UNIVERSITY OF
BIRMINGHAM

Department of Economics

Monetary Transmission Mechanism and Time Variation in the Euro Area

Department of Economics Discussion Paper 12-12

Kemal Bagzibagli

Monetary Transmission Mechanism and Time Variation in the Euro Area*

Kemal Bagzibagli†

November 2012

Abstract

This paper examines the monetary transmission mechanism in the euro area for the period of single monetary policy using factor-augmented vector autoregressive (FAVAR) techniques. The contributions of the paper are fourfold. First, a novel dataset consisting of 120 disaggregated macroeconomic time series spanning the period 1999:M1 through 2011:M12 is gathered for the euro area as an aggregate. Second, Bayesian joint estimation technique of FAVARs is applied to the European data. Third, time variation in the transmission mechanism and the impact of the global financial crisis is investigated in the FAVAR context using a rolling windows technique. Fourth, 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. We find that there are considerable gains from the implementation of the Bayesian technique such as smoother impulse response functions and statistical significance of the estimates. According to our rolling estimations, consumer prices and monetary aggregates display the most time variant responses to the monetary policy shocks. The pre-screening technique considered, elimination of almost half of the dataset seems to do no worse, and in some cases, better in a structural context.

Keywords: Monetary Policy Shocks, FAVAR, Bayesian Methods, Rolling Windows, Euro Area

JEL-Codes: C11, C32, C33, E5

*I am grateful to my supervisors Anindya Banerjee and John Fender for their valuable guidance and great support. I would also like to thank many conference and workshop participants and colleagues for their comments. Responsibility for any errors belongs to me.

†PhD Candidate, Department of Economics, University of Birmingham, Edgbaston, Birmingham, B15 2TT, United Kingdom, E-mail: kxb959@bham.ac.uk

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 entire economy is of crucial importance for good policy-making. Due to this significant necessity, we observe advanced dynamic measurements of the effects of money in the context of exogenous policy shocks taking a considerable place in the economic literature.

In the applied macroeconomic literature, vector autoregressive (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 "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 datasets.[2] Moreover, considering the large information sets used by central banks makes clear that it is not possible to span these sets by low dimensional VAR systems.

According to Bernanke et al. (2005, BBE hereafter), two potential sets of problems emerge due to the use of the so-called "sparse information sets" in the VAR analyses. 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 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.

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

[2] Sims (1980b).

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

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 follow 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", and 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 comprehensive picture of the effects of monetary policy shocks, for example, 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 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 (U.S.) data, whereas only a few of them investigate the Euro area (EA).

Table 1: The Monetary FAVAR Literature

Study	**Estimation**	**Identification**	**Country**
Bernanke et al. (2005)	2-Step PC + Bayesian	Recursive ordering F_t^S vs F_t^F (BBE)	U.S. 59:M1-01:M8
Ahmadi (2005)	Bayesian	Sign Restrictions	U.S. 59:M1-01:M08
Stock and Watson (2005)	2-Step PC	Various Schemes	U.S. 59:M1-03:M12
Belviso and Milani (2006)	Bayesian	Choleski Decomposition	U.S. 60:M1-98:M12
Ahmadi and Uhlig (2007)	Bayesian	Sign Restrictions	U.S. 59:M1-01:M8
Boivin and Giannoni (2007)	2-Step PC	BBE	U.S. 84:M1-05:M2

[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 paper.

[7]The details of the techniques employed in our study are described in sections 2.2 and 2.3.

Boivin et al. (2009)	2-Step	BBE	U.S. 76:M1-06:M6
Bork (2009)	EM Algorithm	BBE	U.S. 59:M1-01:M8
Koop and Korobilis (2010)	Bayesian	BBE	U.S. 53:Q1-06:Q3
Mumtaz et al. (2011)	Bayesian	Sign Restrictions	U.K. 77:Q1-06:Q3
McCallum and Smets (2007)	2-Step PC	BBE	EA[b] 86:Q1-05:Q4
Boivin et al. (2008)	2-Step PC	BGM[a] (2009)	EA[c] 80:Q1-07:Q3
Blaes (2009)	2-Step PC	BBE	EA[d] 86:Q4-06:Q4
Soares (2011)	2-Step PC	BBE	EA[d] 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.

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 the (i) investigation of the post-1999 period using a common monetary policy variable controlled by the European Central Bank (ECB) only and (ii) implementation of the Bayesian one-step estimation technique, details of which are described in Section 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 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 prescreened 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

[8] See section 4.3 for further details of the approach.

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 paper which are fourfold. First, we gather a novel dataset 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. Second, in addition to the commonly used two-step principal components (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 paper by using a rather parsimonious dataset 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 study are as follow. Our FAVAR model suggests estimates for the responses of a wide variety macroeconomic variables to monetary policy 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 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 constant and 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 (63) pre-screened series often yield satisfactory or even better results than using all (120) series" (p.169).

The remainder of the paper is organised as follows: Section 2 describes the methodology of the study which consists of the FAVAR framework, model estimation and identification, and Boivin and Ng 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 paper in three parts consisting of (a) study of the monetary transmission mechanism (MTM) in the EA; (b) time variation and (c) Boivin and Ng analysis of impulse responses with screened data; robustness checks of the results are presented in Section 5; and Section 6 concludes.

[9]Bai and Ng (2008a, p.306).

2 Methodology

2.1 The 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. (2004, 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 short term 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 factor-augmented vector autoregressive (FAVAR) model by BBE.

We can summarise the FAVAR model in state-space representation as follows:[10]:

$$X_{it} = \Lambda_i^f F_t + \Lambda_i^y Y_t + e_t, \quad E(e_t' e_t) = R \tag{1}$$

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + v_t, \quad E(v_t' v_t) = Q \tag{2}$$

where for $i = 1, \ldots, N$, Λ^f is an $N \times K$ matrix of factor loadings, Λ^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[11], $\Phi(L)$ is a conformable lag polynomial of finite order d, and v_t is a $(K + M) \times 1$ error vector that $v_t \sim i.i.d.N(0, Q)$. The error terms of equations (1) and (2) are assumed to be independent of each other, and R is diagonal. Using state-space terminologies, (1) and (2) are the observation (or measurement) and the transition (or state) equations, respectively.

2.1.1 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 (2), the impulse response functions of $\hat{F}_t$ and Y_t are given by,

$$\begin{bmatrix} \hat{F}_t \\ Y_t \end{bmatrix} = \Psi(L) v_t \tag{3}$$

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

Combining equations (1) and (3) leads us to the following transformation:

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

[11] See Section 2.2 for details.

$$X_{it}^{IRF} = \begin{bmatrix} \hat{\Lambda}^f & \hat{\Lambda}^y \end{bmatrix} \begin{bmatrix} \hat{F}_t \\ Y_t \end{bmatrix} = \begin{bmatrix} \hat{\Lambda}^f & \hat{\Lambda}^y \end{bmatrix} [\Psi(L) v_t] \quad (4)$$

which allows us to construct the impulse responses for any element of X_t.

2.2 Estimation

BBE propose two approaches to estimating the model. The first one is a two-step principal components approach, "which provides a nonparametric way of uncovering the common space spanned by the factors of X_t".[12] The second is joint estimation approach of (1) and (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 paper. Details of the techniques are described in the following subsections.

2.2.1 Two-step Principal Components Approach

The two-step PC procedure estimates (1) and (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) in order to estimate the space spanned by the factors using the first $K + M$ principal components 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 principal components exploiting the different behaviour of (so called) 'slow-moving' and 'fast-moving' variables, in the second step."[13,14] However, as 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 principal components used being at least as large as the true number of factors.

In other words,[15] using PC, the first step estimates the factors $(\hat{F}_t^1, \hat{F}_t^2, \ldots, \hat{F}_t^K)$ from the model

$$\begin{bmatrix} X_t^1 \\ X_t^2 \\ \vdots \\ X_t^K \end{bmatrix} = \begin{bmatrix} \Lambda_1^f & 0 & \ldots & 0 \\ 0 & \Lambda_2^f & \ldots & 0 \\ \vdots & \ldots & \ddots & \vdots \\ 0 & \ldots & \ldots & \Lambda_K^f \end{bmatrix} \begin{bmatrix} F_t^1 \\ F_t^2 \\ \vdots \\ F_t^K \end{bmatrix} + e_t$$

Additionally, in order to obtain $(\hat{\Lambda}_1^f, \hat{\Lambda}_2^f, \ldots, \hat{\Lambda}_K^f)$, we estimate the model

[12] Bernanke et al. (2005, p.398).
[13] Boivin et al. (2008, p.6).
[14] See Section 2.3.2 for the specific identifying assumption used in the second step.
[15] Following Belviso and Milani (2006, p.37).

$$\begin{bmatrix} X_t^1 \\ X_t^2 \\ \vdots \\ X_t^K \end{bmatrix} = \begin{bmatrix} \Lambda_1^f & 0 & \dots & 0 \\ 0 & \Lambda_2^f & \dots & 0 \\ \vdots & \dots & \ddots & \vdots \\ 0 & \dots & \dots & \Lambda_K^f \end{bmatrix} \begin{bmatrix} \hat{F}_t^1 \\ \hat{F}_t^2 \\ \vdots \\ \hat{F}_t^K \end{bmatrix} + e_t$$

equation by equation using ordinary least squares (OLS).[16]

In the second step, we replace the unobserved factors in the transition equation (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, we use Kilian (1998) bootstrapping procedure in our analysis.

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) is taken into account, and the dynamic structure of the model (2) is totally ignored.

2.2.2 Bayesian Joint Estimation Approach

In contrast with the two-step method, the Bayesian likelihood, 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 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]

[16] Given the assumption that R is diagonal in (1).

[17] See Stock and Watson (2005).

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

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

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

[21] Belviso and Milani (2006)

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 and Eliasz (2005), we explain the details of the estimation procedure of the Bayesian approach in the subsequent sections.

2.2.3 Estimation Procedure

In order to apply the likelihood methods to equations (1) and (2) jointly, let us transform the model into the following state-space form:

$$\begin{bmatrix} X_t \\ Y_t \end{bmatrix} = \begin{bmatrix} \Lambda^f & \Lambda^y \\ 0 & I \end{bmatrix} \begin{bmatrix} F_t \\ Y_t \end{bmatrix} + \begin{bmatrix} e_t \\ 0 \end{bmatrix} \tag{5}$$

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + v_t \tag{6}$$

As claimed by BBE, inclusion of the observable factor Y_t in the measurement (5) and the transition (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 Φ of the parameters of the lag operator $\Phi(L)$. As proposed by Carter and Kohn (1994), likelihood-based multi-move Gibbs sampling proceeds by alternatively sampling the parameters θ and the unobserved factors F_t. Further details of the procedure are as follows:

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

$$\mathbf{X}_t = \boldsymbol{\Lambda}\mathbf{F}_t + \mathbf{e}_t \tag{7}$$

$$\mathbf{F}_t = \Phi(L)\mathbf{F}_{t-1} + v_t \tag{8}$$

where $\mathbf{X}_t = (X_t', Y_t')'$, $\mathbf{F}_t = (F_t', Y_t')'$, $\boldsymbol{\Lambda} = \begin{pmatrix} \Lambda & \Phi \\ 0 & I \end{pmatrix}$, $\mathbf{e}_t = (e_t', 0. \dots, 0)'$, $\mathbf{e}_t \sim i.i.d.\ N(0, \mathbf{R})$, $\mathbf{R}$ is the variance-covariance matrix of $\mathbf{e}_t$ augmented by zeros, and $\Phi(L)$ is a conformable lag polynomial with finite order d.

In order to rewrite the transition equation (2) as a first-order Markov process, we define $\bar{\mathbf{F}}_t = (\mathbf{F}_t', \mathbf{F}_{t-1}', \dots, \mathbf{F}_{t-d+1}')'$, $\bar{v}_t = (v_t, 0, \dots, 0)'$, and

$$\bar{\Phi} = \begin{bmatrix} \Phi_1 & \Phi_2 & \dots & \Phi_{d-1} & \Phi_d \\ I_{(K+M)} & 0 & \dots & 0 & 0 \\ 0 & I_{K+M} & \ddots & 0 & 0 \\ \vdots & \dots & \dots & \ddots & \vdots \\ 0 & 0 & \dots & I_{(K+M)} & 0 \end{bmatrix} \tag{9}$$

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

Using these definitions, we obtain the following Markov process:

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

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

By replacing $\mathbf{F}_t$ in the measurement equation (1) by newly defined $\bar{\mathbf{F}}_t$, we also obtain

$$\mathbf{X}_t = \bar{\mathbf{\Lambda}}\bar{\mathbf{F}}_t + \mathbf{e}_t \tag{10}$$

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:

$$\mathbf{X}_t = \bar{\mathbf{\Lambda}}\bar{\mathbf{F}}_{\mathbf{t}} + \mathbf{e}_t \tag{11}$$

$$\bar{\mathbf{F}}_t = \bar{\Phi}\bar{\mathbf{F}}_{t-1} + \bar{v}_t \tag{12}$$

As we discuss in Appendix C, available upon request, 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 (11 - 12) are treated as random variables. Furthermore, let us assume that $\tilde{X}_T$ and $\tilde{F}_T$ 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]

2.2.4 Inference

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

$$p(\tilde{\mathbf{F}}_T) = \int p(\tilde{\mathbf{F}}_T, \theta)d(\theta) \tag{13}$$

$$p(\theta) = \int p(\tilde{\mathbf{F}}_T, \theta)d(\tilde{\mathbf{F}}_T) \tag{14}$$

where $p(\tilde{\mathbf{F}}_T, \theta)$ is the joint posterior distribution and the integrals are taken with respect to the supports of θ and $\tilde{\mathbf{F}}_T$. Considering the posterior densities, the estimates of $\tilde{\mathbf{F}}_T$ and θ can be obtained as the means and 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 (θ^0):** First of all, we choose an initial set of values for the parameter set θ. 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 (1992b) 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 estimation of the observation equation (1) and vector autoregression of the transition equation (2) leads to a reasonable guess on the choice of θ^0. Robustness of this choice

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

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 Λ^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) and (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, θ, 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]:

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

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

$$\begin{aligned} &\mathbf{F}_T|\tilde{\mathbf{X}}_T, \theta \sim N(\mathbf{F}_{T|T}, \mathbf{P}_{T|T}) \\ &\mathbf{F}_t|\mathbf{F}_{t+1}, \tilde{\mathbf{X}}_t, \theta \sim N(\mathbf{F}_{t|t,F_{t+1}}, \mathbf{P}_{t|t,F_{t+1}}) \end{aligned} \tag{15}$$

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

• **Step 3 - Inference on the Parameters (θ):** 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 θ. Since the factors are considered as known variables, it is possible to estimate the equations (7-8) separately as standard regression equations. By doing so we can specify the distributions of Λ and R with the former, and that of $vec(\Phi')$ and Q with the latter 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;

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

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

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

where $\bar{R}_{ii} = 3 + \hat{e}_i'\hat{e}_i + \hat{\Lambda}_i'[M_0^{-1} + (\tilde{\mathbf{F}}_T^{(i)\prime}\tilde{\mathbf{F}}_T^{(i)})^{-1}\hat{\Lambda}_i]$ and M_0^{-1} is the variance parameter in the prior on the coefficients of the i^{th} equation, Λ_i.

According to Bernanke et al. (2005), we should draw values for Λ_i, given draws of R_{ii}, from the posterior $N(\bar{\Lambda}, R_{ii}\bar{M}_i^{-1})$ where $\bar{\Lambda}_i = \bar{M}_i^{-1}(\tilde{\mathbf{F}}_T^{(i)\prime}\tilde{\mathbf{F}}_T^{(i)})\hat{\Lambda}_i$ and $\bar{M}_i = M_0 + \tilde{\mathbf{F}}_T^{(i)\prime}\tilde{\mathbf{F}}_T^{(i)}$.

After obtaining all the elements of θ 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

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

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 θ 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. $s \to \infty$, the marginal and joint distributions of the values obtained from iterations, $\tilde{\mathbf{F}}_T^s$ and θ^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 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 and percentiles.

2.3 Identification

Alongwith 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 identification issues are more complex. Whereas identification of the shocks to the transition equation, e.g. a monetary policy shock, is a standard way of restricting either the covariance matrix of the VAR innovations, Q, or the signs of the impulse response functions, factors need to be identified as well in this augmented VAR technique.

2.3.1 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 Λ^f to an identity matrix and the top $K \times M$ block of Λ^y to zero. In our analyses we follow BBE and identify the factors in the same way.

2.3.2 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 paper.[26]

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 our vector of variables."[27] 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 some restrictions on the structure, the number of parameters in which is greater than that in the reduced form. How these restrictions are imposed in the BBE approache is explained in the following subsections.

Before these details, let us consider our reduced form FAVAR in equation (2):

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

If we assume an orthogonal invertible matrix of dimension $[(K+M)\times(K+M)]$ called A, the structural FAVAR can be obtained by premultiplying the reduced form with this rotation matrix A. This gives us, therefore, the following linear relationship between the structural disturbances (w_t) and the reduced form innovations (v_t):

$$w_t = Av_t \tag{16}$$

In this notation, 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.

Parallel to equation (3) the MA representation of the structural form is:

$$\begin{bmatrix} \hat{F}_t \\ Y_t \end{bmatrix} = \Psi^*(L)v_t \tag{17}$$

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

2.3.3 Contemporaneous Timing Restrictions

As shown by Stock and Watson (2005), it is possible to categorise the BBE approach into a group of contemporaneous timing restrictions. Hence, we briefly explain here the idea of these restrictions.[28]

[26] For further details on the issue of identification in general see Favero (2001, Chapters 3 and 6) and Enders (2004, Chapter 5), among others, and Bernanke et al. (2005), and Uhlig (2005) for the schemes employed in our analysis.

[27] Favero (2001, p.85)

[28] The following discussion draws on Stock and Watson (2005) and Favero (2001, Chapter 6).

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 (2):

It is assumed by Sims (1980b) that A is a lower triangular matrix as follows:

$$A = \begin{bmatrix} 1 & 0 & \dots & 0 \\ a_{21} & 1 & \ddots & 0 \\ \vdots & \ddots & \ddots & 0 \\ a_{n1} & \dots & a_{nn-1} & 1 \end{bmatrix} \tag{18}$$

where a_{ij} denotes an unrestricted nonzero element. If we assume a VAR with n variables, this leads to $n(n-1)/2$ exclusion restrictions in (18), which therefore means that A is exactly identified. This "corresponds to a recursive economic structure, with the most endogenous variable ordered last."[29]

It is common in the literature to assume that the fundamental, i.e. structural, disturbances are orthogonal[30] and normalised to have a unit variance, i.e. $E[w_t w_t'] = I$. Considering equation (16), we obtain the covariance matrix of the reduced form innovations as follows:

$$Q_v = E[v_t v_t'] = AE[w_t w_t']A' = AA' \tag{19}$$

Combination of the lower triangular structure of A and equation (19), therefore, leads to nothing but the Cholesky factorisation of Q.

2.3.4 BBE Identification Scheme

We highlighted previously that the BBE approach is a form of contemporaneous timing restrictions. In order to identify a single shock in a structural FAVAR, BBE introduced a scheme which partitions the structural shocks and variables X_t into three groups as "slow-moving" variables, the monetary policy variable, i.e. benchmark short-term interest rate, 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, and monetary aggregates.

Following the Cholesky decomposition and contemporaneous timing restrictions explained above, BBE assume a recursive structure for the transition equation (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

[29] Favero (2001, p.165)

[30] Following Favero (2001, Chapter 6), this is the main assumption separating the traditional Cowles Commission and the VAR models as identification in the former models is obtained without assuming orthogonality of the structural disturbances.

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,[31] let Ψ_0^* be the coefficient matrix that is the leading (zero-lag) term of $\Psi^*(L)$ in equation (17). Additionally suppose that the structural shocks are $\zeta_t = (\zeta_t^{S\prime}, \zeta_t^R)'$, where ζ_t^S is $q_S \times 1$, and ζ_t^R is a scalar.

The contemporaneous timing restrictions of the identification explained above lead to the following block lower triangular structure for Ψ_0^*:[32]

$$\Psi_0^* = \begin{bmatrix} \Psi_{0,SS}^* & 0 \\ \Psi_{0,RS}^* & \Psi_{0,RR}^* \end{bmatrix} \tag{20}$$

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 (20) identify ζ_t^R (the shock of interest), and the space spanned by the ζ_t^S. Identification of ζ_t^R means that "the column of $(\Psi^*(L))$ associated with ζ_t^R is (also) identified and thus the structural impulse responses of X_t with respect to ζ_t^R is identified" (p.19).

One-step FAVAR: As regards 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 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 principal components of the "slow-moving" variables in X_t. Second, estimating the following regression,

$$\hat{C}_t = \beta_{F^s} \hat{F}_t^s + \beta_Y Y_t + e_t \tag{21}$$

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"[33] 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

[31] See Stock and Watson (2005) for further details of this part.

[32] 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.

[33] 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[34], 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)

Therefore, following this important part of the literature, we use the BBE scheme described above and identify the impacts of contractionary 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.

2.4 Boivin and Ng Analysis

The lack of structural analysis in the literature implementing the Boivin and Ng (2006) pre-screening technique has been previously highlighted in Introduction. This subsection describes details of the technique relevant to our analysis.[35]

Boivin and Ng (2006, p.171) propose, as follows, the main idea behind the intuition that "using more data to estimate the factors might not be desirable." There are two assumptions in the asymptotic theory, which the method of principal components 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 in the literature summarised, we typically draw our data from a small number of broad categories such as industrial production, prices, interest rates and monetary aggregates. Think of a dataset consisting of some series chosen from each category according to rank of importance of their common components. Then let us expand the dataset by adding the lower ranked, or 'noisy' series. As Boivin and Ng clearly highlight, two things will happen:

> 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)

[34]See Ibid. and Sims and Zha (2006).

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

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

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

That is, 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 dataset used to identify the impact of BN in a structural context.

3 Preliminary Analyses

Having explained the methodological details, this section lists the preliminary analyses conducted prior to estimating the empirical results, which we present in Section 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 for interpolation of some of the quarterly series. Finally, the details of Boivin and Ng prescreening technique and the results it suggests for our data conclude the section.

3.1 Data

The dataset analysed in the study is a balanced panel of 120 monthly macroeconomic time series for the EA as an aggregate[36], 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, stock 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.[37,38] 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.

[36] EA (17).

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

[38] 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 Banbura 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.

Although the majority of the series in our dataset 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 information used in our FAVAR analysis, we, thirdly, apply the most commonly used disaggregation technique, i.e. Chow and Lin (1971), to the quarterly observations of these series in order to obtain their monthly estimates. [39]

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.[40]

3.2 Number of Factors

Determining the number of factors for large dimensional factor models takes a considerable place in the literature.[41] 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 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 Bernanke et al. (2005), 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 factors, therefore, BBE explore the sensitivity of the results to an alternative number of factors of 5 and observe that "the qualitative conclusions on the effect of monetary policy are not altered by the use of five factors" (pp.408-9).

In light of these aspects of the literature on determining the number of factors, we follow the following procedure in our analysis. First, using replication files of the paper

[39]For comparison of the empirical results with and without these interpolated series see Section 3.4, and for details of the Chow and Lin (1971) technique Appendix D is available upon request.

[40]We thank Professor 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.

[41]Appendix E is available upon request on details of the factor models and the determination of their number of factors.

by Schumacher and Breitung (2008)[42] we test the number of static factors in our data using all panel and information criteria proposed by Bai and Ng (2002) and BIC_3. Table 2 presents the results of the test.

Table 2: Number of Factors: The Information Criteria

Cr.	$K^{\max}_{=2}$	$K^{\max}_{=3}$	$K^{\max}_{=4}$	$K^{\max}_{=5}$	$K^{\max}_{=6}$	$K^{\max}_{=7}$	$K^{\max}_{=8}$	$K^{\max}_{=9}$	$K^{\max}_{=10}$
PC_{p1}	2	3	4	5	6	7	8	9	10
PC_{p2}	2	3	4	5	6	7	8	9	9
PC_{p3}	2	3	4	5	6	7	8	9	10
IC_{p1}	2	3	4	5	6	7	8	9	10
IC_{p2}	2	3	4	5	6	7	8	9	9
IC_{p3}	2	3	4	5	6	7	8	9	10
BIC_3	2	2	2	2	3	3	4	4	4

As we can see from the table, whereas all Bai and Ng (2002) criteria suggest 9-10 factors when we allow maximum of 10 factors, $K^{\max}$, in the test, BIC_3 estimates more parsimonious number of factors.

Second, we calculate the share of variance of the data accounted for by that of the common components in the observation equation (1), i.e. R^2. We compute the R^2 statistic for two sets of variables: (*i*) all 120 variables in the dataset, (*ii*) 20 main variables which our empirical findings will be based on. Figures 1 and 2 present, respectively, the statistics for the sets *i* and *ii*. We find that marginal gain of having 9 factors (IC_2) instead of 4 (BIC_3) is less then 20% for both sets of variables.

Finally, we estimate a two-step FAVAR model[43] with number of factors varying from 1 to 9, and test how the choice of number of factors in the model affects the impulse response functions.[44] We present the results in Figure 3.

We notice that with some exceptions the results are qualitatively robust to the choice of the number of factors. Some variables, however, displayed 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 Unit Labour Cost (ULC), monetary aggregates, and stock market are some of these variables.

Given that (a) relatively smoother results are obtained with 3-6 factors in Figure 3; (b) BIC_3 criterion estimates 4 factors in our dataset; (c) 4 factors account for more than 50% of the variations of the main variables and almost 45% of that of the whole dataset, we prefer to use 4 factors in our empirical analyses. It is important to note that, as reported in Figure 3, our overall results are robust to the choice of the number of factors in our FAVAR model.

[42]We thank the authors for making the files publicly available, and also thank Christian Schumacher for sharing the files and his comments with us.

[43]Two-step approach is chosen here only because of its computational simplicity.

[44]Number of lags is kept at 2 in all models. For details of determination of lag length in the model see Section 3.3.

Figure 1: Number of Factors: R^2 - All Variables

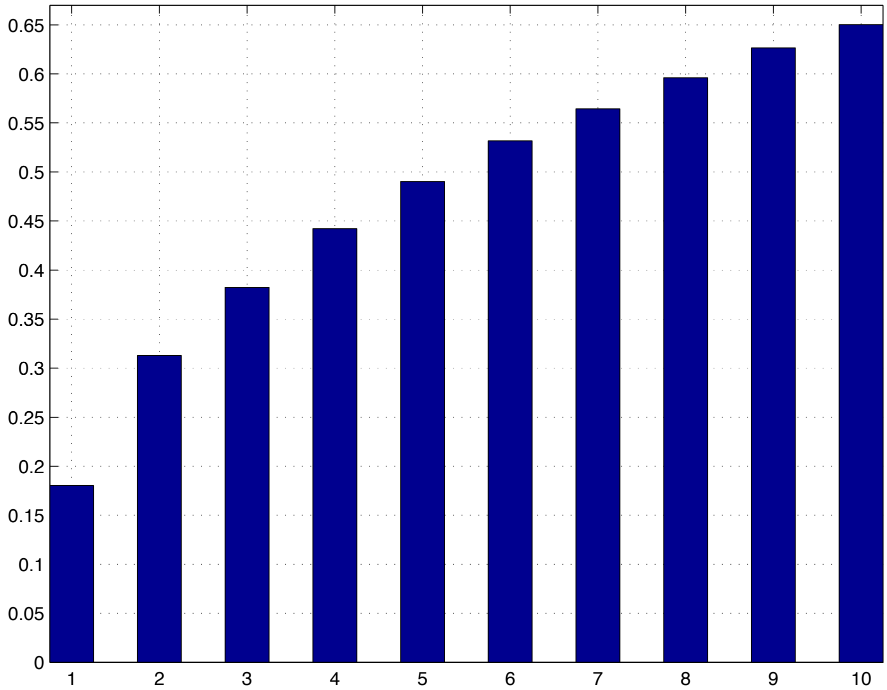
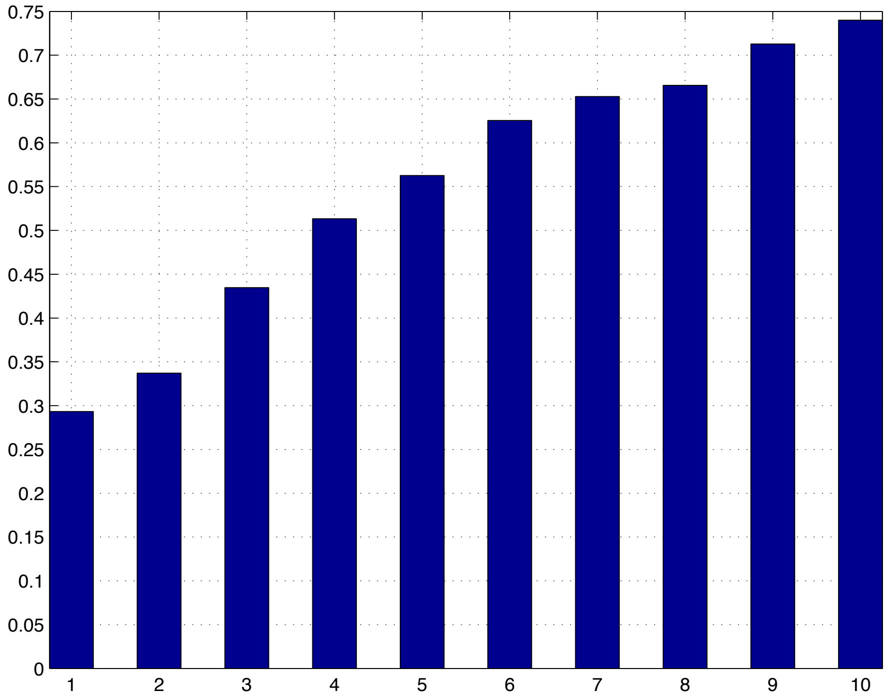


Figure 2: Number of Factors: R^2 - Main Variables



3.3 Number of Lags

Similar to the issue of the choice of the number of factors, the lag length of the transition equation (2) is another specification needs to be determined. The importance of the specification is demonstrated by Braun and Mittnik (1993) who show that estimates of

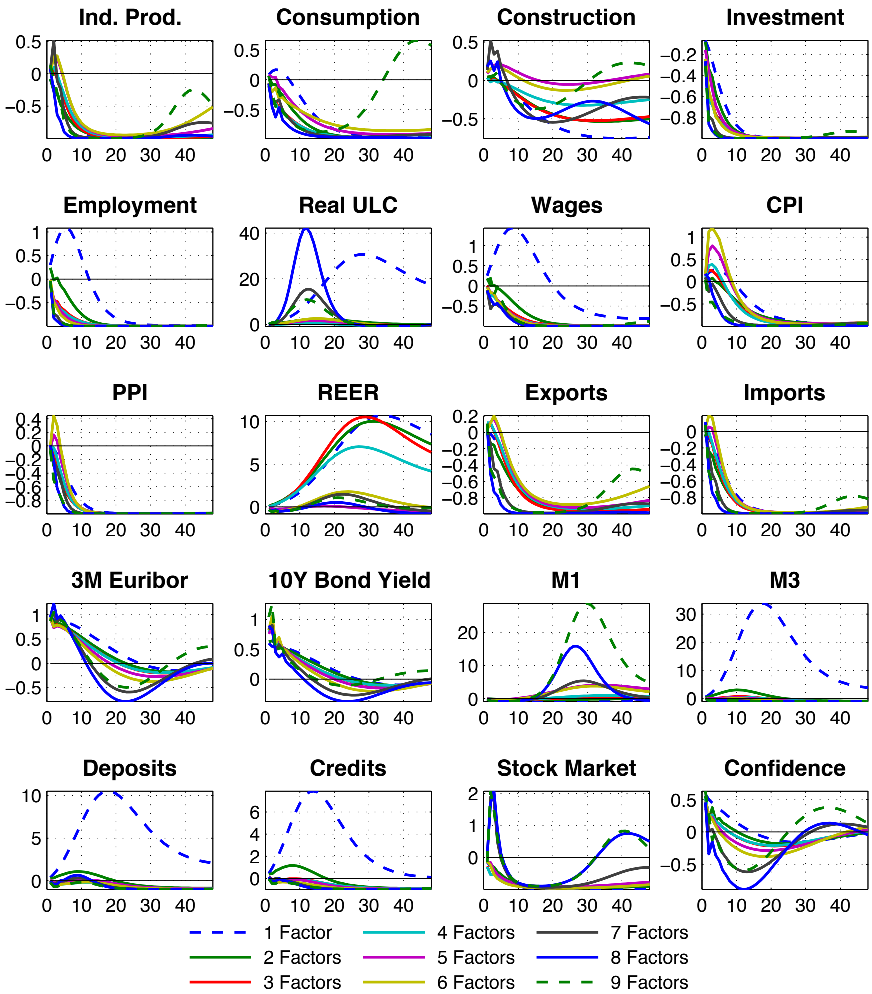


Figure 3: Number of Factors: Impulse Response Functions

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. Lütkepohl (2005) also indicates that whereas overfitting a VAR causes an increase in the mean-square-forecast errors, underfitting 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, Schwarz information criterion (SIC), and Hannan-Quinn. In the FAVAR literature, however, no specific criterion is used, to our knowledge. To illustrate, on the one hand, Bernanke et al. (2005) and Belviso and Milani (2006) use 13 lags in order to "allow sufficient dynamics"[45] in their models analysing similar monthly datasets. 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) dataset.

In order to select lag length of our FAVAR models, we use the following tests. First, we replicate a FAVAR, to be estimated in our empirical analyses, by extracting four "slow-moving" factors from our dataset, and having the short-term interest rate as the

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

only observable factor in the model. Then, using JMulti v-4.24[46] 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 dataset.

As a second test, similar to determination of the number of factors above, we estimate a two-step FAVAR model with four factors and different lag lengths of 1, 2, 4, 7, and 13. In addition to those suggested by the information criteria, 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 4 displays the test results.

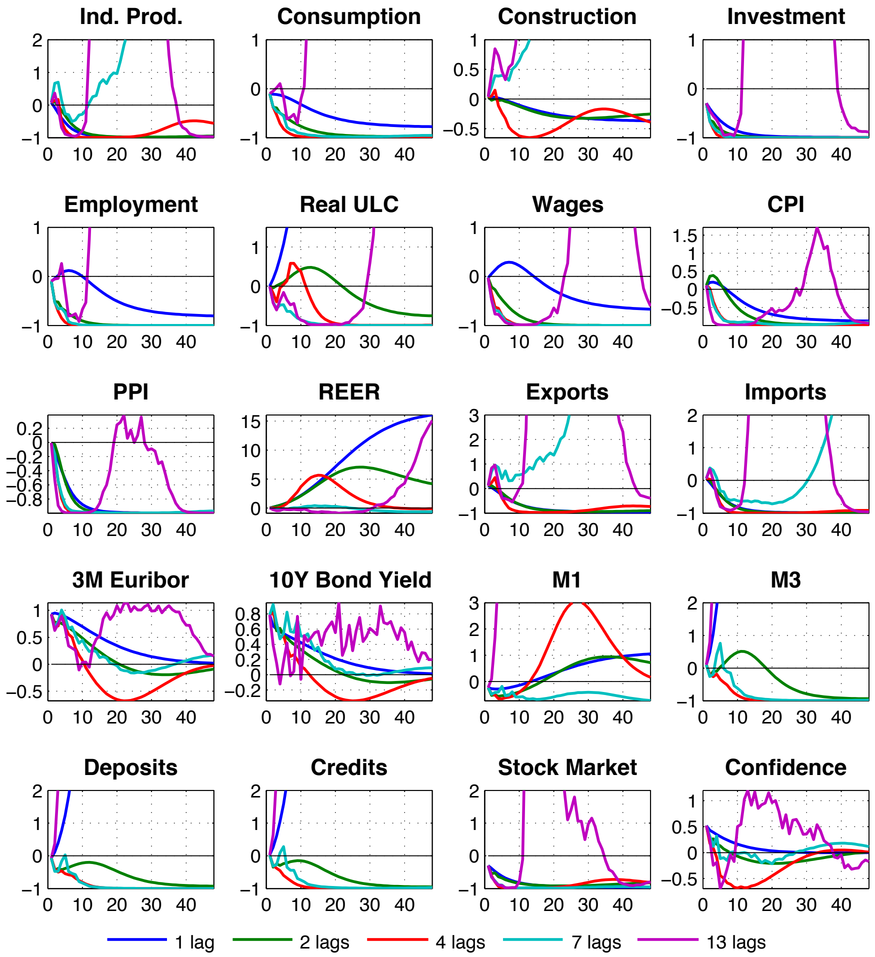


Figure 4: Number of Lags: Impulse Response Functions

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

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.

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

3.4 Interpolation

We have reported earlier that the Chow and Lin (1971) disaggregation 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[47], labour market[48], earnings[49], and balance of payments[50]. In Figure 5 we present the impulse response functions of the main variables used before with and without the interpolated series.[51]

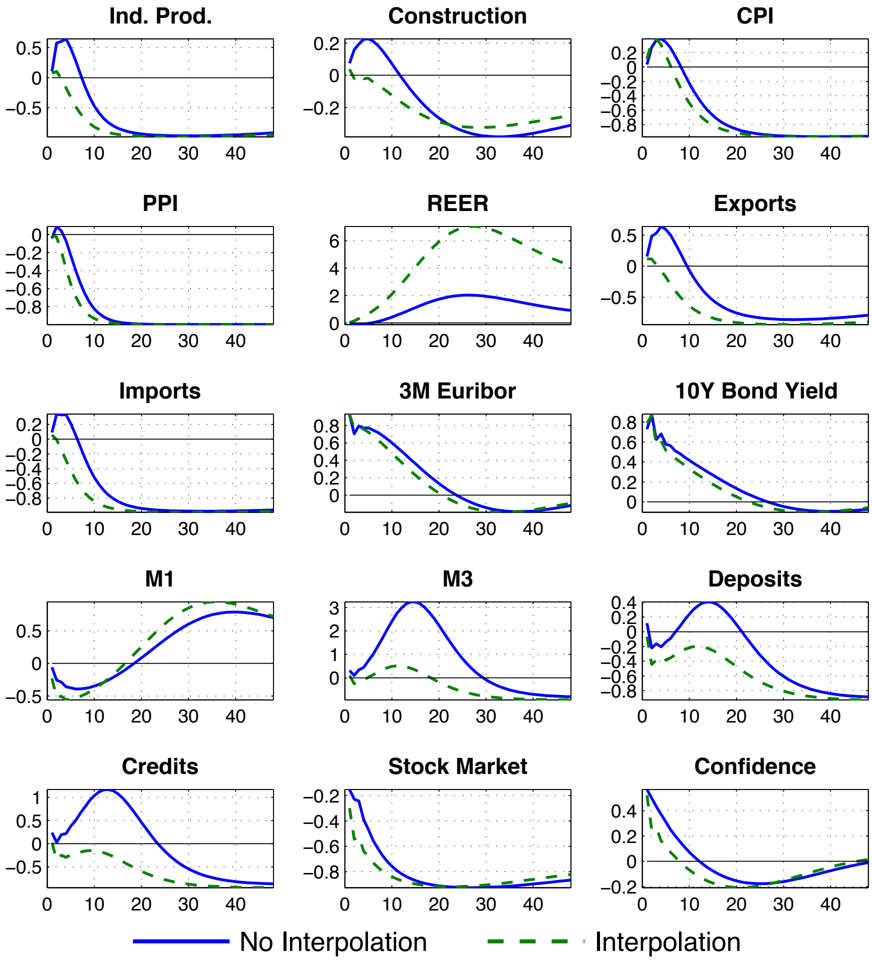


Figure 5: Interpolation of the Quarterly Series

We find that inclusion of extra information into the dataset not only keeps the majority of the responses unchanged but also eliminates some puzzles such as increase in industrial production, construction, exports, imports, and monetary aggregates following a contractionary monetary policy shock. Considering the variables interpolated and the

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

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

[49]Earnings per employee, wages and salaries.

[50]Current, capital and financial accounts.

[51]The results are obtained with a FAVAR(2) with 4 factors estimated with two-step PC model.

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"[52].[53]

As we reported in Section 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, 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 eliminates only a few of these interpolated variables.[54]

4 Empirical Results

In three parts, this section presents the empirical findings of the paper. First, we estimate a FAVAR model by one- (Bayesian) and two-step (PC) methods, and compare the monetary transmission mechanisms (MTM) 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 MTM 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 dataset obtained by Boivin and Ng (2006) prescreening technique applied to the original 120-variable dataset.

4.1 Monetary Transmission Mechanism in the Euro Area

Our main results obtained from the estimation of the one- and two-step FAVAR models are shown in Figures 6 and 7 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 1,000 bootstrap samples. As explained above, the FAVAR models are estimated with 4 factors and 2 lags. Bayesian estimates in Figure 6 employ 10,000 Gibbs sampling iterations, of which the first 2,000 were discarded in order to minimise the impact of initial conditions, i.e. the starting values in Section 2.2.[55] All results are reported in standard deviation (SD) units.

First of all, the estimated MTMs in Figures 6 and 7 are largely consistent with conventional wisdom: following a contractionary monetary policy shock, real activity measures such as industrial production, 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 relatively much wider confidence intervals, e.g.

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

[53]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 dataset.

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

[55]See Section 5 for robustness check for the Gibbs iterations.

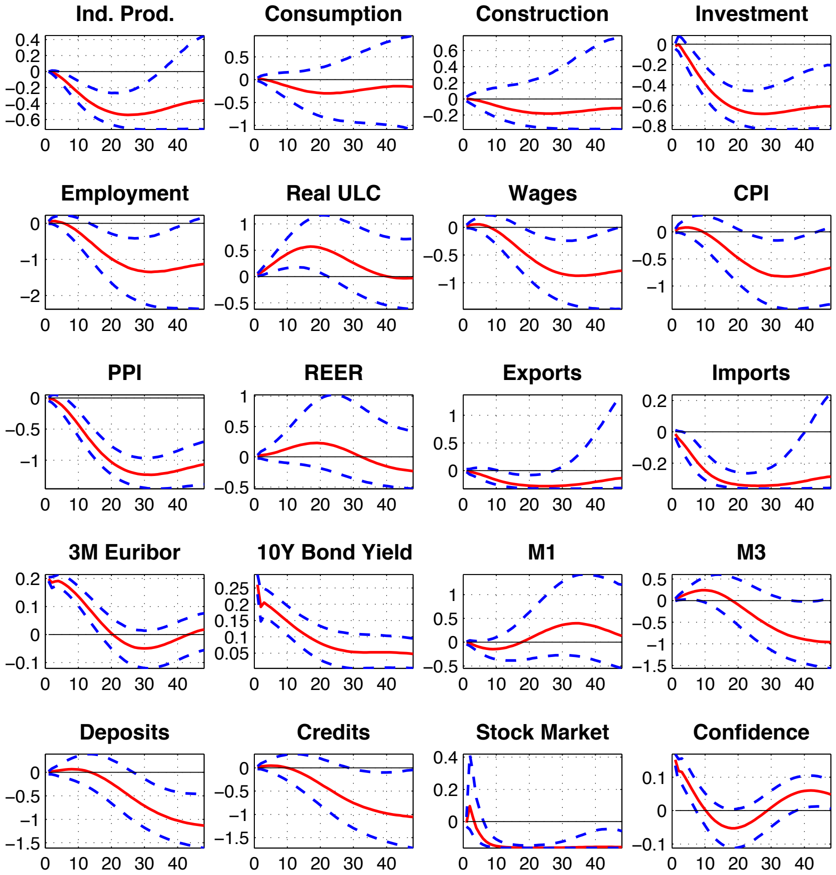


Figure 6: MTM in the EA - One-step FAVAR

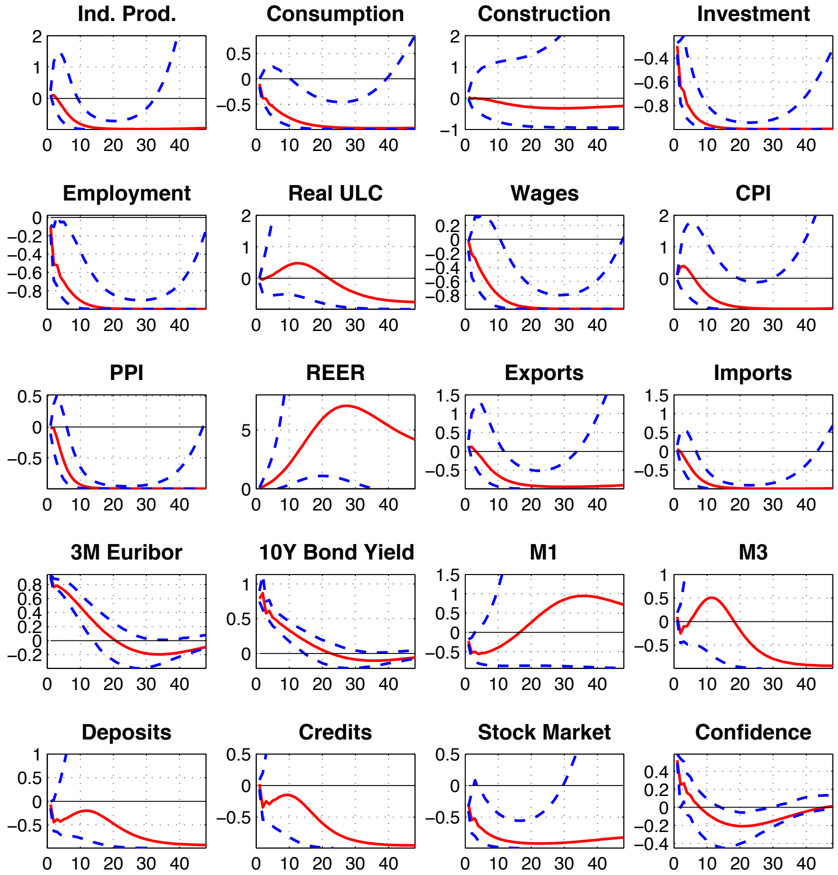


Figure 7: MTM in the EA - Two-step FAVAR

Note - 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.

real ULC, harmonised index of consumer prices (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 the response of the industrial production estimated with one-step method returns towards zero after reaching its maximum of -0.55 *SD* in period 25 following the shock, that with the two-step "is very persistent, inconsistent with long-run money neutrality."[56] The same difference between the methods is also present in responses of consumption, employment, real ULC, wages, CPI, and trade variables.

Our FAVAR model suggests the following common findings. As regards the real activity, we find that the most affected indicators are real investment 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 output and prices lead the real ULC to increase, statistically significantly in only one-step FAVAR model.

While there are slightly positive responses of prices in the first five (two-step) and ten (one-step) months following the shock, our results[57] suggest that our dataset 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 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 European Monetary Union (EMU) 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[58] for 30 months following the shock, the impulse responses are not as strong as suggested 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 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

[56]Bernanke et al. (2005, p.405).

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

[58]According to the definition of the REER series, a rise in the index means loss of competitiveness of the home country (EA).

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.[59] As of period 20, we observe the short-term interest rates turn negative, i.e. decrease below the pre-shock level.[60] A qualitatively similar behaviour is also observed from the responses of the benchmark monetary policy rates in Figure 8, estimated by the one- and two-step approaches.[61]

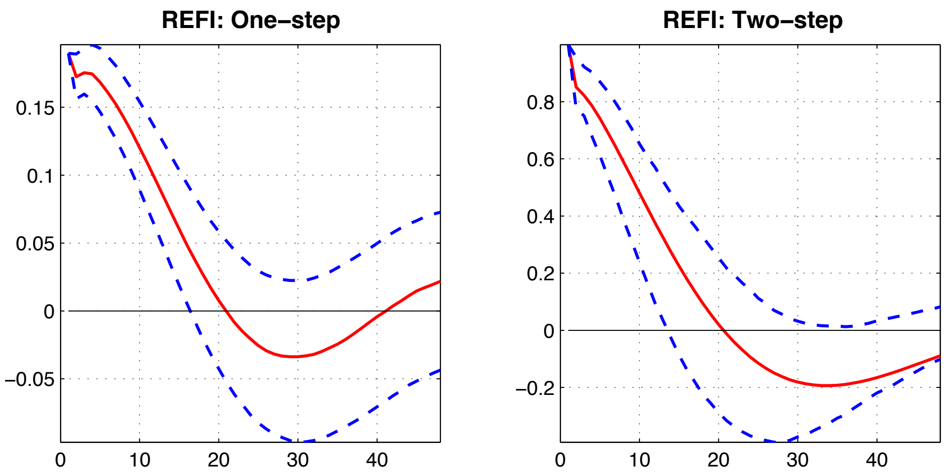


Figure 8: Impulse Responses of the Monetary Policy Variable

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.[62] Given the fact that the "impulse responses contain the endogenous reaction of monetary policy 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 U.S., and Boivin et al.

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

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

[61]Unsurprisingly, short-term interest rates follow the responses of the policy variable, which, if we recall, is the only observable factor in the transition equation (2), and its impulse responses can also be calculated in standard ways.

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

(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.[63] 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 claim 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 decrease in the total deposits held at MFI, total credits granted by which also decline as a result of the shock. As regards the earlier mentioned common issue of statistically insignificant impulse responses in the FAVAR literature, however, 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.[64]

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

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."[65,66] Specific to the FAVAR approach, additionally, the fraction of the variance of a variable accounted for by the common components,[67] R^2, is another tool used to analyse the estimation results.

We report in Table 3 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.

[63] 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).

[64] Consistent with ECB (2010).

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

[66] On technical details Appendix F is available upon request.

[67] i.e. $\hat{\Lambda}^f \hat{F}_t + \hat{\Lambda}^y Y_t$ in the observation equation 1.

Table 3: Variance Decomposition and R^2

Variables	FEVD[a]	R^2
IP	0.31	0.710
Consumption	1.19	0.230
Construction	0.07	0.102
Investment	1.76	0.564
Employment	1.21	0.737
Real ULC	0.05	0.421
Wages	0.73	0.446
CPI	0.35	0.516
PPI	0.95	0.703
REER	0.57	0.150
Exports	0.24	0.418
Imports	0.57	0.465
3M Euribor	17.50	0.987
10Y Yield	13.07	0.458
M1	1.05	0.354
M3	0.74	0.571
Deposits	0.91	0.484
Credits	0.72	0.516
Stock Market	0.61	0.668
Confidence	1.43	0.766

[a] %, at the 60-month horizon.

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"[68], 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.[69] 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 per cent 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 of 5 years, as we discussed in Section 2.3[70], 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 are explained by the factors in the model. To illustrate from real activity measures: industrial production (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%

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

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

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

of the producer prices. As regards 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-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. Following Bernanke et al. (2005, p.414), where 10.3 and 5.2 per cent explanatory rates for the monetary base and M2, respectively, are indicated for the necessity of being less confident in the impulse response estimates for these variables, our overall results finally suggest that our impulse responses are relatively reliable point estimates.

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."[71]

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 dataset. Additionally, and more importantly, given the short history of the third stage of the EMU 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.[72,73] We believe that this is the main reason why TVP-FAVAR models are yet to be applied to the EMU 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 U.S. and the U.K.[74]

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).

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

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

[73] 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 dataset, we could not obtain any reasonable results. We anyway thank the authors for making the files available to the public.

[74] See Korobilis (2012), Barnett et al. (2012), and references therein.

4.2.1 Definition of the Global Financial Crisis Period

We estimate our FAVAR model[75] by the one-step and two-step estimation methods over fixed length samples rolled by twelve, six and three months.[76] The estimation results are then compared by plotting together the impulse response functions of the main twenty macroeconomic indicators calculated in each sample. In order to determine the samples, we consider three alternative definitions of the beginning of the crisis period explained below.

Definition 1. Following the literature[77] and our graphical investigation of the financial markets in the EA, i.e. Euro Stoxx 50., in Figure 9, July 2007 is the first definition. As we can see from the Figure, the stock market peaks in June 2007 before it is hit by the beginning of the run-off. Therefore, the initial window of this definition becomes March 1999 - June 2007, inclusive.[78]

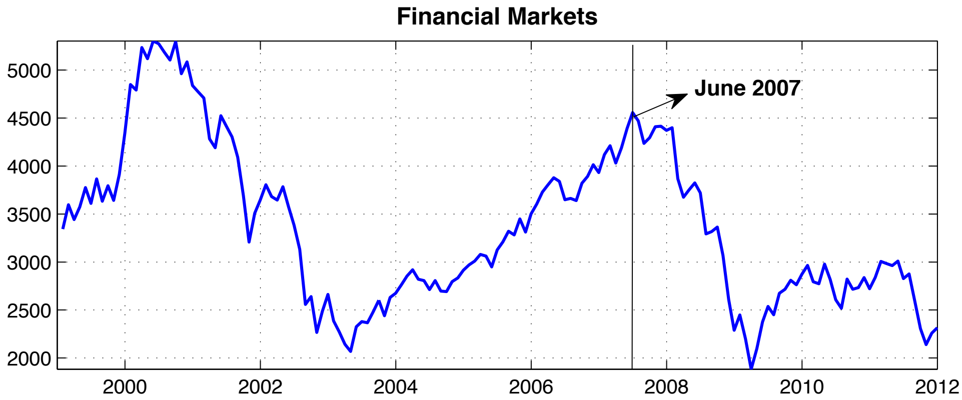


Figure 9: Beginning of the Crisis: Definition 1

Definition 2. We graphically check exactly when the real economy of the Euro Area[79] is hit by the global financial crisis. As Figure 10 shows below, despite the strong run-off in the financial markets, the real economy continues to trend upwards until April 2008, after which it is strongly hit by the crisis. Different than the first definition, in order to be able to roll the windows by three and six months until the end of the whole sample, and also have consistency with the next definition below, we determine the second definition and accordingly it's initial window as March 1999 - March 2008.

Definition 3. There is no doubt that the collapse of Lehman Brothers Holdings Inc. in September 2008 has a significant role in the crisis. As such, we define our final definition according to this important date.

Regardless of the pervious definitions, i.e. the periods when the crisis hit the financial and real sectors of the EA, Definition 3 considers the post-crisis period starting with the collapse of Lehman Brothers in September 2008. Given two sets of initial windows are

[75]Still with 4 factors and 2 lags.
[76]Only six-month rolling is estimated by the one-step method. For details see below.
[77]e.g. Erkens et al. (2012) and Cecioni and Neri (2011).
[78]First three observations are lost due to data transformations explained above in Section 3.1.
[79]i.e. seasonally adjusted volume index of industrial production.

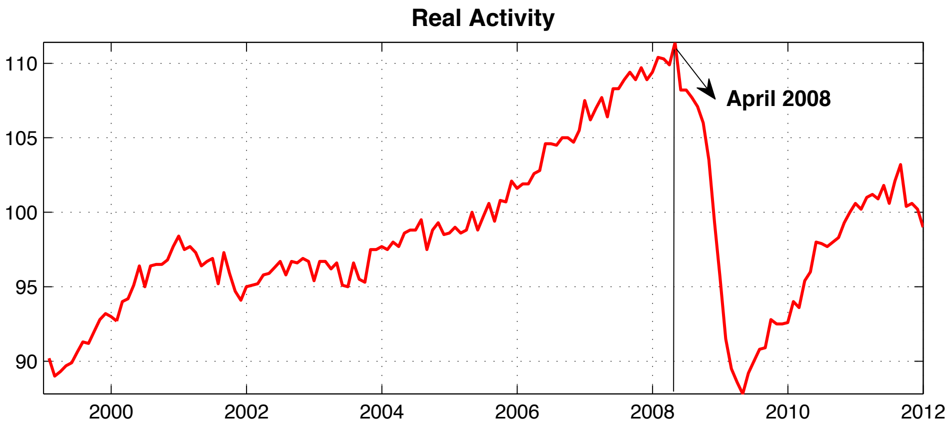


Figure 10: Beginning of the Crisis: Definition 2

determined according to Definition 1 and 2, we decided not to estimate another set of rollings with the initial window stopping at September 2008. Instead, we prefer to use Definition 3 in order to separate the pre- and post-crisis periods when we comment on the results obtained with rolling windows determined with the previous two definitions. See the results below for more details.

4.2.2 Crisis in the Euro Area Economies

It is important to note, given the fact that EA economies are still struggling with the aftermaths of the global financial crisis even when this paper is being written in 2012, we consider all the years following the ones defined above, until the end of our whole sample (Dec. 2011), as the crisis period for the EA.

4.2.3 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 as detailed as possible, i.e. different definitions of the crisis period and rolling augmentations. Following the set of results with the two-step method, we then replicate on p.37 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 Definition 1 and with 6M rollings only. For details of the results obtained with the two-step method, see below.

Following the definitions above, we estimate the model with six sets of rolling windows. In other words, we start with Definition 1 as the initial window, and then roll the windows by twelve, six and three months, giving us first half of the sets. Then we consider the second Definition and replicate the same rolling analysis in the previous one. The estimation results with rollings according to Definition 1 are presented in Figures 11-13, with windows reported below the figures[80], and summarised below. It is important to

[80]For the sake of comparability the impulse responses are plotted without their confidence intervals. Due to having a number of variables and windows, we present statistical significance of four main variables of industrial production, CPI, M1 and M3 in Appendix B, available upon request, for Definition 1 and six-month rollings only. Similar to impulse responses themselves, statistical significance of the rollings

note that no difference is observed between the results with Definition 1 and 2. Therefore, we only focus here on the set of results starting with window March 1999 - July 2007, and present the second set in Appendix B, available upon request. Additionally, as explained below in detail, the results support Definition 3 as the beginning of the crisis period. Hence, we refer to Definition 3 only in the text below.

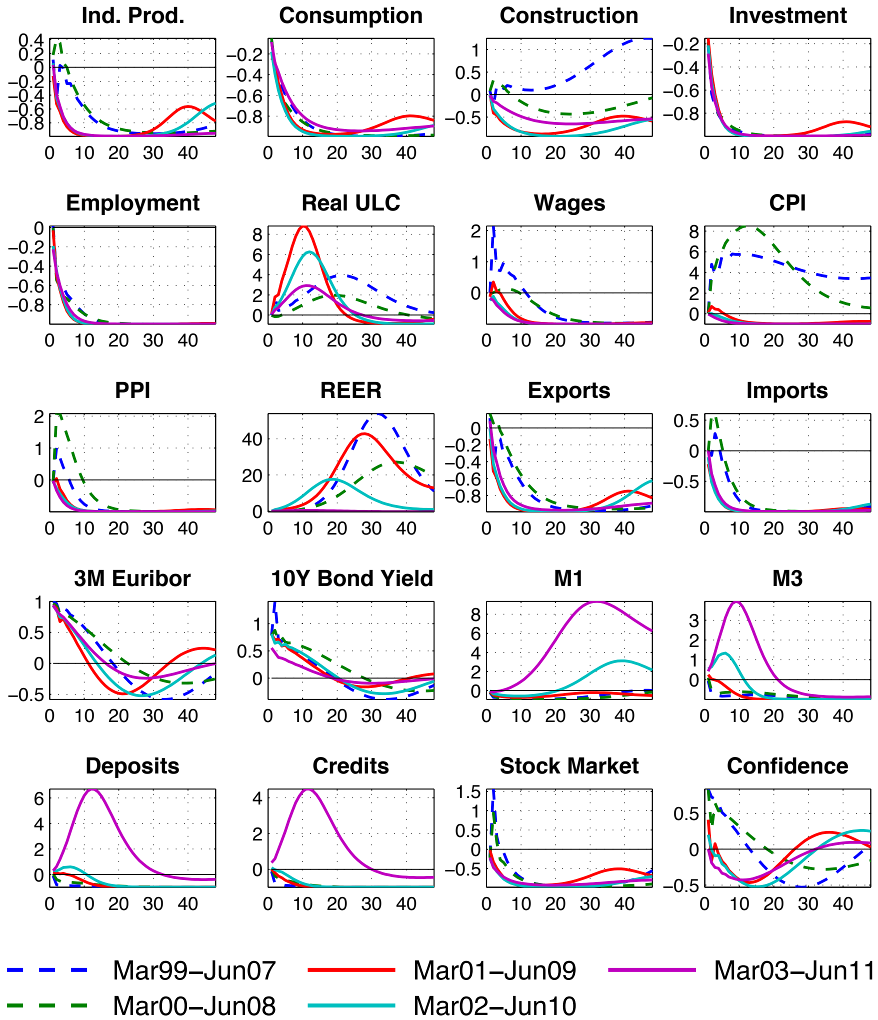


Figure 11: Rolling IRF, Two-step, Definition 1, 12M

not reported are largely identical with the ones below.

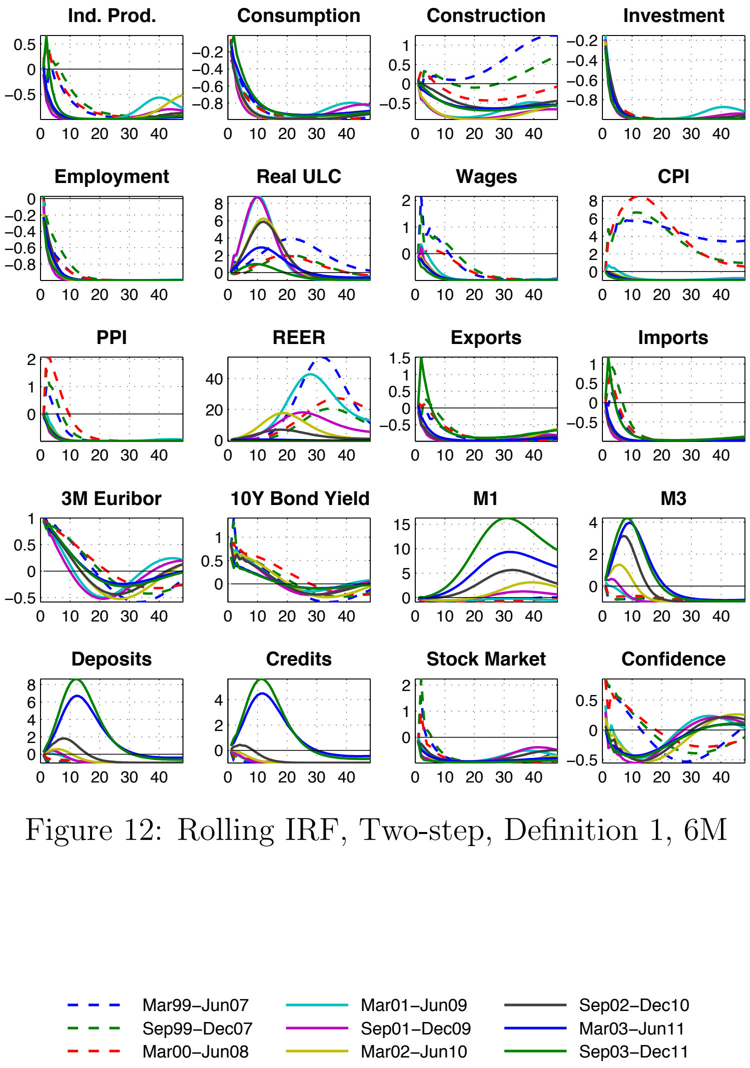


Figure 12: Rolling IRF, Two-step, Definition 1, 6M

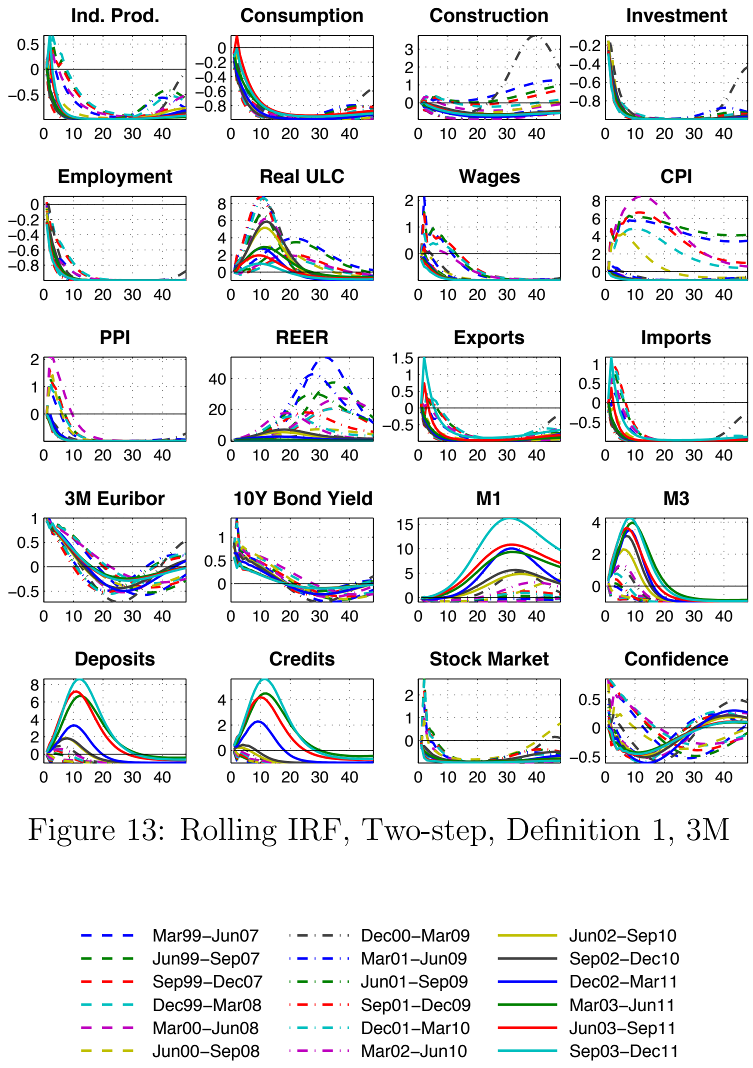


Figure 13: Rolling IRF, Two-step, Definition 1, 3M

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 in Appendix B, available upon request.

Looking at the results, we note the following points robust to the number of samples the windows are rolled through. First of all, there is clear sign of little variation in some of the real variables such as consumption, investment and employment. That is to say, the monetary policy shock hitting the economy either before or after the crisis period has almost identical contractionary impact on these measures of the real economy.[81] Regarding the industrial production (IP), we observe, from Figures 11-13, that there are differences in the speed of the impact of the monetary policy shock pre- and post-Sep-08. Whereas the impact of the contemporaneous impact is mixed, it is clear from the results that, unsurprisingly, IP declines much faster when hit by the contractionary shock during the crisis period. For some of the windows, depending on the frequency of the rolling window, spanning the period March 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 variation 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 between March 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 Sep-08, 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 (Definition 3) 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. Let us refer back to Section 4.1 where we discussed 'temporary portfolio shifts' proposed by Blaes (2009) as an explanation for the puzzling M3 responses to a contractionary monetary policy shock in the EA. Given this explanation, our rolling results also suggest that despite no significant change in the responses of short-term interest rates pre- and post-crisis periods, higher short-term interest rates during the latter period leading to stronger portfolio shifts from long- to short-term assists contained in M3, causing the stronger increase in the money stock relative to the pre-crisis period.

Secondly, our rolling analysis raises an important point about puzzling CPI responses in the literature. As summarised in Section 1, solving the issue of price puzzles has largely

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

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

been the main focus of the (FA)VAR literature. As our results in Section 4.1 and that of other studies frequently cited throughout the paper suggest, despite the issue of statistical significance we highlighted before, the FAVAR approach does capture important dimensions of the business cycle movements and estimates the "expected" 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 the Figures 11-13, our FAVAR model, estimated with constant specifications among the windows, suggests that whilst prices respond persistently negatively to the shocks in the post-crisis period, they strongly puzzle when the shock occurs prior to the crisis. That is to say, as the dashed-line impulse responses in Figures 11-13 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.

4.2.4 Interpolation of the Crisis Period (Oct. - Dec. 2008)

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 Sep. 2008. We also highlighted that window Sep00-Dec08 is eliminated from Figures 12-13 due to very strange impact of the period Sep.-Dec. 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 dataset continued in their normal trends during this period.

Using the replication files of the study by Banbura 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.[83] Then we replicate the rolling analysis in Figure 12.[84] The results of the short exercise are displayed in Figure 14.

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 12 disappear in rolling estimations with the interpolated data in Figure 14. On the other hand, instead of permanent decrease in stock markets following a contractionary shock (Figure 12), interpolated data suggest that a shock hitting the economy in the post-crisis period strongly increases the markets after 20 months (Figure 14). These findings suggest that (strong) liquidity puzzles in the whole (Figure 7) or rolling samples (Figure 12) 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

[83] 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.

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

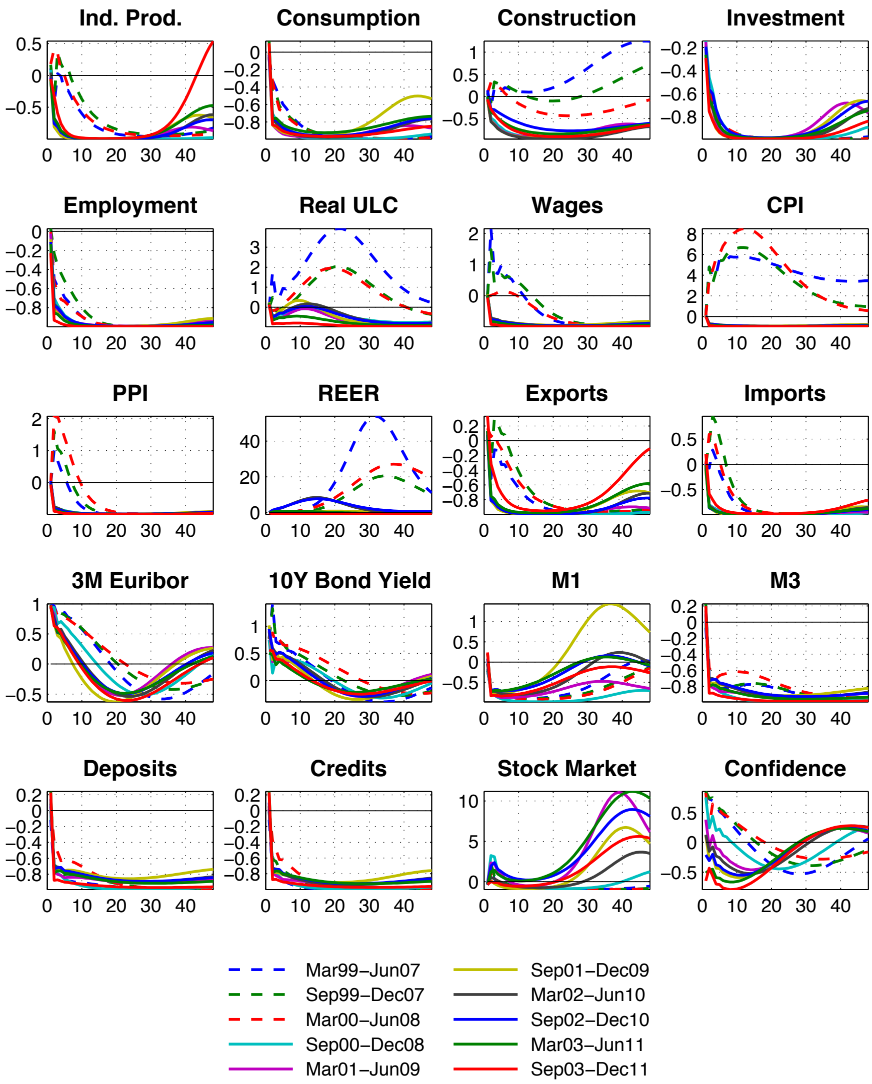


Figure 14: Interpolation of the Crisis Period

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 12 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.

4.2.5 One-step Rolling Estimations

Consistent with the Section 4.1, we carry out the rolling analysis not only with the two-step method but also the one-step Bayesian approach.[85] However, due to the com-

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

putational intensity of the method, and the previous finding that the two-step results are robust to the definitions and rolling augmentations, we apply the Bayesian rolling analysis to the initial window of March 1999 - June 2007 with 6M rollings only. We present the estimation results in Figure 15. 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 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.[86]

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 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.

The difference in the confidence intervals estimated by the one- and two-step methods was discussed in Section 4.1. The main reason why statistical (in)significance of the results in this section has not been highlighted previously is due to bad performance of the two-step method, in fact bootstrapping, in terms of estimating reliable error bands. As we present in Appendix B, available upon request, however, our one-step approach performs relatively very well. To illustrate, it suggests the sharper output responses and some of the liquidity puzzles during the crisis period to be statistically significant findings.

4.3 Boivin and Ng Analysis

Having the main and time varying estimation results explained, we now move to investigation of a limited version of our dataset constructed using the Boivin and Ng analysis (BN, hereafter), described in Section 2.4.

According to our BN analysis, we find idiosyncratic error of 57 series to be most correlated with other series in our dataset. These variables dropped from the dataset are listed in Appendix A. For example, total industrial production (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 dataset, 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 4 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 MTM and time variation.

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

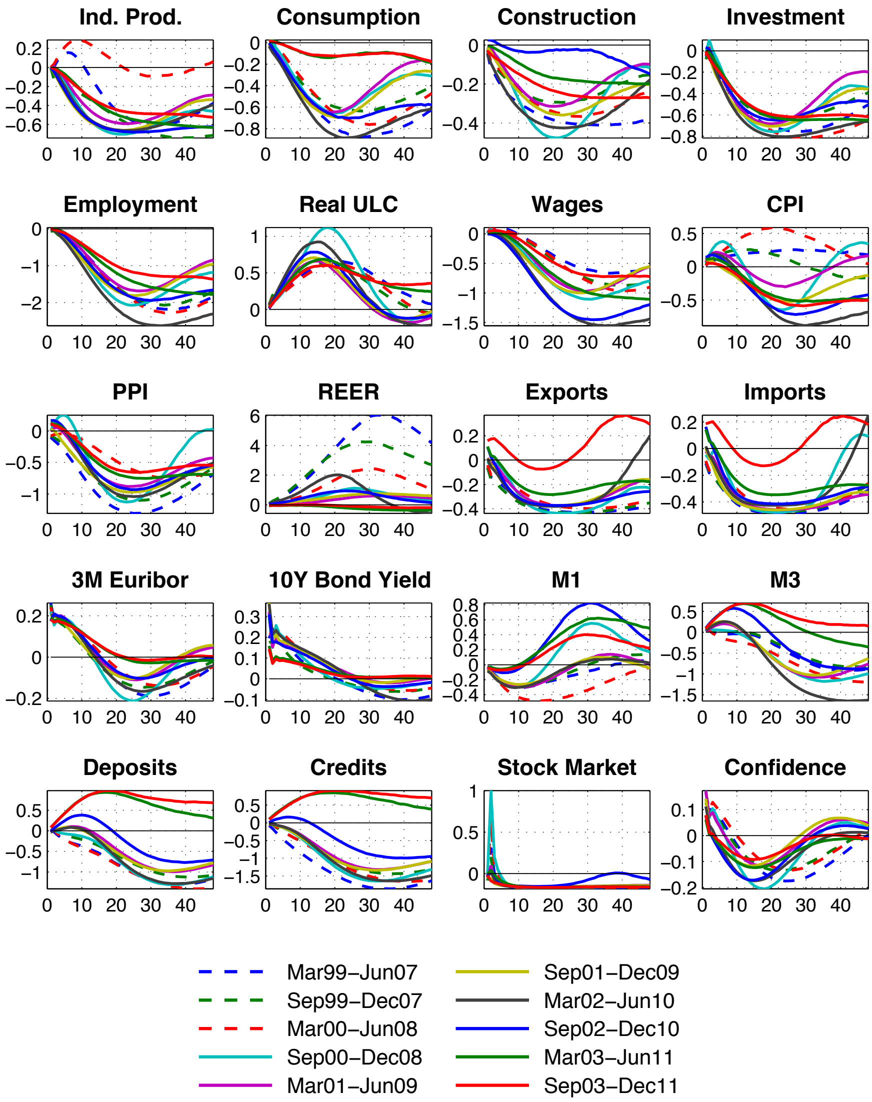


Figure 15: Rolling IRF, One-step, 1999-Jun2007, 6M

Table 4: Boivin and Ng 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.

4.3.1 MTM in the Euro Area

The transmission mechanism of a 25-basis-point contractionary monetary policy shock estimated with one- and two-step FAVAR methods using the new dataset is presented in Figures 16 and 17, with 68% confidence intervals based on 1,000 bootstrap samples. Comparing these results to those in Figures 6 and 7 suggests the following findings.

First of all, and very important, exclusion of the information carried by the variables dropped from the dataset does not change the estimated impact of the shock on the real activity measures[87], 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 dataset case, the eventual negative impact of the shock on prices, i.e. period 20 onwards, is estimated to be statistically significant with the new dataset. 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 6 and 7, both methods estimate that these indicators respond positively and statistically significantly, according to the one-step only, following the monetary tightening.

As regards 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)[88], no puzzle in M1 but a stronger one in M3 (two-step).

[87] Except employment responses estimated by two-step method.
[88] Note M3 in Figure 6 which responds negatively to the shock between periods 20-48.

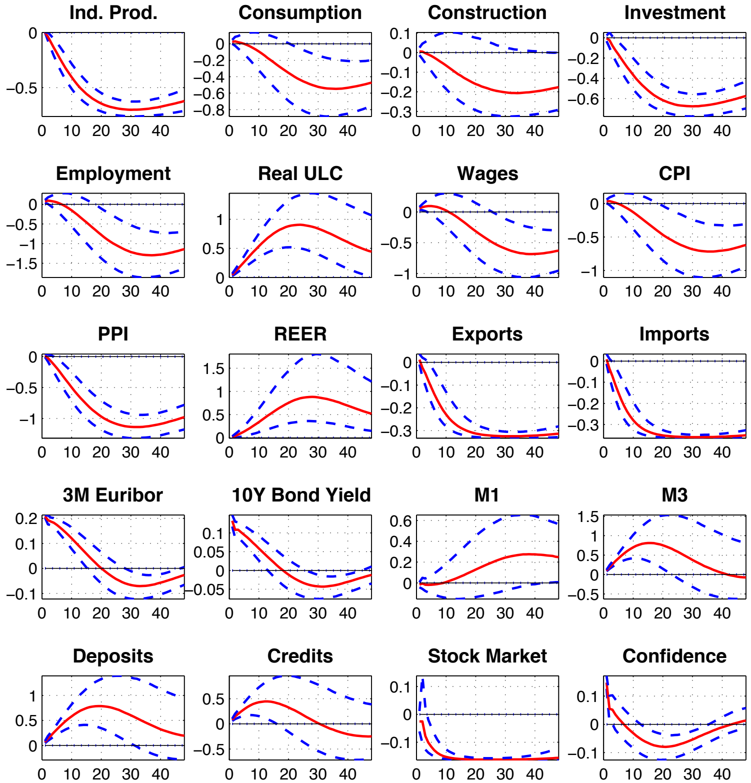


Figure 16: BN - MTM in the EA - One-step

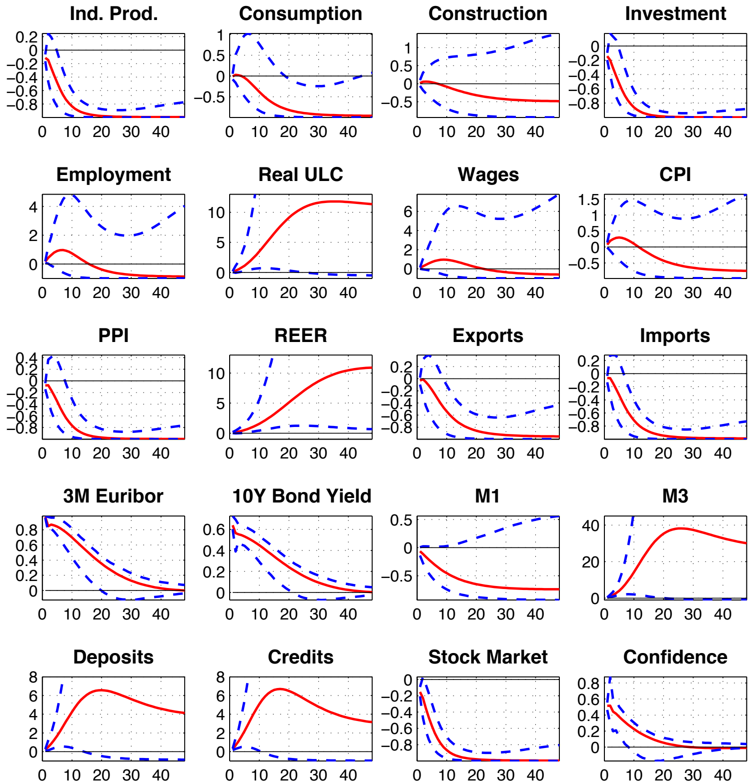


Figure 17: BN - MTM in the EA - Two-step

If we recall the portfolio shift scenario[89], relatively more gradual[90] decline in interest rates after their hike might be the reason behind the strong puzzle in broad money supply. Consistent with long-lasting interest rate responses, we observe that two-step impulse responses 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 responses.

4.3.2 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 12 and 15. Our BN rolling estimation results are presented in Figures 18-19.

Briefly, and very importantly we believe, according to our BN analysis, the very same rolling estimation results 12 and 15 are obtainable with a more parsimonious dataset. The main advantage of this finding is, of course, with a computer intensive Bayesian approach estimation of which becoming much less time-consuming.

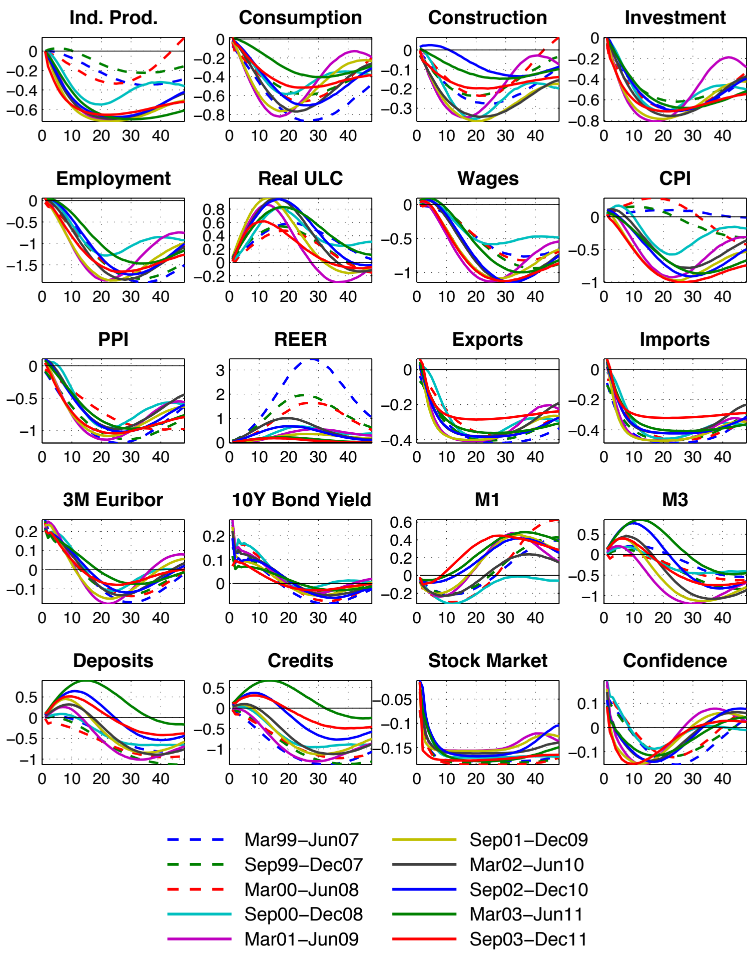


Figure 18: BN - Rolling IRF, One-step, Definition 1, 6M

[89] Blaes (2009)

[90] Statistically insignificant

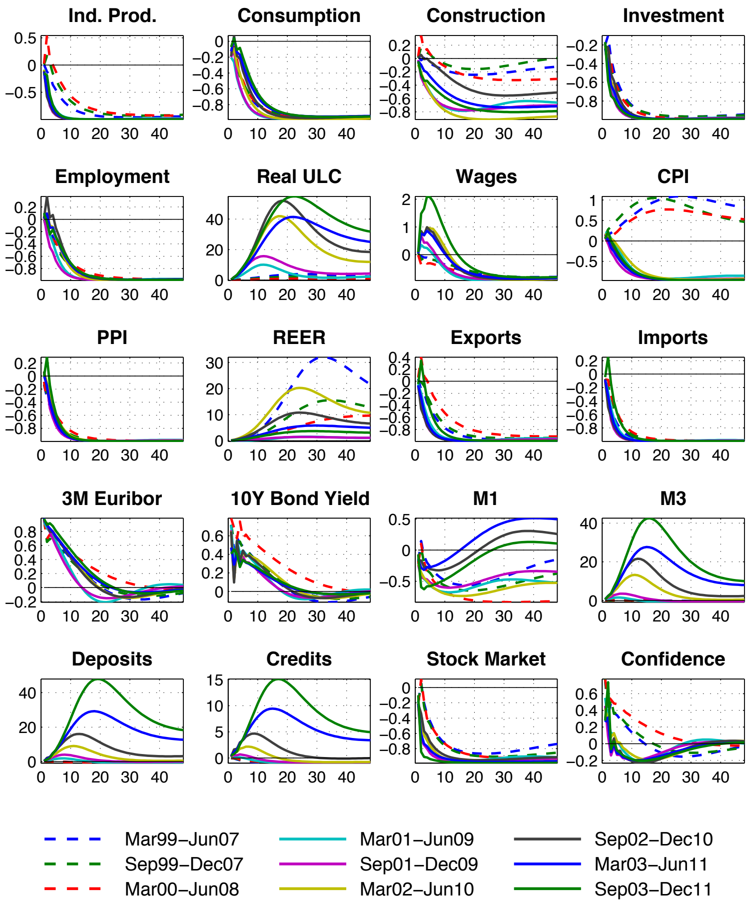


Figure 19: BN - Rolling IRF, Two-step, Definition 1, 6M

5 Robustness

In addition to the preliminary analyses of the paper explained in Section 3, we test robustness of our Bayesian empirical results by looking at convergence and Gibbs iterations in the following subsections.

5.1 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 (1992a), 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, which would be beyond the scope of this paper, 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

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

median of the draws against the second half. The 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.

Figures 20-25 below show the results of our 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. Figures 21-22 and 24-25, 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.

Pre - Boivin and Ng Analysis

5.1.1 MTM in the EA

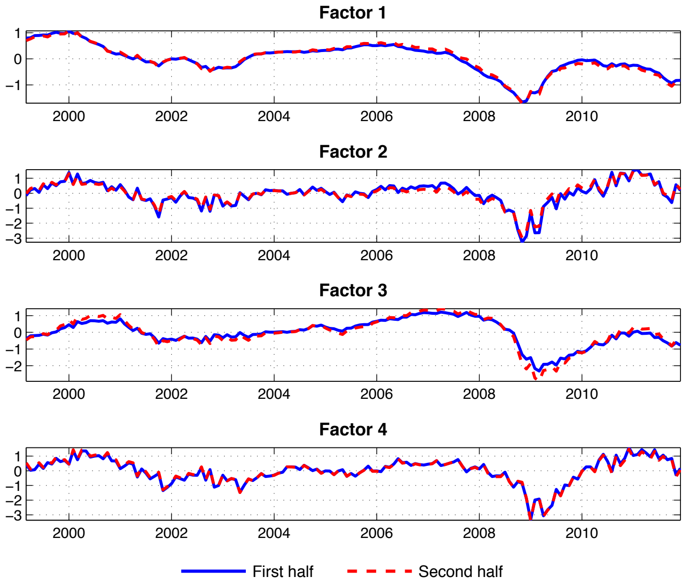


Figure 20: MTM in the EA - Convergence

starting values.

5.1.2 Time Variation

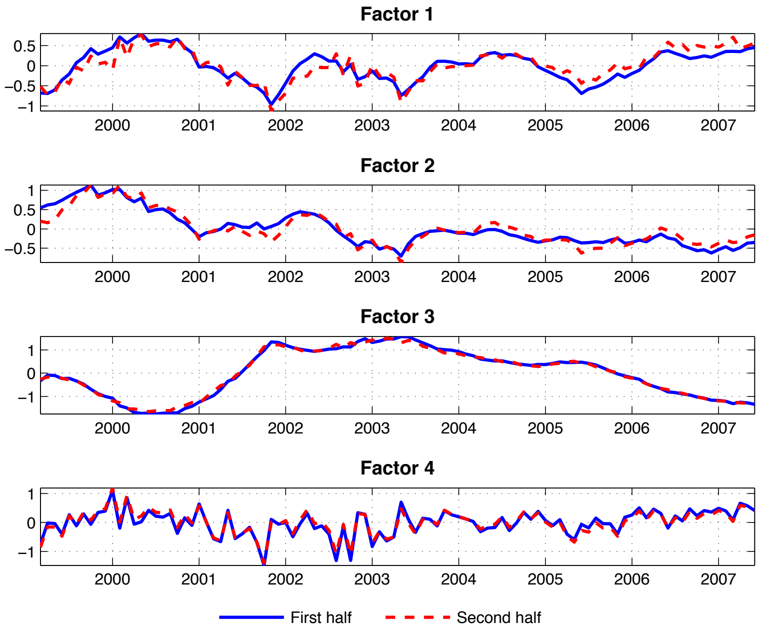


Figure 21: Rolling IRF, Convergence, Def.1-6M, Window:1

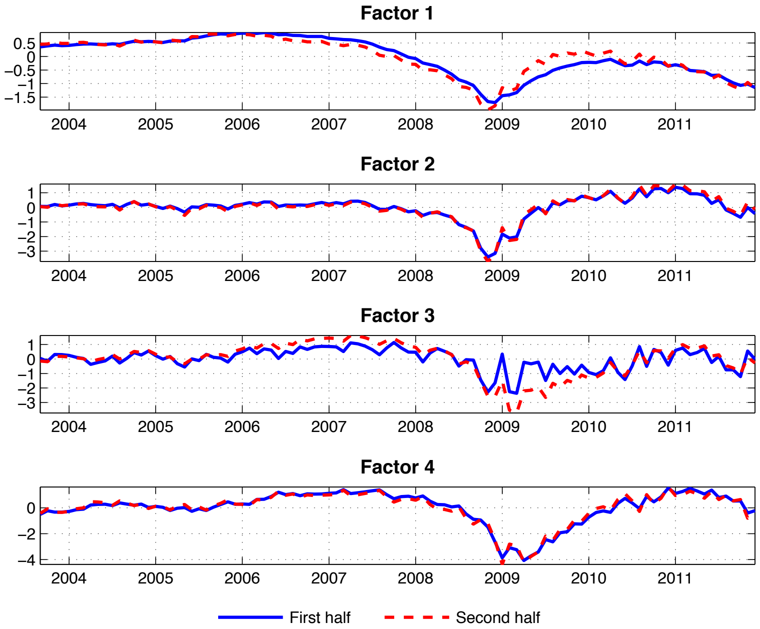


Figure 22: Rolling IRF, Convergence, Def.1-6M, Window:10

Post - Boivin and Ng Analysis

5.1.3 MTM in the EA

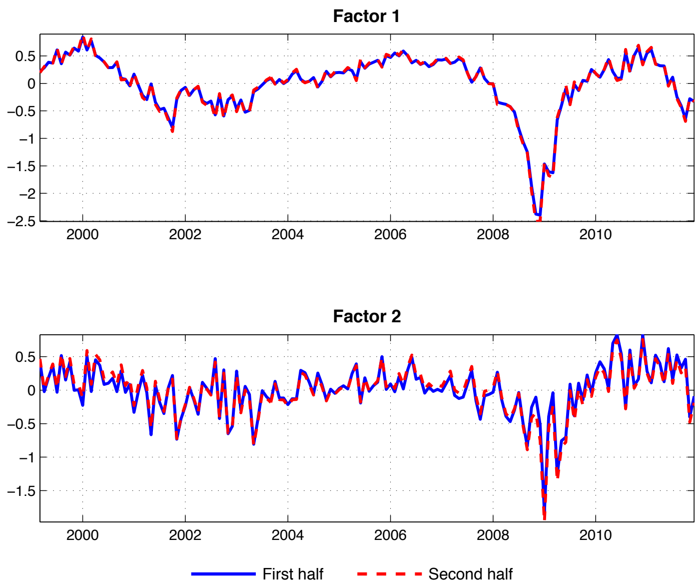


Figure 23: MTM in the EA, Convergence, Post-BN

5.1.4 Time Variation

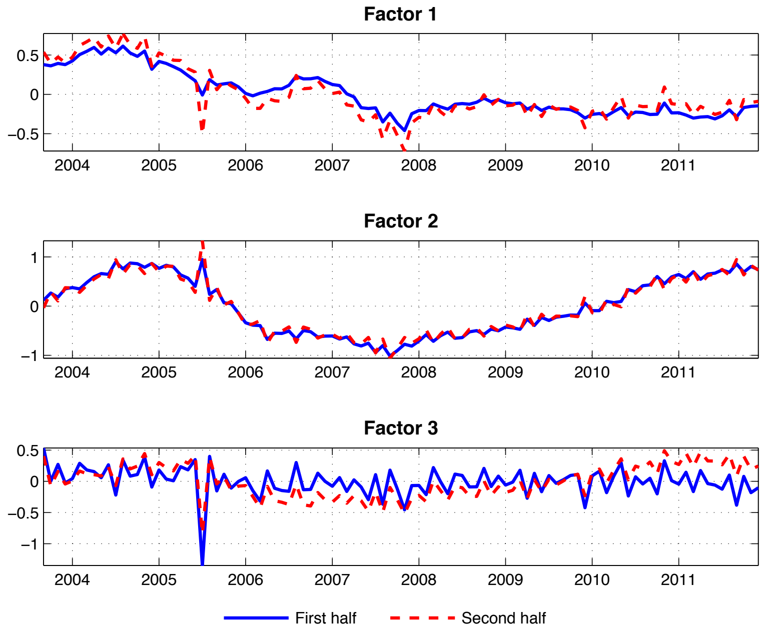


Figure 24: Rolling IRF, Convergence, Post-BN, Window:1

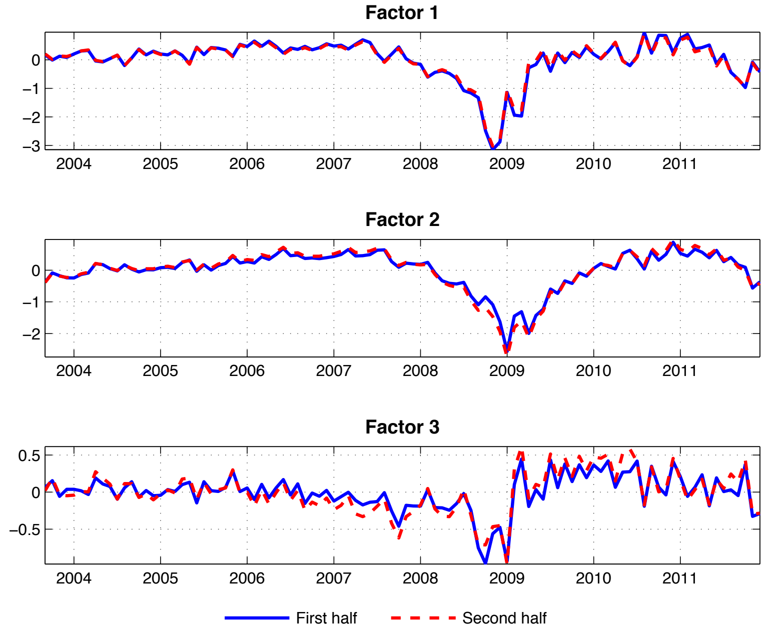


Figure 25: Rolling IRF, Convergence, Post-BN, Window:10

5.2 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 26, 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]

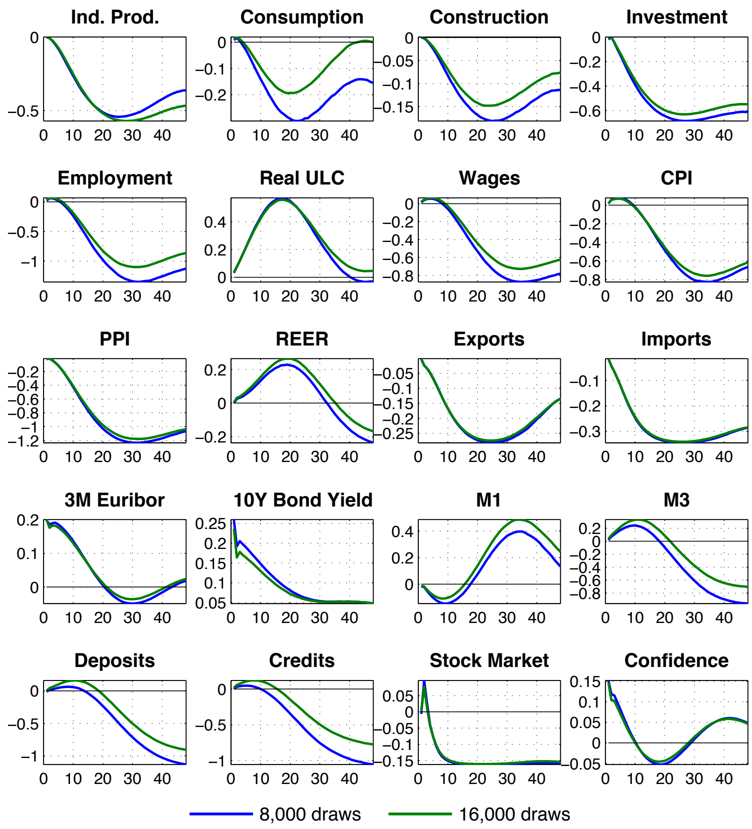


Figure 26: Gibbs Iterations

6 Conclusion

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

Analysing a novel dataset 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 two-step

[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 26.

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 qualitatively 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 differences in the EA with a FAVAR model estimated with the Bayesian methodology, i.e. the main focus of our future research, 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 Euro Area, 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 dataset 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 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 dataset 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 principal components 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 differences in the EA.

References

Ahmadi, P. (2005). *Measuring the effects of a shock to monetary policy: A factor-augmented vector autoregression (FAVAR) approach with agnostic identification*. PhD thesis, Humboldt University.

Ahmadi, P. and Uhlig, H. (2007). Measuring the dynamic effects of monetary policy shocks: a bayesian favar approach with sign restrictions. *Manuscript, University of Chicago*.

Bai, J. and Ng, S. (2002). Determining the number of factors in approximate factor models. *Econometrica*, 70(1):191–221.

Bai, J. and Ng, S. (2007). Determining the number of primitive shocks in factor models. *Journal of Business and Economic Statistics*, 25(1):52–60.

Bai, J. and Ng, S. (2008a). Forecasting economic time series using targeted predictors. *Journal of Econometrics*, 146(2):304–317.

Bai, J. and Ng, S. (2008b). *Large dimensional factor analysis*. Now Pub.

Banbura, M., Giannone, D., and Reichlin, L. (2008). Large Bayesian VARs. ECB Working Paper Series No. 966.

Banbura, M. and Modugno, M. (2010). Maximum likelihood estimation of factor models on data sets with arbitrary pattern of missing data. European Central Bank Working Paper Series No 1189.

Bańbura, M. and Rünstler, G. (2011). A look into the factor model black box: publication lags and the role of hard and soft data in forecasting gdp. *International Journal of Forecasting*, 27(2):333–346.

Banerjee, A., Marcellino, M., and Masten, I. (2008). Forecasting macroeconomic variables using diffusion indexes in short samples with structural change. In *Forecasting in the Presence of Structural Breaks and Model Uncertainty*, chapter 4, Rapach D. and Wohar M. (eds), pages 149–194. Elsevier, Amsterdam.

Barnett, A., Mumtaz, H., and Theodoridis, K. (2012). Forecasting UK GDP growth, inflation and interest rates under structural change: a comparison of models with time-varying parameters. Bank of England Working Paper, 450.

Belviso, F. and Milani, F. (2006). Structural factor-augmented VAR (SFAVAR) and the effects of monetary policy. *Topics in Macroeconomics, Berkeley Electronic Press*, 6(3):1443–1443.

Bernanke, B. and Blinder, A. (1992). The federal funds rate and the channels of monetary transmission. *American economic review*, 82(4):901–921.

Bernanke, B., Boivin, J., and Eliasz, P. (2004). Measuring the effects of monetary policy: a factor-augmented vector autoregressive (FAVAR) approach. National Bureau of Economic Research Working Paper 10220.

Bernanke, B., Boivin, J., and Eliasz, P. (2005). Measuring the effects of monetary policy: A factor-augmented vector autoregressive (FAVAR) approach. *Quarterly Journal of Economics*, 120(1):387–422.

Blaes, B. (2009). Money and monetary policy transmission in the euro area: evidence from FAVAR and VAR approaches. Discussion Paper, Dt. Bundesbank Frankfurt.

Boivin, J. and Giannoni, M. (2007). Global forces and monetary policy effectiveness.

Boivin, J., Giannoni, M., and Mihov, I. (2009). Sticky prices and monetary policy: Evidence from disaggregated US data. *The American Economic Review*, 99(1):350–384.

Boivin, J., Giannoni, M., and Mojon, B. (2008). How has the euro changed the monetary transmission? In Acemoglu, D., R. K. and Woodford, M., editors, *NBER Macroeconomics Annual 2008*, volume 23, chapter 2, pages 77–125. Chicago: University of Chicago Press.

Boivin, J. and Ng, S. (2006). Are more data always better for factor analysis? *Journal of Econometrics*, 132(1):169–194.

Bork, L. (2009). Estimating US monetary policy shocks using a factor-augmented vector autoregression: An EM algorithm approach. CREATES Research Papers 2009-11, School of Economics and Management, University of Aarhus.

Braun, P. and Mittnik, S. (1993). Misspecifications in vector autoregressions and their effects on impulse responses and variance decompositions. *Journal of Econometrics*, 59(3):319–341.

Canova, F., Ferroni, F., and de France, B. (2012). The dynamics of US inflation: can monetary policy explain the changes? *Journal of Econometrics*, (167):47–60.

Carter, C. and Kohn, R. (1994). On gibbs sampling for state space models. *Biometrika*, 81(3):541–553.

Cecioni, M. and Neri, S. (2011). The monetary transmission mechanism in the euro area: has it changed and why? Bank of Italy Working Paper, 808.

Chow, G. and Lin, A. (1971). Best linear unbiased interpolation, distribution, and extrapolation of time series by related series. *The Review of Economics and Statistics*, 53(4):372–375.

Connor, G. and Korajczyk, R. (1993). A test for the number of factors in an approximate factor model. *Journal of Finance*, pages 1263–1291.

Cragg, J. and Donald, S. (1997). Inferring the rank of a matrix. *Journal of Econometrics*, 76(1):223–250.

Cushman, D. and Zha, T. (1997). Identifying monetary policy in a small open economy under flexible exchange rates. *Journal of Monetary economics*, 39(3):433–448.

Depoutot, R., Dossé, J., Hoffmann, S., and Planas, C. (1998). Advanced seasonal adjustment interface DEMETRA. Technical report, Eurostat, Luxembourg.

Donald, S. (1997). Inference concerning the number of factors in a multivariate nonparametric relationship. *Econometrica: Journal of the Econometric Society*, pages 103–131.

Eickmeier, S. and Ziegler, C. (2008). How successful are dynamic factor models at forecasting output and inflation? a meta-analytic approach. *Journal of Forecasting*, 27:237–265.

Eliasz, P. (2005). Likelihood-based inference in large dynamic factor models using gibbs sampling. Princeton University, unpublished Working Paper.

Enders, W. (2004). *Applied econometric time series*. Wiley, Hoboken, NJ, 2nd edition.

Erkens, D., Hung, M., and Matos, P. (2012). Corporate governance in the 2007–2008 financial crisis: Evidence from financial institutions worldwide. *Journal of Corporate Finance*, 18(2):389–411.

European Central Bank (2010). Monetary policy transmission in the euro area, a decade after the introduction of the euro. Monthly Bulletin, May: 85–98.

Favero, C. (2001). *Applied Macroeconomics*. Oxford Univ. Press.

Forni, M., Hallin, M., Lippi, M., and Reichlin, L. (2000). The generalized dynamic-factor model: Identification and estimation. *Review of Economics and Statistics*, 82(4):540–554.

Forni, M. and Reichlin, L. (1998). Let's get real: a factor analytical approach to disaggregated business cycle dynamics. *Review of Economic Studies*, 65(3):453–473.

Gelman, A. and Rubin, D. (1992a). Inference from iterative simulation using multiple sequences. *Statistical science*, pages 457–472.

Gelman, A. and Rubin, D. (1992b). A single sequence from the gibbs sampler gives a false sense of security. *Bayesian statistics*, 4:625–631.

Geman, S. and Geman, D. (1984). Stochastic relaxation, gibbs distributions, and the bayesian restoration of images. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 6:721–741.

Geweke, J. (1977). *The dynamic factor analysis of economic time series models*. Social Systems Research Institute, University of Wisconsin-Madison.

Giannone, D., Reichlin, L., and Sala, L. (2004). Monetary policy in real time. *NBER Macroeconomics Annual*, 19:161–200.

Grenouilleau, D. (2004). A sorted leading indicators dynamic (SLID) factor model for short-run euro-area gdp forecasting. *European Commission Economic Papers*, (219).

Kapetanios, G. (2010). A testing procedure for determining the number of factors in approximate factor models with large datasets. *Journal of Business and Economic Statistics*, 28(3):397–409.

Kelly, L., Barnett, W., and Keating, J. (2011). Rethinking the liquidity puzzle: Application of a new measure of the economic money stock. *Journal of Banking & Finance*, 35(4):768–774.

Kilian, L. (1998). Small-sample confidence intervals for impulse response functions. *Review of Economics and Statistics*, 80(2):218–230.

Kim, C. and Nelson, C. (1999). *State-space models with regime switching.* MIT press Cambridge, MA.

Koop, G. and Korobilis, D. (2009). Bayesian multivariate time series methods for empirical macroeconomics. *Foundations and Trends in Econometrics*, (3):267—358.

Korobilis, D. (2012). Assessing the transmission of monetary policy using time-varying parameter dynamic factor models*. *Oxford Bulletin of Economics and Statistics.*

Leeper, E., Sims, C., Zha, T., Hall, R., and Bernanke, B. (1996). What does monetary policy do? *Brookings Papers on Economic Activity*, (2):1–78.

Lewbel, A. (1991). The rank of demand systems: theory and nonparametric estimation. *Econometrica: Journal of the Econometric Society*, pages 711–730.

Lütkepohl, H. (2005). *New introduction to multiple time series analysis.* Berlin: Springer-Verlag.

Lütkepohl, H. and Krätzig, M. (2004). *Applied time series econometrics.* Cambridge University Press.

Marcellino, M. (2006). Leading indicators. *Handbook of Economic Forecasting*, 1:879–960.

McCallum, A. and Smets, F. (2007). Real wages and monetary policy transmission in the euro area. Kiel Working Paper 1360, Kiel Institute for the World Economy.

McCulloch, R. and Rossi, P. (1994). An exact likelihood analysis of the multinomial probit model. *Journal of Econometrics*, 64(1-2):207–240.

Mumtaz, H. and Surico, P. (2007). The transmission of international shocks: A factor augmented VAR approach.

Mumtaz, H. and Surico, P. (2009). The transmission of international shocks: A factor-augmented VAR approach. *Journal of Money, Credit and Banking*, 41:71–100.

Mumtaz, H., Zabczyk, P., and Ellis, C. (2011). What lies beneath?: A time-varying favar model for the uk transmission mechanism. (WP NO. 1320).

Raftery, A. and Lewis, S. (1992). How many iterations in the gibbs sampler. *Bayesian statistics*, 4(2):763–773.

Raftery, A. and Lewis, S. (1996). Implementing MCMC. *Markov chain Monte Carlo in practice*, pages 115–130.

Sargent, T. and Sims, C. (1977). Business cycle modeling without pretending to have too much a priori economic theory. *New methods in business cycle research*, 1:145–168.

Schumacher, C. and Breitung, J. (2008). Real-time forecasting of german gdp based on a large factor model with monthly and quarterly data. *International Journal of Forecasting*, 24(3):386–398.

Sims, C. (1972). Money, income, and causality. *The American Economic Review*, 62(4):540–552.

Sims, C. (1980a). Comparison of interwar and postwar business cycles: Monetarism reconsidered. *American Economic Review*, 70(2):250–257.

Sims, C. (1980b). Macroeconomics and reality. *Econometrica*, 48(1):1–48.

Sims, C. (1992). Interpreting the macroeconomic time series facts: The effects of monetary policy. *European Economic Review*, 36(5):975–1011.

Sims, C. and Zha, T. (2006). Does monetary policy generate recessions? *Macroeconomic Dynamics*, 10(2):231–271.

Soares, R. (2011). Assessing monetary policy in the euro area: a factor-augmented VAR approach. Banco de Portugal Working Papers.

Stock, J. and Watson, M. (1998). Diffusion indexes. Working Paper 6702.

Stock, J. and Watson, M. (1999). Forecasting inflation. *Journal of Monetary Economics*, 2(44).

Stock, J. and Watson, M. (2002a). Forecasting using principal components from a large number of predictors. *Journal of the American Statistical Association*, 97(460):1167–1179.

Stock, J. and Watson, M. (2002b). Macroeconomic forecasting using diffusion indexes. *Journal of Business & Economic Statistics*, pages 147–162.

Stock, J. and Watson, M. (2005). Implications of dynamic factor models for VAR analysis. Working Paper 11467.

Uhlig, H. (2005). What are the effects of monetary policy on output? Results from an agnostic identification procedure. *Journal of Monetary Economics*, 52(2):381–419.

Zivot, E. and Wang, J. (2006). *Modeling financial time series with S-PLUS*, volume 13. Springer Verlag.

A Data Description

Details of our dataset are as follows. 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. An asterisk (*) denotes the variable is originally available in quarterly frequency.

No.	Description	Tr.	S/F	Source	$\mathbf{j_1}$	$\hat{\tau}_1^*$
1	Industrial Production (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, Beverages And 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 (vis-a-vis World, Trade value, Mil. Euro)	5	1	Eurostat	0.67	20
20	Imports Total	5	1	Eurostat	0.67	19
21	Total Reserves Including Gold (Mil. Euro)	5	1	ECB	0.56	60
22	HICP All-Items (2005=100)	5	1	Eurostat	0.83	26
23	Overall Index Exc. Energy and Unp. Food	5	1	Eurostat	0.53	27

No.	Description	Tr.	S/F	Source	$\mathbf{j_1}$	$\hat{\tau}_1^*$
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, Durables Only	5	1	Eurostat	0.25	85
29	HICP-Non-Energy Ind. Goods, Non-Dur. Only	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 Intermediate, $/BBL)	5	0	WSJ	0.53	25
37	CRB Spot Index (1967=100)	5	0	CRB	0.34	49
38	ECB Commodity Price Index (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 Gov. Bond Yield	1	0	Datastream	0.83	43
43	10Y Gov. 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	Stock Price Index-Basic Materials	5	0	Datastream	0.44	56
51	Stock Price Index-Industrials	5	0	Datastream	0.71	54
52	Stock Price Index-Consumer Goods	5	0	Datastream	0.42	50

No.	Description	Tr.	S/F	Source	$\mathbf{j_1}$	$\hat{\tau}_1^*$
53	Stock Price Index-Health Care	5	0	Datastream	0.33	56
54	Stock Price Index-Consumer Services	5	0	Datastream	0.71	51
55	Stock Price Index-Telecommunication	5	0	Datastream	0.51	54
56	Stock Price Index-Financials	5	0	Datastream	0.52	51
57	Stock Price Index-Technology	5	0	Datastream	0.54	49
58	Stock 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 Maturity 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
68	Overnight Deposits	5	0	Eurostat	0.72	61
69	Repurchase Agreements	5	0	Eurostat	0.37	93
70	Credit to Total Residents Granted by MFI	5	0	Eurostat	0.49	71
71	Loans to General Government Granted by MFI	5	0	Eurostat	0.54	67
72	Loans to Other Residents Granted By MFI	5	0	Eurostat	0.50	120
73	Debt Securities of Euro Area Residents	5	0	Eurostat	0.66	20
74	Central Bank Claims on Banking Institutions	5	0	Eurostat	0.35	66
75	Economic Sentiment Indicator (%)	1	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 Indicator	1	0	Eurostat	0.70	75
80	Services Confidence Indicator	1	0	Eurostat	0.83	75
81	Employment Expec. for the Months Ahead	1	0	Eurostat	0.78	77

No.	Description	Tr.	S/F	Source	$\mathbf{j}_1$	$\hat{\tau}_1^*$
82	Production Expec. for the Months Ahead	1	0	Eurostat	0.82	77
83	Selling Price Expec. for the 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	Stock Price Index-USA (Dow 30, Points)	5	0	Reuters	0.86	99
99	Stock Price Index-UK (FTSE 100, Points)	5	0	Reuters	0.86	98
100	Stock Price Index-JP (Nikkei 225, Points)	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	Gross Domestic Product at Market Prices[b] *	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

No.	Description	Tr.	S/F	Source	$\mathbf{j}_1$	$\hat{\tau}_1^*$
111	Employees Total *	5	1	Eurostat	0.97	110
112	Self Employed Total *	5	1	Eurostat	0.45	110
113	Real Labour Productivity per Person Employed[c] *	5	1	ECB	0.91	107
114	Real Unit Labour Cost *	5	1	Eurostat	0.69	116
115	Earnings per Employee (Current, Euro) *	5	1	Oxford Economics	0.91	116
116	Wages and Salaries (Current, Bil. Euro) *	5	1	Oxford Economics	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	REFI (%)	1	0	Eurostat	0.90	39

[a] (2005=100), [b] (Chained, Mil. 2000 Euro), [c] (2000=100)