we extract the country-level factors from the individual data sets constructed for each country under investigation, we combine country-level variables into a balanced panel in order to obtain the area-wide factors.[23] Given the panel approach of Boivin et al. (2008) applied to the economies of the EA with the two-step FAVAR technique, we believe that our panel analysis conducted with the one-step FAVAR technique will provide important contributions to the empirical results available in the literature.

Technically, we apply the one-step estimation method to the following state-space representations:

**Country-Level Estimation**

$$X_{it}^{CL(j)} = \Lambda_i^{f^{CL}} F_t^{CL} + \Lambda_i^{y^{CL}} Y_t + e_t^{CL} \tag{2.2.1}$$

$$\begin{bmatrix} \hat{F}_t^{CL} \\ Y_t \end{bmatrix} = \Phi^{CL}(L) \begin{bmatrix} \hat{F}_{t-1}^{CL} \\ Y_{t-1} \end{bmatrix} + u_t^{CL} \tag{2.2.2}$$

where $X_{it}^{CL(j)}$ contains 120 country-specific variables ($i = 1, \dots, 120$), $t = 1, \dots, 156$, and $j = \mathrm{EA}, \mathrm{DE}, \mathrm{FR}, \mathrm{IT}, \mathrm{ES}$.

[21]See equations 2.2.2 and 2.2.4 below.
[22]For details of the data sets, see Section 2.3.1.
[23]For graphical comparison of the estimated factors, see Section 2.5.1.

**Area-Wide Panel Approach**

$$X_{it}^{AW} = \Lambda_i^{f^{AW}} F_t^{AW} + \Lambda_i^{y^{AW}} Y_t + e_t^{AW} \tag{2.2.3}$$

$$\begin{bmatrix} \hat{F}_t^{AW} \\ Y_t \end{bmatrix} = \Phi^{AW}(L) \begin{bmatrix} \hat{F}_{t-1}^{AW} \\ Y_{t-1} \end{bmatrix} + u_t^{AW} \tag{2.2.4}$$

where $X_{it}^{AW}$ is a panel of 508 variables ($i$) and 156 observations ($t$).[24,25] The country-level data sets enter the panel in an order according to the size of the economies from the largest to smallest, i.e. EA as an aggregate, Germany, France, Italy, Spain.[26]

### 2.2.2 Time Variation

As we have done in the previous chapter, in order to investigate time variation in, and the impact of the 2007-8 global financial crisis on cross-country heterogeneity in the EA, we utilise the technique of rolling regressions. Due to the computational intensity of the one-step technique and the size of the panel data investigated in the present chapter, we base our analysis of rolling regressions on the country-level data sets only.[27]

We found in Chapter 1 that the empirical results of rolling estimations for the EA as an aggregate (henceforth EA-17) are robust to the initial windows and the frequency of the rolling augmentations. Considering this conclusion and the number of estimations needed to be undertaken, we base our time variation analysis in this chapter on the rolling estimations of our FAVAR model with the initial window of 1999 - June 2007 and rollings

[24] For the number of factors and lag lengths of the estimations, see Sections 2.3.2 and 2.3.3, respectively.

[25] As highlighted earlier in the chapter, note that we obtain 508 series in the panel when we exclude duplicated variables in the country-specific data sets such as commodity indices, exchange rates, interest rates, and international indicators.

[26] Our robustness checks suggest that the estimation results are independent of the order of the country-level data sets in the panel. We thank Aris Spanos for highlighting this check during the presentation of the poster version of the chapter in Birmingham Econometrics and Macroeconomics Conference, May 2-3, 2012, held at the University of Birmingham.

[27] The two-step panel rolling regressions are available upon request.

by 6 months, only.

Estimation of a FAVAR model by the Bayesian one-step method is quite time consuming. Given the number of parameters need to be estimated for several data sets, for various variables, and over 10 rolling samples, we base our empirical results in Section 2.4.3 below on 5,000 Gibbs iterations, initial 2,000 of which are discarded.

### 2.2.3 Pre-screening Analysis

Having investigated the question of cross-country heterogeneity in the transmission of common European monetary policy shocks using constant and rolling samples, we follow the structure of Chapter 1 and analyse the impact of data size on our empirical findings using Boivin and Ng (2006) pre-screening technique.[28]

### 2.2.4 Common Monetary Policy Shocks

We noted earlier that monetary policy shocks identified in the literature for the EA might not be completely homogeneous across countries. We explained the main reason of this conclusion by referring to the combination of the sample periods of the studies covering both pre- and post-1999 periods, and the use of German interest rates as the common policy variable before the creation of the euro.

In our analysis, however, in order to minimise the cross-country heterogeneity in the policy shocks, we focus not only on the post-1999 period but also on the ECB's benchmark policy rate in both country-level and panel estimations.[29] Despite these features of the analysis, it is important to note that the monetary policy shocks identified in our

[28]For details of the technique, see Chapter 1, Section 1.2.4.

[29]i.e. $Y_t$ in equations 2.2.1 - 2.2.4.

country-level FAVARs might still show some heterogeneity across countries. This is due to the fact that the factors estimated from the country-level data sets will give rise to different country-specific sequences of monetary policy shocks because in each country-level FAVAR, factors will be different and the identified shock may thus be different. When it comes to our panel FAVAR approach, however, we believe that there is complete cross-country homogeneity in the shocks identified in the analysis. Given the consistency in the findings of the country-level and panel approaches, summarised in Section 2.4 below, we conclude that there is no concern of heterogeneity in the shocks identified in the country-level approach of the chapter.

In order to have consistency with the previous chapter, the shocks are also standardised here to correspond to a 25-basis-point increase in the policy variable. In addition, the results presented in Section 2.4 below are impulse response functions of the particular variables to a one-off policy shock in the EA.

In line with Chapter 1 and the FAVAR literature on the cross-country heterogeneity in the EA, finally, the focus of the analysis in this chapter is on the unanticipated part of the monetary policy shocks.[30]

## 2.3 Preliminary Analyses

In this section we present the preliminary analyses conducted prior to the estimation of the empirical results. After explaining the data, we report the selection process of the number of factors and lags in the model.

[30]See Chapter 1, p.30 for details on the (un)anticipated aspects of the monetary policy shocks.

### 2.3.1 Data

The country-level data sets analysed in the chapter are identical to the one used for the EA in Chapter 1.[31] That is to say, there are 120 monthly macroeconomic time series for five country-level data sets for Germany, France, Italy, Spain and the EA-17. Regarding the area-wide panel data set, on the other hand, we exclude the international variables duplicated in the first four data sets,[32] and combine these country-level data sets with the one for the EA-17. Therefore, we have 508 variables in the panel data set spanning the period from 1999:1 through 2011:12. We highlighted earlier the contribution of our one-step panel approach to the panel findings of Boivin et al. (2008) on the EA economies. We believe that our panel analysis employing a larger and higher-frequency data set and a different estimation technique is of importance to test the robustness of the findings presented by Boivin et al. (2008).

As explained in detail in Chapter 1, Section 1.3.1, we process the data to (i) correct for a few missing observations; (ii) adjust for seasonality and outliers; (iii) interpolate 14 series per data set from quarterly to monthly frequency; and (iv) induce stationarity.

### 2.3.2 Number of Factors

In order to determine the number of factors to be used in the model, we follow the procedure of Chapter 1. First, we test the number of static factors in our data sets using BIC and Bai and Ng (2002) information criteria.

Second, we calculate the $R^2$ statistics, i.e. the share of variance of the data accounted

[31] See Appendix K for country-level data descriptions.

[32] Exchange rates, and IP, consumer price index, policy variables, long-term interest rates, and stock markets of US, UK and Japan.

for by the common components in the observation equations (2.2.1) - (2.2.3). As we have done in Chapter 1, we compute the statistic for all the variables in the data sets as well as 20 main variables on which our empirical analyses are based. Figures L.1.1 to L.1.4 present the statistics calculated for these sets of variables.

Finally, we obtain a set of estimation results of a two-step FAVAR model[33] with number of factors varying from 1 to 9 in order to test how the choice of number of factors in the model affects the impulse response functions.[34]

We observe from our tests that Bai and Ng (2002) information criteria suggest twice as many factors as estimated by BIC, similar to the case in Chapter 1. In addition, Figures L.1.1 to L.1.4 display that the marginal gain, in terms of accounting for the variation in either all or the main variables, obtained from including double the number of factors suggested by BIC criterion in the model is less that 20% in country-level and panel approaches. In other words, a parsimonious specification in terms of the number of factors in the model leads to 30-45% of the variables being explained by the common components. Finally, our sensitivity tests suggest that the overall qualitative nature of the results are similar when we estimate the country-level or panel models with 2-6 factors. Parsimonious specification of the model also provides relatively smoother impulse responses. The same approach has been applied for determining the number of factors for rolling windows and post-BN estimations.

As a result of these tests, we prefer to use 2-4 factors in the empirical analyses of the chapter. Our choice is supported by Forni et al. (2000) and Favero et al. (2005) who show that "a small number of factors provide an efficient information summary of the main

[33]As in Chapter 1, the two-step approach is chosen only because of its computational simplicity.

[34]Number of lags is kept at 2 in all models. For details of determination of lag length in the model see Chapter 1, Section 1.3.3.

economic time series both at the EA level and for the four largest countries of the EA."[35]

The specification details of our empirical analyses are as in Table 2.3.1 below.

Table 2.3.1: Model Specifications: Number of Factors

| **Estimations** | **DE** | **FR** | **IT** | **ES** | **Panel** |
|---|---|---|---|---|---|
| **Pre - Boivin-Ng** | | | | | |
| Whole Sample | 4 | 2 | 3 | 3 | 4 |
| Rolling Windows | 2-3[a] | 2 | 2-3[a] | 2-3[a] | - |
| **Post - Boivin-Ng** | | | | | |
| Whole Sample | 2 | 2 | 2 | 2 | 2 |
| Rolling Windows | 2 | 2 | 2 | 2 | - |

[a] Changes from window to window.

### 2.3.3 Lag Length

We explained in Chapter 1, Section 1.3.3 how we choose a parsimonious specification for the lag length in our FAVARs estimated for the EA as an aggregate. For the country-level and panel estimations here, we follow the same procedure as follows. First, as previously, we test the lag length using the selection criteria AIC, BIC, FPE, HQ applied to our country-level and panel FAVARs. Second, as in the case for determining the number of factors, we test the sensitivity of the impulse responses to the lag length of the model by estimating a two-step FAVAR for each country and the panel.

Given that (i) the selection criteria suggest either 1 or 2 lags are sufficient to account for the variations in our data, and (ii) as in the EA case in Chapter 1, FAVAR(2) displays the smoothest impulse responses, we prefer to use 2 lags in our empirical analyses in the present chapter.

[35] Boivin et al. (2008, p.87).

## 2.4 Results

Having explained the details of the preliminary analyses, in the following four parts of the section we present the empirical findings of the chapter. First, we investigate the impact of a common monetary policy shock across four largest economies of the EA by estimating a country-level FAVAR model for each country by the one-step method. We base the analysis on the impulse response functions of 20 key macroeconomic variables to a 25-basis-point contractionary policy shock. Second, in order to examine the impact of area-wide factors, we follow the panel approach used by Boivin et al. (2008) and estimate a single FAVAR model with a 508-variable panel of country-level data sets. Third, using a rolling windows approach we study the changes, if there are any, in the impact of common monetary policy shocks across countries over time and especially due to the 2007-8 global financial crisis. Finally, following the Boivin and Ng (2006) technique, we prescreen our data sets and replicate the previous analyses in the same order with smaller-scale country-level and panel data sets.

### 2.4.1 Country-Level Approach

The empirical findings obtained from the estimation of our FAVAR model with country-level data sets are displayed in Figure 2.4.1. We present in these figures the impulse responses of a set of key macroeconomic variables for the four largest EA economies to a common contractionary monetary policy shock for a horizon of up to four years. For the sake of comparability of the impulse-response plots across countries, the confidence intervals are excluded from the figures. Instead, they are presented separately in Appendix M.

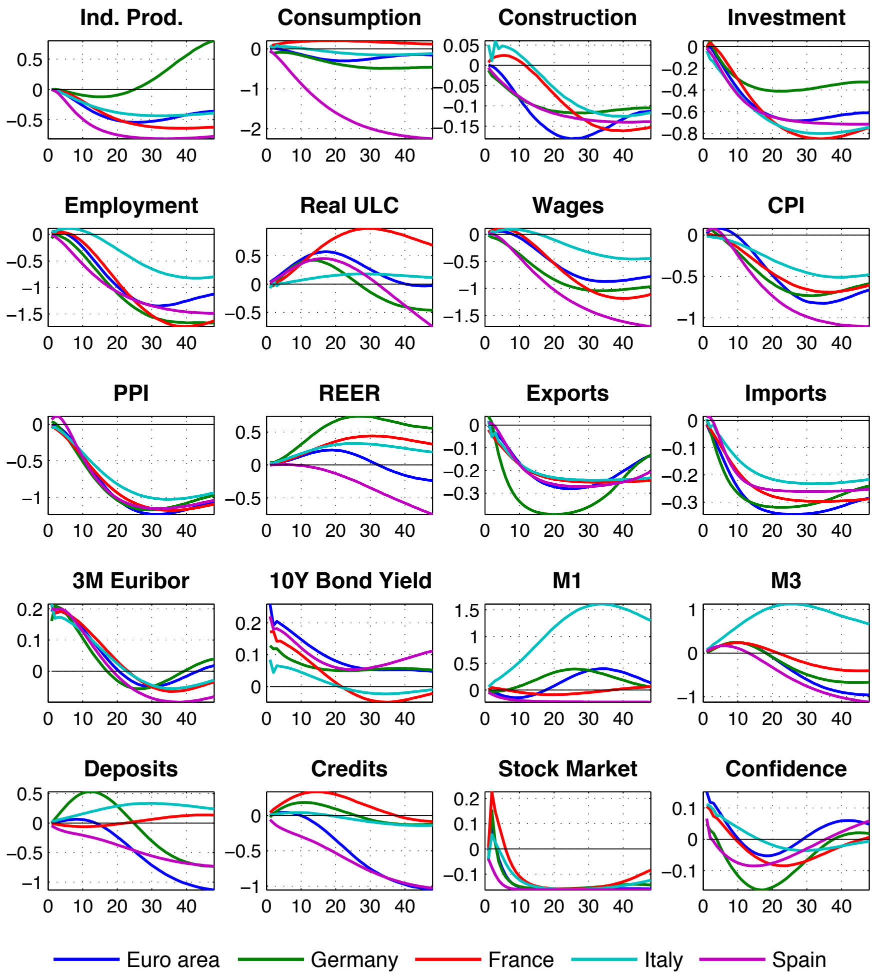



Figure 2.4.1: Cross-Country Heterogeneity - Country-Level Estimations

Note: The impulse responses for the EA as an aggregate, estimated in Chapter 1, are repeated in the figure in order to have consistency with the panel approach in Section 2.4.2 where the impulse responses are estimated and presented for the aggregate EA data for the first time in the thesis. It is also of interest to compare country-specific and area-wide impacts of (contractionary) monetary policy shocks in the EA.

The Bayesian estimations in Figure 2.4.1 are based on 10,000 Gibbs sampling iterations, the first 2,000 of which are discarded. The impulse response estimates are reported in $SD$ terms.

Broadly speaking, despite some "puzzles" in monetary aggregates, our results are largely consistent with the convention on the impact of a surprise monetary tightening on the economy. We emphasise the word "puzzle" because we believe that these so called contradictory responses might be a noteworthy sign of important differences in the transmission of single monetary policy shocks across the main economies of the EMU. The details of the results are as follow.

Let us start with the real activity measures, the majority of which decline qualitatively similarly across countries following a contractionary common monetary policy shock.[36] Our common finding with Smets and Wouters (2003) and McCallum and Smets (2007) in Chapter 1 that the strongest impact of a contractionary monetary policy shock is on investment in the EA as an aggregate is also present in our country-level estimations. In addition to investment, as in our area-wide estimations in the previous chapter, country-specific employment levels are also affected by the shock stronger than other macroeconomic variables. Our findings on statistical significance of the results in Appendix M.1.1 suggest that the contractionary impact of the shock on investment and employment, in addition to IP, is statistically significant. The responses of consumption and construction, on the other hand, are generally statistically insignificant.

The labour market indicators, i.e. real ULC and nominal wages, indicate some differences across countries. We observe from the estimations that whilst real ULC increases strongly in France, in the other countries it either increases less strongly (Italy) or initially rises and then decreases (Germany and Spain), highlighting the possibility of 'structural' differences across countries.[37] Furthermore, when we look at the responses of nominal wages we note that except for initial rises in France and Italy, the medium- and long-term responses are all negative but quantitatively different across countries. Regarding the statistical significance of the results, we find that almost all responses estimated by our

[36]The only serious exception is the final consumption expenditure in France which responds in the opposite direction. For the post-1999 period, Boivin et al. (2008) also find that French consumption increases after the rise in the monetary policy variable. Contrary to our results, Boivin et al. obtain this finding not only for France but also for Germany, Italy and Spain.

[37]See p.129 for details on structural differences across countries.

one-step FAVAR approach are statistically significant except those for Italy.

When we compare the country-level labour market dynamics to the area-wide responses in Chapter 1, we observe the findings to be consistent.[38] We mentioned earlier that the area-wide impulse responses are included in Figure 2.4.1. As we can see from the figure, the increases in the ULC of the four largest EA economies lead the area-wide figure to rise as well. When the ULC in Germany and Spain displays negative responses period 25 onwards, whilst the responses of that in France and Italy turn towards their pre-shock levels, the area-wide ULC gets back to its level prior to the contractionary monetary policy shock. Similarly, the responses of the national nominal wages are in line with our area-wide findings in Chapter 1.

Using a two-step FAVAR approach, McCallum and Smets (2007) investigate cross-country heterogeneity in European real wages for the period 1986Q1-2005Q4. They find that contractionary monetary policy shocks increase real wages in France for the whole horizon investigated, i.e. 16 quarters. McCallum and Smets also estimate an initial rise and then decrease in German, and strong fall in Italian and Spanish real wages. The authors justify their findings by highlighting some statistics[39] from the Inflation Persistence (IPN) and Wage Dynamics (WDN) networks in which Italy and Spain "appear to have the lowest frequency of price adjustment among the (four largest EA countries and Belgium) or, in other words, the highest price stickiness."[40]

Following Normandin (2006), McCallum and Smets (2007) highlight that one can use the sign of the real wage responses as an indication of the relative importance of labor-

[38]See Section 1.4.1, p.43.

[39]Such as the cumulative share of the real GDP response in the total nominal GDP response after 16 quarters, the cumulative share of the employment response in the total wage compensation response after 16 quarters, frequency of monthly price changes, and average wage contract duration. See Table 2 in McCallum and Smets (2007, p.14).

[40]McCallum and Smets (2007, p.14).

market frictions to those in the goods- and financial-markets. Although real wages are missing in our data sets, i.e. as a single series, we follow the comments in McCallum and Smets (2007)[41] and compare the impulse responses of nominal wages and the prices on the basis of the common wisdom described in Table 2.4.1.

Table 2.4.1: Real Wage Responses

| **Nominal Wages*** | **Prices*** | **Comparison** | **Real Wages** |
|---|---|---|---|
| Rise | Rise | $\Delta W > \Delta P$ | Rise |
| Rise | Rise | $\Delta W < \Delta P$ | Fall |
| Rise | Fall | - | Rise |
| Fall | Rise | - | Fall |
| Fall | Fall | $\|\Delta W\| > \|\Delta P\|$ | Fall |
| Fall | Fall | $\|\Delta W\| < \|\Delta P\|$ | Rise |

*Rise (fall) stands for positive (negative) responses in Wages and CPI in Figure 2.4.1.

Comparing the wage and price responses period by period, we obtain the following conclusions on the potential impulse responses of real wages. First, we estimate that real wages continuously drop in Germany, Spain and EA-17 for four years following the monetary tightening. Second, we observe that real wages in France initially rise for one and a half years. When it comes to Italy, finally, our estimations suggest continuous rise in the wages for four years. Following McCallum and Smets (2007), this may suggest that nominal wage stickiness is more important relative to price stickiness in France and Italy than in Germany and Spain, a finding in line with the IPN and WDN statistics cited above.

We mentioned earlier about the mixed conclusion of the literature on the transmission of monetary policy shocks across countries. As we can see, our empirical findings on the

[41] "The nominal wage per employee responds somewhat faster and by more than the GDP deflator. As a result, the real wage per employee drops following the monetary policy shock" (p.10).

impact of the policy shocks on real wages are somewhat different from the ones obtained by McCallum and Smets (2007). If we look at Boivin et al. (2008), we observe findings on the dynamics of wages in the EA which slightly differ from our and McCallum and Smets's results. Among these empirical findings, however, there is a very important common conclusion worth highlighting. The empirical evidence in the literature does suggest that the transmission of monetary policy shocks in the EMU is not homogeneous across real wages of the member states. We believe that this common conclusion, supported by our empirical findings, highlights, importantly, that there may be structural differences across the (four largest) economies of the EA. For instance, labour cost and productivity growth rates, skill composition of national workforces, outturn for productivity, rigidities in wage and price setting, differences in the size of worker flows, the level of employment protection, institutional features of national labour markets, and barriers to domestic and foreign competitions are among the structural differences across the EA labour markets studied in the literature.[42]

Having explained the impact of common monetary policy shocks on cross-country real activities and labour markets, let us look at their effects on country-level prices. Our results suggest that in the medium term consumer prices respond negatively to common monetary tightening. It is also observed that the responses of the national producer prices to the tightening are always negative, except that in Spain where producer prices slightly increase in the first 5 months following the shock. According to the estimates, which are all found to be statistically significant, both consumer and producer prices respond qualitatively homogeneously, where the responses of the latter are almost identical, across

[42] See ECB (2012c); IMF (2012); Jaumotte and Morsy (2012) among others in the IPN and WDN.

the largest EA economies. We discussed in Chapter 1[43] the negative responses of the prices in the EA as an aggregate. As we observe here, our country-level findings are consistent with and explain the area-wide responses to common monetary policy shocks.

Unlike our one-step FAVAR results, Boivin et al. (2008) observe puzzling impulse responses in German price levels. Following their claim that "the price rise in Germany is ... difficult to rationalise" (p.95), the authors propose the possibility that innovations in their artificial EA interest rate may not properly identify surprise monetary shocks for Germany. In order to test robustness of the puzzles, Boivin et al. identify monetary policy shocks for Germany as surprise increase in her short-term interest rate. Their new set of responses suggest almost no puzzle for Germany.[44] When we replicate this exercise by replacing the REFI by German 3M Euribor rate in our two-step estimations for Germany,[45] we observe not only puzzles in prices but also relatively stronger responses of other variables disappearing almost entirely. We believe that this also highlights the importance of the Bayesian FAVAR approach similar to its estimations in Chapter 1 being insensitive to the period when the crisis hit the economies most significantly.[46]

One of the main findings of Boivin et al. (2008) is that monetary union has led the exchange rate channel to becoming more powerful in the EA. That is to say, comparing their full sample estimates (1980Q1-2007Q3) to those for the post-1999 period (1999Q1-2007Q3), Boivin et al. observe EA REER appreciating considerably more in the latter period than the former. Our Bayesian FAVAR estimations support this finding in the literature by suggesting appreciations in REERs in all countries[47] except Spain where the

[43] Section 1.4.1, p.43.

[44] See Boivin et al. (2008) Appendix B.

[45] Available upon request.

[46] See Chapter 1, Section 1.4.2, part Interpolation of the Crisis Period (2008Q4).

[47] Quantitatively differently across countries and either statistically significantly (Germany), marginally significantly (France) or insignificantly (Italy).

exchange rate persistently depreciates following a common contractionary monetary policy shock. The appreciations in German, and French and Italian REERs are, respectively, always and marginally significant according to our estimations. The estimates for Spain, however, are statistically significant only for the period 30 onwards. As we noted in Chapter 1, comparison of our country-level one- and two-step estimations[48] also suggests that the latter method, the one used by Boivin et al. (2008), estimates considerably stronger REER responses relative to the former.

Following the declines in real activities and the appreciations of the REERs, we observe from Figure 2.4.1 that countries' exports and imports respond negatively to the surprise increase in the policy interest rate. In line with the "export-engine" status of Germany in the EA, our estimations suggest the impact of the shock to be stronger on the German export figures relative to other countries and the EA as an aggregate, among which the responses of exports are almost identical. As we can see from the results, on the other hand, the imports respond relatively homogeneously across the economies.

When we replicate the practice in Table 2.4.1 on real wages[49] for net trade, we observe a more heterogeneous impact of the shock. To illustrate, according to our estimations, whereas Spanish and German net trade figures display mixed responses, that in France (Italy) almost always increase (decrease).[50] Given the majority of our estimates show increases in net trade of the four largest economies of the EA, it becomes unsurprising that net trade in the EA as a whole increases continuously for 48 periods following a common contractionary monetary policy shock. Despite our empirical finding, one can

[48]The two-step estimations are not reported here but available upon request.

[49]Because the logic is exactly the same, we did not repeat the same table Nominal Wages and Prices replaced by Exports and Imports, respectively.

[50]French (Italian) net trade decreases (increases) in period(s) 1-6 (1).

expect the monetary tightening to increase the interest rates, as we present below, which thereby reduce the trade balance by appreciating the currency. Depending on the relative elasticities of exports and imports together with the quantity and cost effects of the currency changes,[51] however, it might be possible to observe increases in net trade following a monetary tightening.

When a surprise hike in the benchmark policy rate of the ECB hits the economies, their short- and long-term interest rates respond expectedly homogeneously. The French and Italian government bond yields are estimated, statistically significantly, by our one-step FAVAR method to differ from that of other countries. In other words, whereas bond yields in Germany and Spain increase for four years following a contractionary shock, that in France and Italy follow the short-term interest rates and display negative responses from period 20 onwards. As we will see in the following subsection, however, when we consider area-wide factors, i.e. more cross-country information, in our FAVAR system, the short- and long-term interest rates respond identically across countries and consistently between the term structure.

Similar to interest rates, highly correlated stock markets respond quite homogeneously to exogenous interest rate shocks. Our results suggest that the impact of the shock on the markets are persistent in all countries and the whole area itself. Furthermore, confidence indicators also display qualitatively similar responses across countries. One important finding worth highlighting is that in the medium term following the shock, whereas German confidence decreases the most among the economies, it takes relatively longer for the Italian consumers to decrease their confidence.

We highlighted earlier the importance of the comparison of our empirical results to

[51]See Rose (1991) for the Marshall–Lerner condition.

that in Boivin et al. (2008) due to the parallel methodologies and the EA countries investigated. If we compare our findings summarised above to those in Boivin et al. (2008), we observe a broad agreement on (i) the homogenous responses of prices across the four largest economies of the EA, (ii) the appreciation in REER of all countries under investigation except Spain, (iii) larger responses of the German export figures, and (iv) homogeneous impact of contractionary monetary policy shocks to national imports.

Among the indicators presented in Figure 2.4.1, there is one category left to be interpreted, i.e. the monetary aggregates. One of the main findings of Chapter 1 was that time variation in the responses of monetary aggregates of EA-17 was considerably larger than other key indicators investigated. When it comes to the cross-country impacts of common monetary tightening, monetary aggregates very importantly display the most heterogeneous responses across four largest EA economies. That is to say, the impact of common monetary policy shocks is not only the most time variant on EA-17 monetary aggregates but also is most heterogeneous across the countries. It is important to highlight the consistency of the latter finding with Boivin et al. (2008) who claim that "national monetary aggregates (of Germany, France, Italy, Spain, Belgium and the Netherlands) ... show more heterogeneous responses to monetary policy shocks than most other macroeconomic variables" (p.118).

We highlighted in Chapter 1[52] that a cautious approach to monetary aggregates especially in the post-crisis period is of necessity due to strong monetary responses of the Eurosystem to the global financial crisis. When it comes to cross-country heterogeneity in the responses of monetary aggregates, we still believe that such an approach is important. It is also important to note, however, that both Boivin et al.'s (2008) and our pre-crisis

[52]See Section 1.4.2, p.55 for details.

estimations[53] still suggest heterogeneous behaviour in the monetary aggregates of the four largest EA economies. Therefore, we believe that it is of importance to highlight the following empirical findings on the monetary aggregates together with our justifications.

In particular, our one-step FAVAR estimations suggest that following an exogenous monetary tightening in the post-1999 period, the broad money supply, i.e. M3, increases for four years in Italy, whilst it initially increases and then persistently falls in Germany, France and Spain. The impulse responses we estimated for Germany and Spain are statistically significant. When we analyse the impact of the policy shock on M1, deposits and credits, the main result does not change that the responses are noticeably more heterogeneous across countries than other macroeconomic variables under investigation. As we can clearly see from Figure 2.4.1 and Appendix M.1.1, whilst responses of monetary aggregates of other countries are statistically significantly positive (M1: Italy, Deposits: Germany, Credits: France), Spanish M1, deposits and credits persistently and statistically significantly decrease as a result of a common contractionary monetary policy shock.

We discussed the impacts of the policy shocks on the area-wide monetary aggregates in the previous chapter of the thesis.[54] We observe from our country-level estimations that (i) the liquidity puzzles in the German and Italian M1 lead to increases in the area-wide narrow money supply, (ii) the broad money supply in the area as a whole displays highly similar responses to that in the four largest member states, (iii) the (medium-term) negative responses of (German and) Spanish deposits account for that of the area-wide deposits, and (iv) despite the positive responses of credits in Germany and France to monetary tightening, credits in the whole area closely follows, surprisingly, the negative

[53] See Section 2.4.3 below for details.
[54] Section 1.4.1, p.46.

responses of the credit level in Spain.

According to Boivin et al. (2008), our common empirical finding that national monetary aggregates are the most heterogeneous macroeconomic variables "may reflect the pervasive differences in the national habits and in the availability of savings instruments across countries of the EA" (p.96). In a more recent study, investigating the post-launch-of-euro period, Setzer et al. (2010) claim that "cross-country heterogeneity in monetary dynamics can be explained to a large extent by asymmetries in house price developments on top of different income developments" (p.21). Hughes Hallett and Piscitelli (2002) list a number of key factors rationalising asymmetries in European monetary aggregates. To name a few, "although the overall stock of money is controlled by the ECB's interest rate, the *distribution* of the demand for money will vary in each country according to local conditions" (p.82). "Variations in the demand for money across countries (therefore) will cause differences in activity levels, differences in the supply of, and demand for credit" (p.93), well supported by our heterogeneous credit responses. As potential sources of the money demand variations, Hughes Hallett and Piscitelli (2002) investigate the factors of the interest and the income elasticities of money. They claim that, first, "evidently, differing interest elasticities in the monetary transmission mechanism do produce some differences in performance under a common monetary policy, but those differences are relatively small" (p.77). Second, more effective short-run income elasticities may vary, according to Hughes Hallett and Piscitelli (2002, p.92), because of differences in (i) the velocity of money; (ii) the way financial markets work; (iii) the ownership of assets and their use as collateral; and (iv) the flexibility of markets ("the speed with which income changes monetary conditions").

Following our empirical findings and the rationalisations above, we think it is crucial to highlight, finally, another general point made by Hughes Hallett and Piscitelli (2002, p.82). When we discuss heterogeneity across European countries, it maybe possible to blame the EMU for two aspects. One, there is the problem of "incomplete convergence" making a single policy inappropriate and costly due to different initial conditions. Second, there are some "costs caused by differences in monetary responses once a shock or policy change hits the system (asymmetric transmissions)." According to the Hughes Hallett and Piscitelli's exercise where the initial conditions of the countries are equalised in their model, asymmetric transmissions generate unequal starting points for the next period, making "unequal starting points" the main part of the "problem".

In our opinion, however, the combination of these heterogeneous monetary aggregates with the homogeneous impulse responses of real activities and consumer prices, estimated in this chapter across countries, raises an important point. On the one hand, "cultural and economic diversity is a specific feature of the euro area".[55] This, among other rationalisations cited above, makes it highly likely to observe empirical cross-country difference in the EA. On the other hand, the primary objective of the Eurosystem's monetary policy is to maintain price stability in the whole EA. Given the fact that average annualised inflation rate of the EA since 1999 is 2.07%,[56] we believe that the heterogeneous responses of national monetary aggregates might have done no harm to the transmission of the policy changes to national, and indirectly to area-wide, price levels.

In order to further investigate the question of (asymmetric) transmission of common monetary policy shocks in the EA, the rest of the section contains the results of our panel

[55] Moutot et al. (2008, p.31).

[56] As of February 2013.

approach, time variation and Boivin and Ng (2006) pre-screening analysis.

### 2.4.2 Panel Approach

The panel FAVAR approach of the chapter, as we described in Section 2.2.1, is to replicate the previous cross-country analysis by using area-wide factors, instead of country-specific ones, estimated by the Bayesian method from a panel of the individual data sets under investigation. We mentioned earlier that our panel approach is of importance in the sense that it tests the robustness of not only our country-level findings but also the results obtained by the two-step panel approach of Boivin et al. (2008) applied to the same EA economies.[57] We also believe that this panel, i.e. area-wide, approach provides the thesis with a link to the previous chapter where the area-wide effects of monetary policy shocks are investigated again with area-wide factors but estimated not from a panel of countries but from aggregate macroeconomic indicators.

Figure 2.4.2 presents our estimation results obtained using a panel of 508 variables from the individual data sets.[58] Thanks to the merits of the FAVAR technique, the impulse responses are obtained from the one-time estimation of our computer-intensive model for the whole data set. The results are then grouped and compared accordingly. Different from the country-level approach, in order to make the Gibbs process converge we base the one-step estimations in Figure 2.4.2 on 15,000 Gibbs draws, first 3,000 of which are discarded. Because the general dynamics of the key macroeconomic variables have been described in detail, here we only focus on the robustness of the previous findings to our

[57]As we described in Chapter 1, Section 1.2, the one- and two-step FAVAR methods differ in terms of the estimation of the factors with (one-step) and without (two-step) taking the dynamic structure of the state-space model into account.

[58]Note that the panel consists of the country-level and EA-17 data sets except duplicated variables.

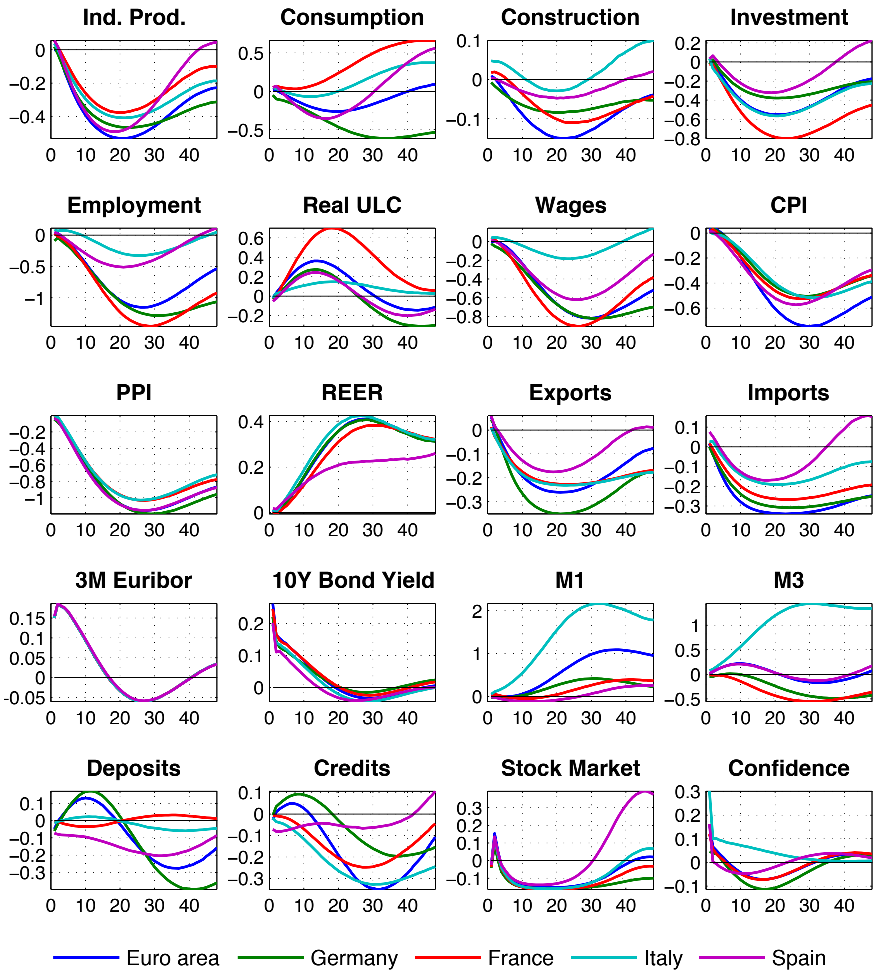



Figure 2.4.2: Cross-Country Heterogeneity - Area-Wide Estimation

panel approach.

First of all, with investment and employment being the most affected, the impact of the shock on real activity is observed to be as homogeneous, if not more, as suggested by our country-level estimations. The impulse responses of consumption and construction, however, suggest more differences across countries. We believe this finding importantly supports the previously highlighted ideas of Hughes Hallett and Piscitelli (2002) and Setzer et al. (2010) that variations in the demand for money and asymmetries in house price developments can account for cross-country heterogeneity in European monetary dynamics.

Broadly speaking, the panel approach suggests results qualitatively quite similar to the country-level approach for real ULC, nominal wages, prices, REERs, trade figures and stock markets. It is important to note that the slight price puzzles, i.e. CPI puzzles in Figure 2.4.1, for EA, Germany and Spain all disappear when more area-wide information is used in the model.

Not surprisingly, the more area-wide information is included into the model, the more homogeneously the interest rates are estimated to respond to common monetary tightenings. In line with the country-level approach, we still observe Italian (German) consumer confidence being the least (most) negatively affected relative to other countries. We even find that the shock leads to statistically significant increase in the indicator. Although there is no clear clarification, statistically significant increases in consumption and construction in addition to that in M1 and M3 may support this finding.

Regarding the monetary aggregates, finally, there is no doubt that the effects of the shock are still most heterogeneous on these variables. To illustrate, we observe from our panel estimations that whereas M1 and M3 in Italy and M1 in EA-17 increase statistically significantly, decreases in German and French broad money supplies are also estimated by the same method to be statistically significant. We believe that this important common finding between our one-step and Boivin et al.'s (2008) two-step FAVAR approaches is crucial in the sense that it highlights the necessity of further research, besides our rationalisations above, on the reasons behind such asymmetric responses of common monetary policy shocks across the largest member states of the EA.

In the Introduction of the chapter, we mentioned the methodological sensitivity of the general conclusion of the literature on cross-country effects of monetary policy shocks. As we have explained above in detail, however, our empirical analysis clearly shows that the findings in the chapter are not only robust to the country-specific and panel approaches, but also in line with the EA aggregates in Chapter 1.

### 2.4.3 Time Variation

It is so far assumed in the empirical analyses of the chapter that the parameters of the FAVAR models are constant over the entire sample. In this section, however, we use a simple technique of rolling windows in order to analyse the potential changes in the previous findings over time and especially due to the 2007-8 global financial crisis. In addition to the contribution of the country-specific and panel approaches above to the aggregate-level findings in Chapter 1, we believe that the question of time variation in cross-country heterogeneity is also of importance.

Given the computational intensity of the one-step FAVAR technique, we eliminate the panel approach here and focus on country-level estimation results only. For the same reason, we base our results on four key macroeconomic variables in this subsection. These variables are (i) IP to observe time variations in real activity; (ii) CPI to check whether one of the main findings of Chapter 1, that the prices, strongly puzzling during the pre-crisis period, respond negatively to the contractionary monetary policy shock when it hits the economy in the post-crisis period, applies to the national price levels; and (iii) given the important finding of this chapter on the dynamics of monetary aggregates across countries, M1 and M3 series. The empirical results displayed in Figures 2.4.3 to 2.4.6 and summarised below depend on rolling FAVARs estimated with the initial sample of 1999 - June 2007 and 6-month rollings. As noted earlier, the Gibbs samplings are based on

5,000 draws initial 2,000 of which are discarded.

Let us start with the rolling estimates of the impact of a contractionary monetary policy shock on national IP indices. It was observed for the full sample in Figure 2.4.1 that the impact of the shock on IP is relatively homogeneous across member states. Our rolling estimations in Figure 2.4.3 clearly suggest that, however, this homogeneity is not robust to the time period from which the estimates are obtained. To illustrate, while we observe qualitatively similar responses across countries when the estimations include the crisis period, i.e. windows Sep00-Dec08 onwards, a more heterogeneous impact of the shock, both qualitatively and quantitatively, is clear in the pre-crisis period, i.e. first three rolling estimations. This finding is supported by the statistical significance of the results that both the asymmetric responses across countries in the first two windows, and the ones in the third window seriously different from one country to another and are all statistically significant. When we start to include some observations from the crisis period, not only do the statistically significant increases in IPs of Spain and France disappear, but the responses also become more similar across countries. If there is any cross-country difference estimated during the crisis period, however, that is the impact of the shock on Spanish production level relative to other nations. As we can see from Figure 2.4.3, December 2009 onwards, inclusive, the contractionary effects of the shock on IP in Spain are much worse than that in other countries.[59] We believe that this finding is of importance and in line with our findings in the next chapter of the thesis on the heterogeneous impacts of the Great Recession and sovereign debt crisis in the EA across core and peripheral member states.[60]

[59]As we can see from Appendix M.1.3, negative impacts of the shock on IPs in all countries are statistically significant.

[60]See Chapter 3, Section 3.6.

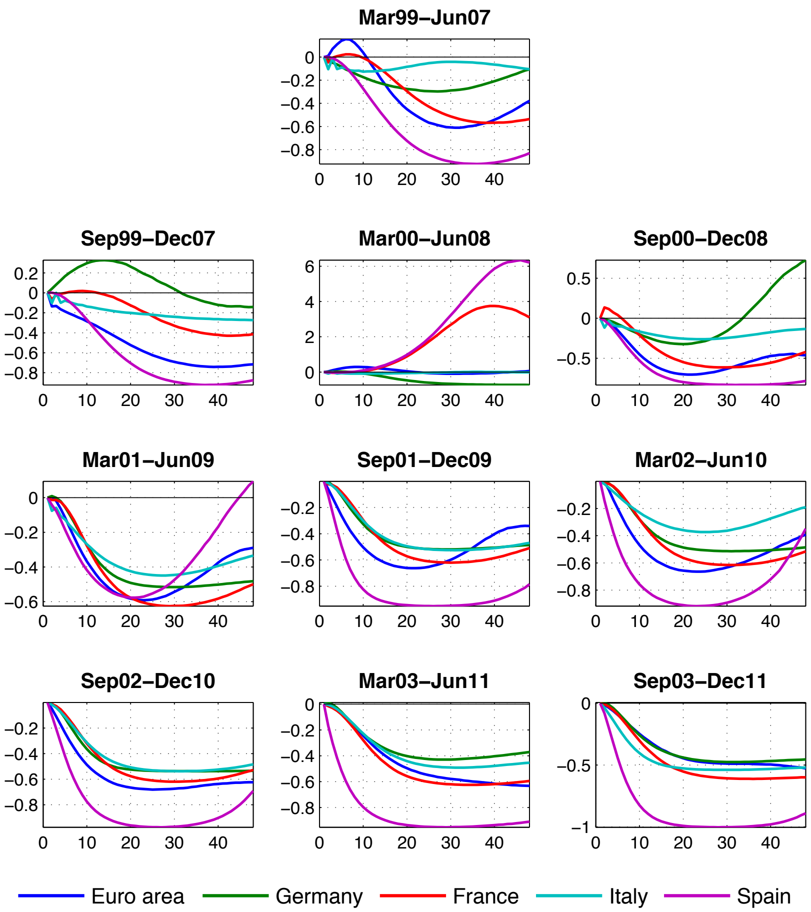



Figure 2.4.3: Rolling Windows - Country Level - IP

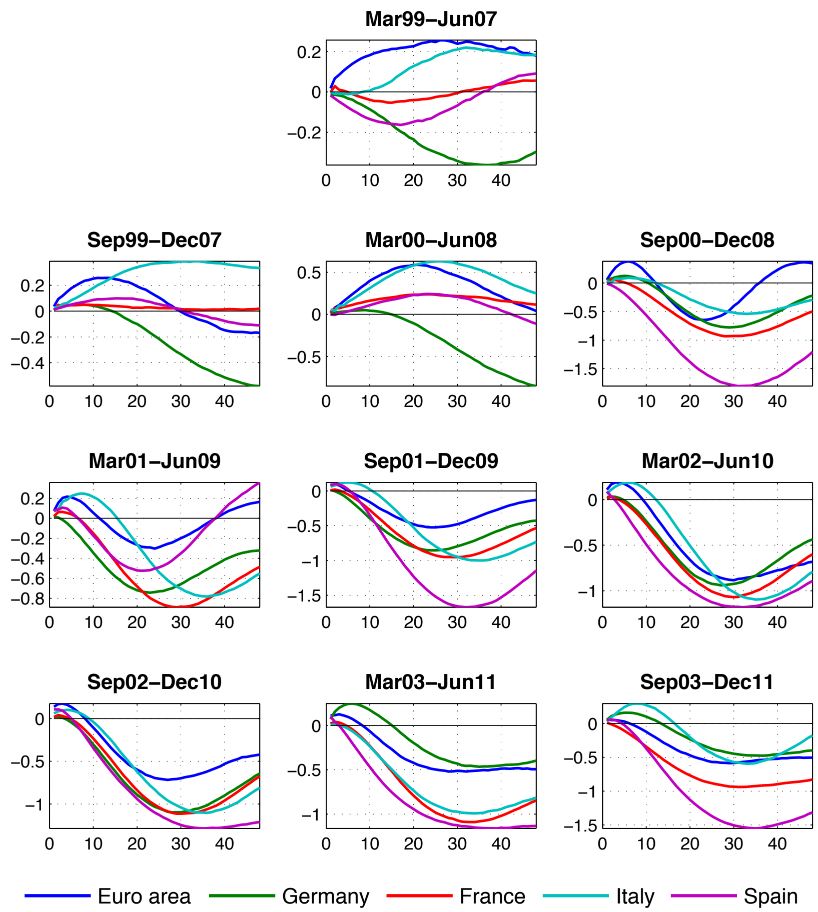



Figure 2.4.4: Rolling Windows - Country Level - CPI

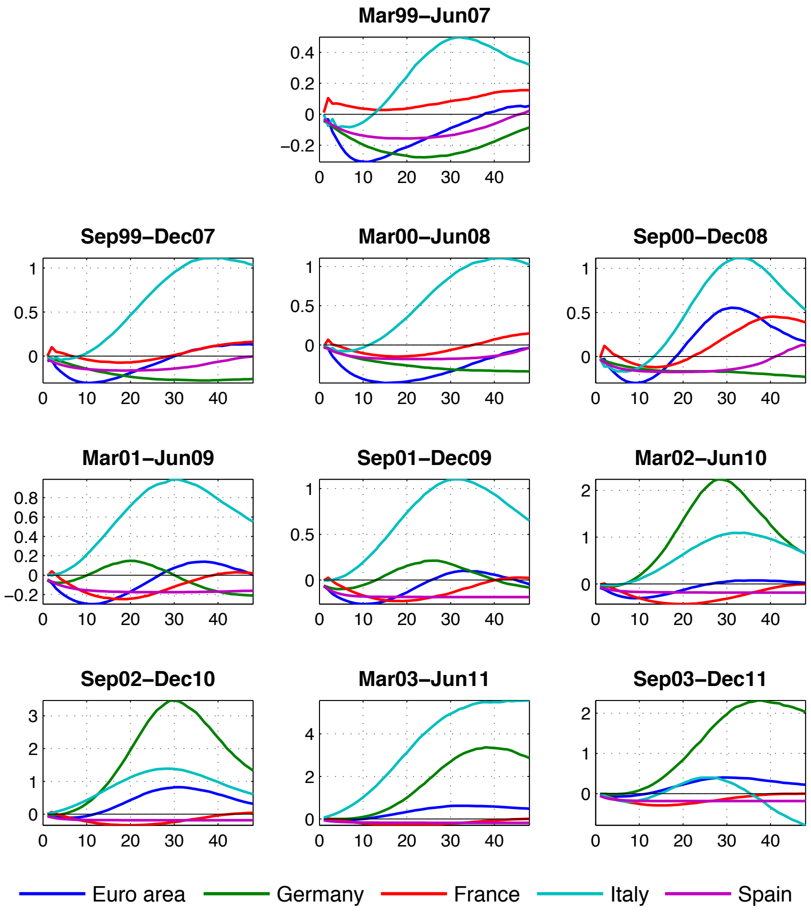



Figure 2.4.5: Rolling Windows - Country Level - M1

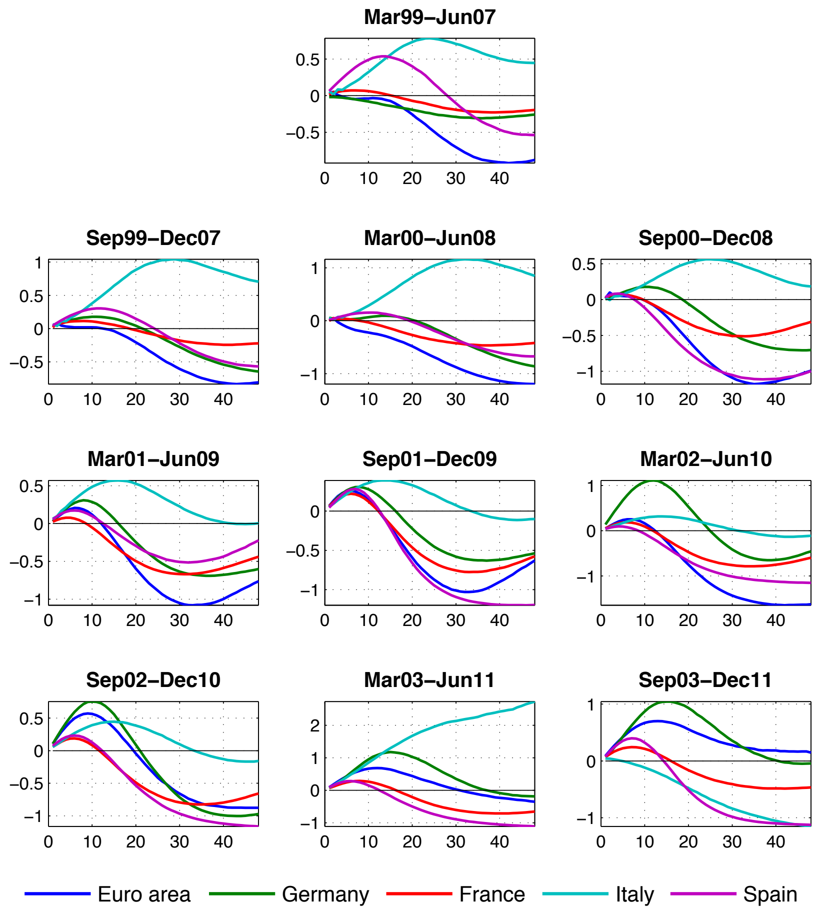



Figure 2.4.6: Rolling Windows - Country Level - M3

Rolling estimations in Figure 2.4.4 investigate the impact of the shock on national price levels over time. Before considering the cross-country heterogeneity, it is worth highlighting that puzzling responses of the prices in France, Spain and Italy may be the main reason why we observed such puzzles in EA-17 rolling estimations in Chapter 1.[61] Especially in window Mar00-Jun08, in all countries, except for Germany, we observe prices increasing almost four years following the monetary tightening. During the crisis period, however, the policy shock leads to statistically significant drops in national price levels. When comparing the impulse responses across countries, we obtain the following conclusions. First, a common shock during the crisis period makes price levels of the four largest economies decrease sometimes considerably more than that of the whole EA. This difference is also observed across the economies themselves. To illustrate, in windows Sep01-Dec09, Sep02-Dec10, and Mar03-Jun11, national prices decrease twice as much, if not more, as the area average. Among the member states, additionally, we also observe considerably stronger decreases in German and Spanish price levels. As we noted earlier, such differences in country-level prices then contribute to time-varying asymmetries in national real wages.

In Chapter 1, area-wide rolling estimations suggested that there was time variation in the impact of the common shocks on monetary aggregates over the pre- and post-crisis periods. According to Figures 2.4.5 and 2.4.6, similar variations are observed for the individual countries. Investigation of the impulse responses across countries also shows that variations are not only over time but also across countries. We observe, on the one hand, Italian and German narrow money supplies (M1) contributing statistically significantly to the liquidity puzzles observed in the area average for the post-crisis period.

[61] Similar to the area-wide puzzles, however, country-level ones are also statistically insignificant.

Although, M1 in Italy rises statistically significantly in the pre-crisis period as well, the negative responses from other nations[62] cause the area-wide M1 to respond negatively to the contractionary monetary policy shock. On the other hand, when there are narrow money liquidity puzzles in EA-17, Germany and Italy, French and especially Spanish money supplies decrease statistically significantly during the crisis-period.

Rolling estimations of the impulse responses of M3 in Figure 2.4.6 also support the previous finding of the study that the transmission of common monetary policy shocks is most heterogeneous across national monetary aggregates. Over time we observe some asymmetries such as the following. On the one hand, we observe statistically significant increases in Spanish M3, following a shock hitting the EA during the pre-crisis period, turning into still significant, even with narrower confidence intervals, decreases during the post-crisis period. On the other hand, Italian M3 responses are almost always positive and statistically significant[63], and German broad money supply decreases (increases) before (after) the crisis.

The empirical results presented so far in the chapter construct the main findings obtained with the full country-level and area-wide data sets. In the following subsection, we now turn to the final aim of the chapter which is to further investigate the impact of the pre-screening technique in a structural context.

### 2.4.4 Pre-screening Analysis

Our structural Boivin and Ng (2006) pre-screening analysis in Chapter 1[64] contributed to the literature by showing that the technique works very well not only in real time fore-

[62]Statistically significant only in Spain.
[63]Decreases in the window Sep03-Dec11 are not significant.
[64]See Section 1.2.4 for details of the technique.

casting but also the policy analysis contexts. Our results highlighted that the technique (i) suggests factor estimates doing no worse than the ones extracted from the full data set, and (ii) especially in the Bayesian FAVAR model, significantly reduces the factor of computer intensity, making the application of the approach more feasible.

In this chapter, we build upon those findings by applying the technique to the question of cross-country analysis. That is to say, given our results about the asymmetries in the transmission of common monetary policy shocks across the largest economies of the EA, we reduce the size of five data sets and test whether the BN technique does any harm or good on the main cross-country findings.

Pre-screening the correlations among idiosyncratic errors of the data using the BN technique provides us with smaller scale versions of the country-level and panel data sets. As a result of the test, we have 71 variables for Germany, 72 for France, 67 for Italy, and 66 for Spain. On average we eliminate 54% of the whole data set. Accordingly, the panel data now contains 290 area-wide macroeconomic variables. Appendix K presents the eliminated variables and their correlation coefficients with other variables. As we did in Chapter 1, we also determine the variables idiosyncratic errors of which are most correlated with our main variables so as to eliminate those instead of the main ones. Table 2.4.2 presents the variables dropped from the data sets instead of the key indicators. The rest of the subsection consists of two parts as cross-country heterogeneity and time variation.

### Cross-Country Heterogeneity

The cross-country impulse responses estimated with the post-BN country-level and panel data sets are displayed in Figures 2.4.7 to 2.4.8. Slightly different from the previous

Table 2.4.2: Pre-screening Exclusions Instead of the Main Variables

| **Variables** | **Most Correlated** | | | |
|---|---|---|---|---|
| | **DE** | **FR** | **IT** | **ES** |
| IP | 8 | 8 | 8 | - |
| Consumption | - | 93 | - | 107 |
| Construction | - | 7 | - | - |
| Investment | - | 8 | - | 107 |
| Employment | 111 | 111 | 111 | 111 |
| Real ULC | 113 | - | - | - |
| Wages | 115 | 115 | 115 | - |
| CPI | 26 | 26 | 26 | 23 |
| PPI | 78 | 35 | 35 | 35 |
| REER | 101 | 101 | 101 | 101 |
| Exports (19) | (20)* | (20)* | (20)* | (20)* |
| Imports (20) | (19)* | (19)* | (19)* | (19)* |
| 3M Euribor | 40 | 40 | 40 | 40 |
| 10Y Yield | 42 | 42 | 42 | 42 |
| M1 | 62 | 62 | 68 | 68 |
| M3 (63) | 62 | 62 | - | 62 |
| Deposits (67) | (63)* | 68 | (70)* | (70)* |
| Credits (70) | 72 | 72 | (67)* | (67)* |
| Stock Market | 51 | 54 | 56 | 56 |
| Confidence | - | - | 94 | 75 |

- Not suggested as the most correlated variable.
* Because two main variables are most correlated with each other, no variable is eliminated.

subsections, we look at the results as a whole and highlight the similarities/differences to the pre-BN ones.

If we start with the impact of a common contractionary monetary policy shock on real activity, we observe the following points. First of all, qualitatively similar declines in the country-level activities are still present in the results. The post-BN panel approach estimates show much more homogeneity across IP indices. The one-step method still captures the previous finding that the most contractionary impact of the common shock is on the Spanish IP. The previous divergent responses of consumption in France and construction in Italy are also robust to the size of the data sets.

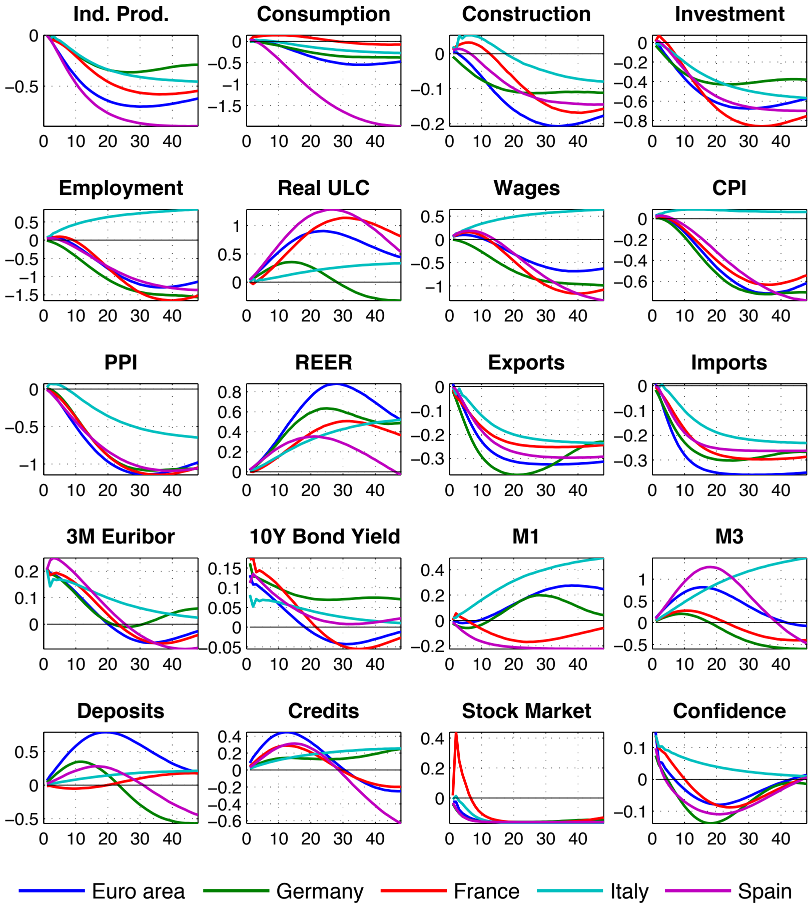



Figure 2.4.7: CC. Heterogeneity - Post-BN - Country Level

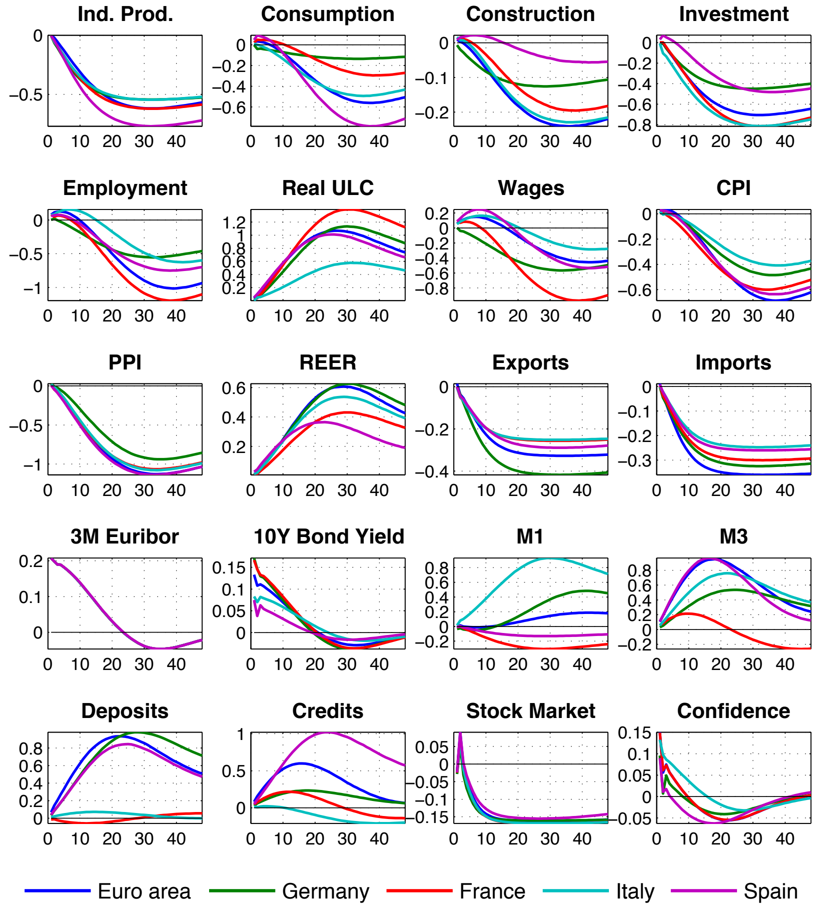



Figure 2.4.8: CC. Heterogeneity - Post-BN - Area Wide

Furthermore, country-specific estimations for Italy highlight a significant finding. As we can see from Figure 2.4.7, the results with less information suggests that following a contractionary monetary policy shock, not only employment and nominal wages, but also consumer prices increase in Italy. When we include more information via the panel approach, however, we observe negative responses of these variables to the shock. The responses of the prices are even found to be statistically significant in the more-informative panel approach. We believe that this empirical finding does highlight (i) the importance of "necessary" information in monetary (FA)VAR approaches,[65] and (ii) the possibility that BN can be misleading in the structural context, combination of which suggests the necessity of further research on BN analysis in structural models.

A consideration of impulse responses estimated for labour market indicators and prices of other countries suggests that our previous results are qualitatively robust to the pre-screening technique. Including Italy, all countries' trade figures, interest rates, stock markets and consumer confidences also support this conclusion. REERs, however, display some differences relative to full-data estimations. Whereas the differences are quantitative for all countries except Spain, post-BN responses suggest a stronger effect of the shock on exchange rates, depreciation in Spanish REER disappears when we include less information into the model. This makes our post-BN results on REER, i.e. country-level and panel, consistent with Boivin et al. (2008) in a sense that countries' REERs strongly appreciate following a common monetary tightening.

Finally, when we look at the effects of a contractionary monetary policy shock on national monetary aggregates estimated with post-BN data sets, we very importantly

[65]See Sims (1992); Bernanke and Blinder (1992); Cushman and Zha (1997); Bernanke et al. (2005), among others.

observe that the monetary aggregates, especially M1 and M3, are still relatively the most heterogeneous variables. Significant differences across national narrow money supplies are also present in the post-BN estimations with country-level and panel data sets.

**Time Variation**

The rolling estimations with post-BN data sets are presented in Appendix N. Overall, the estimations suggest consistency with the full-data rolling results in the sense that (i) the contractionary impact of the shock on Spanish IP is considerably more than other members especially in the post-crisis period, (ii) consumer prices puzzle only in the period prior to the crisis,[66] (iii) monetary aggregates respond heterogeneously not only across countries but also over time, i.e. the responses are relatively less heterogeneous during the pre-crisis period.

As in Chapter 1, this kind of consistency across the results highlights the importance of the pre-screening technique for the structural analyses in terms of significant time saving with the Bayesian one-step method. We believe that this finding and the BN pre-screening technique makes cross-country analysis with the one-step method, which provided more statistically significant results relative to the two-step, more attractive and less time-consuming.

## 2.5 Robustness

This section first presents the convergence of the Gibbs samplings on which the empirical results are based in the chapter. Further the confidence intervals of the impulse responses

[66]Still statistically insignificantly though.

eliminated from the analyses above for the sake of comparability across countries are discussed in the section.

### 2.5.1 Convergence

Convergence of the full-sample and rolling Bayesian estimations, i.e. pre- and post-BN, are presented in Appendix O. The technique followed is the one used in Chapter 1 where the first and second halves of the median of the retained Gibbs samplings draws are plotted on each other, and observed for deviations between the halves. As we can see from the test results, convergence is satisfied in all Gibbs sampling procedures of the one-step estimations in the chapter.

### 2.5.2 Confidence Intervals

Appendix M presents the confidence intervals of the impulse response estimates eliminated from the text for the purposes of comparability across countries. As we highlighted with the results earlier, the majority of the impulse responses are estimated statistically significantly by the one-step FAVAR technique. Similar to our finding in Chapter 1, the statistical significance of the impulse responses estimated by the one-step approach outperforms that by the two-step FAVAR method.[67]

## 2.6 Conclusion

The questions of cross-country heterogeneity and time variation in the EA are investigated in this chapter of the thesis. Similar to the previous chapter, (one-step Bayesian) FAVAR

[67]The two-step confidence intervals of the same set of analyses in the chapter are available upon request.

approach, rolling windows and Boivin and Ng (2006) pre-screening techniques are the techniques used in this chapter. Using a 4×120-variable novel data set for the largest four economies of the EA, i.e. Germany, France, Italy, Spain, we have investigated the cross-country asymmetries of and time variation in the transmission of common monetary policy shocks for the period 1999-2011.

We have argued that the responses of the real activity measurements are almost all negative and relatively homogeneous across countries. The strongest impact of the shock is estimated to be on national investment and total employment indicators. Consistent with Boivin et al. (2008), we observe prices also responding similarly across countries. Our one-step FAVAR approach contributes to the literature by estimating qualitatively homogeneous and statistically significant declines in the national price levels of the largest EA economies.

Our common finding with Normandin (2006), McCallum and Smets (2007) and Boivin et al. (2008) that the transmission of common monetary policy shocks in the EMU is not homogeneous across national real wages highlights that there may be cross-country heterogeneity in the labour-, goods- and financial-frictions in the member states of the EA. The net-trade exercise performed in the chapter also suggests asymmetric nature of the common policy shocks.

We have highlighted in the chapter that according to our rolling estimations, whilst the impact of the shock on real activity measurements is heterogeneous across countries prior to the 2007-8 global financial crisis, when the real economies are hit by the crisis, we observe more homogeneous contractionary impact of the shock. The rolling windows from December 2009 onwards, however, clearly suggest that despite relatively similar impact of the shock across other countries, Spanish IP is the one most severely affected by the monetary tightening, suggesting the importance of country-specific factors during the financial crisis period such as extraordinary unemployment rates and significantly low levels of retail and investment figures in Spain.[68]

Moreover, we have pre-screened our country-level data sets using the technique proposed by Boivin and Ng (2006). In addition to our contribution in Chapter 1, we believe that this structural and cross-country pre-screening analysis in this chapter is also of importance for the literature. We observe from the analysis that pre-screening makes cross-country analysis with the computationally burdensome one-step FAVAR approach more convenient. On the other hand, however, our country-level estimations for Italy highlight the importance of "necessary" information in monetary (FA)VAR approaches. These findings, we believe, make it clear that further structural applications of the BN technique in the literature is needed.

The main contribution of this chapter of the thesis is to show with a novel and most recent data set and various empirical approaches that the responses of the national monetary aggregates are strongly more heterogeneous across the four largest economies of the European monetary union than most other macroeconomic variables. We also provide the literature with the empirical evidence that the responses of EA monetary aggregates are not only strongly heterogeneous across countries but also over time during the single monetary policy era of the EMU. We consider these empirical findings as crucial in order to investigate whether or not "the euro area monetary transmission process is (genuinely) uneven across countries, in a way that could complicate the conduct of the single mone-

[68]See Section 3.6 in the next chapter of the thesis.

tary policy."[69] In light of our analysis of the Eurosystem's unconventional monetary policy actions in the next chapter of the thesis, we have raised the issue of heterogeneous transmission of the policy actions across (heterogeneous) country-specific channels. Therefore, we believe that the main findings of the present chapter contribute to the literature by providing empirical observations on an important aspect of the monetary transmission mechanism in the EA.

Finally, we have argued in the chapter that the overall conclusion of the literature on the asymmetries in the transmission of monetary policy in the EA is not robust to changes in empirical methodology and data. We believe our essay contributes to the literature significantly in the sense that it both supports the general conclusion of some studies cited in the text, and also provides empirical findings quite robust across changes in the methodology such as country-specific and panel estimations, time variation, and data pre-screening.

Following our empirical results obtained with the Bayesian one-step FAVAR approach, in the next chapter we further investigate the question of cross-country analysis of the EA using the panel VAR technique of Gambacorta et al. (2012), and in the context of unconventional monetary policy at the zero lower bound during the global financial crisis.

[69] Angeloni and Ehrmann (2003, p.6).

# APPENDIX K

# DATA DESCRIPTION

Details of our country-level data sets are as below. The transformation (Tr.) codes are 1 - no transformation; 2 - first difference; 5 - first difference of logarithm. The variables denoted as "1" ("0") in column 4 are assumed to be slow- (fast-) moving. Data details in brackets apply to the following same category series unless otherwise stated. Following our BN pre-screening analysis, column $\hat{\tau}_1^*$ presents the correlation coefficients between the residuals of the series and the ones listed in column $j_1$.

| No. | Description | Tr. | S/F | Source | EA-17 | | DE | | FR | | IT | | ES | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | $\hat{\tau}_1^*$ | $j_1$ | $\hat{\tau}_1^*$ | $j_1$ | $\hat{\tau}_1^*$ | $j_1$ | $\hat{\tau}_1^*$ | $j_1$ | $\hat{\tau}_1^*$ | $j_1$ |
| 1 | IP Total (2005=100) | 5 | 1 | OECD | 0.91 | 8 | 0.86 | 8 | 0.92 | 8 | 0.86 | 8 | 0.56 | 9 |
| 2 | IP-Intermediate Goods | 5 | 1 | Eurostat | 0.64 | 8 | 0.43 | 8 | 0.77 | 8 | 0.48 | 8 | 0.71 | 9 |
| 3 | IP-Energy | 5 | 1 | Eurostat | 0.54 | 7 | 0.28 | 102 | 0.19 | 102 | 0.23 | 7 | 0.19 | 57 |
| 4 | IP-Capital Goods | 5 | 1 | Eurostat | 0.70 | 8 | 0.63 | 1 | 0.83 | 8 | 0.48 | 8 | 0.44 | 9 |
| 5 | IP-Durable Consumer Goods | 5 | 1 | Eurostat | 0.43 | 8 | 0.30 | 52 | 0.32 | 109 | 0.24 | 29 | 0.47 | 8 |
| 6 | IP-Non-Durable Consumer Goods | 5 | 1 | Eurostat | 0.32 | 5 | 0.28 | 8 | 0.51 | 8 | 0.53 | 8 | 0.52 | 8 |
| 7 | IP-Mining And Quarrying | 5 | 1 | Eurostat | 0.54 | 3 | 0.26 | 34 | 0.66 | 10 | 0.23 | 3 | 0.29 | 117 |
| 8 | IP-Manufacturing | 5 | 1 | Eurostat | 0.91 | 1 | 0.86 | 1 | 0.92 | 1 | 0.86 | 1 | 0.87 | 9 |
| 9 | IP-New Orders | 5 | 1 | Eurostat | 0.77 | 8 | 0.81 | 8 | 0.88 | 8 | 0.48 | 8 | 0.87 | 8 |
| 10 | Construction Production Index | 5 | 1 | Eurostat | 0.29 | 2 | 0.25 | 2 | 0.66 | 7 | 0.25 | 69 | 0.47 | 15 |
| 11 | Unemployment Rate (%) | 1 | 1 | Eurostat | 0.79 | 12 | 0.93 | 12 | 0.72 | 12 | 0.84 | 12 | 0.97 | 12 |
| 12 | Youth Unemployment Rate | 1 | 1 | Eurostat | 0.79 | 11 | 0.93 | 11 | 0.72 | 11 | 0.84 | 11 | 0.97 | 11 |
| 13 | Unemployment Total (1000 persons) | 5 | 1 | Eurostat | 0.41 | 39 | 0.46 | 112 | 0.33 | 42 | 0.25 | 40 | 0.51 | 79 |
| 14 | Retail Sale of Food, Bev. & Tobacco[a] | 5 | 1 | Eurostat | 0.52 | 17 | 0.47 | 17 | 0.80 | 17 | 0.28 | 17 | 0.62 | 17 |
| 15 | Retail Sale of Non-Food Products | 5 | 1 | Eurostat | 0.72 | 17 | 0.78 | 17 | 0.74 | 17 | 0.87 | 17 | 0.75 | 17 |
| 16 | Retail Sale of Textiles | 5 | 1 | Eurostat | 0.68 | 15 | 0.65 | 15 | 0.71 | 15 | 0.81 | 15 | 0.41 | 17 |
| 17 | Retail Trade | 5 | 1 | Eurostat | 0.72 | 15 | 0.78 | 15 | 0.80 | 14 | 0.87 | 15 | 0.75 | 15 |
| 18 | Passenger Car Registration (2005=100) | 5 | 1 | OECD | 0.24 | 113 | 0.32 | 114 | 0.21 | 88 | 0.23 | 1 | 0.33 | 15 |
| 19 | Exports Total[b] | 5 | 1 | Eurostat | 0.67 | 20 | 0.64 | 20 | 0.65 | 20 | 0.64 | 20 | 0.31 | 20 |
| 20 | Imports Total | 5 | 1 | Eurostat | 0.67 | 19 | 0.64 | 19 | 0.65 | 19 | 0.64 | 19 | 0.31 | 19 |
| 21 | Total Reserves Including Gold (Mil. Euro) | 5 | 1 | ECB | 0.56 | 60 | 0.43 | 105 | 0.34 | 105 | 0.45 | 105 | 0.30 | 101 |
| 22 | HICP All-Items (2005=100) | 5 | 1 | Eurostat | 0.83 | 26 | 0.76 | 26 | 0.93 | 26 | 0.93 | 26 | 0.67 | 23 |
| 23 | Overall Index Exc. Energy and Unp. Food | 5 | 1 | Eurostat | 0.53 | 27 | 0.85 | 27 | 0.61 | 22 | 0.86 | 22 | 0.67 | 22 |
| 24 | HICP-Energy And Unprocessed Food | 5 | 1 | Eurostat | 0.89 | 25 | 0.92 | 25 | 0.86 | 25 | 0.76 | 25 | 0.81 | 25 |
| 25 | HICP-Liquid Fuels | 5 | 1 | Eurostat | 0.89 | 24 | 0.92 | 24 | 0.86 | 24 | 0.76 | 24 | 0.81 | 24 |
| 26 | HICP-Goods | 5 | 1 | Eurostat | 0.83 | 22 | 0.83 | 24 | 0.93 | 22 | 0.93 | 22 | 0.49 | 23 |
| 27 | HICP-Services | 5 | 1 | Eurostat | 0.53 | 23 | 0.85 | 23 | 0.47 | 23 | 0.32 | 92 | 0.37 | 85 |
| 28 | HICP-Non-Energy Ind. Goods, Durable | 5 | 1 | Eurostat | 0.25 | 85 | 0.25 | 15 | 0.32 | 23 | 0.32 | 59 | 0.31 | 75 |

| No. | Description | Tr. | S/F | Source | EA-17 | | DE | | FR | | IT | | ES | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | $\hat{\tau}_1^*$ | $j_1$ | $\hat{\tau}_1^*$ | $j_1$ | $\hat{\tau}_1^*$ | $j_1$ | $\hat{\tau}_1^*$ | $j_1$ | $\hat{\tau}_1^*$ | $j_1$ |
| 29 | HICP-Non-Energy Ind. G., Non-durable | 5 | 1 | Eurostat | 0.22 | 22 | 0.28 | 23 | 0.28 | 23 | 0.42 | 34 | 0.24 | 94 |
| 30 | PPI-Industry | 5 | 1 | Eurostat | 0.79 | 35 | 0.53 | 78 | 0.87 | 35 | 0.81 | 35 | 0.89 | 35 |
| 31 | PPI-Intermediate and Capital Goods | 5 | 1 | Eurostat | 0.37 | 83 | 0.40 | 82 | 0.33 | 107 | 0.49 | 30 | 0.53 | 83 |
| 32 | PPI-Durable Consumer Goods | 5 | 1 | Eurostat | 0.40 | 95 | 0.33 | 62 | 0.33 | 96 | 0.23 | 19 | 0.23 | 111 |
| 33 | PPI-Non-Durable Consumer Goods | 5 | 1 | Eurostat | 0.35 | 25 | 0.27 | 76 | 0.41 | 64 | 0.34 | 31 | 0.38 | 26 |
| 34 | PPI-Mining and Quarrying | 5 | 1 | Eurostat | 0.29 | 31 | 0.40 | 30 | 0.30 | 33 | 0.42 | 29 | 0.27 | 18 |
| 35 | PPI-Manufacturing | 5 | 1 | Eurostat | 0.79 | 30 | 0.55 | 25 | 0.87 | 30 | 0.81 | 30 | 0.89 | 30 |
| 36 | Crude Oil (West Texas Int., $/BBL) | 5 | 0 | WSJ | 0.53 | 25 | 0.53 | 89 | 0.60 | 25 | 0.57 | 25 | 0.57 | 25 |
| 37 | CRB[c] Spot Index (1967=100) | 5 | 0 | CRB | 0.34 | 49 | 0.39 | 101 | 0.37 | 101 | 0.30 | 101 | 0.38 | 75 |
| 38 | ECB Commodity Price Index (2000=100) | 5 | 0 | ECB | 0.57 | 105 | 0.54 | 105 | 0.57 | 105 | 0.57 | 105 | 0.52 | 101 |
| 39 | 3M Euribor (%) | 1 | 0 | Datastream | 0.98 | 40 | 0.97 | 40 | 0.98 | 40 | 0.97 | 40 | 0.96 | 40 |
| 40 | 6M Euribor | 1 | 0 | Datastream | 0.98 | 39 | 0.97 | 39 | 0.98 | 39 | 0.97 | 39 | 0.97 | 41 |
| 41 | 1Y Euribor | 1 | 0 | Datastream | 0.96 | 40 | 0.95 | 40 | 0.96 | 40 | 0.96 | 40 | 0.97 | 40 |
| 42 | 5Y Government Bond Yield | 1 | 0 | Datastream | 0.83 | 43 | 0.87 | 43 | 0.92 | 43 | 0.94 | 43 | 0.92 | 43 |
| 43 | 10Y Government Bond Yield | 1 | 0 | OECD | 0.83 | 42 | 0.87 | 42 | 0.92 | 42 | 0.94 | 42 | 0.92 | 42 |
| 44 | Spread 3M-REFI | 1 | 0 | Calculated | 0.91 | 45 | 0.91 | 45 | 0.91 | 45 | 0.91 | 45 | 0.84 | 45 |
| 45 | Spread 6M-REFI | 1 | 0 | Calculated | 0.95 | 46 | 0.94 | 46 | 0.94 | 46 | 0.94 | 46 | 0.93 | 46 |
| 46 | Spread 1Y-REFI | 1 | 0 | Calculated | 0.95 | 45 | 0.94 | 45 | 0.94 | 45 | 0.94 | 45 | 0.93 | 45 |
| 47 | Spread 5Y-REFI | 1 | 0 | Calculated | 0.82 | 48 | 0.94 | 48 | 0.92 | 48 | 0.94 | 48 | 0.92 | 48 |
| 48 | Spread 10Y-REFI | 1 | 0 | Calculated | 0.82 | 47 | 0.94 | 47 | 0.92 | 47 | 0.94 | 47 | 0.92 | 47 |
| 49 | Euro Stoxx 50 (Points) | 5 | 0 | Eurostat | 0.58 | 51 | 0.64 | 51 | 0.82 | 54 | 0.75 | 56 | 0.85 | 56 |
| 50 | Share Price Index-Basic Materials | 5 | 0 | Datastream | 0.44 | 56 | 0.51 | 49 | 0.65 | 49 | 0.39 | 39 | 0.44 | 51 |
| 51 | Share Price Index-Industrials | 5 | 0 | Datastream | 0.71 | 54 | 0.64 | 49 | 0.77 | 49 | 0.67 | 49 | 0.59 | 49 |
| 52 | Share Price Index-Consumer Goods | 5 | 0 | Datastream | 0.42 | 50 | 0.32 | 49 | 0.63 | 49 | 0.54 | 56 | 0.35 | 107 |
| 53 | Share Price Index-Health Care | 5 | 0 | Datastream | 0.33 | 56 | 0.37 | 54 | 0.43 | 49 | 0.41 | 52 | 0.32 | 107 |
| 54 | Share Price Index-Consumer Services | 5 | 0 | Datastream | 0.71 | 51 | 0.51 | 22 | 0.82 | 49 | 0.65 | 49 | 0.53 | 49 |
| 55 | Share Price Index-Telecommunication | 5 | 0 | Datastream | 0.51 | 54 | 0.37 | 49 | 0.49 | 54 | 0.58 | 51 | 0.67 | 49 |
| 56 | Share Price Index-Financials | 5 | 0 | Datastream | 0.52 | 51 | 0.51 | 25 | 0.80 | 49 | 0.75 | 49 | 0.85 | 49 |

| No. | Description | Tr. | S/F | Source | EA-17 | | DE | | FR | | IT | | ES | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | $\hat{\tau}_1^*$ | $j_1$ | $\hat{\tau}_1^*$ | $j_1$ | $\hat{\tau}_1^*$ | $j_1$ | $\hat{\tau}_1^*$ | $j_1$ | $\hat{\tau}_1^*$ | $j_1$ |
| 57 | Share Price Index-Technology | 5 | 0 | Datastream | 0.54 | 49 | 0.44 | 54 | 0.72 | 49 | 0.29 | 33 | 0.32 | 87 |
| 58 | Share Price Index-Utilities | 5 | 0 | Datastream | 0.57 | 49 | 0.27 | 35 | 0.59 | 51 | 0.61 | 49 | 0.65 | 49 |
| 59 | Currency in Circulation (Mil. Euro) | 5 | 0 | Eurostat | 0.41 | 85 | 0.27 | 85 | 0.47 | 61 | 0.32 | 28 | 0.30 | 106 |
| 60 | Capital And Reserves | 5 | 0 | Eurostat | 0.56 | 21 | 0.32 | 70 | 0.24 | 108 | 0.45 | 67 | 0.31 | 61 |
| 61 | Money Stock: M1 | 5 | 0 | ECB | 0.72 | 68 | 0.77 | 62 | 0.81 | 62 | 0.99 | 68 | 1.00 | 68 |
| 62 | Money Stock: M2 | 5 | 0 | ECB | 0.82 | 63 | 0.87 | 63 | 0.81 | 61 | 0.80 | 61 | 0.61 | 63 |
| 63 | Money Stock: M3 | 5 | 0 | ECB | 0.82 | 62 | 0.87 | 62 | 0.59 | 62 | 0.64 | 62 | 0.61 | 62 |
| 64 | Deposits with Agreed Maturity up to 2Y | 5 | 0 | Eurostat | 0.54 | 95 | 0.57 | 68 | 0.56 | 62 | 0.45 | 73 | 0.62 | 80 |
| 65 | External Assets | 5 | 0 | Eurostat | 0.83 | 66 | 0.53 | 66 | 0.76 | 66 | 0.32 | 66 | 0.31 | 112 |
| 66 | External Liabilities | 5 | 0 | Eurostat | 0.83 | 65 | 0.53 | 65 | 0.76 | 65 | 0.32 | 65 | 0.25 | 38 |
| 67 | Total Deposits of Residents Held At MFI | 5 | 0 | Eurostat | 0.55 | 95 | 0.50 | 63 | 0.43 | 68 | 0.80 | 70 | 0.64 | 70 |
| 68 | Overnight Deposits | 5 | 0 | Eurostat | 0.72 | 61 | 0.69 | 61 | 0.48 | 61 | 0.99 | 61 | 1.00 | 61 |
| 69 | Repurchase Agreements | 5 | 0 | Eurostat | 0.37 | 93 | 0.23 | 32 | 0.47 | 63 | 0.40 | 73 | 0.31 | 63 |
| 70 | Credit to Total Residents Granted by MFI | 5 | 0 | Eurostat | 0.49 | 71 | 0.47 | 72 | 0.42 | 72 | 0.80 | 67 | 0.64 | 67 |
| 71 | Loans to General Govt. Granted by MFI | 5 | 0 | Eurostat | 0.54 | 67 | 0.35 | 67 | 0.27 | 67 | 0.76 | 67 | 0.25 | 24 |
| 72 | Loans to Other Residents Granted By MFI | 5 | 0 | Eurostat | 0.50 | 120 | 0.47 | 70 | 0.42 | 70 | 0.56 | 70 | 0.55 | 61 |
| 73 | Debt Securities of EA Residents | 5 | 0 | Eurostat | 0.66 | 20 | 0.29 | 70 | 0.24 | 96 | 0.48 | 42 | 0.30 | 42 |
| 74 | Central Bank Claims on Banking Inst. | 5 | 0 | Eurostat | 0.35 | 66 | 0.29 | 65 | 0.29 | 59 | 0.20 | 106 | 0.25 | 102 |
| 75 | Economic Sentiment Indicator (Index) | 5 | 0 | Eurostat | 0.83 | 80 | 0.76 | 80 | 0.86 | 77 | 0.75 | 80 | 0.88 | 79 |
| 76 | Construction Confidence Indicator (%) | 1 | 0 | Eurostat | 0.94 | 84 | 0.95 | 84 | 0.90 | 84 | 0.75 | 84 | 0.84 | 84 |
| 77 | Industrial Confidence Indicator | 1 | 0 | Eurostat | 0.82 | 82 | 0.79 | 82 | 0.86 | 75 | 0.82 | 82 | 0.63 | 81 |
| 78 | Retail Confidence Indicator | 1 | 0 | Eurostat | 0.60 | 93 | 0.55 | 75 | 0.59 | 43 | 0.64 | 11 | 0.86 | 80 |
| 79 | Consumer Confidence Indicator (2005=100) | 5 | 0 | OECD | 0.70 | 75 | 0.73 | 75 | 0.53 | 75 | 0.60 | 94 | 0.88 | 75 |
| 80 | Services Confidence Indicator (%) | 1 | 0 | Eurostat | 0.83 | 75 | 0.76 | 75 | 0.83 | 75 | 0.75 | 75 | 0.86 | 78 |
| 81 | Employment Expec. for the Months Ahead | 1 | 0 | Eurostat | 0.78 | 77 | 0.72 | 77 | 0.72 | 77 | 0.63 | 77 | 0.63 | 77 |
| 82 | Production Expec. for the Months Ahead | 1 | 0 | Eurostat | 0.82 | 77 | 0.79 | 77 | 0.80 | 77 | 0.82 | 77 | 0.62 | 77 |
| 83 | Selling Price Expec. for the Months Ahead | 1 | 0 | Eurostat | 0.78 | 77 | 0.67 | 77 | 0.67 | 95 | 0.72 | 77 | 0.55 | 77 |
| 84 | Assessment of Order Books | 1 | 0 | Eurostat | 0.94 | 76 | 0.95 | 76 | 0.90 | 76 | 0.75 | 76 | 0.84 | 76 |

| No. | Description | Tr. | S/F | Source | EA-17 | | DE | | FR | | IT | | ES | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | $\hat{\tau}_1^*$ | $j_1$ | $\hat{\tau}_1^*$ | $j_1$ | $\hat{\tau}_1^*$ | $j_1$ | $\hat{\tau}_1^*$ | $j_1$ | $\hat{\tau}_1^*$ | $j_1$ |
| 85 | Price Trends Over The Next 12 Months | 1 | 0 | Eurostat | 0.52 | 81 | 0.41 | 84 | 0.63 | 95 | 0.74 | 43 | 0.48 | 95 |
| 86 | IP-USA (2005=100) | 5 | 1 | OECD | 0.26 | 40 | 0.32 | 95 | 0.43 | 40 | 0.39 | 82 | 0.36 | 39 |
| 87 | IP-UK | 5 | 1 | OECD | 0.24 | 69 | 0.27 | 65 | 0.21 | 22 | 0.20 | 7 | 0.32 | 57 |
| 88 | IP-JP | 5 | 1 | OECD | 0.33 | 23 | 0.30 | 26 | 0.40 | 70 | 0.22 | 23 | 0.41 | 22 |
| 89 | CPI-USA | 5 | 1 | OECD | 0.54 | 25 | 0.53 | 36 | 0.60 | 25 | 0.59 | 25 | 0.58 | 25 |
| 90 | CPI-UK | 5 | 1 | OECD | 0.38 | 79 | 0.40 | 75 | 0.45 | 30 | 0.40 | 24 | 0.47 | 78 |
| 91 | CPI-JP | 5 | 1 | OECD | 0.26 | 79 | 0.29 | 89 | 0.29 | 89 | 0.31 | 79 | 0.28 | 89 |
| 92 | US Federal Funds Target Rate (%) | 1 | 0 | FED | 0.54 | 80 | 0.50 | 95 | 0.52 | 11 | 0.51 | 97 | 0.54 | 97 |
| 93 | UK Bank Of England Base Rate | 1 | 0 | BoE | 0.68 | 76 | 0.80 | 11 | 0.65 | 81 | 0.47 | 96 | 0.57 | 110 |
| 94 | JP Overnight Call Money Rate | 1 | 0 | BoJ | 0.50 | 95 | 0.56 | 40 | 0.52 | 48 | 0.62 | 11 | 0.68 | 80 |
| 95 | 10Y Bond Yield USA | 1 | 0 | OECD | 0.78 | 96 | 0.66 | 48 | 0.76 | 96 | 0.69 | 96 | 0.69 | 96 |
| 96 | 10Y Bond Yield UK | 1 | 0 | OECD | 0.78 | 95 | 0.68 | 48 | 0.76 | 95 | 0.69 | 95 | 0.69 | 95 |
| 97 | 10Y Bond Yield JP | 1 | 0 | OECD | 0.48 | 46 | 0.52 | 76 | 0.54 | 12 | 0.51 | 92 | 0.54 | 92 |
| 98 | Share Price Index-USA (Dow 30, Points) | 5 | 0 | Reuters | 0.86 | 99 | 0.86 | 99 | 0.86 | 99 | 0.87 | 99 | 0.85 | 99 |
| 99 | Share Price Index-UK (FTSE 100, Points) | 5 | 0 | Reuters | 0.86 | 98 | 0.86 | 98 | 0.86 | 98 | 0.87 | 98 | 0.85 | 98 |
| 100 | Share Price Index-JP (Nikkei 225, Points) | 5 | 0 | Reuters | 0.56 | 98 | 0.54 | 98 | 0.55 | 98 | 0.57 | 98 | 0.56 | 98 |
| 101 | US Dollar-Euro (Monthly average) | 5 | 0 | Eurostat | 0.93 | 105 | 0.87 | 105 | 0.91 | 105 | 0.92 | 105 | 0.83 | 105 |
| 102 | Pound Sterling-Euro | 5 | 0 | Eurostat | 0.64 | 105 | 0.58 | 105 | 0.63 | 105 | 0.63 | 105 | 0.60 | 105 |
| 103 | Swiss Franc-Euro | 5 | 0 | Eurostat | 0.32 | 99 | 0.36 | 98 | 0.38 | 98 | 0.34 | 98 | 0.34 | 104 |
| 104 | Japanese Yen-Euro | 5 | 0 | Eurostat | 0.66 | 105 | 0.63 | 101 | 0.64 | 101 | 0.66 | 105 | 0.63 | 101 |
| 105 | REER (1999=100) | 5 | 0 | Eurostat | 0.93 | 101 | 0.87 | 101 | 0.91 | 101 | 0.92 | 101 | 0.83 | 101 |
| 106 | Capacity Utilisation Rate (%)* | 1 | 1 | ECB | 0.50 | 77 | 0.73 | 77 | 0.50 | 12 | 0.51 | 81 | 0.52 | 77 |
| 107 | Gross Domestic Product[d] * | 5 | 1 | Eurostat | 0.91 | 113 | 0.96 | 113 | 0.85 | 113 | 0.84 | 113 | 0.66 | 108 |
| 108 | Final Consumption Expenditure* | 5 | 1 | Eurostat | 0.79 | 107 | 0.30 | 47 | 0.43 | 93 | 0.65 | 107 | 0.66 | 107 |
| 109 | Gross Fixed Capital Formation* | 5 | 1 | Eurostat | 0.70 | 107 | 0.63 | 107 | 0.59 | 8 | 0.44 | 49 | 0.61 | 107 |
| 110 | Employment Total (1000 persons)* | 5 | 1 | Eurostat | 0.97 | 111 | 0.98 | 111 | 1.00 | 111 | 0.90 | 111 | 0.87 | 111 |
| 111 | Employees Total* | 5 | 1 | Eurostat | 0.97 | 110 | 0.98 | 110 | 1.00 | 110 | 0.90 | 110 | 0.87 | 110 |
| 112 | Self Employed Total* | 5 | 1 | Eurostat | 0.45 | 110 | 0.58 | 76 | 0.60 | 43 | 0.26 | 70 | 0.43 | 110 |

| No. | Description | Tr. | S/F | Source | EA-17 | | DE | | FR | | IT | | ES | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | $\hat{\tau}_1^*$ | $j_1$ | $\hat{\tau}_1^*$ | $j_1$ | $\hat{\tau}_1^*$ | $j_1$ | $\hat{\tau}_1^*$ | $j_1$ | $\hat{\tau}_1^*$ | $j_1$ |
| 113 | Real Labour Prod. per Person Employed[e*] | 5 | 1 | ECB | 0.91 | 107 | 0.96 | 107 | 0.85 | 107 | 0.84 | 107 | 0.68 | 111 |
| 114 | Real Unit Labour Cost* | 5 | 1 | Eurostat | 0.69 | 116 | 0.84 | 113 | 0.61 | 113 | 0.64 | 113 | 0.38 | 109 |
| 115 | Earnings per Employee (Current, Euro)* | 5 | 1 | Oxd. Econ. | 0.91 | 116 | 0.97 | 116 | 0.85 | 116 | 0.88 | 116 | 0.65 | 113 |
| 116 | Wages and Salaries (Current, Bil. Euro)* | 5 | 1 | Oxd. Econ. | 0.91 | 115 | 0.97 | 115 | 0.85 | 115 | 0.88 | 115 | 0.49 | 115 |
| 117 | Current Account (Net, Mil. Euro, World)* | 2 | 1 | OECD | 0.39 | 116 | 0.39 | 114 | 0.48 | 115 | 0.34 | 25 | 0.77 | 119 |
| 118 | Capital Account* | 2 | 1 | OECD | 0.44 | 51 | 0.16 | 53 | 0.36 | 58 | 0.19 | 34 | 0.51 | 119 |
| 119 | Financial Account* | 2 | 1 | OECD | 0.52 | 21 | 0.31 | 115 | 0.21 | 6 | 0.35 | 25 | 0.77 | 117 |
| 120 | ECB Official Refinancing Operation Rate (%) | 1 | 0 | Eurostat | 0.90 | 39 | 0.85 | 39 | 0.89 | 39 | 0.88 | 39 | 0.91 | 39 |

[a] (2005=100), [b] (vis-a-vis World, Trade value, Mil. Euro), [c] Commodity Research Bureau, [d] (Chained at Market Prices, Mil. 2000 Euro), [e] (2000=100)
An asterisk (*) denotes the variable is originally available in quarterly frequency.

APPENDIX L

# MODEL SPECIFICATIONS

## L.1 Explanatory Power of Factors

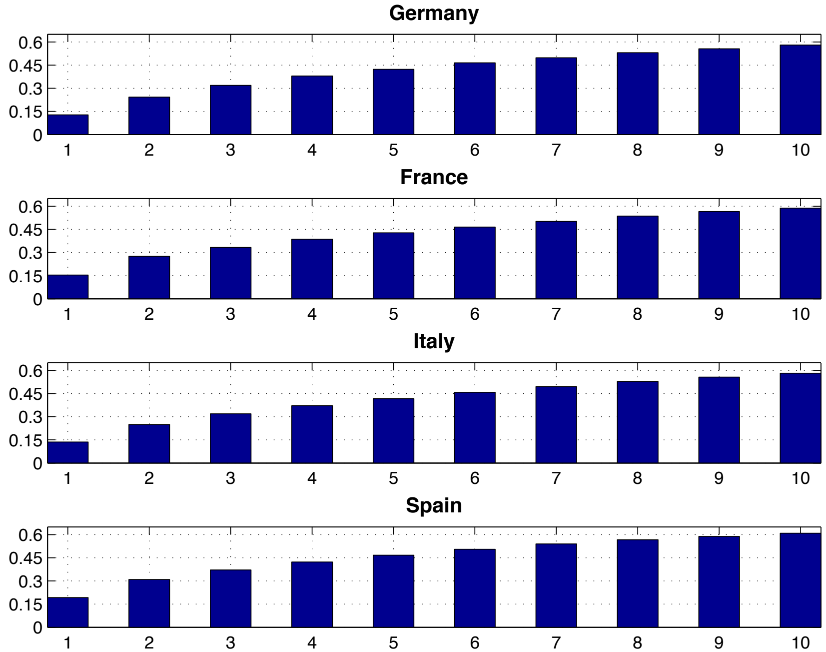



Figure L.1.1: All Variables - Country Level

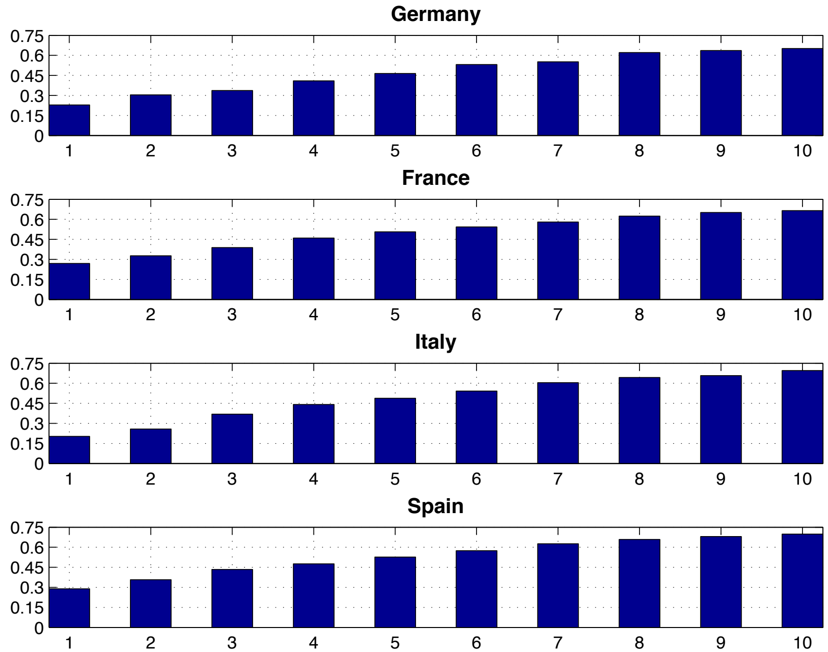



Figure L.1.2: Main Variables - Country Level

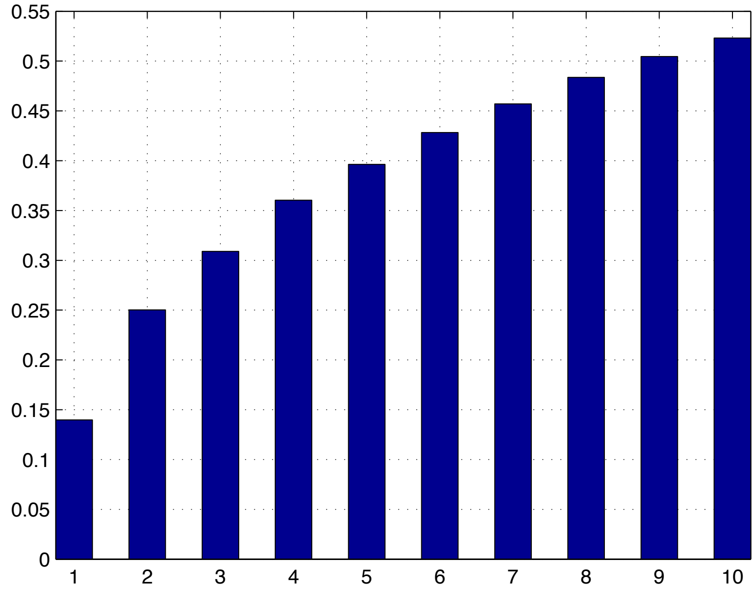



Figure L.1.3: All Variables - Area Wide

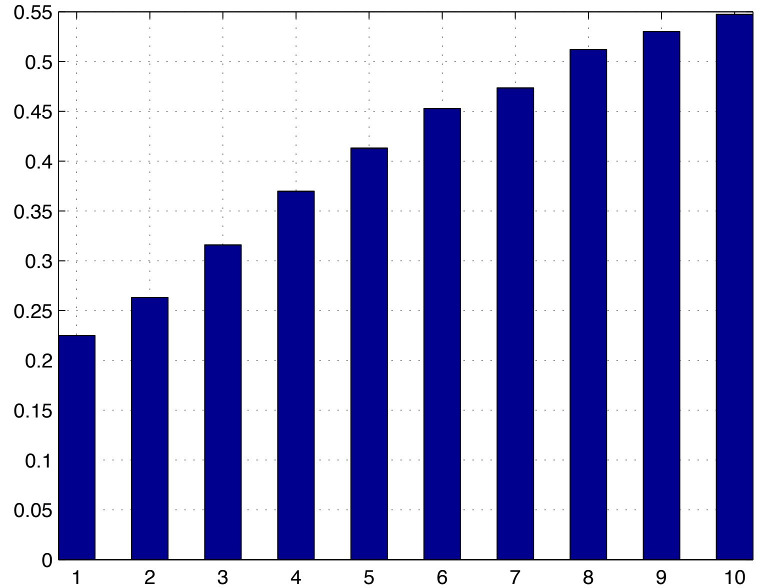



Figure L.1.4: Main Variables - Area Wide

APPENDIX M

# CONFIDENCE INTERVALS

This appendix presents the confidence intervals of the impulse responses analysed in the text. The dashed lines in the figures are the 16th and 84th quantiles of the Gibbs draws.

## M.1 Pre-BN Analysis

### M.1.1 Country-Level Approach

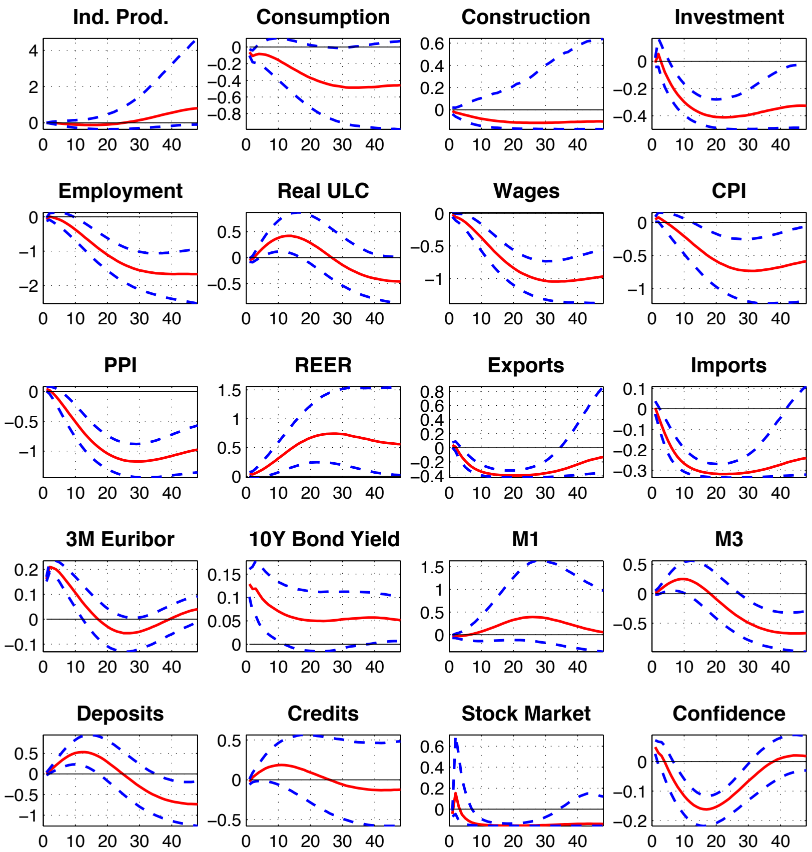



Figure M.1.1: Confidence Intervals - Country-level: Germany

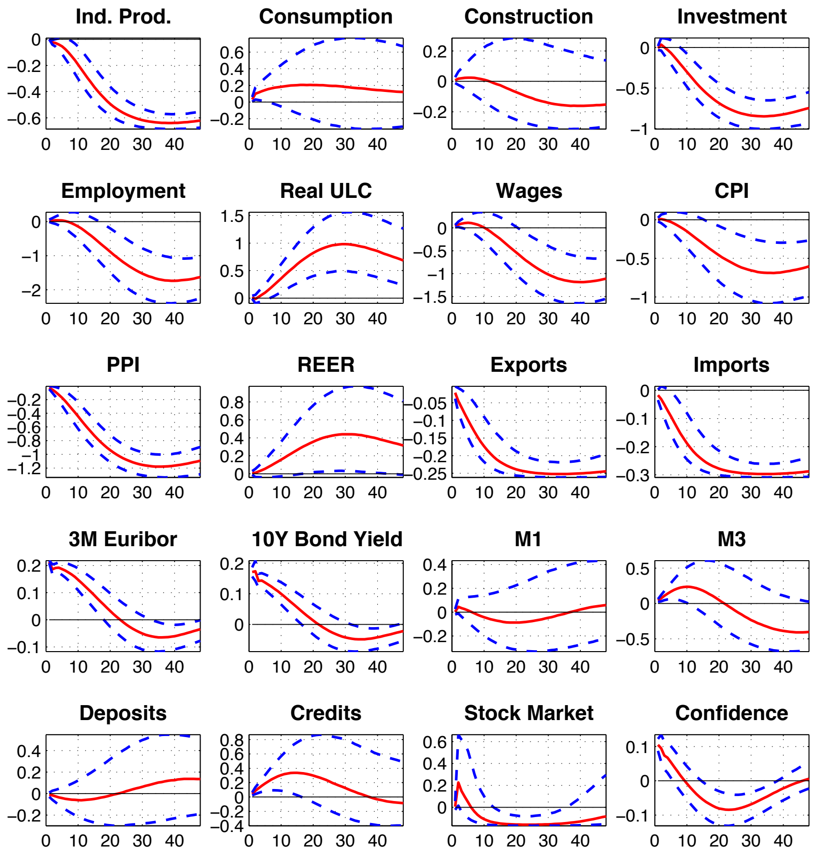



Figure M.1.2: Confidence Intervals - Country-level: France

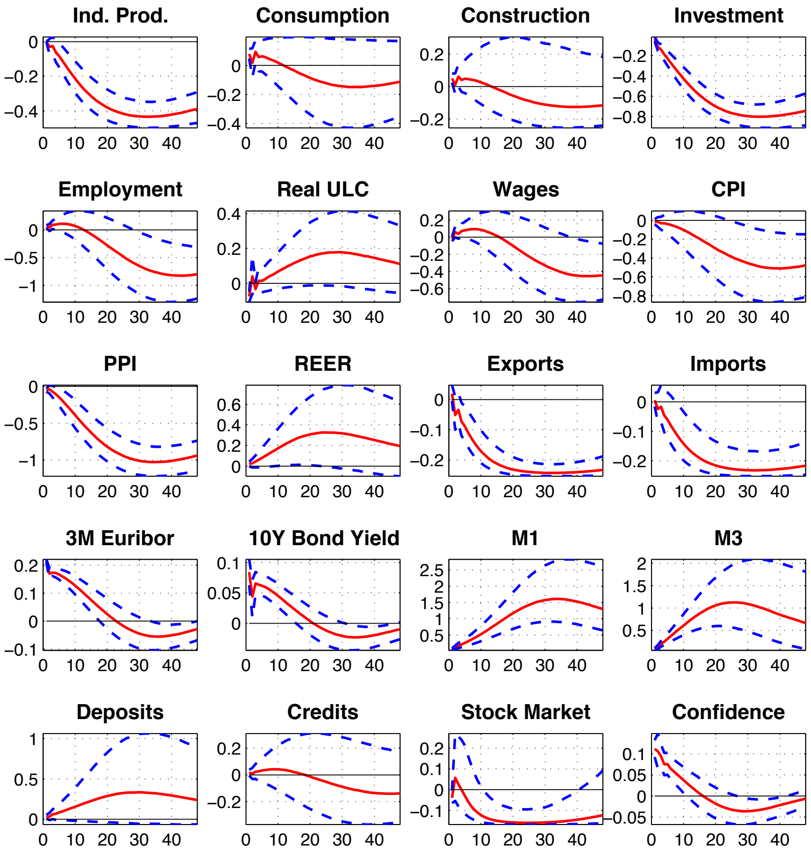



Figure M.1.3: Confidence Intervals - Country-level: Italy

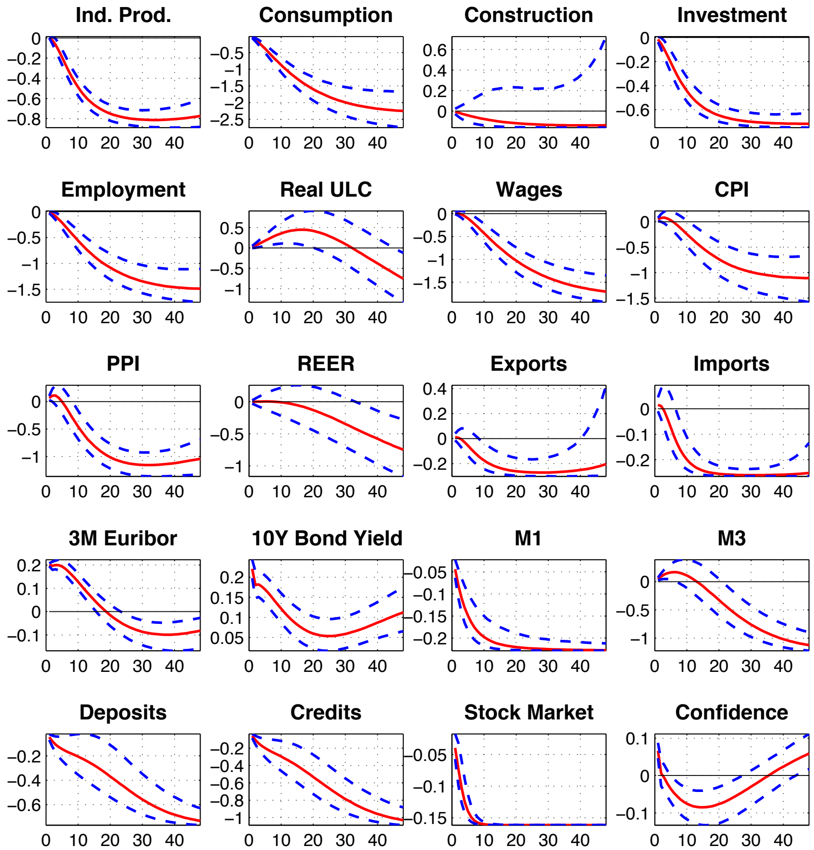



Figure M.1.4: Confidence Intervals - Country-level: Spain

## M.1.2 Panel Approach

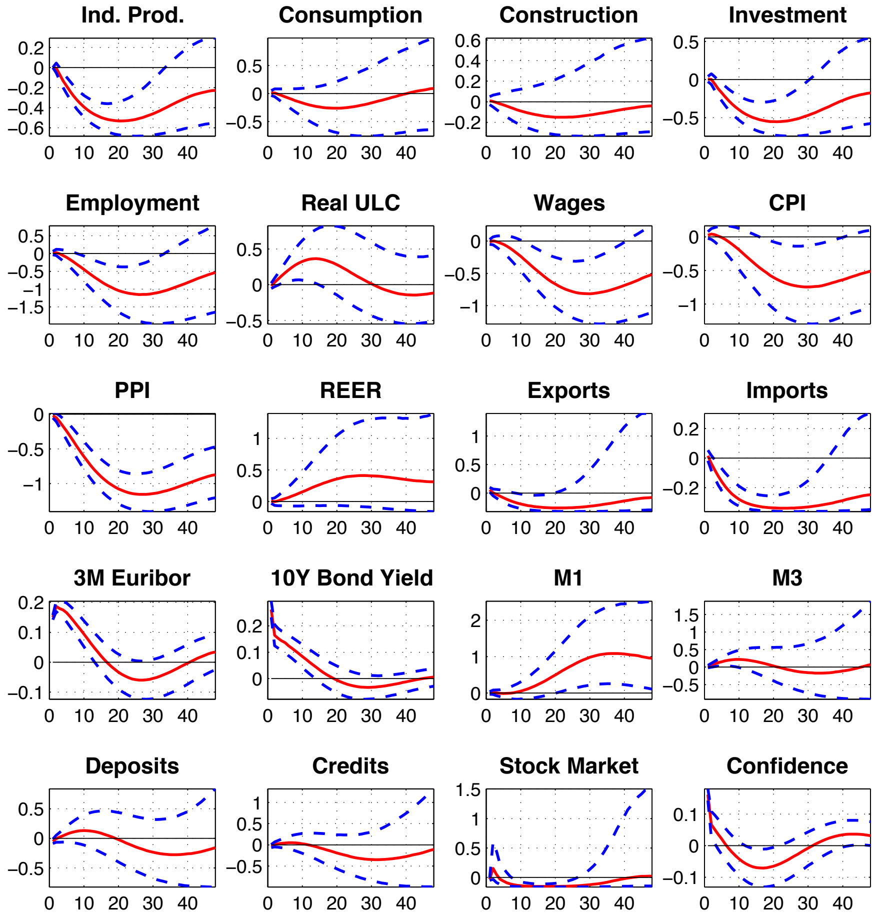



Figure M.1.5: Confidence Intervals - Area-wide: EA

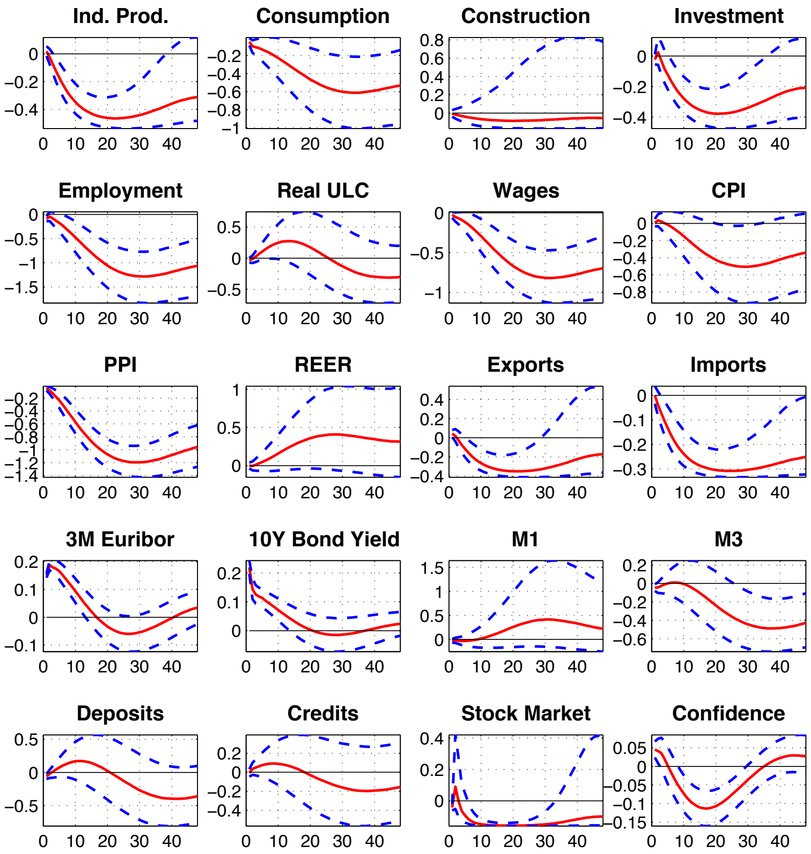



Figure M.1.6: Confidence Intervals - Area-wide: Germany

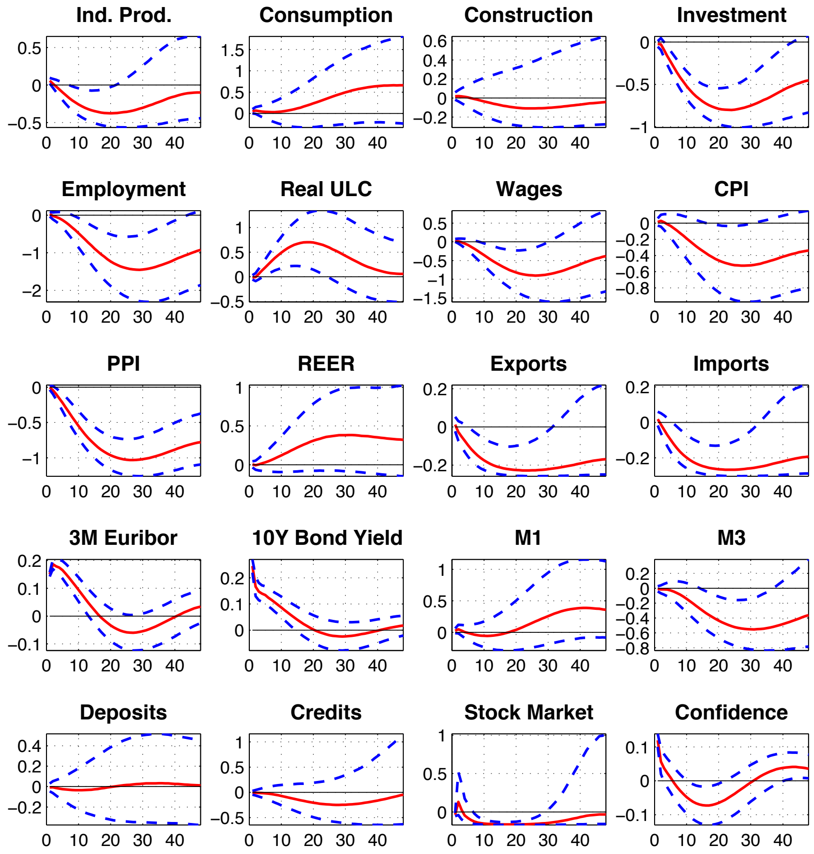



Figure M.1.7: Confidence Intervals - Area-wide: France

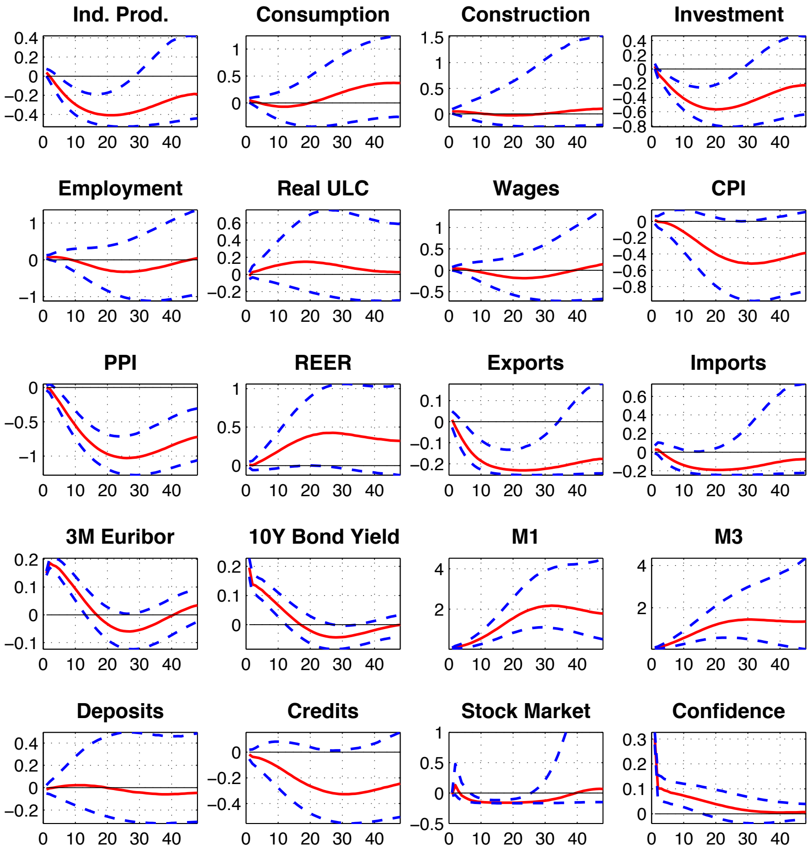



Figure M.1.8: Confidence Intervals - Area-wide: Italy

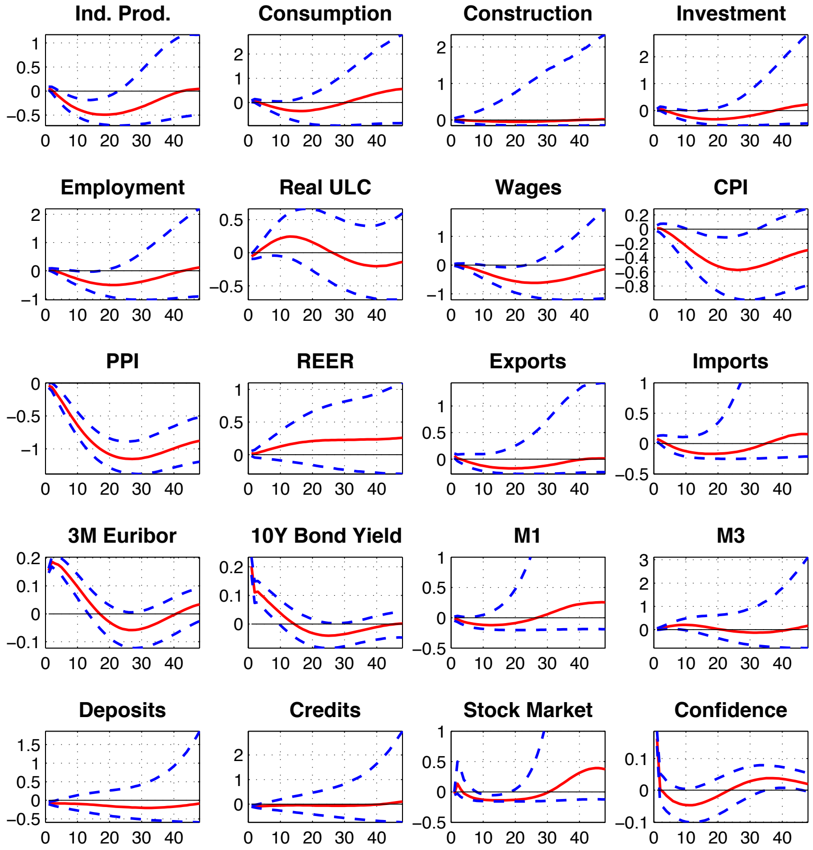



Figure M.1.9: Confidence Intervals - Area-wide: Spain

## M.1.3 Time Variation

### Germany

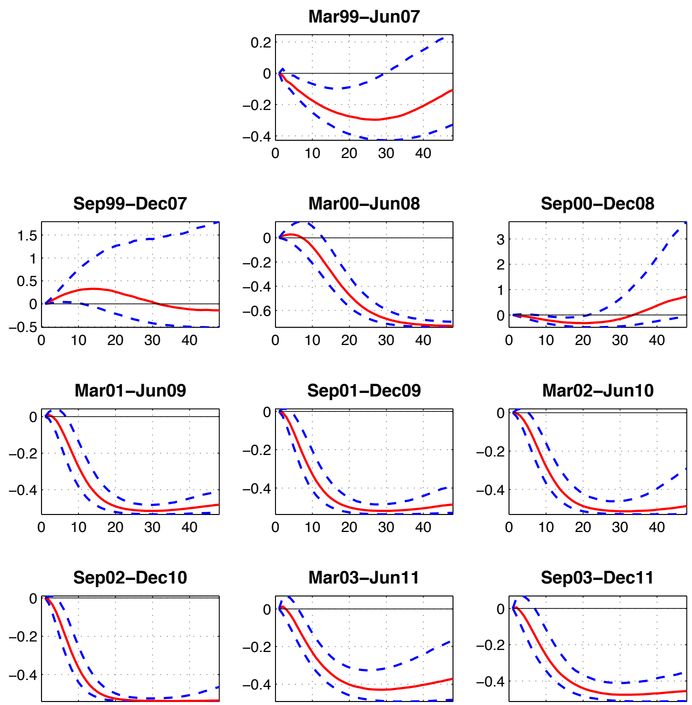



Figure M.1.10: Rollings - CL - IP: Germany

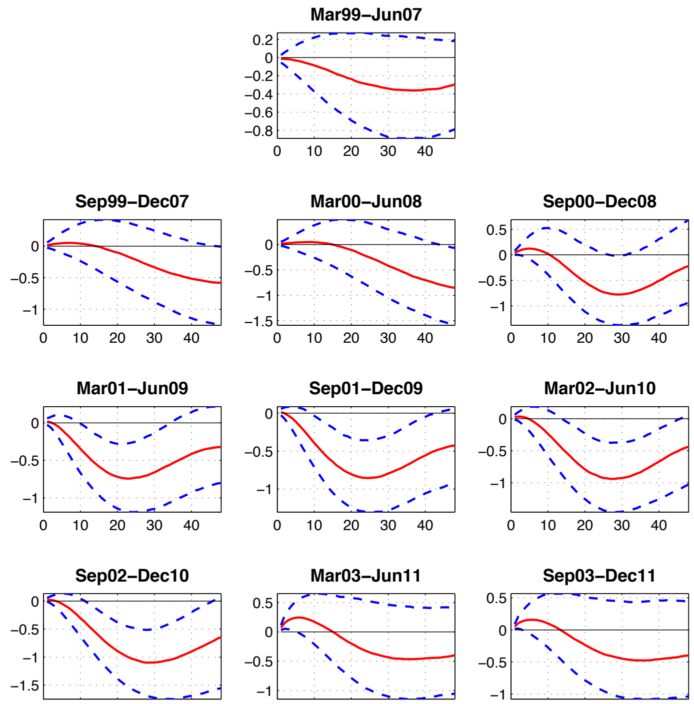



Figure M.1.11: Rollings - CL - CPI: Germany

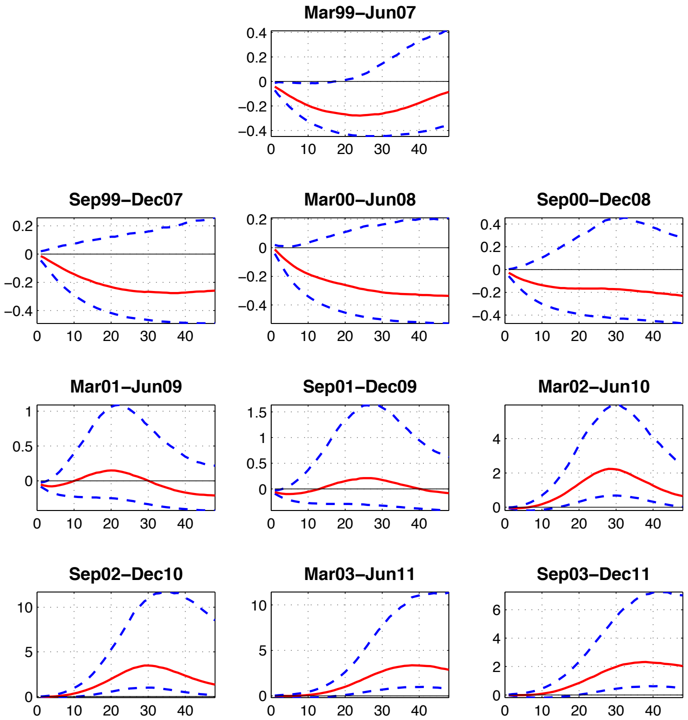



Figure M.1.12: Rollings - CL - M1: Germany

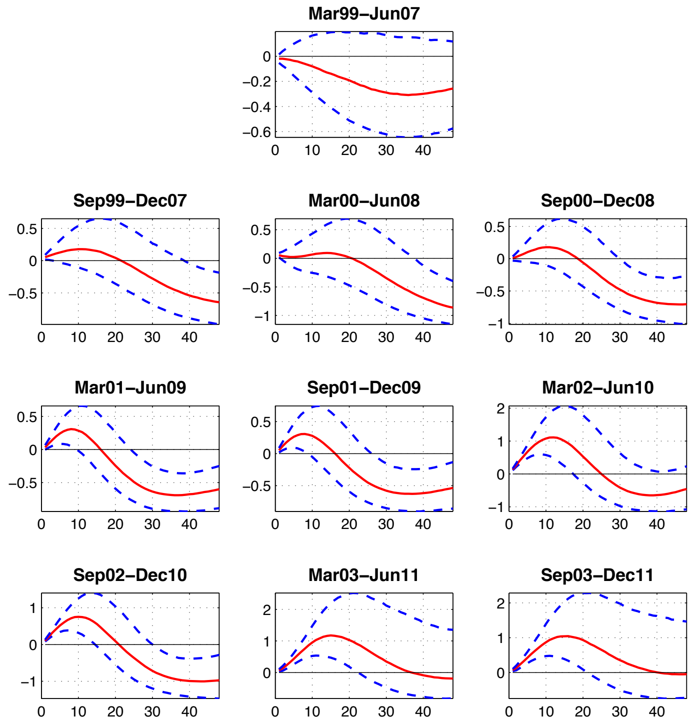



Figure M.1.13: Rollings - CL - M3: Germany

## France

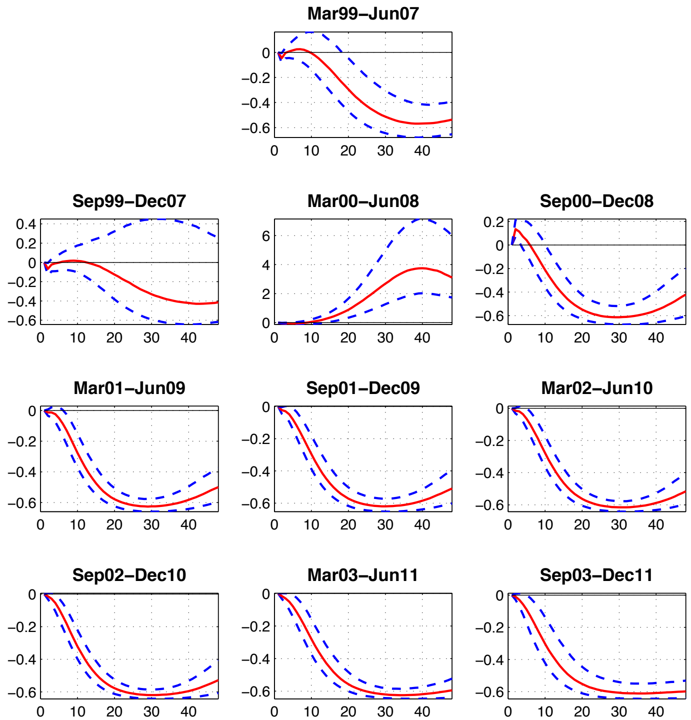



Figure M.1.14: Rollings - CL - IP: France

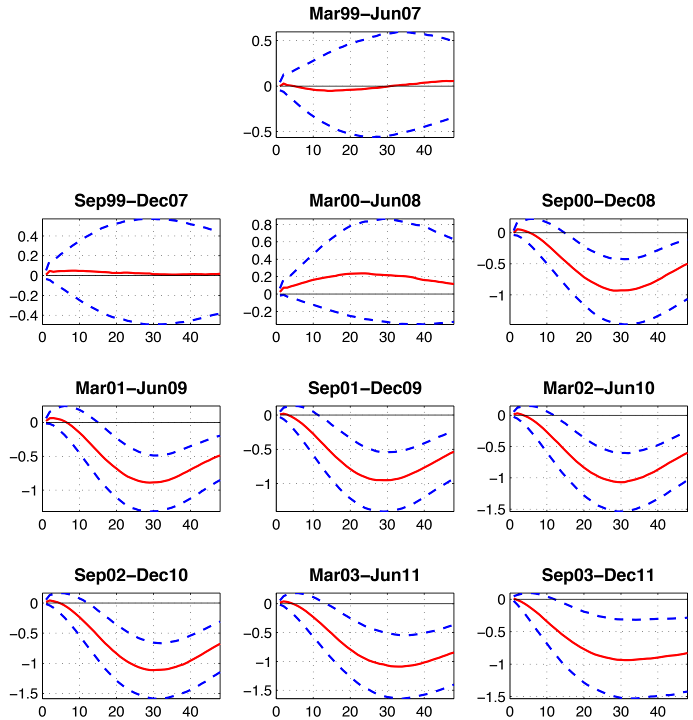



Figure M.1.15: Rollings - CL - CPI: France

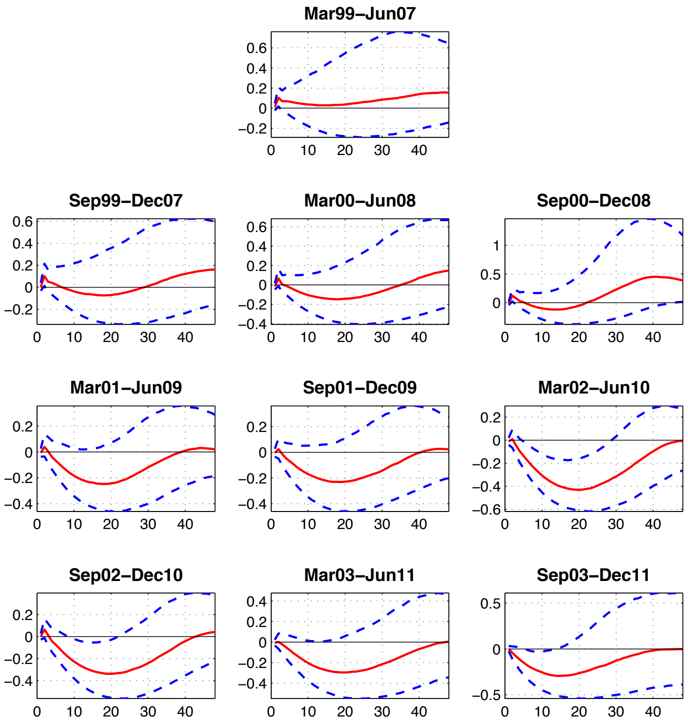



Figure M.1.16: Rollings - CL - M1: France

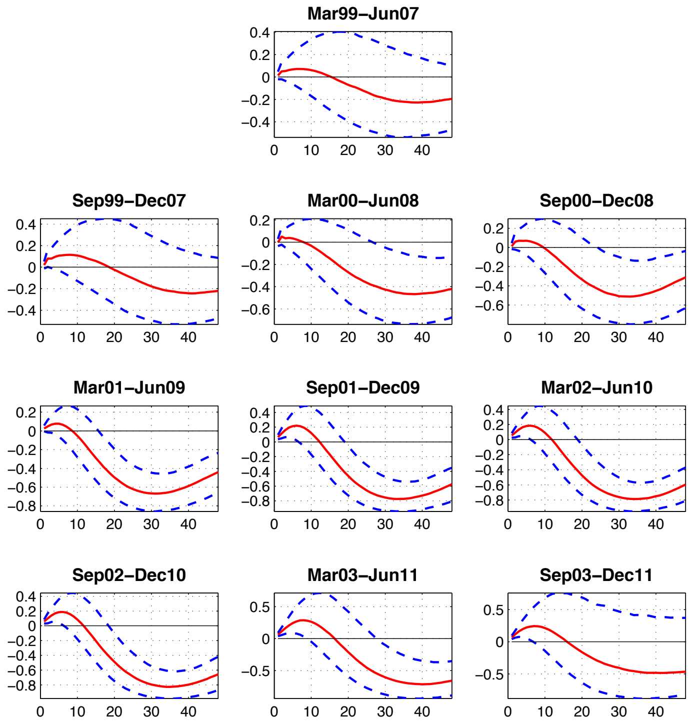



Figure M.1.17: Rollings - CL - M3: France

## Italy

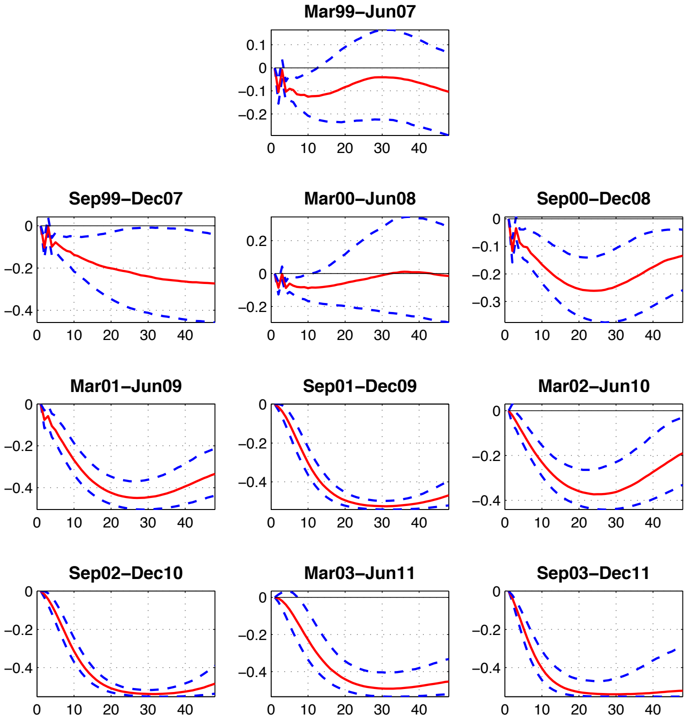



Figure M.1.18: Rollings - CL - IP: Italy

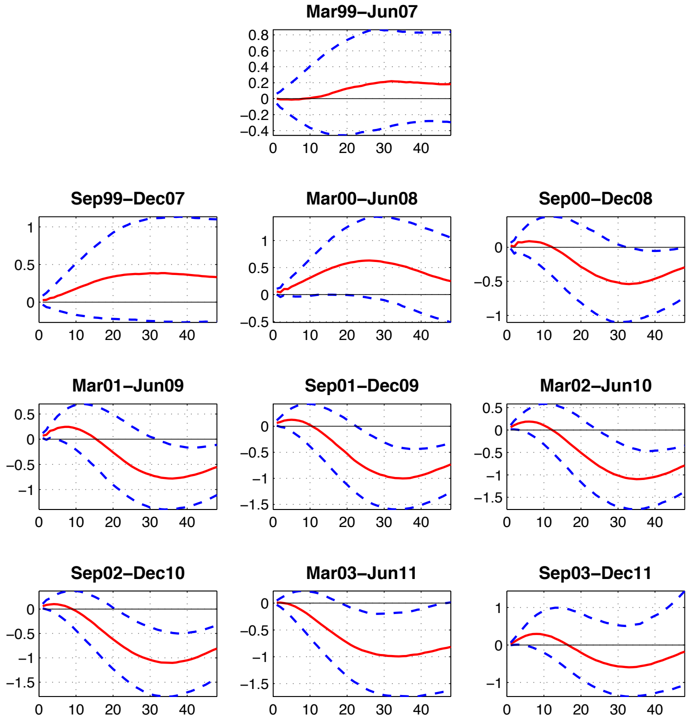



Figure M.1.19: Rollings - CL - CPI: Italy

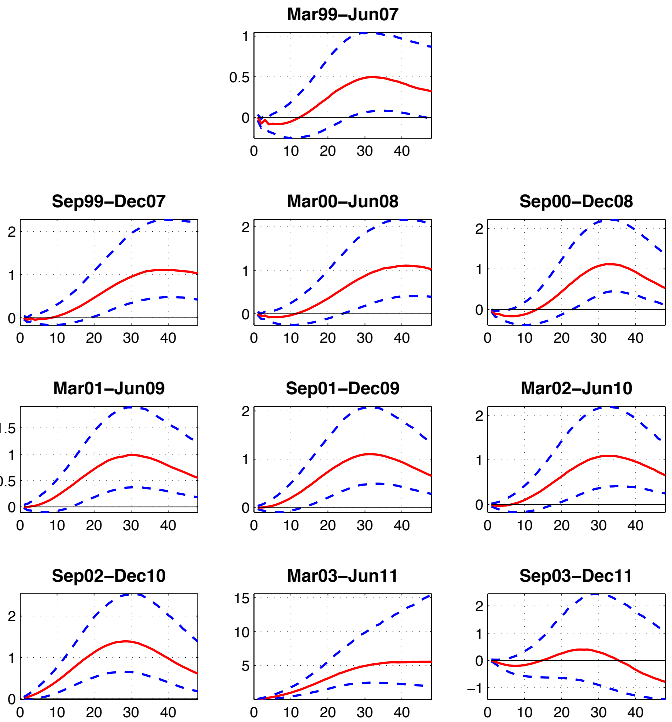



Figure M.1.20: Rollings - CL - M1: Italy

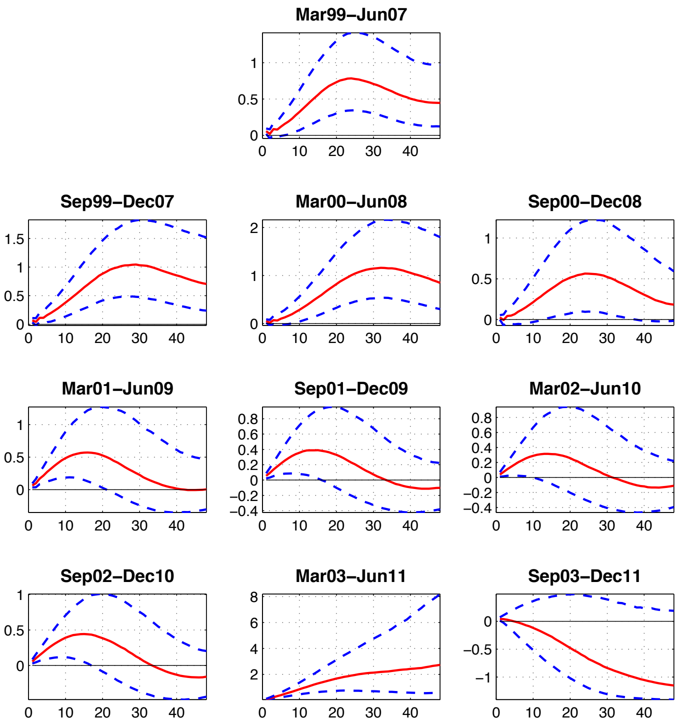



Figure M.1.21: Rollings - CL - M3: Italy

## Spain

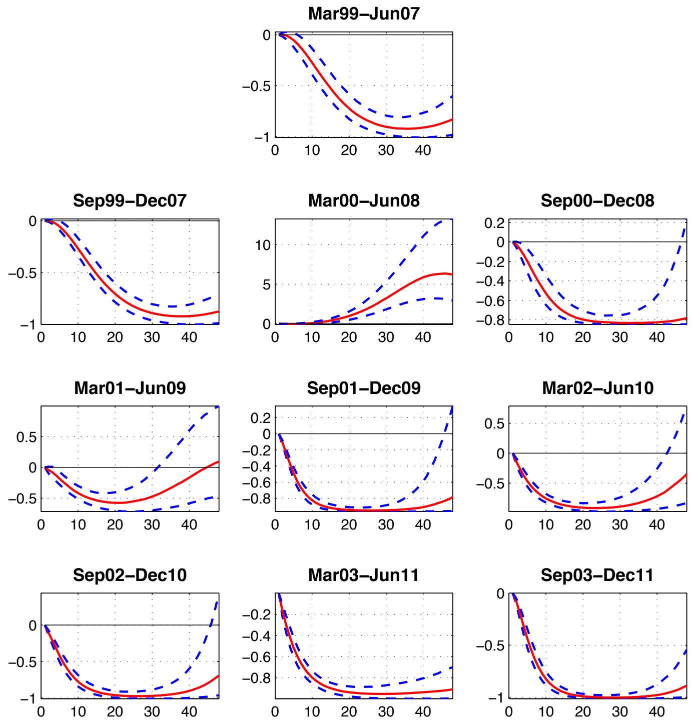



Figure M.1.22: Rollings - CL - IP: Spain

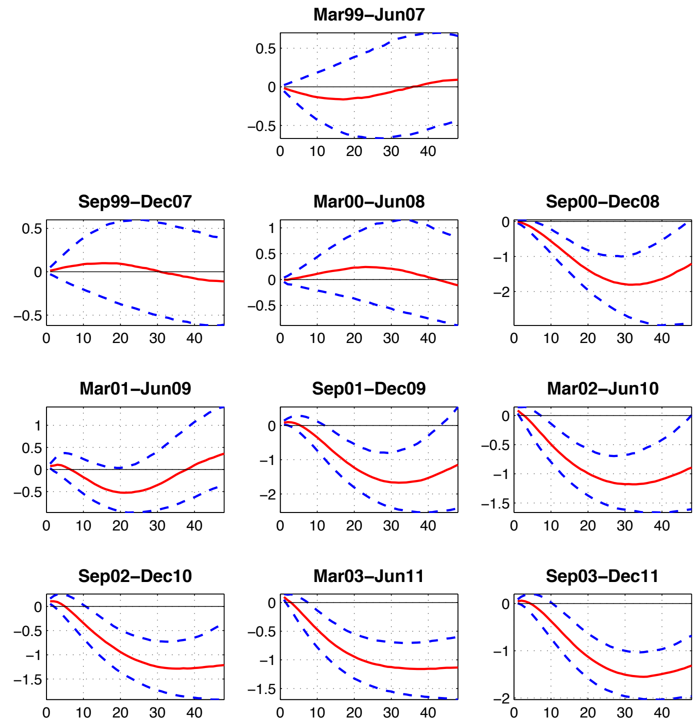



Figure M.1.23: Rollings - CL - CPI: Spain

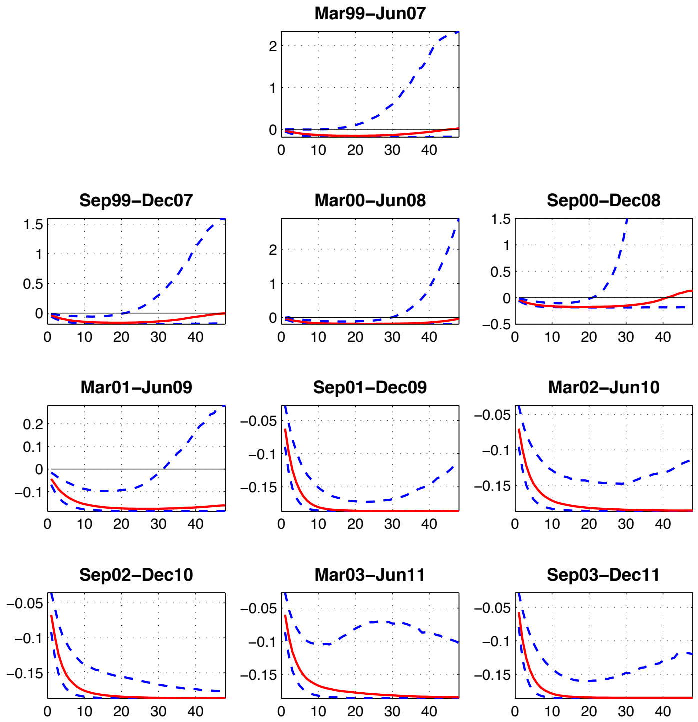



Figure M.1.24: Rollings - CL - M1: Spain

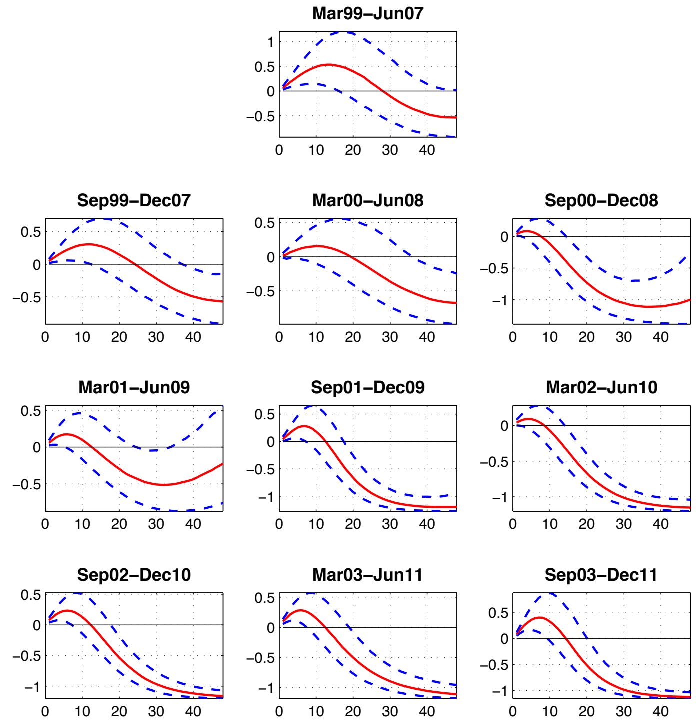



Figure M.1.25: Rollings - CL - M3: Spain

## M.2 Post-BN Analysis

### M.2.1 Country-Level Approach

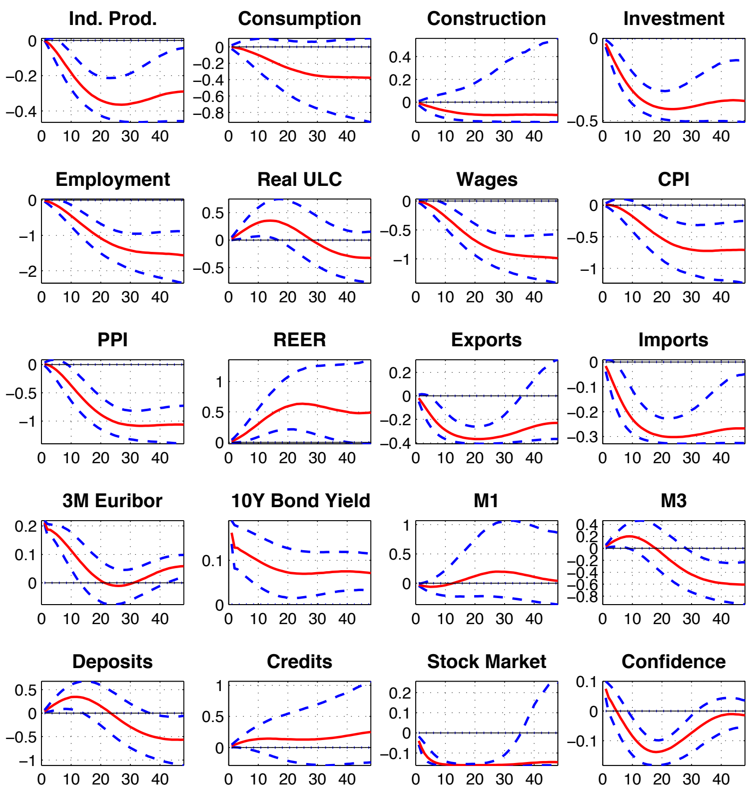



Figure M.2.1: Post-BN - CL: Germany

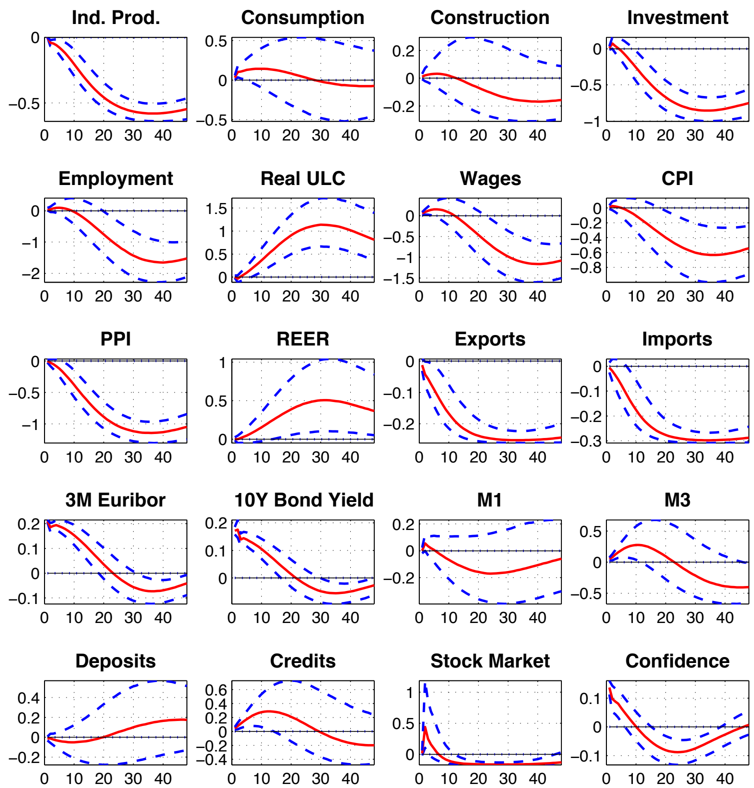



Figure M.2.2: Post-BN - CL: France

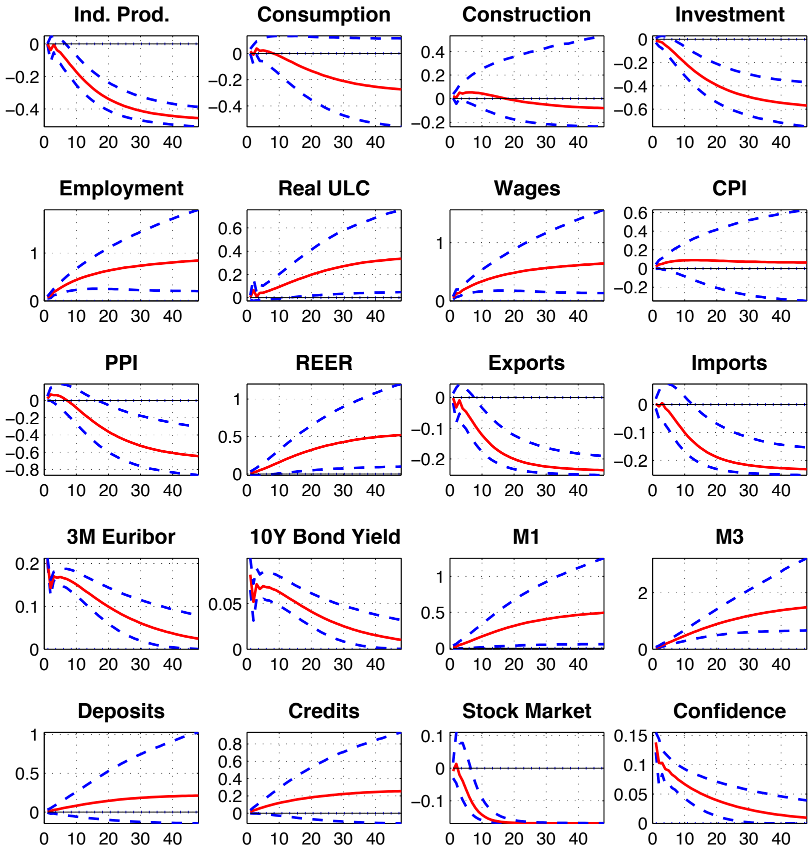



Figure M.2.3: Post-BN - CL: Italy

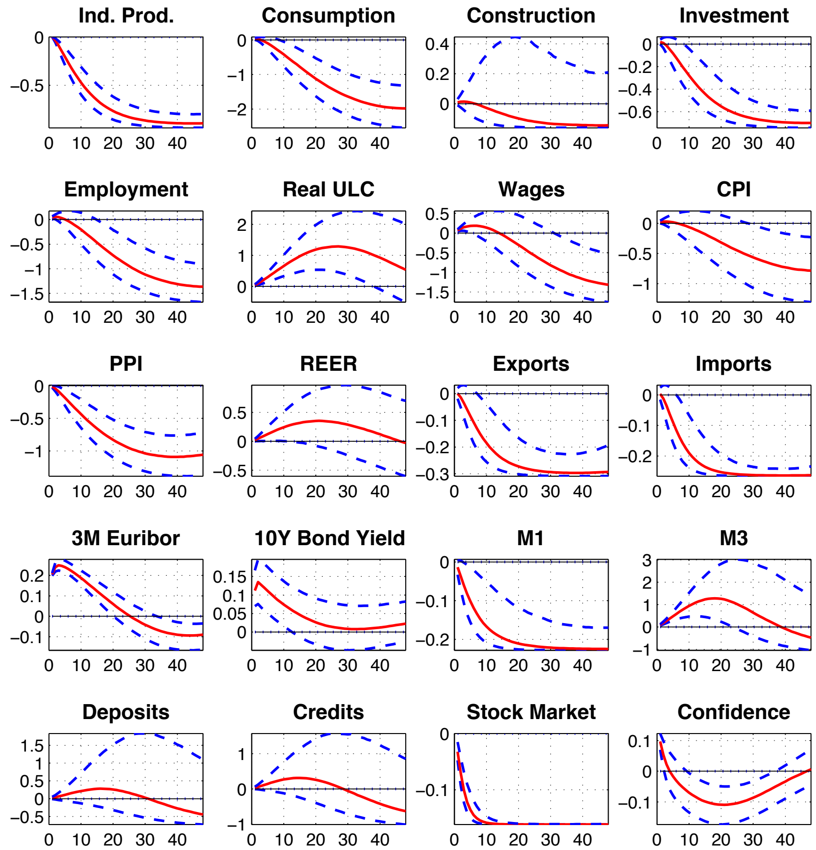



Figure M.2.4: Post-BN - CL: Spain

### M.2.2 Panel Approach

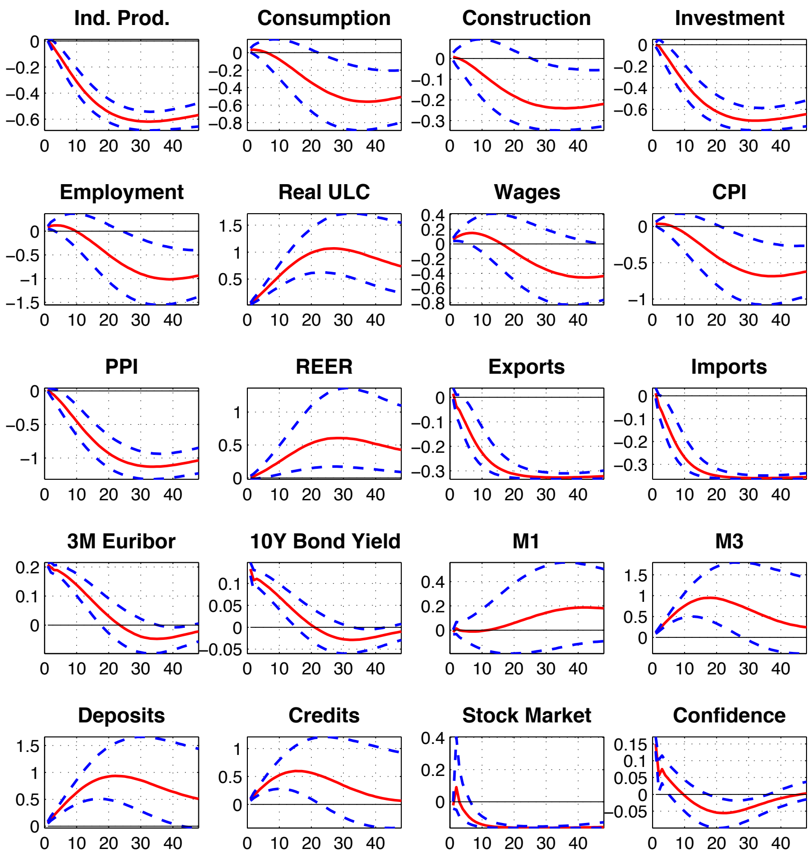



Figure M.2.5: Post-BN - AW: EA

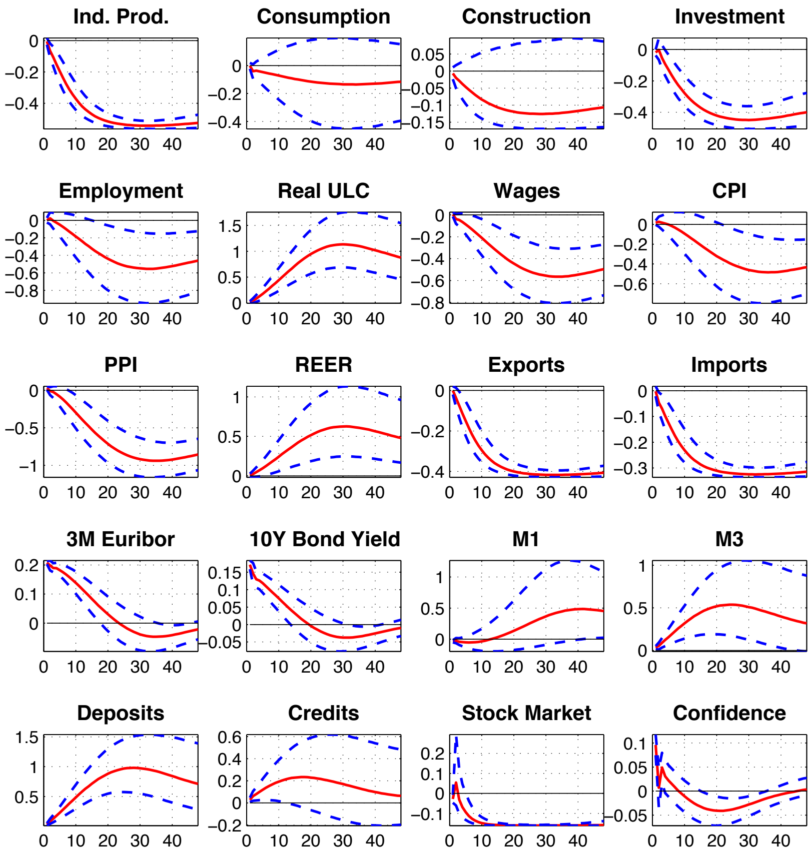



Figure M.2.6: Post-BN - AW: Germany

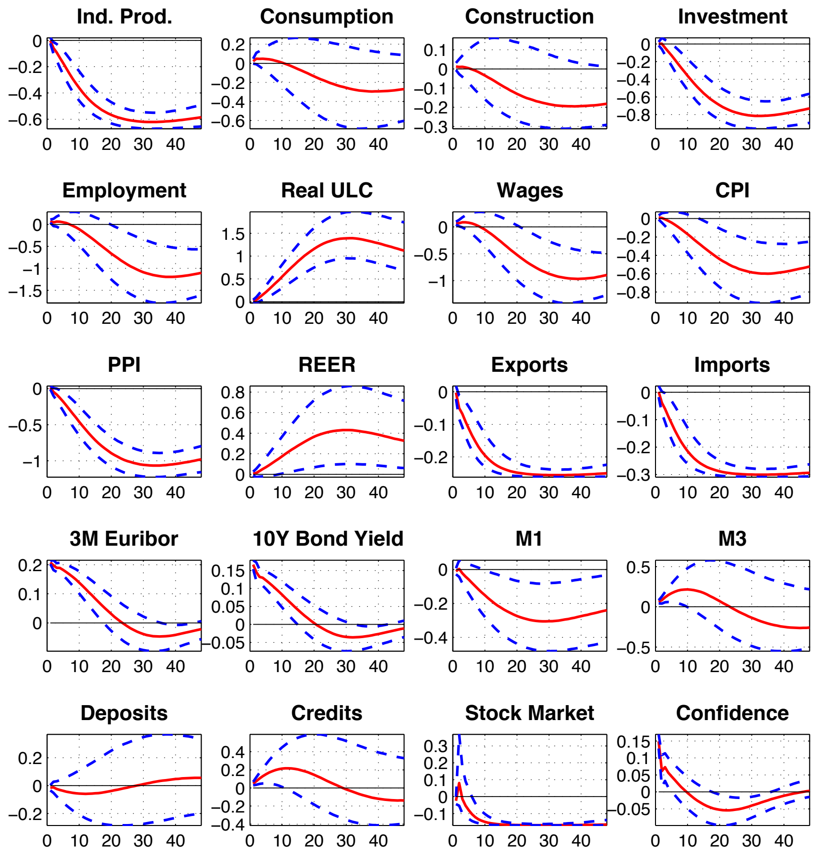



Figure M.2.7: Post-BN - AW: France

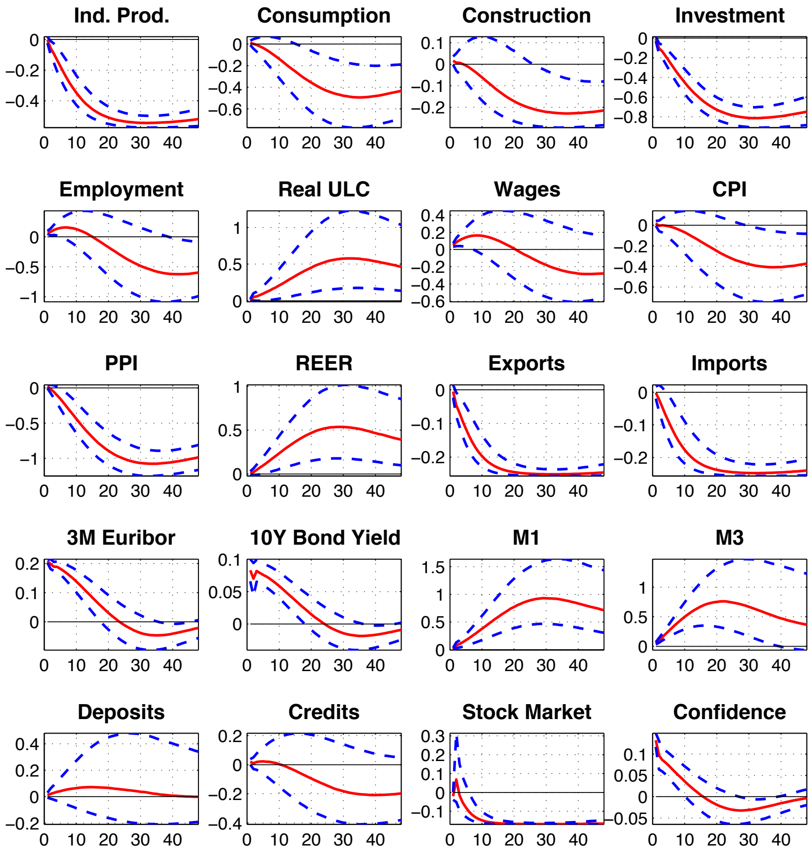



Figure M.2.8: Post-BN - AW: Italy

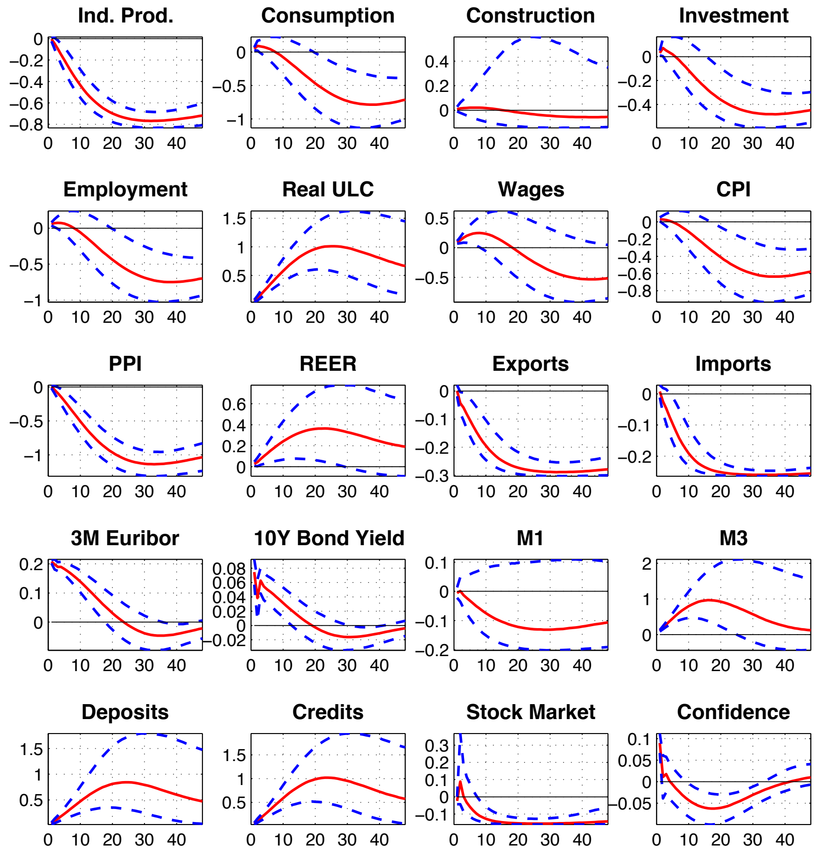



Figure M.2.9: Post-BN - AW: Spain

## M.2.3 Time Variation

### Germany

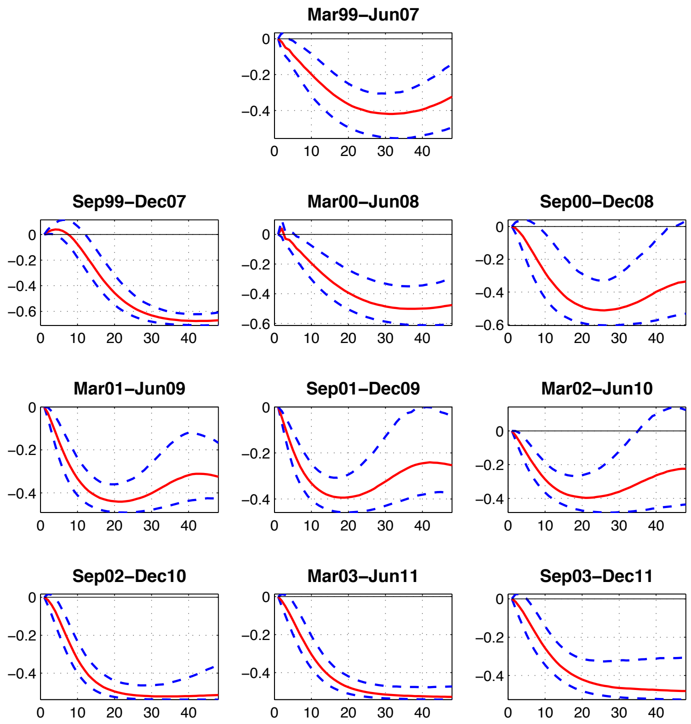



Figure M.2.10: Post-BN - Rollings - CL - IP: DE

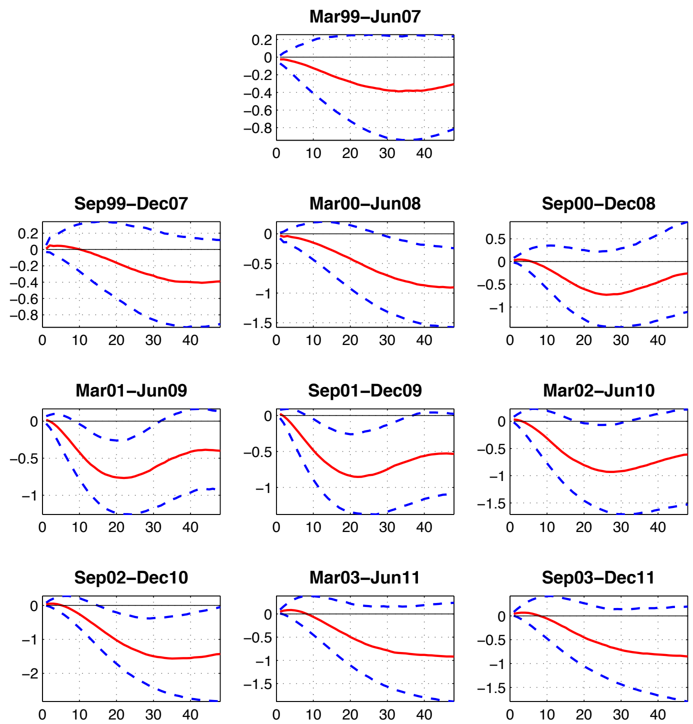



Figure M.2.11: Post-BN - Rollings - CL - CPI: DE

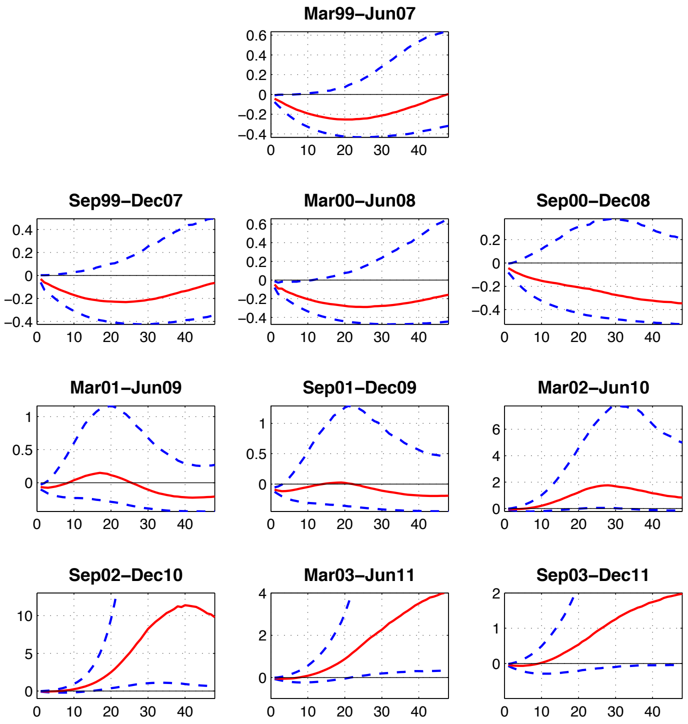



Figure M.2.12: Post-BN - Rollings - CL - M1: DE

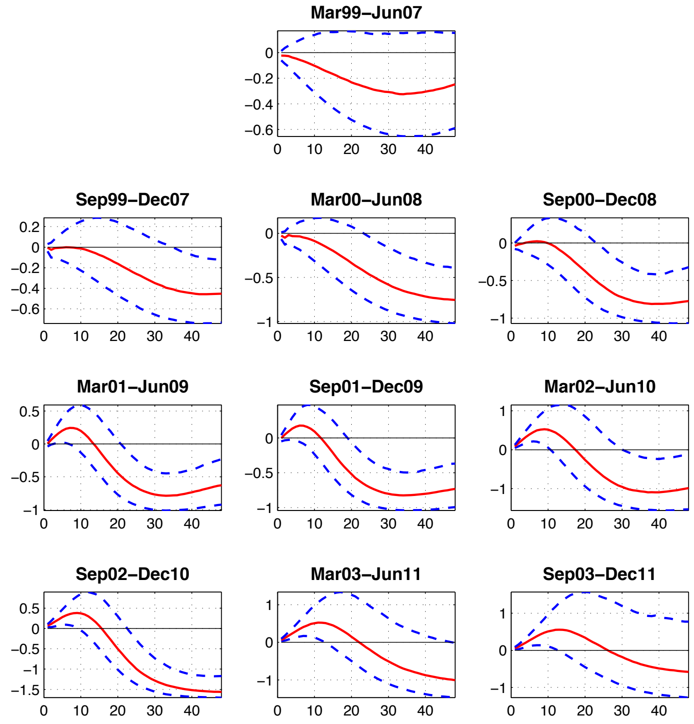



Figure M.2.13: Post-BN - Rollings - CL - M3: DE

## France

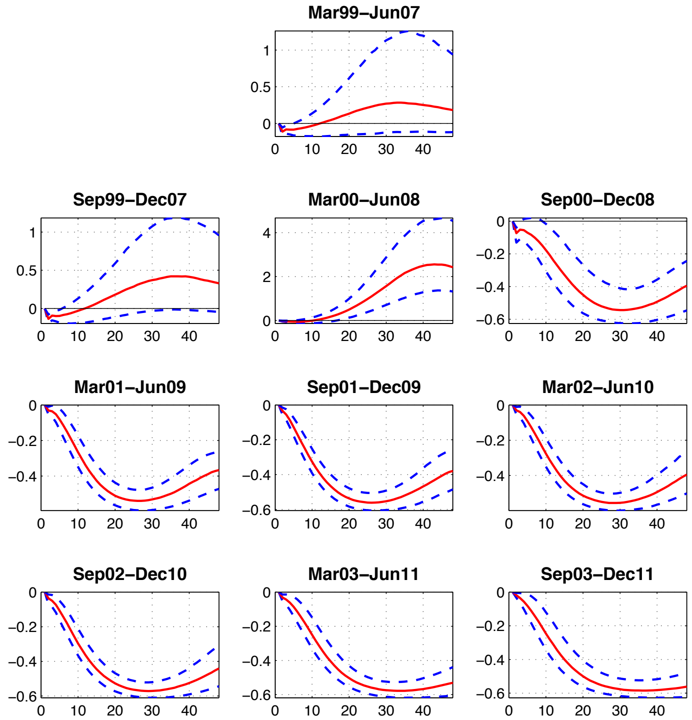



Figure M.2.14: Post-BN - Rollings - CL - IP: FR

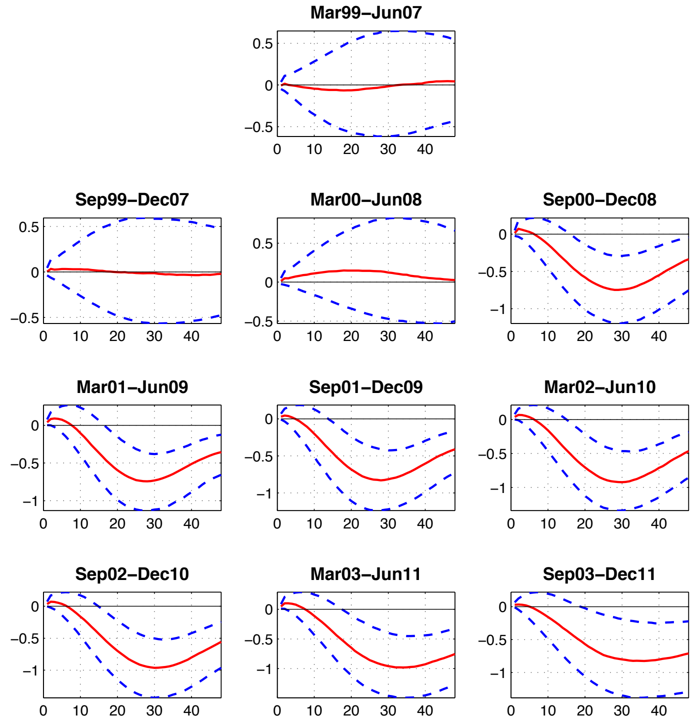



Figure M.2.15: Post-BN - Rollings - CL - CPI: FR

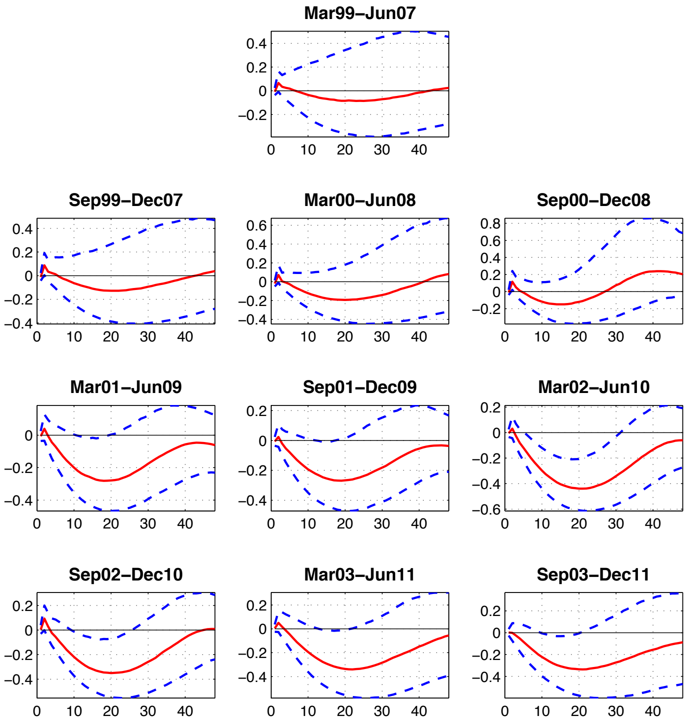



Figure M.2.16: Post-BN - Rollings - CL - M1: FR

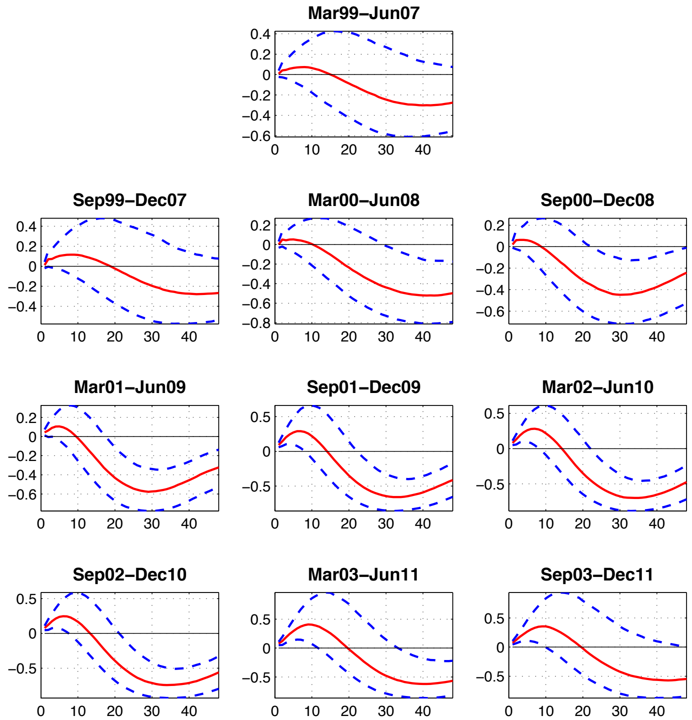



Figure M.2.17: Post-BN - Rollings - CL - M3: FR

## Italy

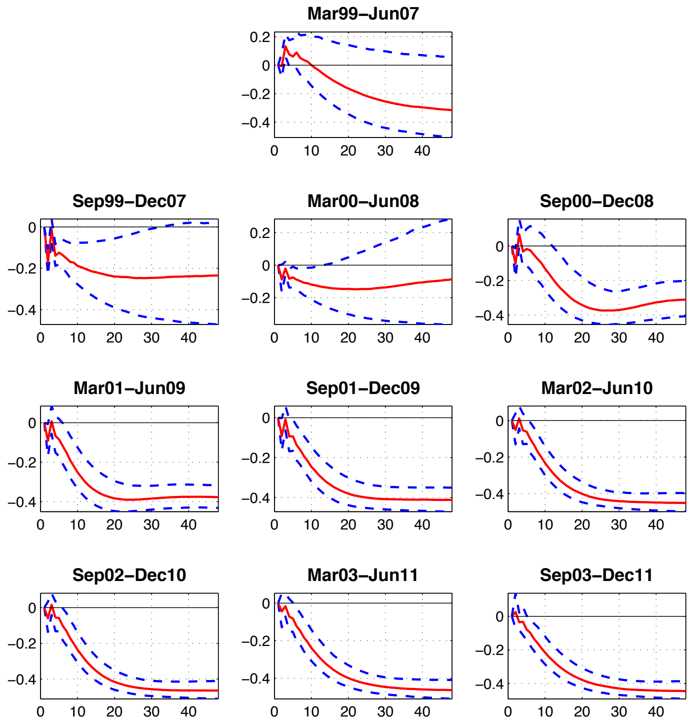



Figure M.2.18: Post-BN - Rollings - CL - IP: IT

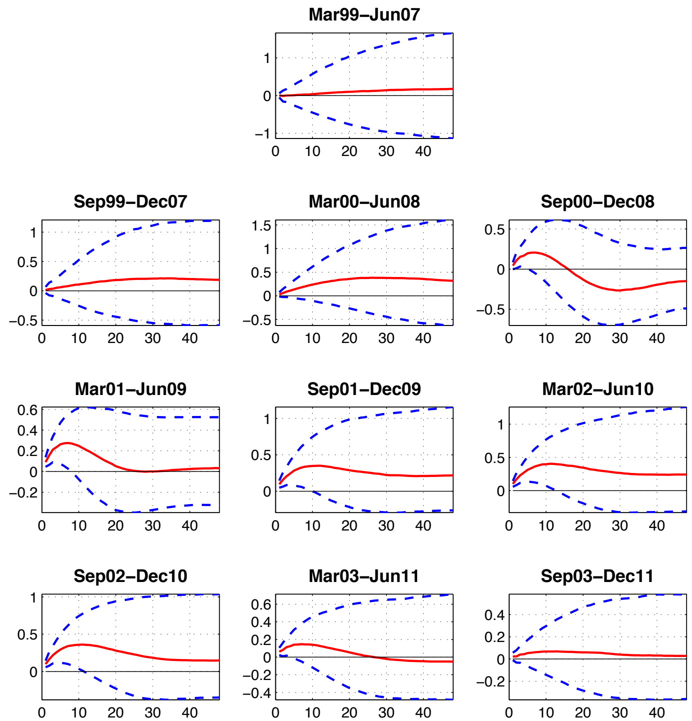



Figure M.2.19: Post-BN - Rollings - CL - CPI: IT

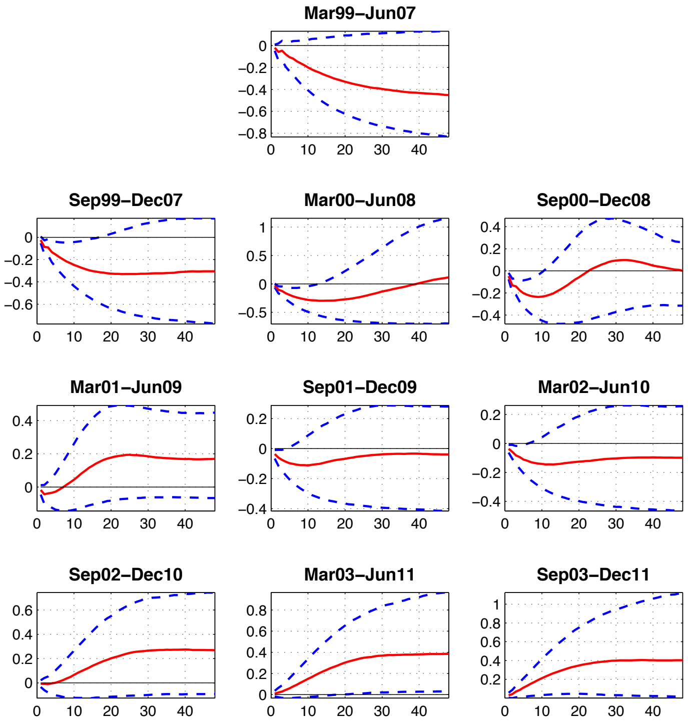



Figure M.2.20: Post-BN - Rollings - CL - M1: IT

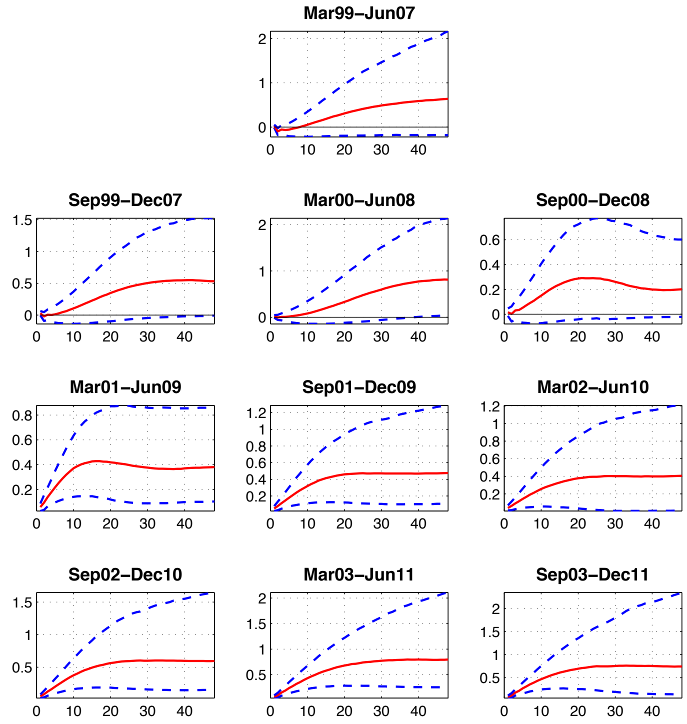



Figure M.2.21: Post-BN - Rollings - CL - M3: IT

## Spain



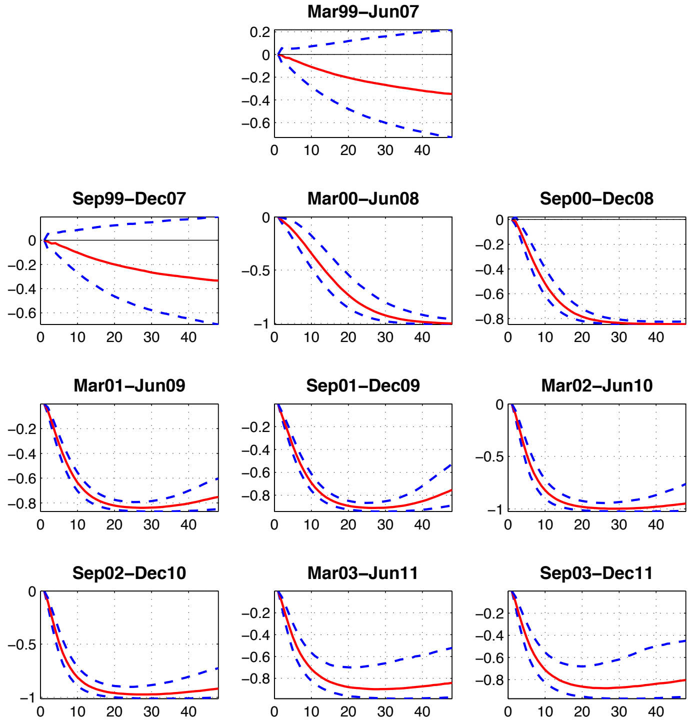



Figure M.2.22: Post-BN - Rollings - CL - IP: ES

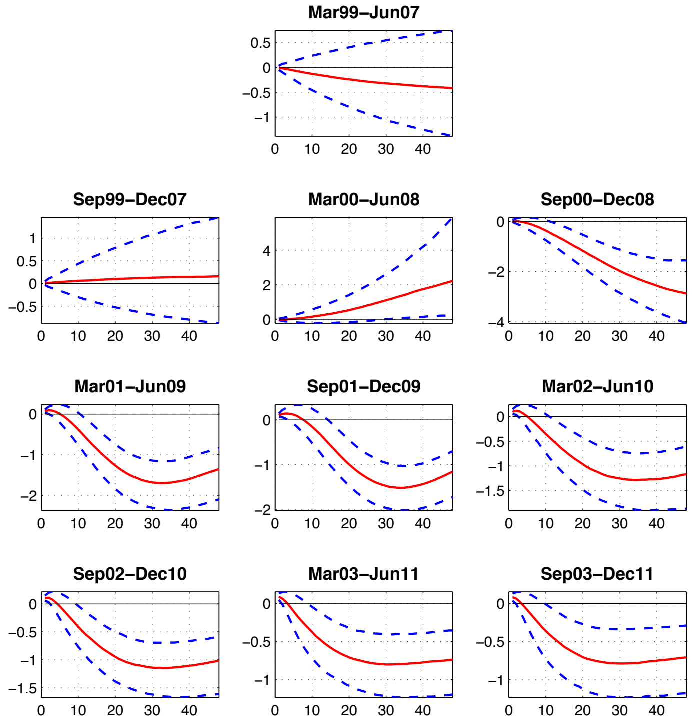



Figure M.2.23: Post-BN - Rollings - CL - CPI: ES

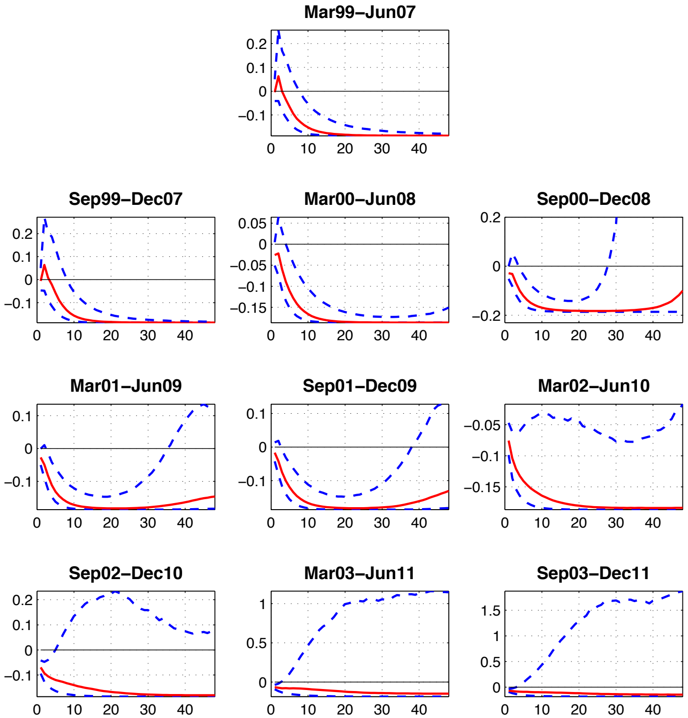



Figure M.2.24: Post-BN - Rollings - CL - M1: ES

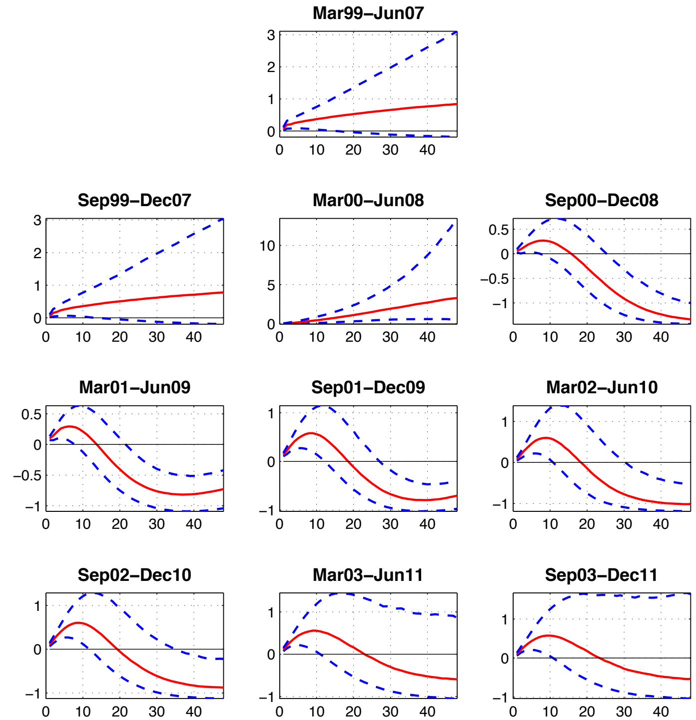



Figure M.2.25: Post-BN - Rollings - CL - M3: ES

APPENDIX N

# POST-BN ROLLING REGRESSIONS

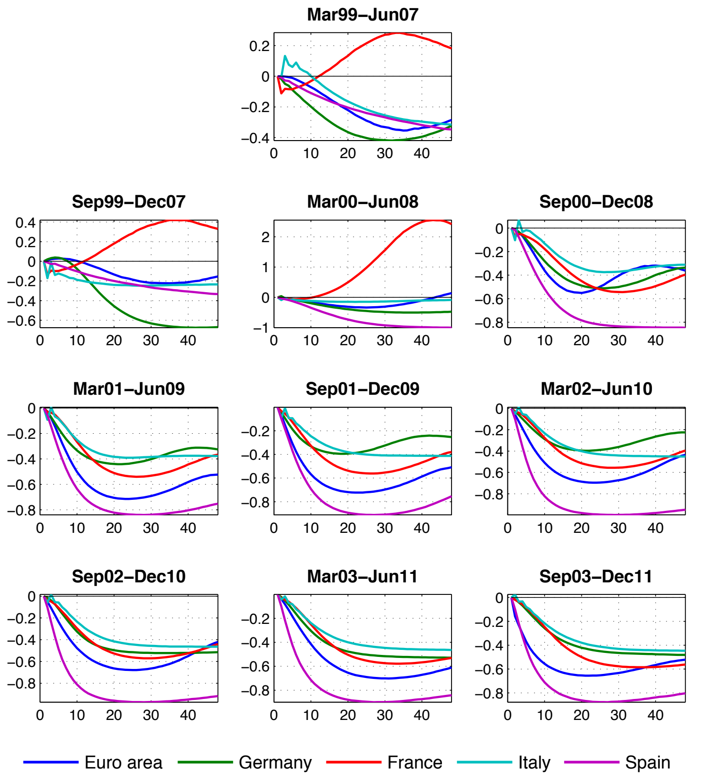



Figure N.0.1: Rolling Windows - Post-BN - CL - IP

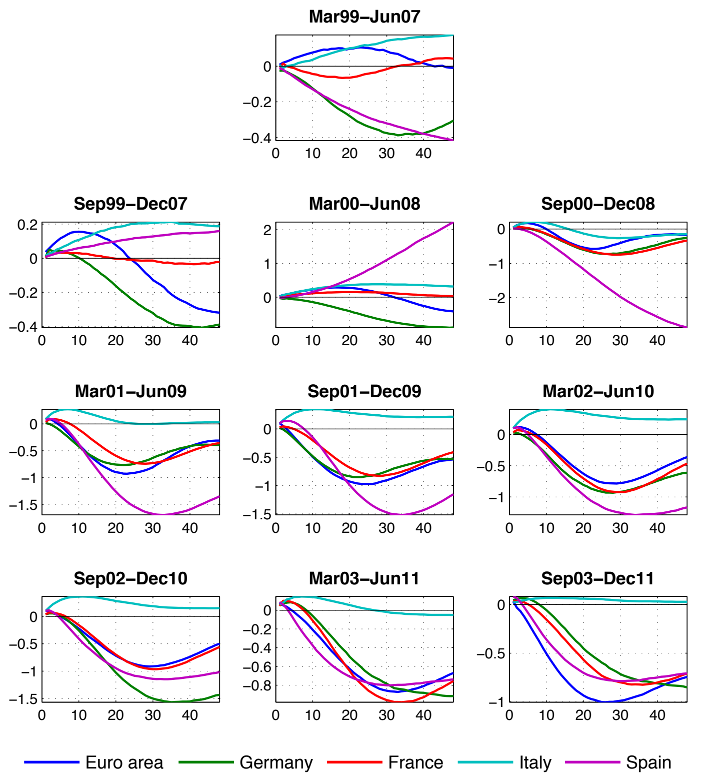



Figure N.0.2: Rolling Windows - Post-BN - CL - CPI

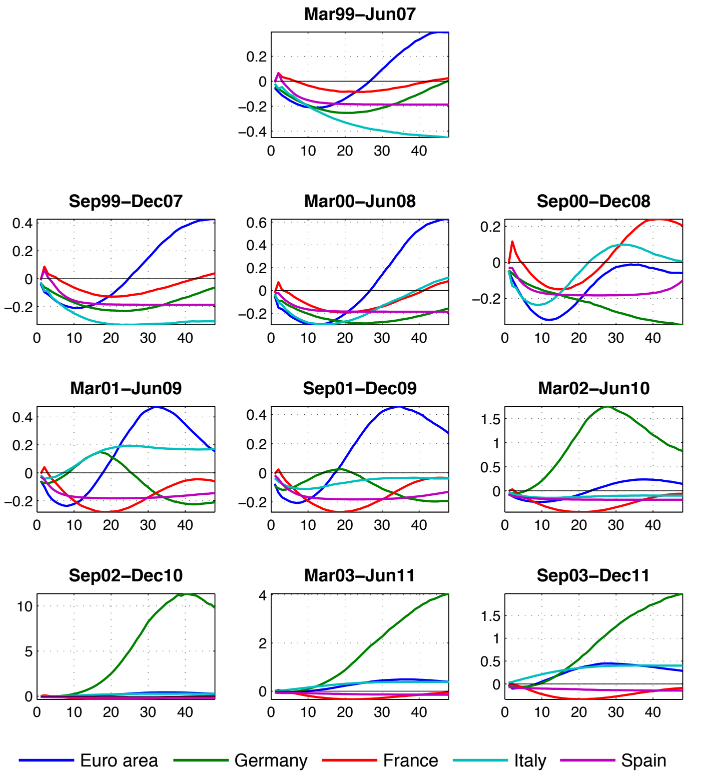



Figure N.0.3: Rolling Windows - Post-BN - CL - M1

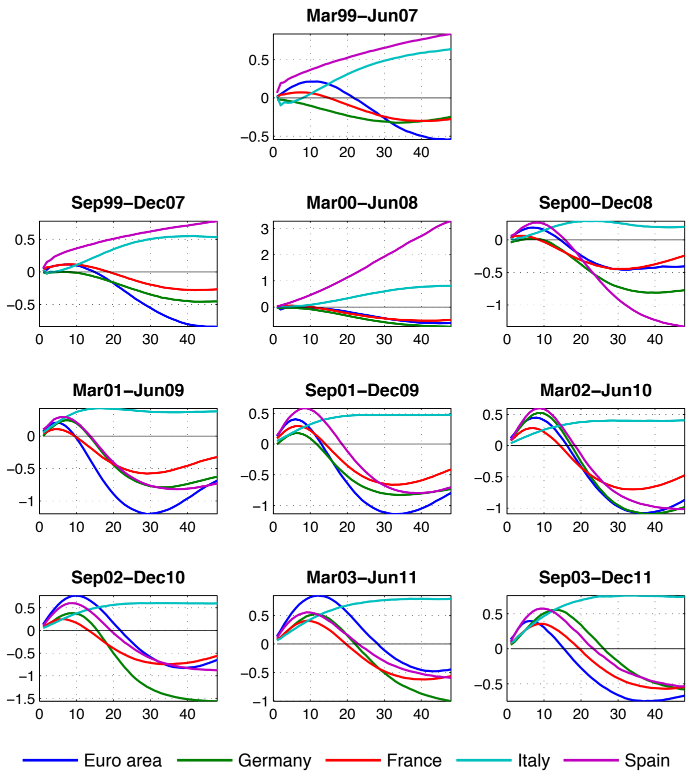



Figure N.0.4: Rolling Windows - Post-BN - CL - M3

APPENDIX O

# CONVERGENCE OF GIBBS SAMPLINGS

## O.1 Country-Level and Panel Approaches

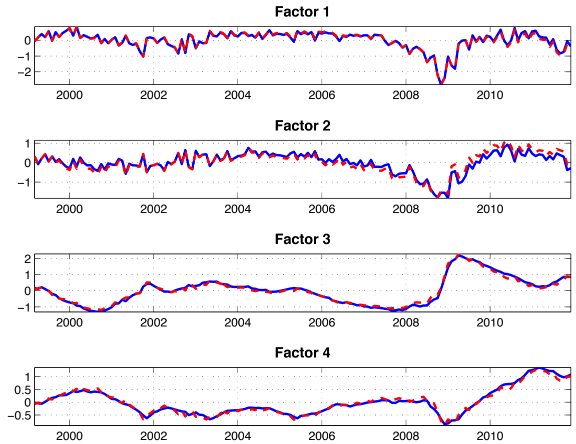



Figure O.1.1: Convergence: Panel

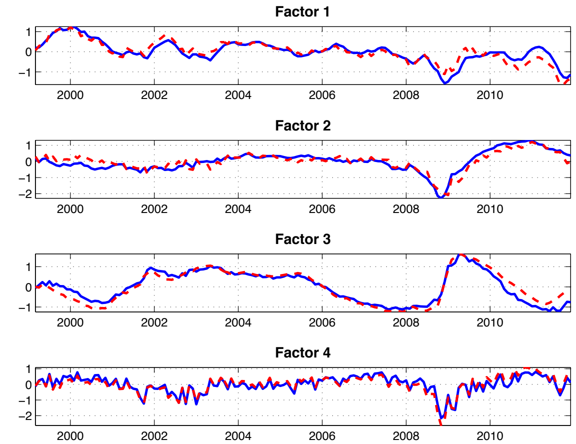



Figure O.1.2: Convergence: Germany

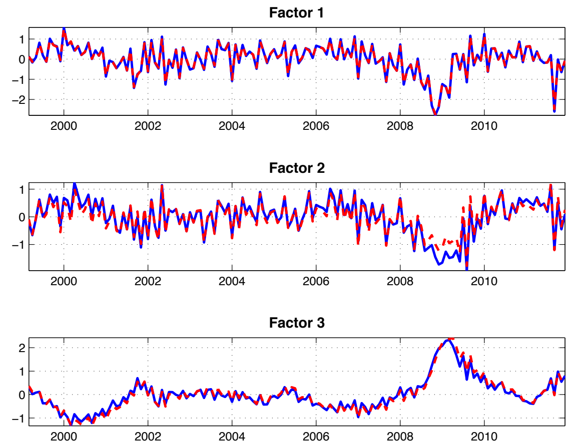



Figure O.1.3: Convergence: Italy

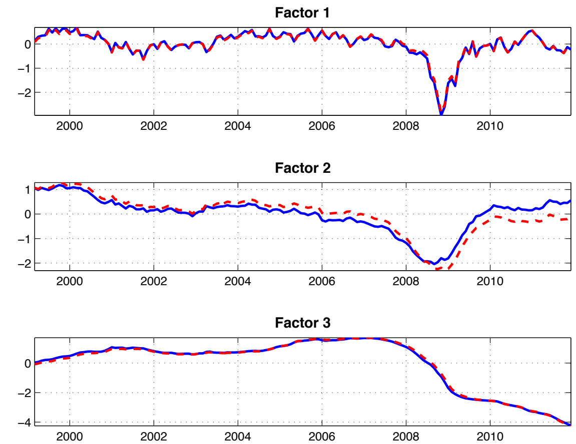



Figure O.1.4: Convergence: Spain

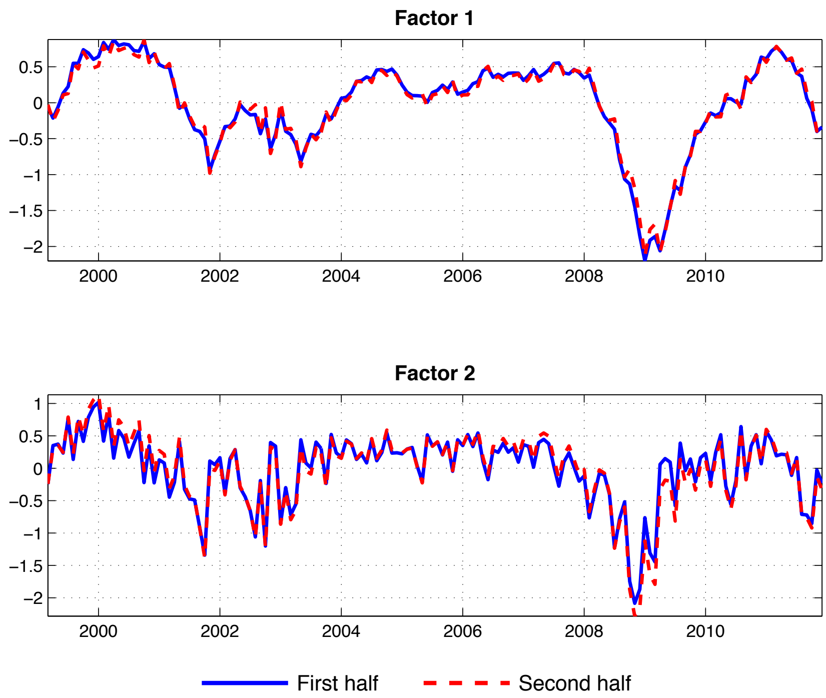



Figure O.1.5: Convergence: France

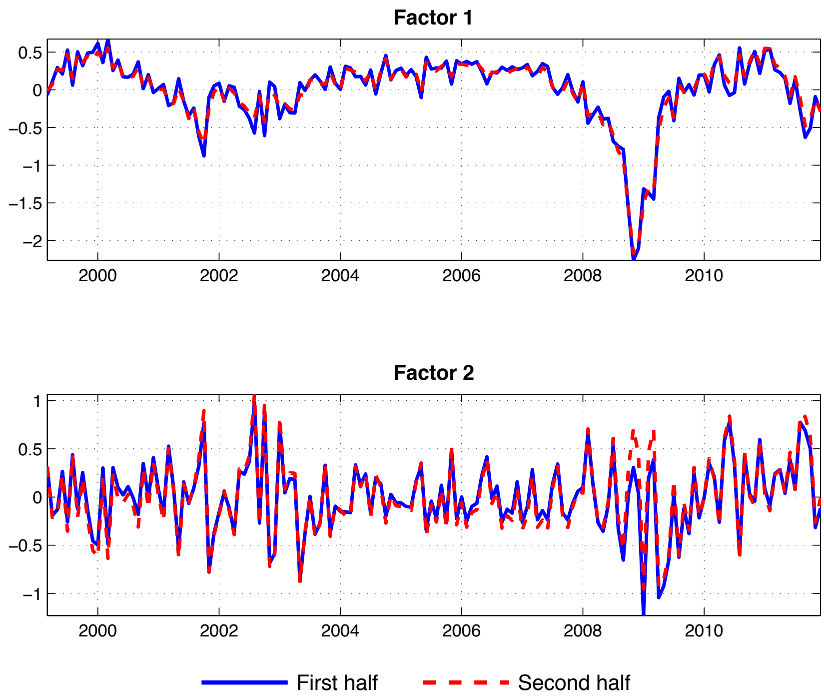



Figure O.1.6: Convergence - Post-BN: Panel

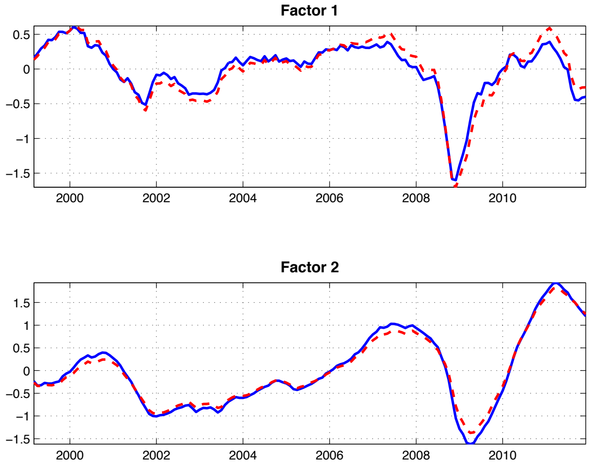



Figure O.1.7: Convergence - Post-BN: Germany

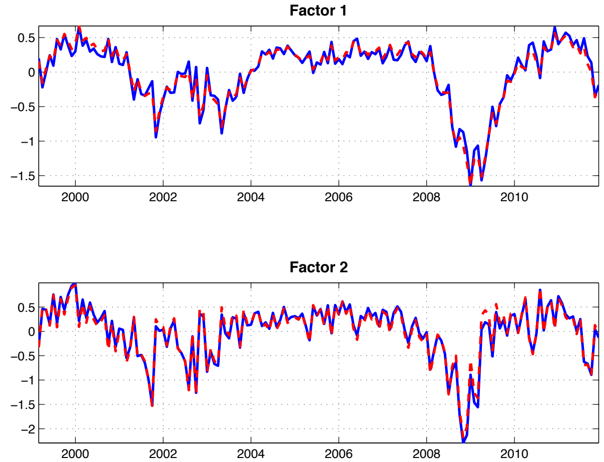



Figure O.1.8: Convergence - Post-BN: France

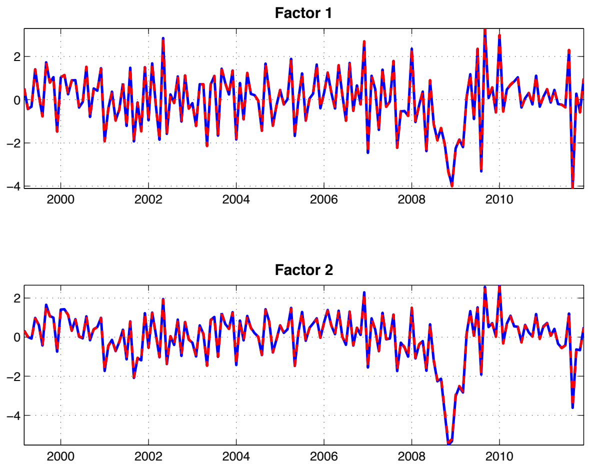



Figure O.1.9: Convergence - Post-BN: Italy

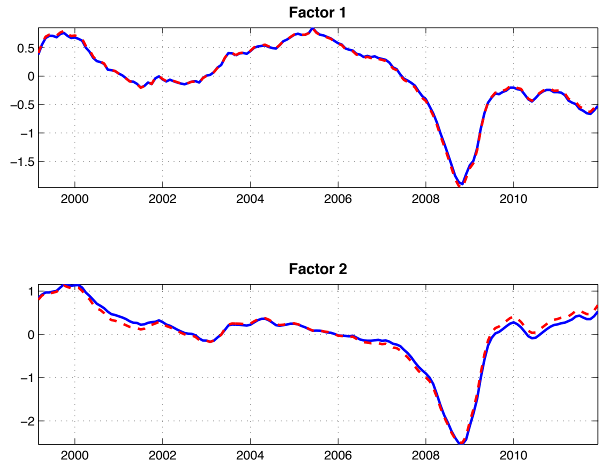



Figure O.1.10: Convergence - Post-BN: Spain

First half  Second half

## O.2 Time Variation

Because the number factors are varying across rolling windows estimated for other countries, we present the pre-BN convergence plots only for France. Convergence is obtained for other countries in a similar way for France.

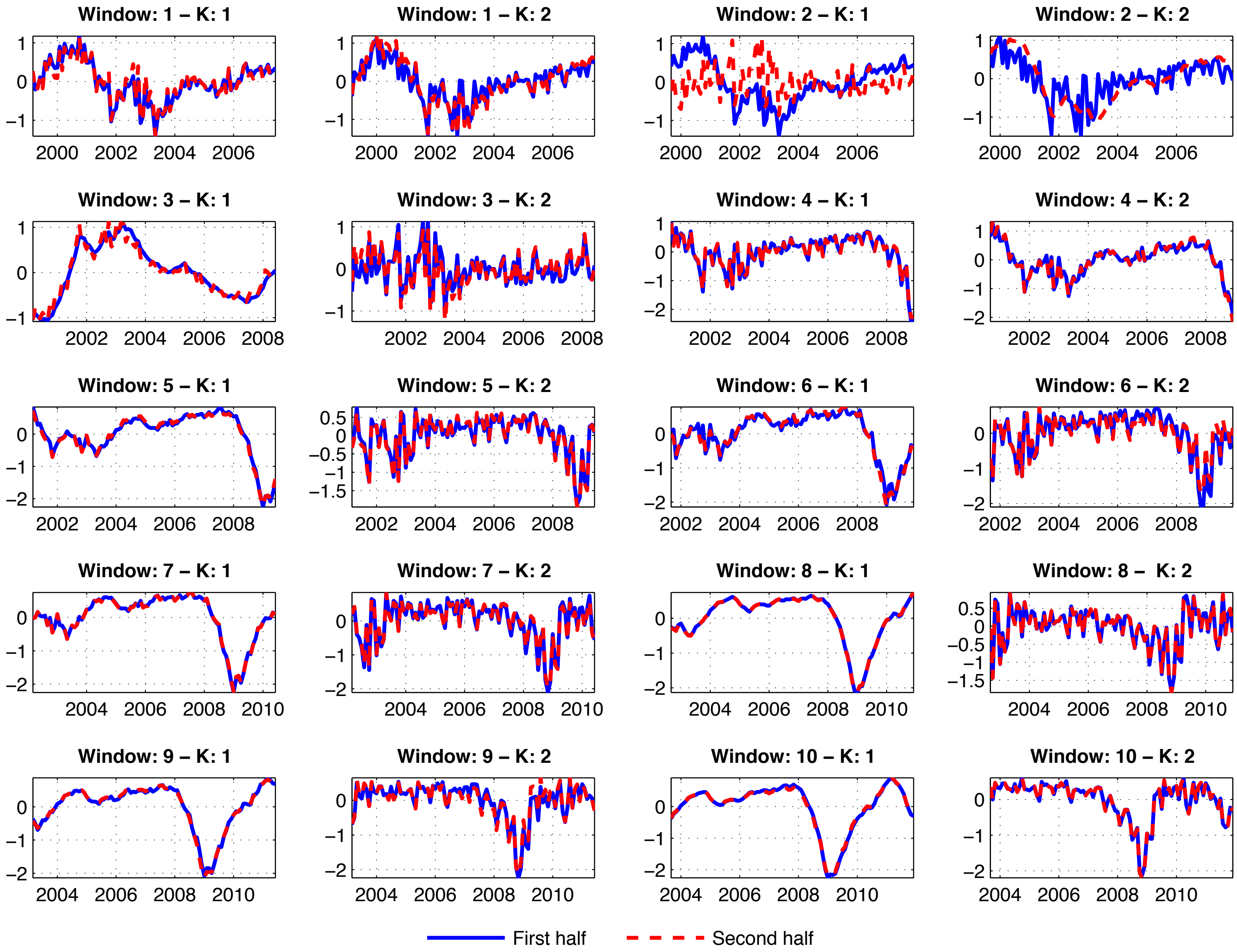



Figure O.2.1: Convergence - Rollings: France

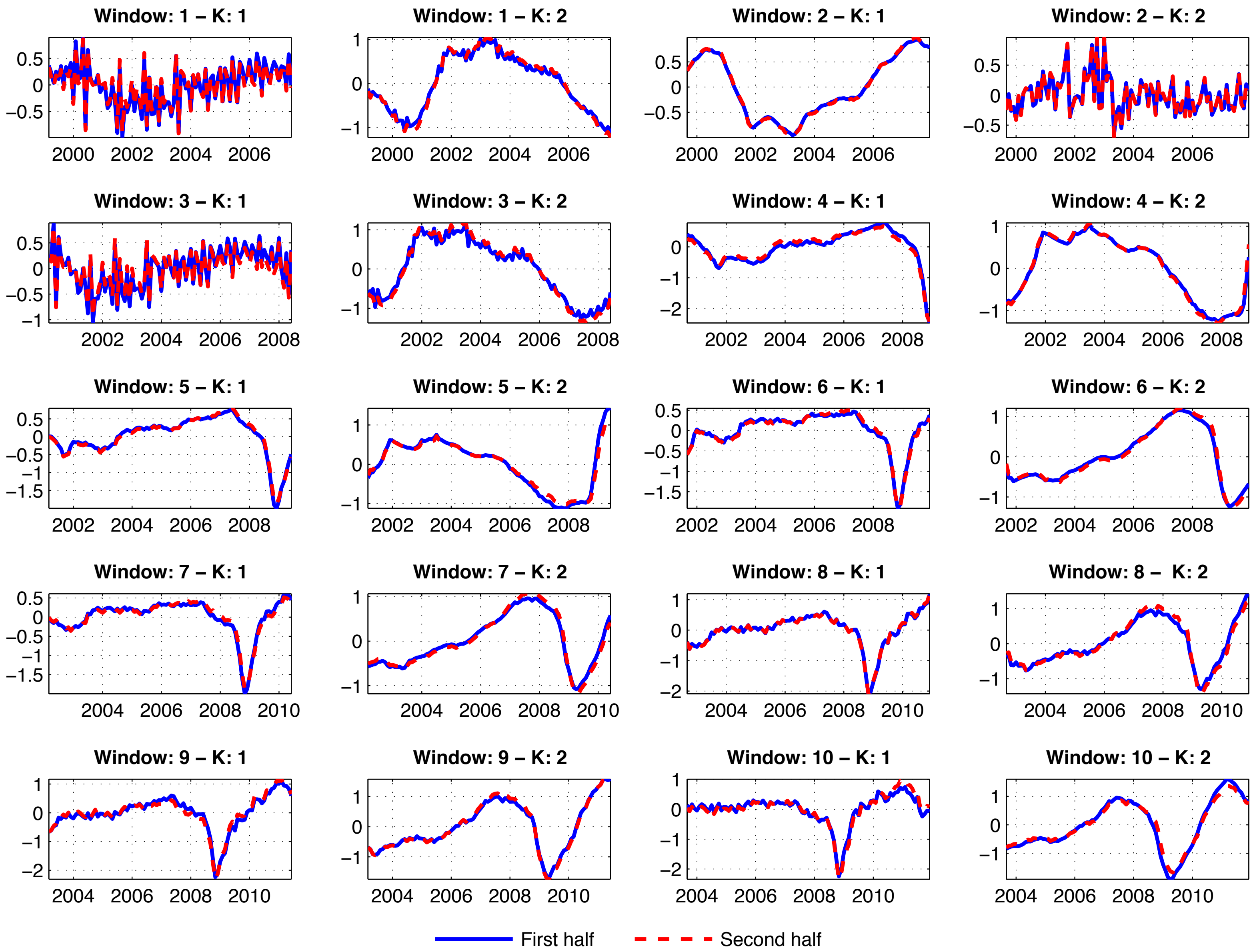



Figure O.2.2: Convergence - Rollings - Post-BN: Germany

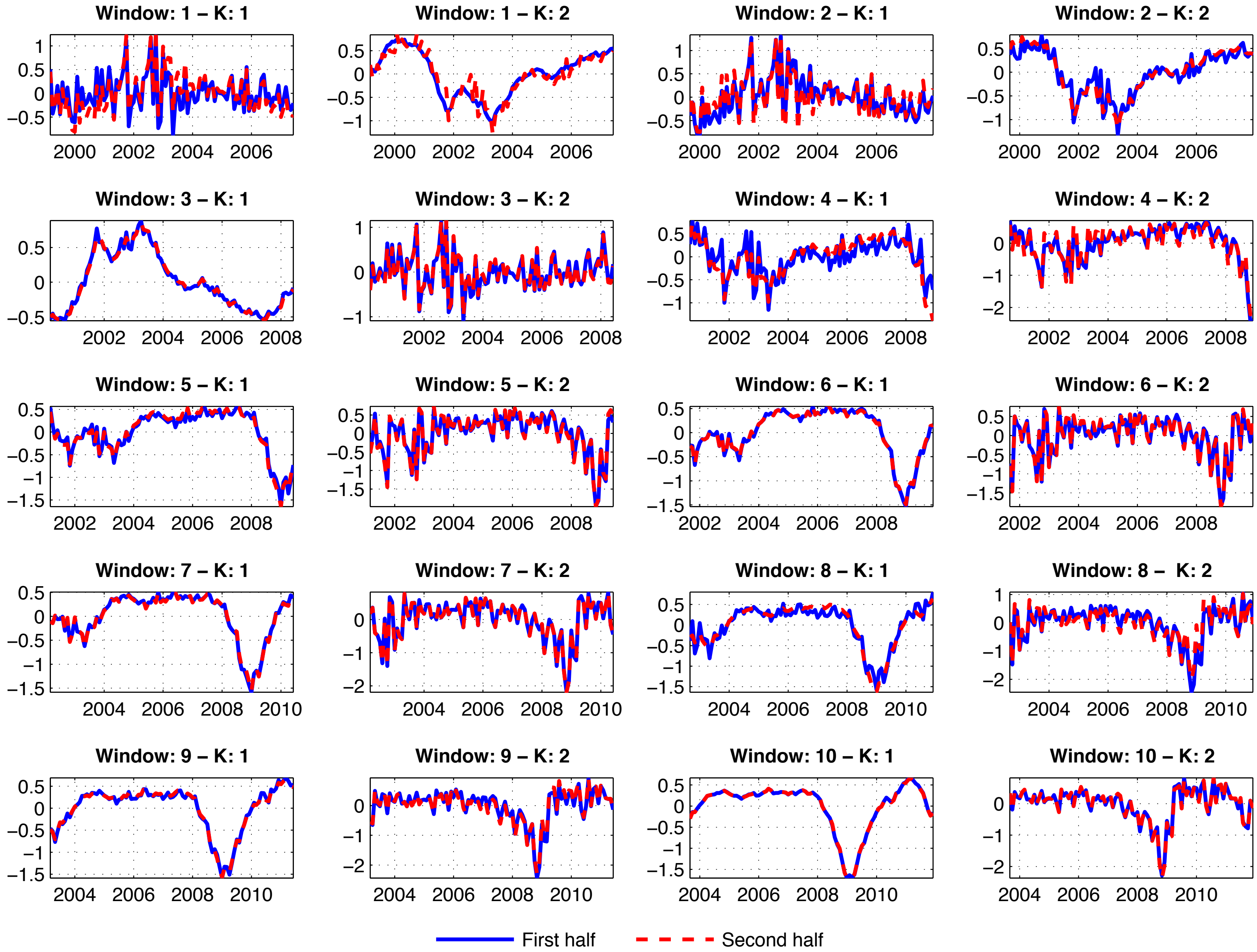



Figure O.2.3: Convergence - Rollings - Post-BN: France

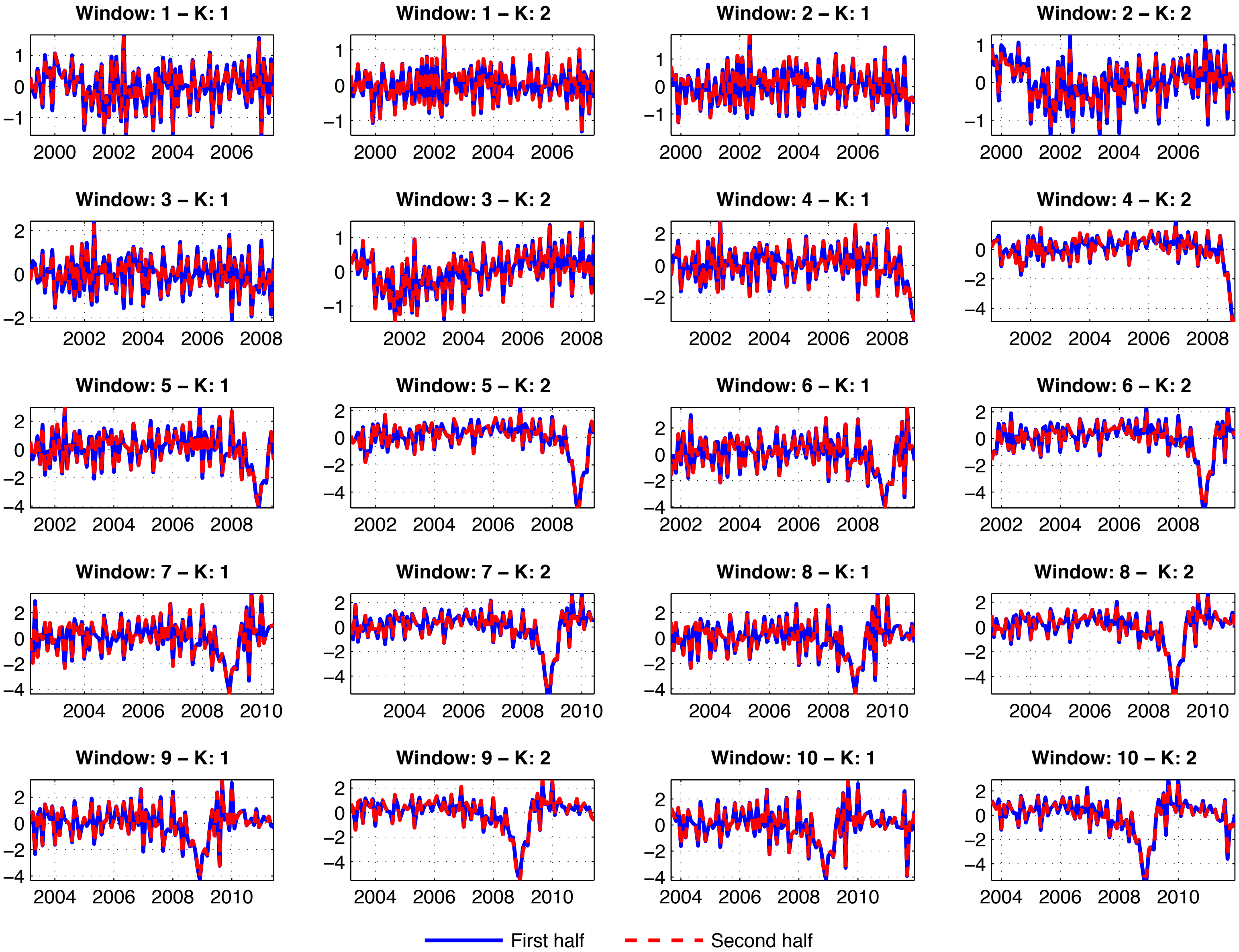



Figure O.2.4: Convergence - Rollings - Post-BN: Italy

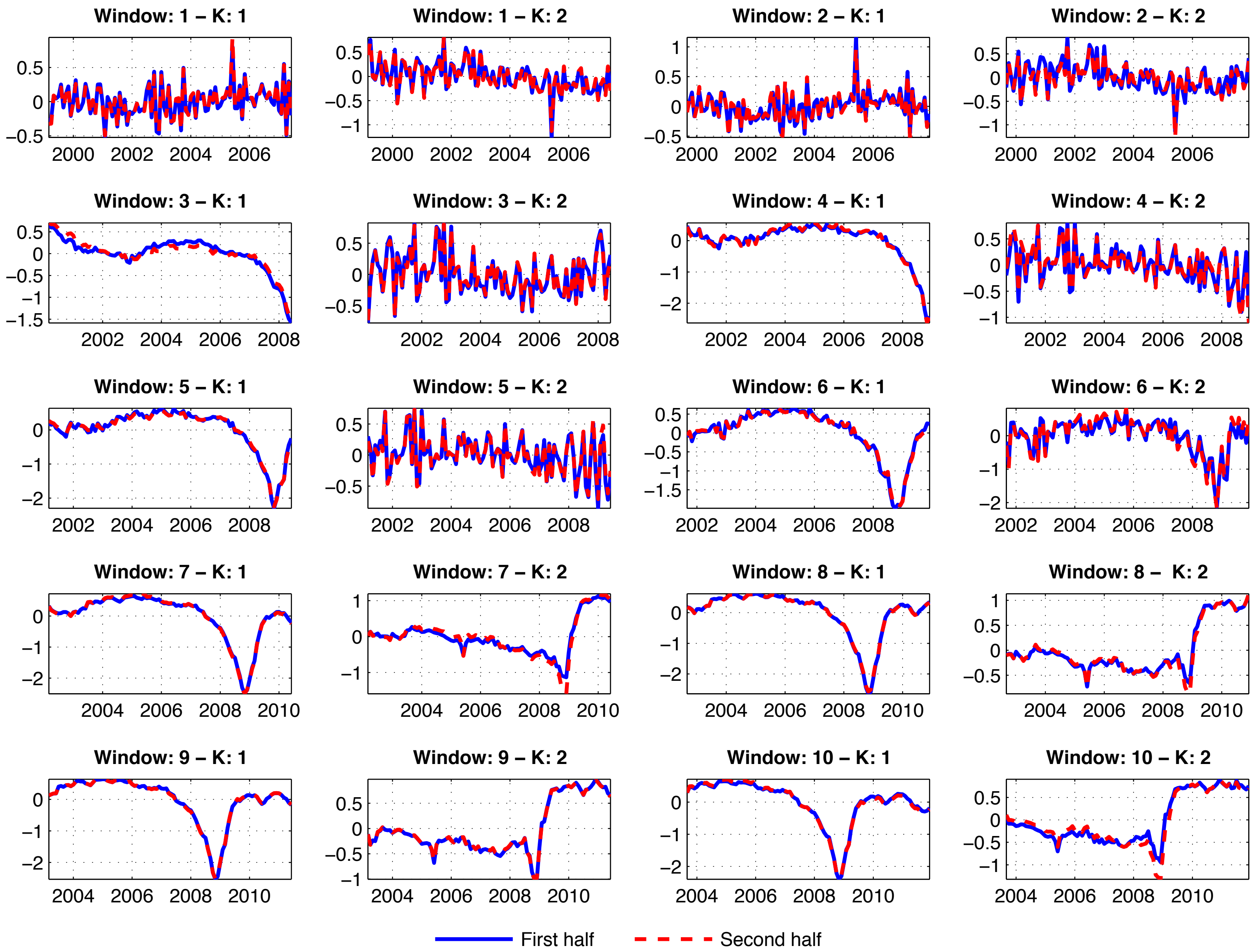



Figure O.2.5: Convergence - Rollings - Post-BN: Spain

CHAPTER 3

# THE EFFECTS OF UNCONVENTIONAL MONETARY POLICY ACROSS EURO AREA ECONOMIES

## 3.1 Introduction

As a result of the subprime mortgage crisis in the US, in August 2007, there was growing turmoil in the global financial markets (See Figure 3.1.1). A number of European banks publicly announced their direct and indirect exposures to the US subprime mortgage market, which automatically led to severe losses and liquidity shortages in the European banking system.

Like other big central banks worldwide, the Eurosystem[1] urgently responded to the developments in the markets with several "unconventional" measures, "unprecedented in nature, scope and magnitude".[2] As summarised by Nagel (2012, p.14), "the aim of these measures [was] to sustain financial inter-mediation in the euro area, foster the flow of credit to enterprises and households, and support the monetary policy transmission mechanism."

[1]The Eurosystem is composed of the ECB and the national central banks (NCBs) of those countries that have adopted the euro as their legal tender.

[2]ECB (2011, p.90).

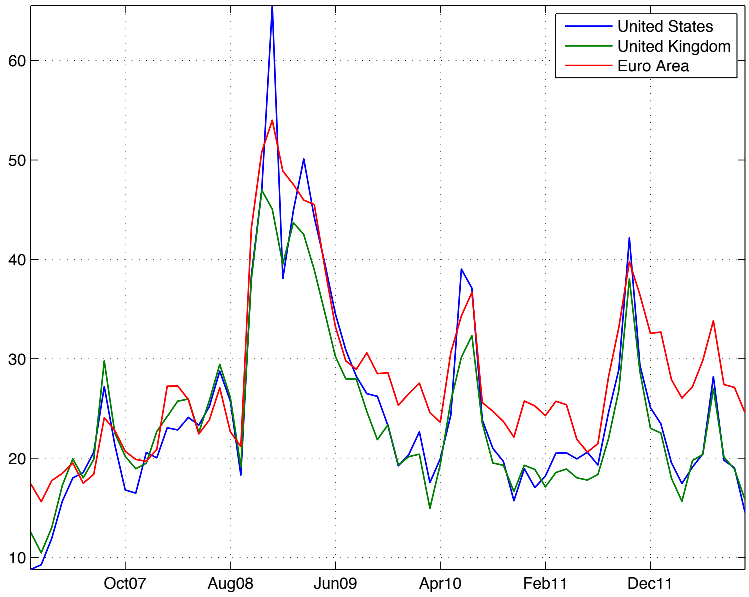



Figure 3.1.1: Volatility in Financial Markets

Chicago Board Options Exchange Market Volatility Index (VIX, %, SA) - Source: Datastream

Note: VIX indices measure the stock market volatility expectations in the next 30 days using a forward looking approach based on option prices. The indices are quoted in percentage points, and higher values stand for higher expected movements, in percentage points, over the next 30-day period. For details see Whaley (2009).

Borio and Disyatat (2009) highlight that it is the choice of market(s) targeted by these policies that is 'atypical' or 'unprecedented', and it is this choice that makes the policies unconventional. For example, according to Borio and Disyatat, the target of the central banks' unconventional policies has been term money market rates, long-term government bond yields and various risk spreads.[3] Figure 3.2.1 displays the balance sheet policies of the Eurosystem which started in August 2007 with the extra liquidity provided on an ad hoc basis, and followed by, in December 2007, the liquidity support in dollars to the European banking sector.

On the other side of the Atlantic, the Business Cycle Dating Committee of the National Bureau of Economic Research (NBER) determined that the peak in economic ac-

[3]See Section 3.1.1 for the transmission mechanism of unconventional monetary measures.

tivity occurred in December 2007, following the expansion that began in November 2001. Following the collapse of Lehman Brothers in September 2008, financial turmoil turned into a global financial crisis, the so called 'Great Recession'.

'The virtual breakdown of the money market', as stated by the ECB,[4] caused short-term interest rates to increase to 'abnormally high levels' (See Figure 3.1.2). During this period of great uncertainty, banks increased their liquidity reserves, removed risky assets from their balance sheets, and tightened loan conditions. Unsurprisingly, the crisis began to spread to the real economy.

In October 2008, the ECB started to carry out weekly refinancing operations with a fixed-rate tender procedure with full allotment.[5] As described by the ECB (2012a), the Bank "effectively took the place of the money market" in the EA. The ECB also responded to the crisis in the form of the Covered Bond Purchase Programme started in June 2009. In order to help revive the market in covered bonds, the ECB used one of its monetary policy instruments so called 'structural operations', and started to purchase "certain assets that are eligible as collateral".[6]

In May 2010, the ECB introduced the Securities Markets Programme (SMP) in order to "address the malfunctioning of securities markets and restore an appropriate monetary policy transmission mechanism."[7] The programme allowed the ECB and the NCBs to intervene in certain debt securities markets, mostly government bond markets, as described in ECB (2012a).

Following the rise in tensions in the European financial markets in the second half of

[4]See ECB (2012a).

[5]i.e. "the interest rate is set in advance and the ECB provides as much liquidity as the banks request, provided they offer collateral of sufficient quality" (ECB, 2012a).

[6]ECB (2012a).

[7]Ibid.

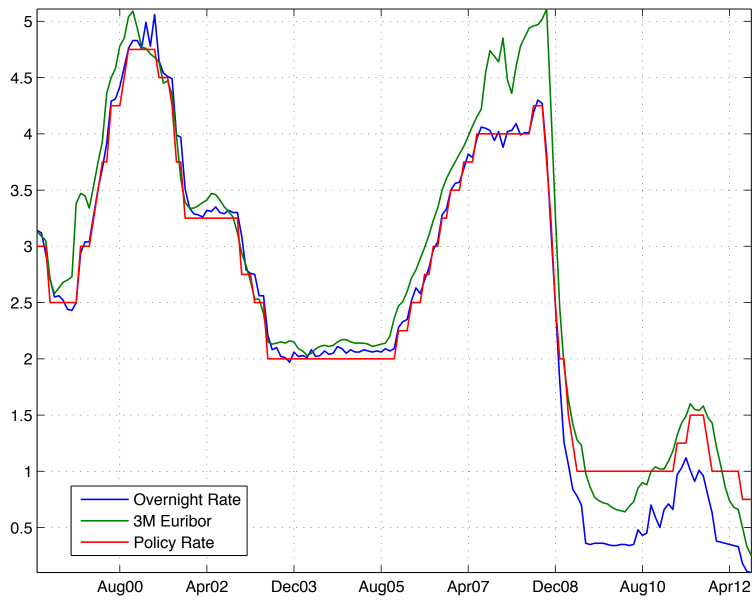



Figure 3.1.2: Interest Rates (EA, %)

Source: Eurostat

2011, mainly due to the developments in default probabilities on the sovereign debt, the ECB announced two longer-term refinancing operations (LTRO), with a maturity of 36 months and full allotment, to be conducted on 21 December 2011 and 29 February 2012. Furthermore, the Bank reduced the reserve ratio to 1% (from 2%) as of 18 January 2012. Within these measures, the ECB allowed the NCBs to accept additional bank loans as collateral. According to ECB (2012a), "the responsibility entailed in the acceptance of such credit claims [were] borne by the national central bank authorising their use."

After the collapse of Lehman Brothers, the Federal Reserve (Fed) and the Bank of England (BoE) balance sheets initially developed similarly to that of the Eurosystem. Whereas the Fed introduced the Term Auction Facility, the BoE set up the Asset Purchase Facility Fund in order to provide sufficient liquidity to their financial sectors. During the crisis, these central banks, similar to the Eurosystem, performed various unconventional monetary policy measures, while their policy rates were rapidly lowered towards their lower bounds.

In the absence of the ECB's (and other central banks') responses to the crisis, there would certainly have been (i) risks of bank failures, given the liabilities of the banks reaching maturity in 2012; (ii) extra sales of sovereign bond holdings, which would significantly increase the pressure on the sustainability of (especially peripheral) sovereigns; and (iii) significant reductions in bank lending.[8] Given this worst-case scenario, there is no doubt that, in general, the central banks' responses to the crisis achieved their ultimate targets of functioning financial intermediations, credit flows, and monetary policy transmission mechanism. As stated by Mishkin (2012), "[i]ndeed, ..., aggressive nonconventional monetary policy during the recent financial crisis helped prevent the Great Recession from turning into a Great Depression and also helped the economy avoid a deflationary episodes as occurred during the Great Depression era" (p.672). As we summarise in Table 3.1.1, this is the common finding of the literature on the effectiveness of unconventional monetary policy actions of the central banks worldwide.

"While there was a high degree of commonality in central banks' response to the crisis, [as highlighted by Gambacorta et al. (2012, p.6)] there was also a considerable degree of heterogeneity in the design of central bank balance sheet policies". In other words, while the policies typically led the central banks' balance sheets to increase, their compositions varied across economies. To illustrate, while lending to the financial sector and large-scale purchases of private sector and government securities account for the expansion of the Fed and BoE's balance sheets, the Eurosystem's unconventional monetary policy, as summarised above, primarily focused on lending to financial institutions.[9] Therefore, as

[8] See Davies (2011).

[9] See Gambacorta et al. (2012, p.6).

Table 3.1.1: The Global Financial Crisis and Unconventional Monetary Policy

| **Study** | **Approach** | **Country/Sample** | **Conclusion** |
|---|---|---|---|
| Bernanke et al. (2004b) | Event study and VAR models | US, JP - 1982M6-2004M8 | Significant impact of Fed statements on shaping public expectations of future policy actions. No significant impact of Bank of Japan communications on one-year ahead expectations. |
| Meier (2009) | Event study | UK - 2009M2-2009M6 | Economically significant effects of the Bank of England's first round of asset purchases. |
| Giannone et al. (2011) | Bayesian VAR model | EA as an aggregate<br>• 1991M1-2008M8<br>• 1999M1-2010M3<br>• 'Policy' and 'no policy scenarios' for the period Sep 2008 - Mar 2010 | ECB's unconventional monetary policy measures "supported financial intermediation, credit expansion and monetary policy transmission in the euro area in the face of financial crisis, as was intended" (p.6). |
| Peersman (2011) | Structural VAR model | EA as an aggregate - 1999M1-2009M12 | Compared to a traditional interest rate innovation, an expansionary shock to the monetary base or central bank balance sheet displays a more sluggish pass-through effect on economic activity (hump-shaped) and consumer prices (permanent). |
| Gagnon et al. (2011) | Event studies and time series regressions | US, UK, JP - 85M1-08M6/08M12-10M3 | Central bank asset purchases mainly affect bond yields and other asset prices by reducing term or risk premia through portfolio balance effects. |
| Joyce et al. (2011a) | VAR & GARCH-M models | UK - 1990M12-2009M12 | |
| Joyce et al. (2011b) | Review of QE | UK | |
| D'Amico and King (2012) | Fixed-effects panel | US - 17 Mar - 30 Oct 2009 | |

| Study | Approach | Country/Sample | Conclusion |
|---|---|---|---|
| Krishnamurthy and Vissing-Jorgensen (2011) | Event studies and time series regressions | US - 1926-2008 / 26 Aug 10 - 02 Nov 10 | Fed's large-scale asset purchases (LSAPs) were successful in reducing medium and long-term interest rates. |
| Swanson (2011) | High-frequency event studies | US - 2 Feb - 6 Apr 1961 | |
| Hamilton and Wu (2012) | Term-structure model of risk-averse arbitrageurs | US - 1990M1-2011M1 | |
| Giannone et al. (2012) | Bayesian VAR model | EA as an aggregate<br>• 1990M1-2011M4<br>• 'Policy' and 'no policy scenarios' for the period Aug 2007 - Apr 2011 | Relative to a 'no policy scenario', ECB's response to the crisis is associated with:<br>• higher bank loans to households and, in particular, to non-financial corporations<br>• a significant improvement on economic activity. |
| Borio and Zhu (2012) | Review of 'risk-taking channel' of monetary transmission mechanism | | "To the extent that risk perceptions and risk tolerance become more pervasive influences on behaviour, the direct and indirect impact of monetary policy on expenditures through its nexus with risk-taking may well grow" (p.248). |
| Neely (2012) | Portfolio balance model and event-study methodologies | AU, DE, CA, JP, UK, US - 1985M2-2010M4 | US LSPAs had substantial effects on long-term interest rates and the spot value of the dollar. |
| De Santis (2012) | Cointegration, dynamic OLS and structural VAR model | AT, DE, BE, GR, ES, FI, FR, IE, IT, PT, NL - 1 Sep 08 - 4 Aug 11 | Factors which accounts for sovereign spreads in the EA: (i) an aggregate regional risk factor; (ii) the country-specific credit risk, (iii) the spillover effect from Greece. |

Abbreviations: AT-Austria, AU-Australia, BE-Belgium, CA-Canada, DE-Germany, GR-Greece, ES-Spain, FI-Finland, FR-France, IE-Ireland, IT-Italy, JP-Japan, NL-Netherlands, PT-Portugal, UK-United Kingdom, US-United States.

we can see from Figure P.0.1, securities account for the majority of the assets of the Fed and BoE whilst lending has been the main item of the Eurosystem balance sheet during the crisis period. Country-specific effects of the policies are as summarised in Table 3.1.1.

Gambacorta et al. (2012) contribute to the literature on the investigation of the effectiveness of unconventional monetary policy by applying a cross-country approach to eight advanced economies.[10] The authors investigate the impact of exogenous shocks to central bank assets on the dynamics of output and prices using a structural panel VAR model over the crisis period (Jan 2008 - Jun 2011). The main finding of the paper is that following an expansionary unconventional monetary policy shock, output and prices temporarily and statistically significantly increase in the countries. Gambacorta et al. (2012) also observe homogeneous responses of the economic activity and prices across the countries.

In this chapter, we follow the methodology of Gambacorta et al. (2012), described in Section 3.3, in order to investigate the effects of unconventional monetary policy actions of the Eurosystem across thirteen countries of the EA (EA-13). In particular, we estimate a four-variable[11] structural panel VAR model for Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Slovenia, and Spain, for the crisis period from January 2008 to September 2012.[12] To our knowledge, this paper is the first to investigate the effectiveness of expansionary unconventional monetary policy shocks across EA economies, and to do so using a panel VAR technique.

Our mean group estimations suggest that, in line with the literature summarised in

[10]Canada, EA, Japan, Norway, Sweden, Switzerland, the United Kingdom, and the United States.

[11]Output, prices, market volatility, central bank assets.

[12]Among seventeen states of the EA, Cyprus, Estonia, Malta and Slovakia are excluded because these countries adopted euro within the sample period of the analysis. We only focus on the countries which had experienced the structural transformation from independent monetary policy to monetary union before the beginning of our sample period.

Table 3.1.1, both output and prices increase statistically significantly as a result of an expansionary monetary policy shock during the crisis period. We observe the responses of output to be transitory, lasting for 15 periods following the shock, while that of prices are stronger and much more persistent. Furthermore, our country-level results highlight that whereas prices rise relatively homogeneously across countries of the interest, economic activities display important heterogeneity. In particular, following an expansionary shock to NCB total assets, we observe core countries' (e.g. Germany, France, the Netherlands) economic activities increasing for up to three years whilst that of the peripheral countries (e.g. Greece, Portugal, Spain) contracting persistently.

According to the main findings of Chapter 2, we raised the issue of heterogeneous transmission of (un)conventional monetary policy actions across the EA economies through (heterogeneous) channels.[13] Given the support of the empirical findings of the present chapter to that argument, we believe it is important to describe the theoretical aspects of the monetary transmission mechanism. The following subsection contains these details.

### 3.1.1 Monetary Transmission Mechanism

According to traditional textbooks, e.g. Mishkin (2012), (expansionary) monetary policy is expected to affect the aggregate demand through three basic mechanisms: traditional interest rate channel, asset price channels, and credit view. Given the emphasis of our paper on unconventional monetary measures, we summarise the asset price channel, and the credit view.[14,15]

[13]See Section 2.6, p.154.

[14]This part follows Mishkin (2012, Chapter 26).

[15]For details of other channels such as 'traditional interest rate effects', 'exchange rate effects on net exports', 'cash flow channel', and 'unanticipated price level channel', see Mishkin (2012, p.665).

First, expansionary monetary policy is expected to increase share prices which will have a positive impact on Tobin's $q$[16] and the value of consumers' financial wealth. Following the $q$ theory of Tobin (1969) and the life-cycle hypothesis of Ando and Modigliani (1963), higher share prices will lead to higher investment spending and consumption due to, respectively, higher $q$ of businesses and higher lifetime resources of consumers.

Second, the credit view suggests that financial frictions in credit markets (i.e. adverse selection and moral hazard) lead to two types of monetary transmission channels: bank lending and balance sheets of firms and households. According to the bank lending channel, expansionary monetary policy, which increases bank reserves and bank deposits, leads to higher bank loans. Due to the importance of bank loans for borrowers in financing their activities, this increase in loans leads investment (and possibly consumer) spending to rise, hence improve the economic activity.

The other credit channel, i.e. the balance sheet channel, highlights the importance of financial frictions in credit markets. There is no doubt that a decline in the net worth of business firms increases the possibility of adverse selection and moral hazard problems. Lower net worth of businesses, on the one hand, means less collateral for lenders' loans (adverse selection). On the other hand, lower levels of net worth raises the moral hazard problem due to higher incentives for risky investment projects caused by lower equity stakes. Given the importance of adverse selection and moral hazard problems in credit markets, balance sheet channel suggests that higher share prices, following an expansionary monetary policy, lead to increase in the net worth of firms which lowers financial frictions and increases lending. As a result, investment and aggregate demand

[16] Tobin (1969) defines $q$ as the ratio between the market value of capital and its replacement cost, and proposes that "[t]he rate of investment - the speed at which investors wish to increase the capital stock should be related, if to anything, to $q$ ..." (p.21).

increase in the economy.

The final balance sheet channel through which monetary policy can affect the aggregate demand is related to liquidity effects on consumer durable and housing expenditures. According to Mishkin (2012, p.669), "if consumers expect a higher likelihood of finding themselves in financial distress, they would rather hold fewer illiquid durable or housing assets and more liquid financial assets." Therefore, an increase in consumer cash flow, arising from the improvement of financial assets, decreases the probability of financial distress, which increases the expenditure on durables and housing, and hence the aggregate demand. Furthermore, the increase in the demand for housing leads to higher house prices which itself also creates positive wealth effects on the aggregate demand. Besides this wealth effect, as highlighted by Hofmann (2003) and Goodhart and Hofmann (2008), there is also a collateral effect of house prices which suggests better borrowing capacity, given the fact that houses are commonly used as collateral for loans, and enhanced household spending. On the construction side, according to Goodhart and Hofmann (2008), residential investment is the main channel of house-price fluctuations to economic activity. The authors name this effect as 'the Tobin $q$ for residential investment' which suggests higher housing construction due to increase in the value of housing relative to its construction cost.

The descriptions above mainly apply to conventional monetary policy of lowering short-term (nominal) interest rates.[17] However, the transmission mechanism of unconventional monetary policy does not significantly differ from the conventional channels.

[17]Mishkin (2012) highlights the emphasis of interest-rate transmission mechanism on the real interest rate, and claims that "the key is the phenomenon of *sticky prices*, the fact that the aggregate price adjusts slowly over time, so that expansionary monetary policy, which lowers the short-term nominal interest rate, also lowers the short-term real interest rate" (p.663).

To illustrate, as we cited earlier, Borio and Disyatat (2009) emphasise that the choice of market targeted by the central bank is “atypical” or “unprecedented”. “It is this choice that makes the policies ‘unconventional’, not the overall approach of seeking to influence specific elements of the transmission mechanism other than the policy rate.”[18] Borio and Disyatat claim that “the main channel through which they [unconventional measures] affect economic activity is by altering the balance sheet of private sector agents [portfolio balance sheet channel], or influencing expectations thereof [signalling channel]” (p.2). That is to say, the unconventional measures affect interest rates (e.g. term money market rates, long-term government bond yields) by changing the supply of assets held by the private sector[19] and “by lowering expectations of future short rates or by reducing the term premium on longer term bonds.”[20]

Besides the portfolio balance sheet and signalling channels, Borio and Zhu (2012) stress “a [possible] missing link in the transmission mechanism” called the ‘risk-taking channel’. According to Borio and Zhu, easier funding conditions and fewer risky assets in portfolios “may reduce perceived risks and induce higher risk-taking”.[21] Borio and Zhu claim that “to the extent that risk perceptions and risk tolerance become more pervasive influences on behaviour, the direct and indirect impact of monetary policy on expenditures through its nexus with risk-taking may well grow” (p.248). Given the safe haven status of core EA countries, and significant defaults risks and bailouts of the peripheral sovereigns in the EA, we believe that the risk channel is of importance for the explanation of cross-country heterogeneity observed in our empirical analysis.[22]

[18] Borio and Disyatat (2009, p.5).
[19] Given the ‘imperfect substitutability’ strand of the literature on the asset side of private sector balance sheet. See Brainard and Tobin (1968).
[20] Fender (2012, p.209).
[21] Borio and Disyatat (2009, p.14).
[22] See Sections 3.4 - 3.6.

Our investigations of the monetary transmission mechanism and the developments in various EA macroeconomic indicators during the crisis, clearly suggest that (i) neither asset price and portfolio balance sheets channels nor the signalling channel functioned well in the periphery, especially in Greece; (ii) despite significant increases in central bank assets, sharp decreases in peripheral sentiment, bank lending and the money supply prevented the transmission of the policy measures into the real economy; and (iii) the risk-taking channel, i.e. "persistence-enhancing mechanism"[23], played its enhancement (diminishment) role for the core (periphery) during the Great Recession.[24]

### 3.1.2 Structure of the Chapter

The rest of the chapter is organised as follows. Section 3.2 presents the data under investigation. The methodology of the chapter is described in Section 3.3. Section 3.4 contains the empirical findings of the chapter which we test for various model variations and extensions in Section 3.5. We link the empirical findings of the chapter to the actual heterogeneity between core and periphery in Section 3.6. Section 3.7 concludes the chapter.

## 3.2 Data

The data set of the chapter is a balanced panel of monthly macroeconomic time series for thirteen EA economies spanning the period from January 2008 to September 2012.[25] The countries under investigation are Austria, Belgium, Finland, France, Germany, Greece,

[23]See Borio and Zhu (2012, p.237).
[24]For details see Section 3.6.
[25]A balanced panel could be gathered for this sample when the chapter was written.

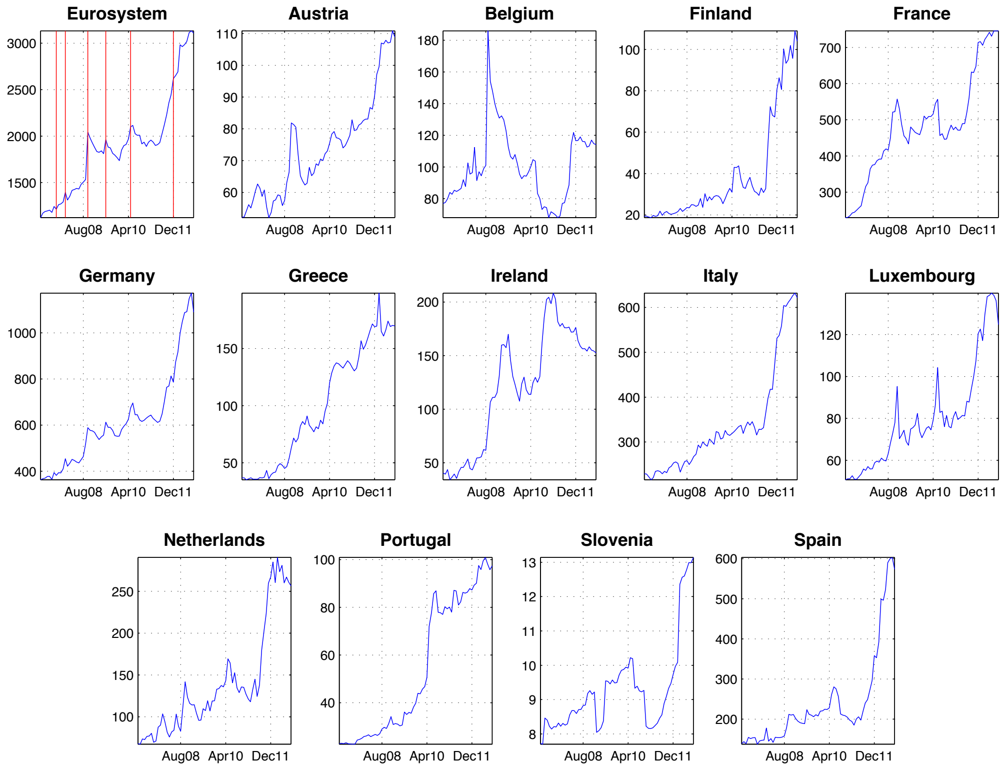



Figure 3.2.1: Total Assets of the Eurosystem

Outstanding amounts at the end of the periods (Billions of Euro, SA)

Note: ECB's Response to the Crisis (red lines): *Aug 07* - Extra liquidity on an ad hoc basis, *Dec 07* - Swap agreement with the Fed, *Oct 2008* - Extraordinary liquidity measures, *Jun 09* - Purchase programme for covered bonds, *May 10* - Securities Markets Programme (SMP), *Dec 11* - LTRO.

Ireland, Italy, Luxembourg, the Netherlands, Portugal, Slovenia, and Spain.

Our benchmark four-variable panel VAR model consists of economic activity, price level, financial market volatility and central bank balance sheet. We proxy these variables using, respectively, IP, CPI, VIX and central bank total assets/liabilities. All series are corrected for missing observations, if any, and adjusted for outliers and seasonal behaviour using Demetra+ package. Table 3.2.1 presents the details of the data set.

Table 3.2.1: Data Set

| Series | Type/Unit | Source |
|---|---|---|
| **Benchmark Model** | | |
| Industrial Production | Volume Index, 2005=100 | Eurostat |
| CPI | Index, 2005=100 | Eurostat |
| VIX | Index, % | Datastream |
| Total Assets | End of period, Millions of Euro | NCBs |
| **Model Extensions** | | |
| Base Money | End of period, Millions of Euro | ECB SDW |
| Eurosystem Assets | End of period, Millions of Euro | ECB SDW |
| GDP | Volume Index, 2005=100 | Eurostat |
| REFI | End of period, % per annum | Eurostat |
| Government Exp. | Chained Volume, Millions of Euro | OECD/NCB |
| Public Debt | End of period, Millions of Euro | Eurostat |
| MFI Private Lending | End of period, Millions of Euro | NCB |
| NEER | Index, 1999Q1=100 | ECB SDW |
| Gold Price | Euro per troy once | Datastream |
| Bond Yield | End of period, % per annum | ECB SDW |
| Unemployment Rate | Monthly average, % | Eurostat |

## 3.3 Methodology

The estimation methodology of the chapter closely follows Gambacorta et al. (2012).[26,27]

The panel VAR approach is based on the following reduced-form model:

$$X_t = \beta X_{t-1} + u_t \tag{3.3.1}$$

where $X_t$ is a vector of endogenous variables, i.e. $X_t = [ip, cpi, VIX, ta]'$, all of which, except the VIX index, enter the system in a log-level form.[28]

[26]We are grateful to the authors for sharing the replication files of their paper.

[27]Our special thanks also go to Charles Rahal for his great efforts in our collaborative work on the methodology and the estimation procedure of the chapter.

[28]See Sims et al. (1990) for the benefits of estimation of VARs in levels in terms of implicit cointegrating relationships in the data.

### 3.3.1 System of Equations

In the first step of the estimation procedure, we group the equations of each variable across countries and then estimate them as a system of seemingly unrelated regression (SUR) models in order to account for the cross-country correlations in the residual series of each variable. The SUR estimator ($\hat{\beta}$) is given by:

$$\hat{\beta} = \left(X'_{t-1}(\hat{\Sigma}^{-1} \otimes I)X_{t-1}\right)^{-1} \left(X'_{t-1}(\hat{\Sigma}^{-1} \otimes I)X_t\right) \tag{3.3.2}$$

where $E[u'u] = \Sigma$ is the covariance matrix of these regressions, estimated as:

$$\hat{\Sigma} = \frac{1}{T}\sum_{t=1}^{T} \hat{u}_t \hat{u}_t{}' \tag{3.3.3}$$

### 3.3.2 Bootstrapping

Having the cross-country correlations accounted for, we secondly simulate the system of equations using bootstrapping technique, which again uses the aforementioned SUR methodology to group each variable together across countries. We then compute the eigenvalues of the companion matrices of country-specific bootstrap VARs in order to check the dynamic stability of the system.

### 3.3.3 Structural VAR

In order to obtain a structural re-parameterisation of the system, let us start with the reduced-form representation (3.3.1). If we assume that $A$ represents the contemporaneous relationships between the variables, and $B$ represents the correlations across the structural shocks ($\varepsilon_t$), then the 'true' structure of the model becomes:

$$AX_t = \Gamma X_{t-1} + B\varepsilon_t \tag{3.3.4}$$

If we pre-multiply (3.3.4) by $A^{-1}$, we obtain:

$$X_t = A^{-1}\Gamma X_{t-1} + A^{-1}B\varepsilon_t \tag{3.3.5}$$

which implies $\beta = A^{-1}\Gamma$ in (3.3.1). As we cited in Chapter 1, it is common in the literature to follow Bernanke (1986) and assume orthogonality between the structural shocks, and normalise them to have a unit variance, i.e. $E[\varepsilon_t \varepsilon_t'] = I$. Therefore, from (3.3.1) and (3.3.5), the relationship between the reduced-form errors and the structural shocks can be shown as:

$$u_t = A^{-1}\varepsilon_t \qquad \text{or} \qquad Au_t = \varepsilon_t \tag{3.3.6}$$

We discussed in Chapter 1 the alternative identification schemes in the literature,[29] one of which is a recursive ordering of the variables in a VAR system.

### Recursive Identification

Following Fry and Pagan (2007), the recursive structure of the system allows us to obtain the estimates of $A$, e.g. by OLS, expressed as:

$$\hat{u}_t = \hat{A}^{-1}\hat{\varepsilon}_t \tag{3.3.7}$$

Given the number of estimable parameters in $\hat{A}$, this system is not presently identified. For the general case, assume we call $S$ the matrix which contains the estimated standard deviations of the structural shocks ($\varepsilon_t$) on the diagonals and zeros elsewhere. Therefore,

$$\hat{u}_t = \hat{A}^{-1}SS^{-1}\hat{\varepsilon}_t = T\eta_t \tag{3.3.8}$$

[29]See Section 1.2.3, p.25.

where $T = \hat{A}^{-1}S$, and $\eta_t = S^{-1}\hat{\varepsilon}_t$ with unit variance. Given the recursive structure of the system, $T$ is lower triangular, similar to $A$. Suppose we can find a square matrix $Q$ such that $Q'Q = QQ' = I$,[30] then;

$$\hat{u}_t = TQ'Q\eta_t = T^*\eta_t^* \tag{3.3.9}$$

where $T^* = TQ'$ and $\eta_t^* = Q\eta_t$. This transformation allows us to generate new estimated shocks, such as those to central bank total assets ($\eta_t^*$), again with an identity covariance matrix due to the fact that:

$$E[\eta_t^*\eta_t^{*\prime}] = QE[\eta_t\eta_t']Q' = I \tag{3.3.10}$$

From (3.3.9) and (3.3.10), we obtain:

$$\hat{\Sigma} = E[\hat{u}_t\hat{u}_t{}'] = T^*T^{*\prime} \tag{3.3.11}$$

In order to recover $\eta^*$ from (3.3.10), one possibility is to assume a Cholesky decomposition of $\hat{\Sigma}$. Therefore, we generate a set of shocks ($\eta_t^*$) with a covariance matrix identical to $\eta_t$, but which will have a different impact upon $u_t$, and also on $X_t$. According to Fry and Pagan (2007, p.6), "it is this ability to create a large number of candidate shocks that is the basis of sign restriction methods", which we describe below.[31]

**Impulse Responses**

Having identified a system with a recursive structure as above, the impulse response functions can be obtained from the following MA representation of the system:

[30]See the part Generating Orthogonal Matrices below.
[31]See the part Sign Restrictions.

$$
\begin{aligned}
[A - \Gamma L]X_t &= \varepsilon_t \\
X_t &= C(L)\varepsilon_t \\
X_t &= C_0\varepsilon_t + C_1\varepsilon_{t-1} + \ldots + C_s\varepsilon_{t-s} \qquad (3.3.12)
\end{aligned}
$$

$$
\begin{aligned}
C(L) &= [A - \Gamma L]^{-1} \qquad (3.3.13) \\
C_0 &= A^{-1}
\end{aligned}
$$

$C_0$ represents the contemporaneous response, and we interpret the matrix $C_s$ within the MA representation as:

$$
C_s = \frac{\partial X_{t+s}}{\partial \varepsilon_t} \qquad (3.3.14)
$$

The element $\{i, j\}$ of $C_s$ represents the impact of a (one standard deviation) shock which hits the $j^{th}$ variable at time $t$ on the $i^{th}$ variable of the system at $t + s$.

### Sign Restrictions

The general idea of identification of VAR systems through sign restrictions is to generate candidate impulse responses which are then accepted or rejected based on the underlying economic theory. Following from the general discussion of recursive-structure VAR models and the calculation of impulse response functions, we describe the details of the sign restriction scheme as below.

**Generating Orthogonal Matrices:** We mentioned earlier that it is necessary to generate orthogonal $Q$ matrices such that $Q'Q = QQ' = I$. According to Fry and Pagan (2007), one way in which we can generate Q involves re-ordering the variables, still within a recursive framework. However, this does not exhaust all of the possible ways of combining the shocks while retaining the orthogonal structure. We follow the Givens transformation as per Gambacorta et al. (2012), as opposed to the QR decomposition which is obtained through a series of Householder transforms. We specify the Q matrix as:

$$Q_{3,4} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & \cos(\theta) & -\sin(\theta) \\ 0 & 0 & \sin(\theta) & \cos(\theta) \end{bmatrix} \tag{3.3.15}$$

From the equality that $\cos^2(\theta) + \sin^2(\theta) = 1$, we obtain $Q_{3,4}Q'_{3,4} = Q'_{3,4}Q_{3,4} = I_4$. Taking a quasi-Bayesian approach, $\theta_j$ draws are taken to be uniformly distributed over $(0, \pi)$, where $j$ represents the $j^{th}$ bootstrap draw. As we further describe below, in each bootstrap draw, the approach generates new candidate impulse responses which are then tested whether they satisfy the sign restrictions.

If we combine $Q'_{3,4}$ with the lower triangular $T$ matrix in (3.3.9), we obtain $T^*$ as follows:

$$\begin{aligned} T^* = TQ'_{3,4} &= \begin{bmatrix} t_{1,1} & 0 & 0 & 0 \\ t_{2,1} & t_{2,2} & 0 & 0 \\ t_{3,1} & t_{3,2} & t_{3,3} & 0 \\ t_{4,1} & t_{4,2} & t_{4,3} & t_{4,4} \end{bmatrix} * \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & \cos(\theta) & \sin(\theta) \\ 0 & 0 & -\sin(\theta) & \cos(\theta) \end{bmatrix} \\ &= \begin{bmatrix} t_{1,1} & 0 & 0 & 0 \\ t_{2,1} & t_{2,2} & 0 & 0 \\ t_{3,1} & t_{3,2} & \lambda_{3,3} & \lambda_{3,4} \\ t_{4,1} & t_{4,2} & \lambda_{4,3} & \lambda_{4,4} \end{bmatrix} \end{aligned} \tag{3.3.16}$$

where,

$$\begin{aligned} \lambda_{3,3} &= t_{3,3} * \cos(\theta) & \lambda_{4,3} &= t_{4,3} * \cos(\theta) - t_{4,4} * \sin(\theta) \\ \lambda_{3,4} &= t_{3,3} * \sin(\theta) & \lambda_{4,4} &= t_{4,3} * \sin(\theta) + t_{4,4} * \cos(\theta) \end{aligned}$$

and $T$ is the Cholesky decomposition.

### Identification by a Combination of Zero and Sign Restrictions

We have mentioned earlier that in this chapter of the thesis, we follow Gambacorta et al. (2012), and employ a mixture of zero and sign restrictions to identify exogenous shocks to NCB total assets in the EA, which we call unconventional monetary policy shocks.

As suggested by Christiano et al. (1999) and Gambacorta et al. (2012), in order to isolate the (un)conventional monetary policy shocks, we need identifying restrictions to estimate the parameters of the feedback rule which relates the monetary authority policy actions to the state of the economy.

Our identification scheme is based on the following set of assumptions. First, it is assumed that the policy shocks have a lagged impact on output (*ip*) and prices (*cpi*). That is to say, following the recursive structure of the system,[32] the contemporaneous response of the variables to the policy shocks is restricted to be zero. Second, we assume an expansionary shock to central bank balance sheet not to increase stock market volatility (*VIX*). "This restriction is needed in order to disentangle exogenous innovations to the central bank balance sheet from their endogenous response to financial turmoil, and from financial market disturbances."[33] Third, we explained in the Introduction of the chapter the immediate responses of the central banks to mounting uncertainty in global financial markets. We also highlighted the mitigating power of the balance sheet policy actions on the markets. As such, it is assumed in the scheme that the central bank assets increase in response to exogenous rise in the market volatility whilst the contemporaneous impact of the policy interventions on the markets is different from zero. Following these assumptions, we summarise our identifying restrictions in Table 3.3.1.

[32] See below for details.
[33] Gambacorta et al. (2012, p.10).

Table 3.3.1: Identification Restrictions

| Output | Prices | VIX | Central Bank Assets |
|---|---|---|---|
| 0 | 0 | $\leq$0 | >0 |

Given the focus of the chapter on unconventional monetary policy shocks, as it is common in the VAR literature, we order the policy variable, i.e. central bank total assets ($ta$) last in the system. The main assumption here is that the monetary policy is the most endogenous variable to the system; that policymakers observe shocks to other variables when determining their optimal response. Therefore, the ordering of the system is

$$X_t = [ip, cpi, VIX, ta]' \tag{3.3.17}$$

We have derived in (3.3.16) the relationship between the reduced-form and structural shocks as:

$$\hat{u}_t = \begin{bmatrix} t_{1,1} & 0 & 0 & 0 \\ t_{2,1} & t_{2,2} & 0 & 0 \\ t_{3,1} & t_{3,2} & \lambda_{3,3} & \lambda_{3,4} \\ t_{4,1} & t_{4,2} & \lambda_{4,3} & \lambda_{4,4} \end{bmatrix} * \eta_t^* \tag{3.3.18}$$

If we combine the identifying restrictions summarised above with the matrix in (3.3.18), it turns out that the elements of the fourth column are restricted as below:

$$\begin{aligned} \lambda_{3,4} &= t_{3,3} * \sin(\theta) \leq 0 \\ \lambda_{4,4} &= t_{4,3} * \sin(\theta) + t_{4,4} * \cos(\theta) > 0 \end{aligned}$$

Following from the MA representation of the impulse responses functions (3.3.14), the identifying sign restrictions are imposed on the elements $\{3,4\}$ and $\{4,4\}$ of the matrices $C_0$ and $C_1$. That is to say, in order for a bootstrap draw to be kept in the estimations, an expansionary shock to central bank assets must have a positive impact on the assets, whilst the response of the market volatility to the shock must be negative for the horizon of one period (i.e. contemporaneous + 1) for all countries in the panel simultaneously. Otherwise the procedure discards the draw as it does not satisfy the restrictions imposed by economic theory. To display the impulse responses, finally, we order the draws in an ascending order (1,2,...,#draws) and use this order to compute the median and quantiles (i.e. 16th and 84th) for confidence intervals of the impulse responses.

## 3.4 Results

Having explained the methodological details of the chapter, this section contains the findings of our empirical analysis. Figures 3.4.1 - 3.4.4 present the benchmark estimation results obtained with a four-variable panel VAR model. The estimations[34] are based on 10,000 bootstraps, and the results are displayed, in standard deviation ($SD$) units, with the 16th and 84th percentiles of the draws. In order to have a successful decomposition for all individual countries in the panel about 15 draws, on average, are needed.

In Figure 3.4.1, we display the weighted average of the country-level impulse responses for the variables of the system.[35] Our mean group estimations suggest that, first, following an expansionary shock to NCB assets, during the Great Recession period, real output of EA-13 countries increases, statistically significantly, for a year. From period 16 onwards, the median impulse responses suggest that there is a slightly contractionary effect of the shock on the area-wide real activity.

[34]Obtained with Regression Analysis of Time Series (RATS) package, version 8.1.

[35]The impulse responses are weighted according to the following shares of the individual central bank assets in the aggregate assets of the thirteen NCBs: Germany (25.7%), France (20.1%), Italy (14.2%), Spain (10%), Netherlands (5.8%), Ireland (5%), Belgium (4.2%), Greece (4.1%), Luxembourg (3.4%), Austria (3.1%), Portugal (2.3%), Finland (1.6%), Slovenia (0.4%).

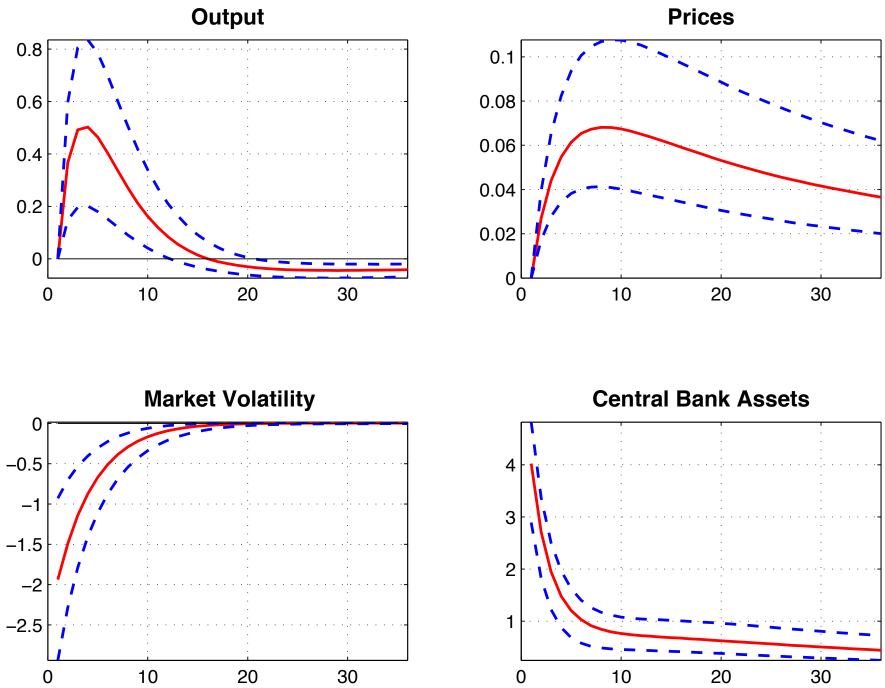



Figure 3.4.1: Weighted Average of Country-Level Responses

The dashed lines are the 16th and 84th percentiles of 10,000 bootstraps.

Second, consumer prices display statistically significant and persistent increase as a results of the expansionary policies of the NCBs. Qualitatively similar results are obtained by Gambacorta et al. (2012) with a panel VAR of eight developed countries, where the EA is taken into account as an aggregate. Our results suggest that the empirical evidence on prices in the EA responding persistently to exogenous balance sheet policies is robust to the consideration of cross-country correlations either within the EA itself or among other advanced economies. When cross-country correlation is omitted, according to the country-specific structural VAR models of Peersman (2011), although statistical significance of the responses is lost for the first twelve months following the shock, EA consumer prices still display positive and persistent responses to unconventional policy actions in medium term.

Third, the average impulse responses of the VIX index of the EA suggest that the tensions in financial markets continuously decrease for almost 20 months as a result of the exogenous rise in total assets of the NCBs. Following a one *SD* shock, finally, NCB assets instantly and strongly increase before they gradually decline for three years. In addition to mean group results, Figures 3.4.2 - 3.4.4 present our individual country estimations, where the first subplots display the average country-level responses of the particular variable.

If we start with the impact of an expansionary shock to NCB assets on the real economy, we observe the following. First, the majority of the economies in the EA respond positively to the unconventional monetary policy measures implemented by the NCBs. As we can see from Figure 3.4.2, although there is some extent of homogeneity across these countries, the economies of Finland, Luxembourg and Slovenia respond relatively stronger than that of other countries. Relative to the area-wide average, real activity in Germany and Italy also respond stronger in the first ten months following the shock. The estimations suggest that the positive impact of the shock lasts, on average, for twenty periods. These country-level estimations of the chapter are in line with the general conclusion of the literature on the effectiveness of central bank balance sheet policies, summarised in Table 3.1.1.

Secondly, according to Figure 3.4.2, not all countries in the EA experience positive impacts of the Eurosystem unconventional policy actions. In line with debates on the heterogeneity between core and peripheral countries in the EA,[36] our country-level estimations suggest that economic activity in the periphery, especially in Greece, statistically significantly declines following an exogenous increase in NCBs' total assets. Whereas we observe both initially positive and only slightly negative responses of Italian, Portuguese and Spanish (increase in the first ten periods only) economic activities, the Greek economy responds to the expansionary policy shock negatively. Our model estimates the contrac-

[36]See, among others, Economist (2012); Feldstein (2012); IMF (2012).

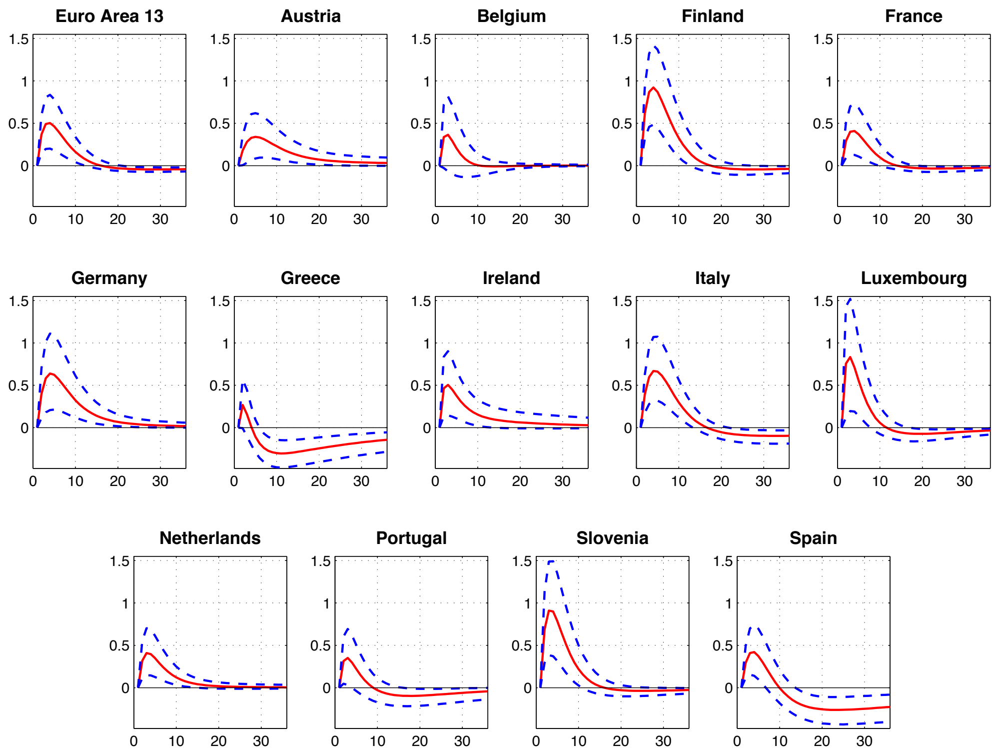



Figure 3.4.2: Impulse Responses of Output

The dashed lines are the 16th and 84th percentiles of 10,000 bootstraps.

tion in Greece to be strong, relative to medium-term decline in other peripheral economies, statistically significant, and persistent for three years following the policy expansion.

Before we try to suggest possible explanations for the heterogeneous results across European countries, we look at the responses of country-level prices to the exogenous shocks to NCB total assets. Figure 3.4.3 shows that (i) the impact of the shock on consumer prices in Belgium, Ireland and the Netherlands are statistically not different than zero; (ii) prices in all other countries respond statistically significantly to the shock; (iii) price level in Germany increases relatively less than all other countries; (iv) price levels in Italy and France increase around the level of the aggregate responses (EA-13); and (v) the impact of the unconventional monetary policy on the rest of the countries' price levels is much more stronger. To illustrate, consumer prices in Greece and Spain

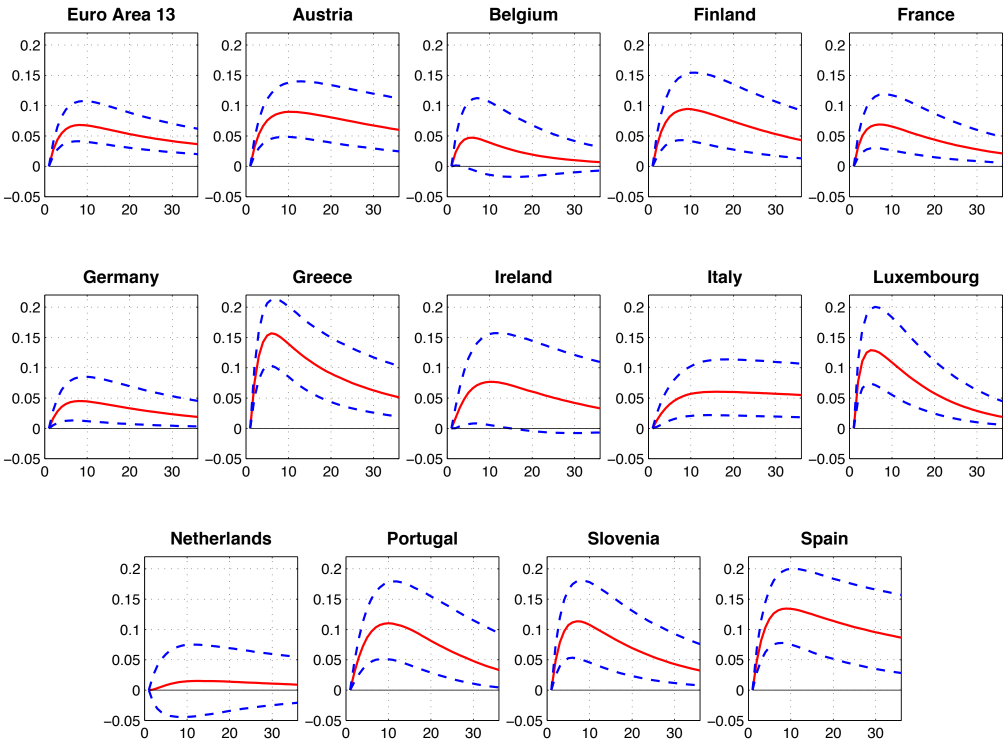



Figure 3.4.3: Impulse Responses of Prices

The dashed lines are the 16th and 84th percentiles of 10,000 bootstraps.

increase almost three times more than those in the German economy. It also takes longer for the prices in these peripheral economies (including Italy) to return to their pre-shock levels.

Finally, we display the responses of the NCB assets to the exogenous shocks in Figure 3.4.4. Overall, the NCB balance sheets display qualitatively similar responses across countries. Other than the differences in contemporaneous jumps of the variables, however, the only considerable difference is the impact of the shock on NCB of Ireland and Portugal. As we can see from the figure, it takes considerably longer for the total assets of the Central Bank of Ireland and Banco de Portugal to return to their pre-shock levels. On the one hand, these two peripheral countries, and some extent Spain, share the burden of the sovereign debt crisis in the EA with Greece. However, on the other hand, we observe in

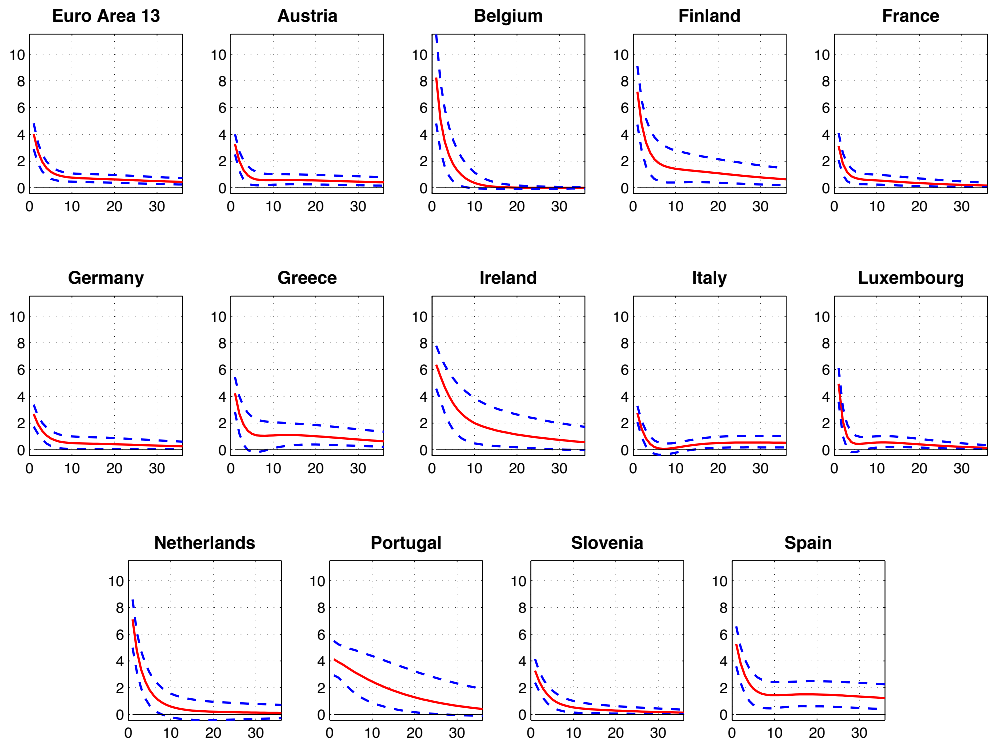



Figure 3.4.4: Impulse Responses of NCB Assets

The dashed lines are the 16th and 84th percentiles of 10,000 bootstraps.

the impulse responses of output that neither Ireland nor Portugal display as contractionary responses as Greece and Spain. In addition to other country-specific factors, examined in Section 3.6, we think that the responses of Irish and Portuguese central banks to the shock might have prevented their economic activities from responding negatively in our empirical model.

The assumption above on NCBs behaving differently in a monetary union depends on the decentralised structure of the implementation of monetary policy in the Eurosystem. As described by Moutot et al. (2008), the NCBs are independent with regard to their operational tasks despite being an integral part of the Eurosystem. That is to say, main refinancing, longer-term refinancing, fine-tuning reverse and structural reverse operations, outright transactions, foreign exchange swaps, and collection of fixed-term deposits are all executed in the Eurosystem in a decentralised manner by the NCBs. Briefly, monetary policy in the Eurosystem is based on a centralised decision-making system by the Governing Council which consists of the governors of the NCBs of the EA countries and the six members of the Executive Board.[37]

Before we try to rationalise our empirical results in Section 3.6, we test robustness of the findings to model variations and extensions in the following section.

## 3.5 Robustness

The variations and extensions to our benchmark model are as follows.[38] First, we replace the NCB assets in the system of equations with common variables[39] of the Eurosystem base money and total assets.

Second, we replace IP with monthly interpolation estimates of real gross domestic product (GDP).[40]

Third, as we can see from Figure 3.5.1, when we calculate the optimal lag length of the country-specific VARs (i.e. 13 VARs) with selection criteria, we find that BIC estimates a lag length of one to be the optimal specification for all the countries under investigation. Not for all but for a majority of the systems a lag length of one is found to be optimal by other criteria. A lag length of two (if we ignore AIC and FPE which are clearly affected by the maximum lag length used in the tests), is also suggested by some other information criteria, and we therefore test the robustness of our empirical results to VAR(2).

[37]See Articles 12.1 and 14.3 of the Statute of the European System of Central Banks and ECB (2011), and Chapters III and IV of the Maastricht Treaty for further details of the Eurosystem.

[38]To limit computational time, the robustness estimations are based on 5,000 bootstraps.

[39]The same variable is used in each equation of the system.

[40]Monthly GDP series are estimated using Chow and Lin (1971) interpolation technique with IP volumes as related series.

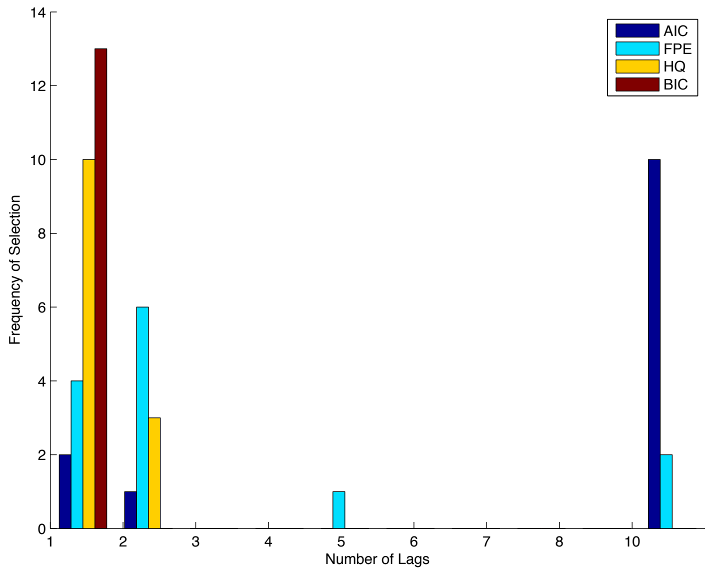



Figure 3.5.1: Lag Length Selection

Fourth, we extend the sign restriction horizon from one to five periods, and the model itself with various series such as the ECB's benchmark policy rate, public debt,[41] volume of general government expenditure, government bond yields, MFI lending to private sector, nominal effective exchange rate, gold price[42] and unemployment rate.

Figure 3.5.2 presents the impulse response functions of output with the robustness tests.[43] As a result of the robustness checks, our benchmark results turn out to be robust to model variations and extensions. That is to say, we still observe two sets of output responses across countries. On the one hand, we have core countries' economic activities which respond positively and statistically significantly to an exogenous expansionary balance sheet policy. Economic activity in peripheral economies, on the other hand, display (statistically) significant decline during the crisis period despite the expansionary balance

[41] The model is extended with REFI and public debt following Gambacorta et al. (2012).

[42] Gold prices and foreign exchange rates enter the balance sheets of the Eurosystem central banks, i.e. via the items gold and gold receivables, and claims in foreign currency, which respectively account for, on average, 8% and 24% of the ECB's total assets during the period 2007-11.

[43] For the sake of comparability of the median responses, confidence intervals of the impulse responses have been removed from the figure. The confidence intervals, available upon request, display qualitatively similar conclusions as in Figure 3.4.2.

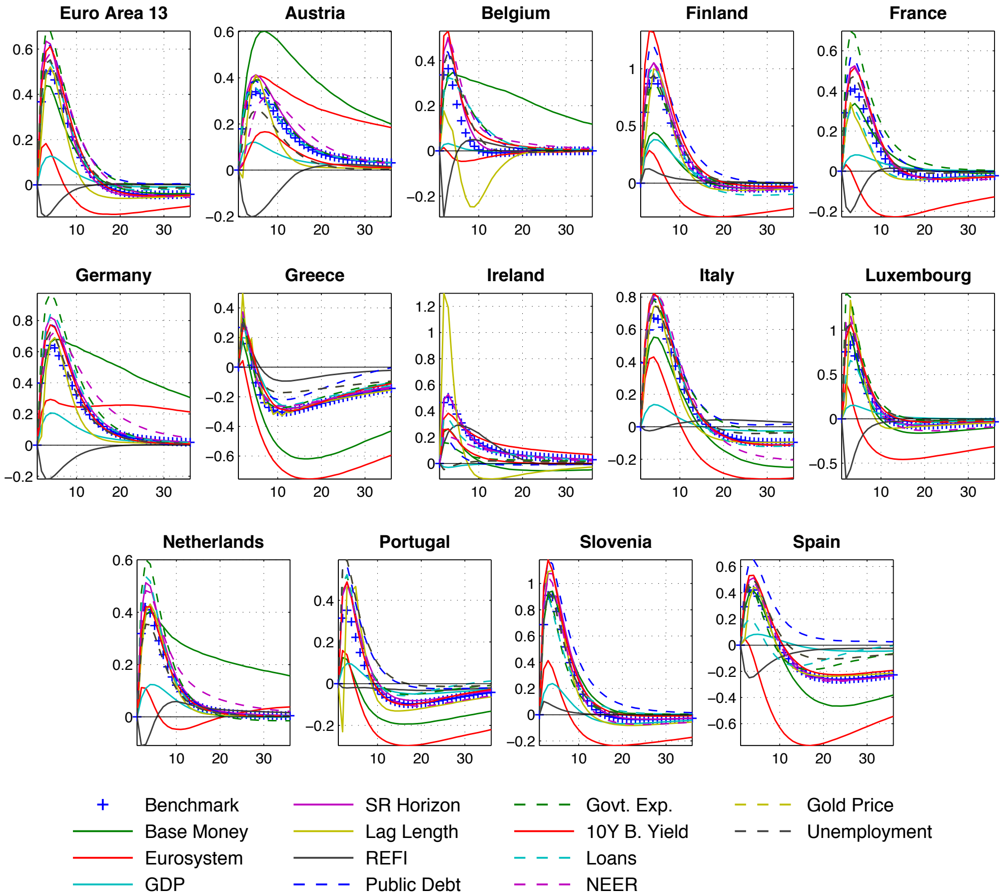



Figure 3.5.2: Robustness Checks on the Impulse Responses of Output

sheet policies of the Eurosystem.

Although robustness checks are overall consistent with the benchmark estimation results, some caution is required for the test which identifies unconventional monetary policy shocks as innovations to the Eurosystem total assets. As strong responses of output in almost all periphery, and even in France, suggest, using an area-wide variable as large as Eurosystem total assets in a panel approach like ours might increase the impact of the shock substantially. As we can see from Figure 3.5.2, this condition may generate contradictory impulse responses, at least relative to our benchmark and other various robustness estimations. Therefore, we believe that this finding supports our choice of identifying unconventional monetary policy shocks using NCB assets instead of area-wide aggregate measures.

We can also apply the same cautious approach to the robustness checks using the Eurosystem base money. When we compare the base money to the total assets of the NCBs, we observe that the former is significantly higher than the latter, except for the largest four economies of the EA which account for 70% of the aggregate NCB total assets.

In addition to these robustness checks, finally, we test the impact of governor change at the ECB which occurred towards the end of our sample, i.e. November 2011. In particular, we follow Leduc et al. (2007) and estimate our panel VAR model with an exogenous binary dummy variable which takes the value of zero (0) for the period of Jean-Claude Trichet's presidency at the ECB in our sample (January 2007 - October 2011) and one (1) for the period onwards when Mario Draghi became the governor of the ECB (November 2011 - September 2012). Because the estimations with the dummy variable are almost identical with our benchmark results on output and prices,[44] the impulse responses are excluded from Figure 3.5.2.

The following section investigates key macroeconomic indicators in core and peripheral economies of the EA in order to shed light on these robust but contradictory responses of national economic activities to expansionary monetary policy shocks.

## 3.6 The Periphery Puzzle

We presented in the previous two sections the contradictory responses of economic activities across core and periphery to exogenous increases in central bank balance sheets. In particular, the negative responses of real activities in Greece and Spain, especially,

[44] Both the median and percentile estimates.

were the most surprising findings of the chapter. Let us call this finding 'the periphery puzzle' of the analysis, because we believe it is less surprising to observe statistically zero responses of economic activities in the periphery to expansionary balance sheet shocks during the crisis period than statistically significant negative responses.

In this section, we try to shed some light on the periphery puzzle by investigating the developments in core and peripheral economies of the EA during the Great Recession period. Figure 3.6.1 displays various key macroeconomic indicators for the EA as an aggregate, and selective core and peripheral countries.

In Section 3.1.1, we described the transmission mechanism of monetary policy, the main channels of which, in the context of unconventional monetary policy, are (i) the balance sheet channel transferring the impact of monetary policy into the real economy through improvement of net worth of businesses, financial frictions, lending, investment and durable consumption conditions, (ii) the signalling channel through which an expansionary monetary policy leads aggregate demand to increase mainly by improving private sector agents' expectations and their investment and consumption activities, and (iii) the risk-taking channel which highlights the importance of risk for the transmission of policy actions to the real economy by taking into account the 'pervasive influences' of risk perceptions and risk tolerance on agents' behaviours.

Having these channels in mind, let us look at Figure 3.6.1. A number of observations are worth highlighting. First, the global financial crisis, unsurprisingly, led share prices to decline substantially. According to the asset price and the balance sheet channels, this means lower net worth of and lending to firms, decrease in consumption, investment and hence aggregate demand. When we add unconventional policy actions of the Eurosystem

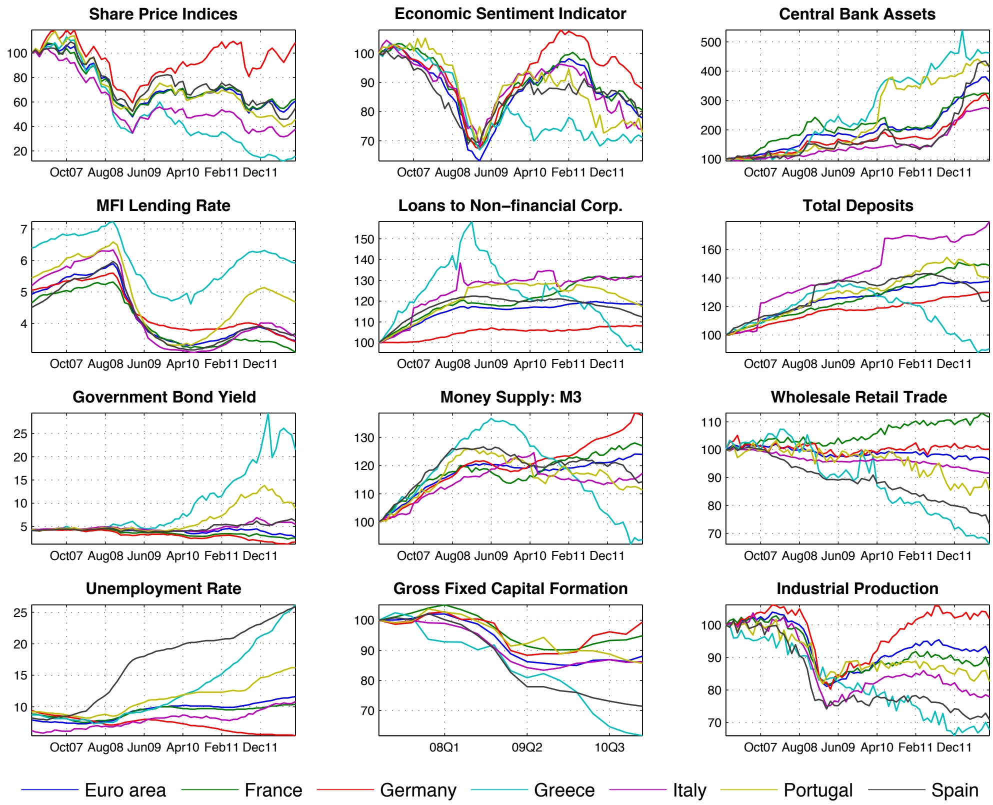



Figure 3.6.1: Core and Periphery in the Crisis Period

January 2007=100, except interest and unemployment rates.
Sources: Eurostat and NCBs. All series are seasonally adjusted.

into the picture, however, we observe that the interventions, e.g. June 2009 - covered bonds purchase programme and May 2010 - Securities Markets Programme, not only stopped the sharp decline in share prices but also helped the markets recover some of the loss. To illustrate, despite the sovereign debt crisis, there is a clear upward trend in the markets from February 2009 to June 2011. The recovery is most visible in the German financial markets. We believe that one can interpret these observations as signs of the working of the transmission channels, i.e. portfolio balance sheet channel, described above for those countries experiencing the positive impacts of the policy actions.

Figure 3.6.1 also highlights the fact that, however, these interpretations do not apply to Greece where the financial markets almost continuously declined in the sample period under investigation. As we can see from the graph, the loss in the Greek markets was more than 80% between January 2007 and September 2012. We believe that it is not difficult to rationalise the developments in the markets given severe fiscal problems including default on the sovereign debt, bailout packages obtained from the Troika,[45] skyrocketed government bond yields and unemployment figures, and the following social unrest in Greece. It is more important in the context of our paper to highlight that despite the clear separation of the increase in total assets of Bank of Greece relative to other NCBs, the interventions were not successful in creating the desired wealth and net worth effects on the private sector agents.

Although the overall conclusion does not differ from the one outlined above, we briefly investigate the other indicators as well. We highlighted in Section 3.1.1 the role of bank loans in the transmission mechanisms. As the second row of Figure 3.6.1 clearly displays, the Greek economy faced the highest private sector lending rates, among the main economies of the core and periphery. The combination of the highest lending rates with the lowest level of economic sentiment made loans to Greek non-financial corporations to steadily decline by 68% from January 2009 onwards. On the liability side of the banking sector balance sheets, deposits also declined sharply in Greece whilst they constantly increased in other countries. Joyce et al. (2012) similarly observe that following stresses within the EA, "steady and very substantial outflow of euro deposits" occurred from the peripheral countries into banks in other EA countries.

The last financial indicator in Figure 3.6.1 is the broad money supply of the economies. In line with loans and deposits, whereas the money stock in the EA and the individual countries steadily increase during the crisis period, country-specific developments in

[45] The European Commission, the ECB and the International Monetary Fund (IMF).

Greece led to significant fluctuations in the money supply.

It is important to note here that "[c]redit policy[46] derives much of its effectiveness from interposing the central bank (and hence indirectly the government) between private sector lenders and borrowers and, in so doing, improving credit flows."[47] As we can see from the developments in the Greek banking sector, it is hard to identify such improvements.

When we look at the real sector indicators, clear heterogeneity across the core and periphery emerge. If we proxy aggregate demand with deflated wholesale retail trade, on the one hand, we observe that transmission of Eurosystem balance sheet policies has been successful in the EA as a whole, France, Germany and, to some extent, Italy. On the other hand, retail figures in periphery, especially in Greece and Spain, have displayed significant declines during the global financial crisis period, hardly surprising with so many people unemployed in the region.

The textbook descriptions in Section 3.1.1 made it clear that investment is the leading indicator of the effectiveness of expansionary monetary policy measures. As we present in Figure 3.6.1 and Table 3.6.1, whereas it is possible to observe such positive relationship between real activity and the policy actions in Germany and France, the crisis and country-specific factors had substantial contractions in investment and IP in the periphery, despite extraordinary monetary policies of the Eurosystem.

To sum up, the empirical finding of our panel VAR approach that unlike the EA as a whole and the majority of individual countries in the panel, real activities of peripheral countries, especially Greece and Spain, respond negatively to an expansionary shock to

[46]Borio and Disyatat (2009) categorise central bank balance sheet policies into four groups as credit policy, quasi-debt management policy, bank reserves policy, and exchange rate policy. According to this classification, Eurosystem's unconventional actions during the crisis period are classified as credit policy.

[47]Borio and Disyatat (2009, pp.14-5).

Table 3.6.1: Core and Periphery in the Crisis Period

| Gross Fixed Capital Formation[a] | | | | | | |
|---|---|---|---|---|---|---|
| EA-13 | FR | DE | GR | IT | PT | ES |
| -11.95 | -5.15 | -0.61 | -38.33 | -13.74 | -14.31 | -28.56 |
| **Industrial Production[b]** | | | | | | |
| -9.05 | -12.92 | 1.81 | -32.18 | -22.13 | -17.38 | -29.09 |

Percentage changes [a]from 2007Q1 to 2011Q1, [b]from Jan2007 to Sep2012.
FR-France, DE-Germany, GR-Greece, IT-Italy, PT-Portugal, ES-Spain.
Source: Author's calculations.

central bank balance sheet, turns out to be in line with the actual developments in the key macroeconomic indicators of these countries.

We earlier cited Borio and Zhu (2012) about the role of risk-taking channel in the monetary transmission mechanism which "should be expected to act purely as a 'persistence-enhancing' mechanism, qualitatively akin to a kind of 'financial accelerator'."[48] Although we follow Borio and Zhu on the point that the risk-taking channel is not the most important channel of monetary policy, we do believe that it is worth being considered among the factors above explaining the heterogeneity observed in our empirical results and the actual indicators across core and periphery. Our observations above, we believe, clearly suggest that despite the common unconventional monetary measures by the Eurosystem, country-specific risk factors made the transmission mechanism in the periphery run out of the "persistence-enhancement".

De Santis (2012) lists 'aggregate regional risk factor', 'the country-specific credit risk' and 'the spillover effect from Greece' as three factors which "can explain the recorded developments in sovereign spreads". The author highlights that whereas the German Bund has benefited from the "safe haven status" during the crisis, sovereign solvency risk and rating agencies' downgrades, in periphery especially, might account for sovereign

[48]Borio and Zhu (2012, p.237).

spreads in the EA. Furthermore, Meier (2009, p.9) states that "unconventional monetary policy can be effective to the extent that ... it directly reduces risk premia or outright quantitative restrictions in financial markets." Combination of these arguments with the risk-taking channel of Borio and Zhu (2012) may suggest that enhanced (diminished) persistence, falling (rising) financial and political risks in core (periphery) have played a noteworthy role in positive (negative) impulse responses we have obtained for the real activities of the EA economies.

## 3.7 Conclusion

In this chapter of the thesis we have investigated the effectiveness of unconventional monetary policies of the Eurosystem on the economic activities and price levels of thirteen EA countries during the global financial crisis. The main contribution of the chapter is the country-level investigation of the balance sheet policies in the EA using the panel VAR methodology of Gambacorta et al. (2012).

Our area-wide mean group estimations are in line with other studies on the EA as an aggregate. That is to say, an expansionary shock to central bank balance sheets, when the interest rates are at the zero lower bound, leads economic activity to increase temporarily, while increasing the price level permanently. When we look at the effectiveness of the policy measures on the country-level basis, on the other hand, our estimations suggest empirical findings worth highlighting.

The paper supports Gambacorta et al. (2012) in the sense that the panel approach is capable of detecting cross-country heterogeneity present in the data. In particular, we find that whilst the expansionary balance sheet policy shocks lead to statistically significant increases in core countries' economic activities, the responses of the periphery, i.e. Greece and Spain, are statistically and economically negative.

Our investigation of the developments in key macroeconomic indicators in core and peripheral economies of the EA highlights the fact that country-specific factors played a significant role in disrupting the transmission mechanism of unconventional monetary policies to individual economic activities. To illustrate, during the crisis, we have, on the one hand, the core, i.e. Germany, benefiting from the 'safe haven' status which attracted considerable deposit shifts within the EA especially from Greece. On the other hand, periphery suffered not only from significant losses in the financial sector but also considerably low levels of demand and investment conditions.

To be sure, our empirical observations do not, and cannot, suggest that the unconventional monetary policy measures were the cause of significant damages in peripheral economic activities. We believe that in the absence of these policies, we could have experienced far worse impacts of the crisis not only on peripheral Europe but also across the world. Our empirical practice highlights that, however, despite these effective policy actions, which target the whole EA in the case of the Eurosystem, it is still possible to observe contractionary responses of country-level economic activities. Therefore, future research is of crucial importance in order to investigate the "one-size-fits-all" aspects of the monetary policy in the EA having experienced the aftermath of the global financial crisis. In addition to event-study analysis with relatively large Bayesian VAR techniques, incorporation of structural differences and country-specific financial turmoils and defaults risks into dynamic stochastic general equilibrium context, might be the next steps for us to further investigate the cross-country heterogeneity in the EA.

# APPENDIX P

# COMPOSITION OF CENTRAL BANK BALANCE SHEETS

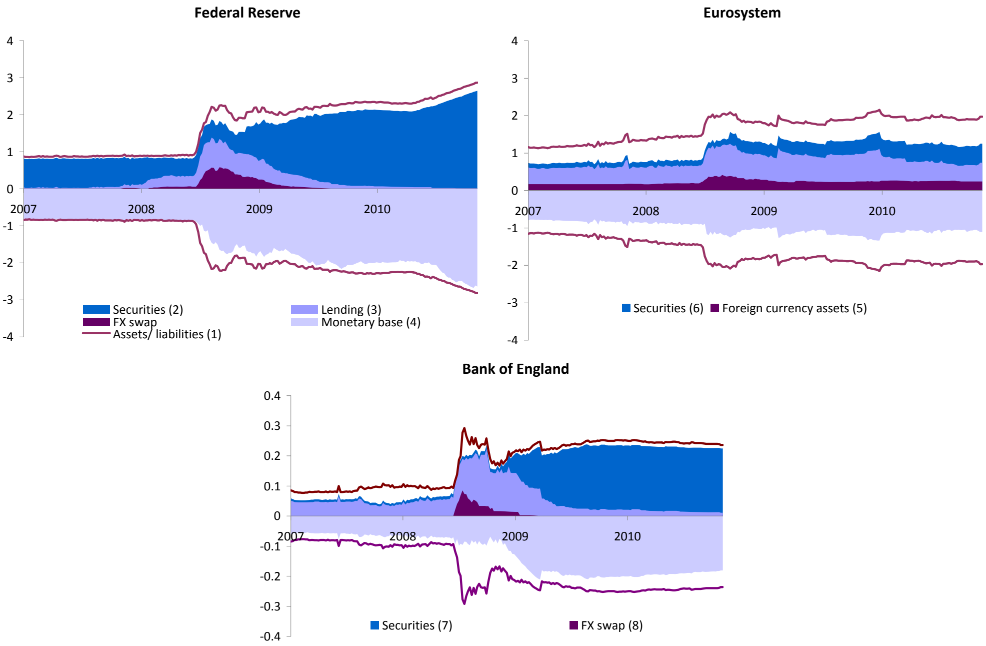



Figure P.0.1: Central Bank Balance Sheets

Trillions of respective currency units. Source: Gambacorta et al. (2012, Appendix).

Note: "(1) Total assets/liabilities. (2) Securities held outright. (3) Repurchase agreements, term auction credit, other loans and Commercial Paper Funding Facility. (4) Defined as the sum of currency in circulation and banks' deposits with the central bank. For the Eurosystem, including the deposit facility. (5) Including US dollar liquidity auctions. (6) Securities issued by euro area residents, in euros. (7) Bonds and other securities acquired via market transactions and securities holdings of Bank of England Asset Purchase Facility Fund. The accounts of the Fund are not consolidated with those of the Bank. The Fund is financed by loans from the Bank which appear on the Banks balance sheet as an asset. (8) Outstanding amount of US dollar liquidity auctions."

# CONCLUSION

We started Chapter 1 of the thesis by saying "there is no doubt that measuring the interaction between monetary policy and the evolution of the entire economy is of crucial importance for good policy-making." In light of the detailed aspects of the transmission of the single monetary policy across the EA economies studied in this thesis, we believe that the following policy implications are of importance for the ECB and other policy makers.

First, the empirical findings of the thesis on cross-country heterogeneity in the EA highlighted the importance of structural differences across countries. As described in the Economic Survey for Euro Area 2012 by the OECD, product, labour and financial markets, housing and taxation are among the main policy areas to be reformed in order to rebalance the EA economies. We believe that these reforms are also of importance in order to cure cross-country heterogeneity in the monetary transmission mechanism in the EA.

Second, the estimated heterogeneous responses between the core and peripheral EA countries during the global financial crisis question the effectiveness of the unconventional Eurosystem policy measures. As supported by the area-wide findings of the thesis, there is a general consensus in the literature on the effectiveness of the policy actions for the EA as an aggregate. However, as our country-level investigation importantly highlighted, it is difficult to observe the same conclusion for the individual member states. We therefore conclude that it is of importance to further investigate structural differences in the responses of the central banks worldwide to the crisis. We believe that more country-level oriented policies could result in better conditions in the EA countries most distressed by the Great Recession. For instance, according to Ciccarelli et al. (2013), who highlight the economical and statistical significance of the non-financial borrower balance sheet channel in the EA, "the current policy may still be insufficient if not targeted to increase credit availability for small firms (due to the firm channel) especially in the countries under financial stress" (p.27). Given the concentration of the EA product markets on the small and medium enterprises (SMEs), we believe that, similar to Ciccarelli et al., more SME-oriented policy measures by the Eurosystem could significantly stimulate economic activity in especially the peripheral EA.

Finally, the combination of the general conclusion of this thesis on the considerable heterogeneity in the EA and the recent significant effects of the problems in even tiny economies like Cyprus on the whole EA importantly suggests that the "no exit" aspect of the Economic and Monetary Union is worth detailed investigation for the long-term success of this unique project.

In order to describe the conclusions of the thesis on which these policy implications are based on, the following summarises the whole study. This thesis investigates the transmission mechanism of the single monetary policy in the EA. Using an aggregate data set for the EA, Chapter 1 investigates time variation in the impacts of contractionary shocks to policy rate of the ECB using PC and Bayesian FAVAR methods. Chapter 2 is an exploration of cross-country heterogeneity in the transmission of the policy shocks across the four largest economies of the EA. The techniques again consist of Bayesian FAVAR estimation, rolling windows and Boivin and Ng (2006) pre-screening techniques. Chapter 3 investigates the global financial crisis period with a focus on the effects of unconventional monetary policy actions of the Eurosystem across thirteen individual countries, estimated by a panel VAR technique.

Chapter 1 provides results for a contractionary monetary policy shock in the EA that are largely consistent with conventional wisdom. Our comparison of the results estimated by the PC (two-step) and the Bayesian (one-step) FAVAR techniques suggests that in addition to qualitatively similar results across the methods, there are considerable gains from the computationally burdensome Bayesian technique such as smoother impulse response functions and statistical significance of the estimates. Our rolling windows analysis shows that the most time-variant responses to monetary policy shocks are for consumer prices and monetary aggregates in the EA as an aggregate. The analysis also estimates that the contractionary impact of the monetary tightening on the economic activity is stronger during the global financial crisis than the pre-crisis period. In line with the responses of real activity, the cost of labour displays faster and stronger increases when there is a contractionary shock in the post-crisis period. In other words, the strong contractions in real output during the crisis period also leads to stronger increases in the real ULC. Looking at impulse responses and rolling windows obtained with a limited data set determined by the pre-screening technique of Boivin and Ng (2006), our structural FAVAR analysis shows that factors extracted from as few as 67 series might do no worse, and as our Bayesian estimations suggest, might do better than ones extracted from 120 series.

The main conclusion of Chapter 2 is to show, with a novel updated data set and various empirical approaches, that the impacts of common monetary policy shocks in the EA on national monetary aggregates are more strongly heterogeneous across European economies than most other macroeconomic variables. Our empirical finding is of importance in the sense that it supports the general conclusion of Hughes Hallett and Piscitelli (2002); Boivin et al. (2008); Setzer et al. (2010) on the heterogeneity in the monetary aggregates across the EA economies. Our rolling windows approach also finds that monetary aggregates are not only most heterogeneous across countries but also over time during the single monetary policy era of the EMU. This finding of the paper highlights the significance of the question of whether or not there exists a genuinely uneven monetary transmission mechanism in the EA, "in a way that could complicate the conduct of the single monetary policy", as highlighted by Angeloni and Ehrmann (2003, p.6). Given the unconventional monetary actions by the Eurosystem during the Great Recession, studied in Chapter 3, the main conclusion of Chapter 2 also emphasises the possibility of heterogeneous transmission of the policy actions across the EA economies through (heterogenous) country-specific channels.

In line with the literature, our Bayesian FAVAR approach also suggests heterogenous impacts of the monetary policy shocks on country-level real wages, highlighting the possibility of cross-country heterogeneity in the labour-, goods- and financial-frictions in the EA. Furthermore, we show in the chapter that the strongest impact of a contractionary monetary policy shock is estimated to be on national investment and total employment indicators. Similar to IP and consumer prices, the responses of investment and employment displayed homogeneous responses across the four largest economies of the EA. When we look at the post-crisis period, however, we observe heterogeneity across countries. To illustrate, according to the rolling windows analysis, the Spanish real activity displayed severe contractions in the post-crisis period relative to the core countries, suggesting the importance of country-specific factors during the crisis.

According to the empirical analysis in Chapter 3, on the one hand, the area-wide estimations of the effects of unconventional monetary policy suggest, in line with other studies on the EA as a whole, temporary (permanent) increases in economic activity (consumer prices). On the other hand, country-level impulse responses display serious heterogeneity across core and peripheral economies. In particular, Chapter 3 concludes that whilst the expansionary balance sheet policy shocks lead to statistically significant increases in core countries' economic activities, the responses of the periphery, i.e. Greece and Spain, are statistically and economically negative. When we investigate the developments in key macroeconomic indicators in core and peripheral economies during the Great Recession period, we observe that country-specific factors such as defaults risks and bailouts played a significant role in disrupting the transmission mechanism of unconventional monetary measures of the Eurosystem to individual economic activities.

We believe that the combination of common monetary policy and diverse cultural and fiscal structures of the EA economies provides a unique laboratory for the analysis of cross-country heterogeneity and changes over time. Therefore, our results mark the way forward for a research agenda that may provide important insights into the cross-country dynamics of the EA.

First, the incorporation of structural differences in preferences, technology levels and frictions constraining private agents across countries into a multi-country DSGE framework is of utmost importance for us to further investigate and rationalise the empirical findings of the thesis. Within this structural context, the interaction between monetary and fiscal policies, and country-specific financial turmoils and default risks are also of importance to obtain more realistic analysis of cross-country heterogeneity in the EA. In line with our one-step FAVAR analysis in Chapter 2, these structural studies will provide important contributions to the two-country structural model by Boivin et al. (2008) applied to the EA economies.

Second, we cited Setzer et al. (2010) in Chapter 2 who claim that asymmetries in house price developments can explain, to a large extent, the heterogeneity in monetary dynamics across EA economies. In addition to Setzer et al.'s money demand equation analysis, which incorporates housing wealth and collateral effects, we believe that it is of importance to further investigate the real estate markets and their possible significance for heterogeneity in economic and financial structure of the EA. Following the housing literature, mainly focused on the US and the UK, DSGE, country-specific and panel structural VAR, heterogeneous-agent VAR (HAVAR), and FAVAR models are among those which we can use to investigate the question of real estate dynamics and cross-country heterogeneity in the EA.

Third, as more data become available for European economies, we believe that the application of TVP-FAVAR models will be possible. Similar to the gaps in the literature filled by this thesis, the TVP-FAVAR approach is yet to be explored for the EA, especially in the context of cross-country heterogeneity. As time goes by, the responses across countries are likely to become less heterogeneous due to forces of convergence. We believe that TVP-FAVAR analysis will be an important way of testing this hypothesis for the economies of the EA.

Fourth, there are macroeconomic indicators such as employment or GDP not available in monthly frequency. Our thesis provides the literature with empirical findings on these key indicators by means of Chow and Lin (1971) interpolation techniques. In order to provide robustness tests for our empirical findings, and further investigate the EA macroeconomic indicators, MIDAS and mixed frequency VAR techniques are important alternatives for future research.

Fifth, we highlighted the necessity of a cautious approach to the findings of our FAVAR approaches due to strong portfolio shifts and cross-border movements in the EA during the global financial crisis period. In light of these important aspects of the crisis on the monetary dynamics, we consider it important to incorporate more detailed unconventional monetary measures into future FAVAR data sets.

Finally, given the significance of the Great Recession for the peripheral European economies, it is of importance to further analyse "the periphery puzzle" of our thesis, discussed in detail in Chapter 3. That is to say, we need more empirical investigations of country-level impacts of unconventional monetary policy actions in the EA in order to shed more light on contradictory and heterogeneous responses of peripheral economic activities. For example, the event-study methodologies of Meier (2009); Giannone et al. (2011, 2012), among others, are important alternatives to our panel VAR approach in Chapter 3. The application of the methodologies to the question of cross-country heterogeneity in the EA will contribute to the literature by investigating the 'policy' and 'no-policy' scenarios for core and peripheral economies of the EA.

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