Heterogenous effects of the monetary policy in the euro area: a factor-augmented VAR (FAVAR) approach*

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March 21, 2019

Abstract

This paper presents a quantitative assessment of the heterogeneous effects that a common monetary policy shock exerts on different economies in a euro area (EA). To that end, a FAVAR model is used to trace out the effects of an increment of ECB's intervention rate on industrial production, unemployment and harmonised prices in seven countries of the EA. The results show that the effects of a contractionary monetary shock on the industry are homogenous across the selected countries, falling after the intervention - except for Greece. This is a result of the synchronisation of the industrial business cycle and common funding patterns in the sector. However, the unemployment responses are heterogeneous both in size and sign, suggesting that the lack of a common European regulatory framework for labour has prevented the integration of the labour markets in the EA, and a common framework would improve the synchronisation of the business cycles among the EA countries. Finally, the effects on prices are heterogeneous in size but not in sign, showing a more moderate response than on production terms and even neutral for some countries.

Keywords: Monetary policy, heterogeneity, FAVAR, Euro Area

JEL Codes: C38, E32, E52

*The author would like to thank without implicating Stefan Niemann, Luca Gambetti, Haroon Mumtaz and Marcus Chambers, for their very constructive comments, which will lead to a much-improved presentation.

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Introduction

The Great Financial Crisis highlighted the absence of synchronisation across countries in the Euro Area (EA). Some of them were hit particularly hard, such as Greece, Ireland or Portugal that were bailed-out to cope with the collapse of their economies; while others got into less severe turbulence, including Germany and France. The crisis revealed the existence of many Europes and the benefits of a currency area are questioned since then, giving rise to sceptical thoughts about the future of the EA and European Union (EU).

More specifically, the performance of the European Central Bank (ECB) and its conventional monetary policy was criticised for the poor results in most affected countries. A common monetary policy is justified on the grounds of the Optimal Currency Areas (OCA) theory, but it assumes common responses to changes in interest rates across its members. For instance, rising interest rates to offset an increase in the medium-term expected inflation of an OCA member may have adverse effects on other members with lower expectations. Here there is a dilemma concerning the intervention, and it creates a challenge for the OCA's monetary authority. This intervention creates heterogeneity, which depends on the level of synchronisation of business cycles and the integration of trade and labour markets in the context of the OCA theory. However, cross-country structural differences such as price and wage rigidities, or productivity may also create heterogeneities since they determine the performance of the monetary transmission mechanisms (MTM) in a country. These different MTMs would result in heterogeneous effects of a common monetary policy, and they have not been deeply identified.

This paper answers the question as to whether there are heterogeneous effects of monetary policy in the EA, and if so, what is the source of such heterogeneity. Therefore, an empirical exercise is carried out to extract facts for the eurozone, looking at the differences among the responses to a common monetary shock across a selected sample of countries in the EA. The hypothesis ex-ante is that there should be heterogeneities in the responses to monetary shocks among countries mainly produced by the lack of real integration in the currency area.

The contribution of this paper is twofold. First, this paper analyses the effects of a common monetary shock on the real side of the national labour markets. While the literature has indirectly found cross-country heterogeneities in the response of unemployment to a common monetary shock, it does not identify the source of such heterogeneity. This study addresses the issue of the heterogeneous responses of unemployment to a monetary shock and investigates the source of heterogeneity. Second, this paper conducts a cross-country study on macroeconomic and sectoral issues for the EA, focusing on the industrial production, and this is relevant to country surveillance and analyses of intra-euro area adjustment processes. Cross-country heterogeneities in the sectoral composition of the aggregate production play a crucial role in determining the effects of a common monetary policy. The empirical evidence suggests that sectoral specialisation matters, but it is important to address its effects on the effectiveness of monetary policy. This study also investigates the cross-country sectoral responses to a common monetary shock.

Unlike other authors, a factor-augmented vector autoregressive (FAVAR) model is estimated to test the hypothesis and analyse the different responses as in Bernanke et al. (2005). It is fitted on the industrial production indexes, unemployment and inflation rates among other macroeconomic variables; and then, an analysis of the country responses to a common monetary shock is carried out. This analysis requires a large number of macroeconomic variables to estimate the responses, which would be unfeasible in a vector autoregressive (VAR) model, and it is only feasible if one uses factors to reduce the dimensionality problem.

The remainder of this paper is organised as follows. Section 1 presents a literature review of selected papers related to this field, differentiating between the concepts of asymmetric and heterogeneous effects. Section 2 describes the econometric framework in which the empirical model is based, the FAVAR model, the estimation process and the dataset used in the estimation. The findings are discussed in section 3, considering the impulse response functions and a variance decomposition analysis. Section 4 concludes presenting the conclusions.

1 Literature Review

There is extensive literature about the different effects of monetary policy. The literature divides these differences into two categories that analyse the heterogeneity in two different dimensions. On the one hand, there is a brach studying the asymmetric effects of the monetary policy, namely sign/size heterogeneity within a country. It aims at analysing the different responses of the economy as a result of *a*) contrary monetary shocks, increments and reductions on the interest rates, and *b*) and nonlinearities, which consist of time variation and disproportionate responses.[1] On the other hand, there is another branch analysing the heterogeneous effects of the monetary policy or cross-country heterogeneity. This paper defines heterogeneity as the different responses of production, employment and prices to a common monetary policy shock across countries.

Cover (1992) presents an empirical analysis of asymmetric effects in output distinguishing positive and negative shocks, known as the traditional Keynesian asymmetry, of the money supply in the United States (US) between 1951 and 1987. The author, using a two-step procedure to estimate a system of two equations, confirms the existence of asymmetric effects and finds that adverse shocks have stronger and more persistent effects on output than positive shocks, which have neutral effects.[2] This empirical model is replicated in Karras (1996) in a panel of 18 countries in Europe using a panel data approach and finds results in line with Cover (1992). Meanwhile, Ravn and Sola (2004) expand the asymmetric effects from the sign side to the size and variance side. The authors used two different datasets with US data between 1948 and 1995 and they found that not only the sign matters but the size and variance counted for the effects. Matthes and Barnichon (2015) confirms their results by using an alternative framework.[3]

As a common conclusion, these papers point out the necessary precaution when doing monetary policy, as there are asymmetric effects on many different dimensions that are relevant and have not been considered by policymakers.

Analogously to the asymmetric effects branch, many researchers study cross-country heterogeneities of the monetary policy. Carlino and Defina (1998) use a structural VAR across US' states during the 1958-1992 period. The authors find heterogeneous responses in output to a FED's monetary policy shock. The paper also provides evidence on the reasons behind these cross-state differences, pointing to the share of manufacturing as one of the causes of this effect. Also, firm density has

[1] Note that while the Asymmetric Effects approach uses the money supply and the intervention rate as sources of the monetary policy shock, this paper only considers the ECB intervention rate.

[2] The first step estimates the model-supply and output processes and the second one tests for asymmetries including different shock specifications: no lagged, four lagged shocks, eight lagged shocks and expected money.

[3] The authors present a new methodology using Gaussian Mixture Approximations (GMA) to estimate nonlinear dynamic effects structural shocks.

no significant effects on the size of the response, but a higher concentration of small banks would decrease the state's sensitivity to monetary policy shocks. Thus, they find no evidence for a credit channel operating at the state level.

Altavilla (2002) presents one of the first attempts to test for this matter in the EA. Using a Structural Vector Autoregression (SVAR) model for ten countries in the European Monetary Union (EMU) between 1979 and 1998, the author confirms soft asymmetries among those countries and identifies two sources of heterogeneity: a) lack of integration in real and nominal terms and b) output structure - boosted by the degree of wage bargaining. Huchet (2003) obtained similar results, by using the procedure in Cover (1992), and extended them by testing for sign asymmetry responses across eight EMU countries over the period 1980-1998.

By contrast, Clausen and Hayo (2006) applied macro-econometric modelling techniques in a semi-structural system for Germany, France and Italy between 1979 and 1998. This technique allowed the authors to analyse both sides of the market and they found asymmetries in both the demand side of output and supply side of inflation and that the effect of monetary policy on the aggregate demand was almost zero. The authors found that monetary policy had similar effects on Germany and Italy but weaker effects in France. Caporale and Soliman (2009), in line with Altavilla (2002), applied a Vector Error Correction model (VECM) for the endogenous variables, and a stationary VAR in first differences for the exogenous variables findings that there were significant differences between EU countries in the monetary policy effects. They analysed six core countries[4] in the European Exchange Rate Mechanism (ERM) system between 1981 and 1998, and determined the differences in magnitude and duration of the effects across the selected countries.

More recently, Boivin et al. (2008) test for changes in the MTM of the big six EA countries as a consequence of the euro adoption in the 1988-2007 period. Using a FAVAR model, the authors find significant heterogeneity across countries in the effect of monetary shocks before the launch of the euro, but after the adoption of the euro, the MTMs across countries have become more homogeneous. The authors find empirical evidence that suggests that the responses of the GDP to a monetary policy shock are homogenous across the analysed countries, but the components of the demand are not. In this line, Ciccarelli et al. (2013) implement a panel VAR to test for heterogeneous MTMs in two blocks of countries in the EA between 2002

[4] Austria, Denmark, France, Germany, Netherlands and Italy.

and 2011. Unlike Boivin et al. (2008), the authors find significant and heterogeneous responses in terms of the GDP across countries, with similar patterns within the group of financially distressed countries. In line with previous studies, Mandler et al. (2016) used a Bayesian VAR (BVAR) for the four large euro-area countries (Germany, France, Spain and Italy), and they found strong cross-country differences in terms of output and prices between 1999 and 2014.

To sum up, the literature on heterogeneous effects focuses on the EA, as it is a unique process that allows researchers to test for the effects of a common monetary policy. While most of the papers are for the period pre-euro, few papers address the heterogeneity since the implementation of the euro. However, a common concern for the selected literature is the sample size issue and the implementation of large-scale models.

This paper tests for heterogeneous responses to a common monetary policy shock in the EA and seven country members in the period 2000-2013. The selected countries are Finland, France, Germany, Greece, Italy, Spain and Portugal. To that end, in line with Boivin et al. (2008), a FAVAR model is estimated. The results, in line with the literature, suggest the existence of heterogeneities but not in all the macroeconomic variables. While the literature focuses on GDP responses, I find that the responses of the industrial production are homogenous across the selected countries, which suggest there are no country-specific features at a sectoral level in the transmission mechanism of the monetary policy. However, the responses of the unemployment are significantly heterogeneous, which is consistent with the heterogeneous responses of the GDP that the literature finds, such as Boivin et al. (2008), Mandler et al. (2016) and Ciccarelli et al. (2013). Finally and confirming Boivin et al. (2008) findings, the responses are moderate heterogeneous in terms of the inflation and neutral at a 90% level in most of the countries.

2 The FAVAR framework, estimation and data

As mentioned, this paper uses FAVAR methodology to test for heterogeneous effects of a common monetary shock on a set of macroeconomic variables in different countries in the EA. This framework benefits from two characteristics.

On the one hand, it allows using large datasets that increase the amount of information and extend the comparative analysis across countries without arising dimensionality problems, such as in large VAR models. On the other hand, it mitigates the omitted-variable bias as a consequence of being based on factors and the principal component analysis. As Bernanke et al. (2005) and Boivin and Giannoni (2008) indicate, the computational simplicity of the two-stage methodology eases the treatment of the issues mentioned above and results in a very accurate tool to analyse the dynamic effects of monetary policy in a large set of macroeconomic variables.

Thus, the FAVAR model allows comparing the responses of industrial production, unemployment and prices to a common monetary policy shock measured from changes in the main refinancing rate.

2.1 The FAVAR framework

Bernanke et al. (2005) introduced the FAVAR model and it is based on a system of two simultaneous equations that describe a linear state-space model. However, the grounds of this specification comes from Stock and Watson (1998), who propose a dynamic framework that concentrates the information from a large set of variables on few *diffusion indexes* to improve the forecast accuracy of primary macroeconomic variables. Two equations define the original set-up of the FAVAR model:

$$X_t = \Lambda F_t + \epsilon_t \quad , \quad \epsilon_t \sim WN(0, \Sigma_\epsilon) \tag{1}$$

$$F_t = \sum_{h=1}^{p} \phi_h F_{t-h} + \upsilon_t \quad , \quad \upsilon_t \sim WN(0, \Sigma_\upsilon) \tag{2}$$

Equation (1) is known as the output equation and X_t is a $(N \times 1)$ vector and represents the total set of information, X, available at period t from where the factors are extracted, containing N macroeconomic variables; and F_t, a $(r \times 1)$ vector, denotes the factors and they supposed to represent opaque economic concepts, such as financial market conditions, credit conditions or climate of the economy for which there is no accurate data. The output matrix, denoted by Λ, is a $(N \times r)$ matrix and allows to decompose the effects of the factors on the set of macroeconomic variables.

Equation (2) is known as the state equation, where factors are assumed to follow a dynamic linear process, and more specifically a VAR process of finite order p, $VAR(p)$; and ϕ_h is a matrix $(r \times r)$ that represents the coefficients associated to the h-th lag. The terms ϵ_t and υ_t, a $(N \times 1)$ and $(r \times 1)$ vector respectively, are assumed to be white noise (WN) with contemporaneous covariance matrices denoted by Σ_ϵ and Σ_υ

respectively. One of the properties of the $VAR(p)$ is that can be rewritten as a $VAR(1)$ using its companion form.

Factor models are a specific kind of latent-variable model in statistics. However, the FAVAR framework divides the factors into two elements. On the one hand, there are k unobservable factors, which are underlying forces driving the system. On the other hand, there are m observable factors, which are known variable related to policy decisions. While Boivin and Giannoni (2008) chose the interest rate of intervention for the monetary policy, the specification of Bernanke et al. (2005) allows adding other relevant observable factors. Therefore, there are $r = k + m$ factors in the model. Separating the different factors the system equation (1) becomes:

$$X_t = \Lambda^f f_t + \Lambda^Y Y_t + \epsilon_t \tag{3}$$

where Λ^f is a $(N \times k)$ matrix that captures the effects of the unobservable factors, denoted by f_t, a $(k \times 1)$ vector; and Λ^Y is a $(N \times m)$ matrix that captures the effects of the observable factors, denoted by Y_t, a $(m \times 1)$ vector. Equations (1) and (3) imply that $F_t = [f_t', Y_t']'$ and $\Lambda = [\Lambda^f, \Lambda^Y]$.

Using the companion form, equation (2) by can be written as a $VAR(1)$:

$$Z_t = \Theta Z_{t-1} + \mathrm{v}_t \quad , \quad \mathrm{v}_t \sim WN(0, \Sigma_{\mathrm{v}}) \tag{4}$$

where $Z_t' = \left[F_t', F_{t-1}', \ldots, F_{t-p+1}'\right]$ is a $(r \cdot p \times 1)$ vector; $\mathrm{v}_t' = [v_t', 0_r, \ldots, 0_r]$ is a $(rp \times 1)$ vector, and 0_r denotes a vector with r zeros. The new coefficients and error term is given by:

$$\Theta = \begin{bmatrix} \phi_1 & \phi_2 & \ldots & \phi_{p-1} & \phi_p \\ I_r & 0 & \ldots & 0 & 0 \\ 0 & I_r & \ldots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \ldots & I_r & 0 \end{bmatrix} \quad \text{and} \quad \Sigma_{\mathrm{v}} = \begin{bmatrix} \Sigma_v & 0 \\ 0 & 0 \end{bmatrix}$$

where Θ is a $(r \cdot r \times r \cdot p)$ matrix and I_r is the identity matrix of order r. Note that the coefficients associated to equation (2) are located in the first r raws of Θ. Σ_{v} is a $(rp \times rp)$ matrix, which contains Σ_v in the first r raws and r columns.

The system of equations conformed by equations (3) and (4) implies the existence of an implicit joint dynamic within the macroeconomic variables and is assumed to follow an autoregressive process. Furthermore, such joint dynamics could describe the MTMs and therefore FAVAR methodology is more flexible than those used by other authors to capture the different levels and channels that exist within the MTMs.[5]

Note that other frameworks could be used to test the heterogeneity as described in section 1 (pp. 2). For example, the panel VAR used in Ciccarelli et al. (2013) allows distinguishing between two groups of countries while controlling with country fixed effects. However, this specification does not support the assumptions of cross-sectional independence, since the trade and not-very-integrated capital markets create correlations among countries. Also, a conventional VAR approach does not support 15 variables per country, since the number of parameters would drastically reduce the degrees of freedom and inference cannot be relied on.

2.2 Estimation

This paper uses a two-step principal components analysis (PCA) approach as proposed in Stock and Watson (1998) to estimate (3)-(4), but the model can be estimated using other methodologies. The authors also present a single-step Bayesian likelihood approach, and it emerges as a serious alternative to the two-step procedure, since it reduces the uncertainty from the principal components estimation of the factors.[6] Unlike other authors,[7] Bernanke et al. (2005) shows a comparison between both methods to estimate the dynamic effects of monetary policy and find that there are no major differences between the two techniques in terms of industrial production effects.[8] The single-step approach could be implemented by maximum likelihood via Kalman filter or subspace algorithms. However, single-step methods present the disadvantage of being more computationally demanding the two-step approach, and the improvement in accuracy may not be notable.

[5] There is an increasing literature using the FAVAR approach to analyse the MTMs, such as Boivin et al. (2008), Mumtaz and Surico (2009), Boivin et al. (2010), Dave et al. (2013) and Buch et al. (2014).

[6] Mumtaz and Surico (2009) implements a two-step approach with Bayesian methods.

[7] For example Uhlig and Ahmadi (2012) and Mumtaz and Surico (2009).

[8] The authors find significative changes in other variables, such as money aggregates or the consumer price index.

2.2.1 Two-step principal components approach

Following Stock and Watson (1998), the procedure is divided into two stages. Firstly, the variance space spanned by the factors is estimated based on PCA analysis. Second, equations (3) and (4) are estimated using ordinary least squares (OLS).

The first step starts with the extraction of k most important components of X_t using PCA to estimate the space spanned by the factors, denoted by $C = \text{span}(f_t, Y_t)$. To that end, PCA diagonalises the variance-covariance matrix of the information space[9], which extracts $r = k+m$ eigenvectors associated with the r largest eigenvalues and a transformation of the eigenvectors are the principal components or common trends of the macroeconomic variables contained in X, denoted as $\tilde{f} = PCA_r(X'X)$.[10] Stock and Watson (1998) prove the consistency of $\tilde{f}$, even when there is some time variation in Λ and small amounts of data contamination, as long as the number of variables is very large, $N \gg T$. Consistency also depends on the fact that number of principal components used is at least as large as the true number of factors, but Bai and Ng (2002) provides three information criteria that consistently estimate this parameter. Therefore, the space spanned by PCA, $\hat{C} = \text{span}(\tilde{f}_t)$, is a consistent estimation of C, but this estimation does not exploit the fact that Y_t is observed and the identification of the monetary shock by recursive methods would not be valid. Thus, obtaining the estimation of the unobservable factors, $\hat{f}_t$, involves determining the part of $\hat{C}$ that is not spanned by Y_t.

There are different strategies to solve this problem. Bernanke et al. (2005) proposes an strategy based on the classification of the macroeconomic variables contained in X into two types: slow moving variables, which are not contemporaneously correlated with the intervention rate that is contained in Y, and fast moving variables which are contemporaneously correlated with the intervention rate. It extracts k principal components from X, $\tilde{\tilde{f}}$, and extract principal components from the subset of slow-moving variables, $\tilde{f}^s$, and estimates the multiple regression $\tilde{\tilde{f}}_t = \beta_s \tilde{f}^s_t + \beta_R R_t + e_t$. $\hat{f}$ is then constructed as $\tilde{\tilde{f}} - \beta_R R$. Then the VAR in equation (4) can be estimated with $\hat{F}'_t = [\hat{f}_t, Y'_t]'$. Note that this strategy does not impose the constraint that the intervention rate is one of the principal components. However, this strategy relies

[9] The set of information is given by X and it does not contain Y.

[10] Stock and Watson (1998) show that PCA requires some assumptions to identify the factors. PCA identifies common rotations, $\widetilde{\Lambda f}$, and therefore it is assumed that $\tilde{\Lambda}'\tilde{\Lambda}/N = I_k$, with $\tilde{\Lambda}$ equal to the eigenvectors of $X'X$, what results in $\tilde{f} = X'\tilde{\Lambda}/N$.

on the assumption that slow moving variables are not contemporaneously correlated with the intervention rate, and that classification can be subjective.

By contrast, I follow the factor estimation suggested by Boivin and Giannoni (2008). It proposes a more direct more direct approach which consists of imposing the constraint that the intervention rate is one of the principal components. To that end, the authors use an iterative process that guarantees that the estimated factors recover dimensions of the common dynamics not captured by the intervention rate.[11] First, the first k principal components are extracted from X, $\tilde{f}^0$, and the authors estimate the multiple regression $X_t = \beta_f \tilde{f}_t^0 + \beta_R R_t + e_t$ to obtain $\hat{\beta}_R$. Second, $\tilde{X}^0$ is computed as $X - \hat{\beta}_R R$. Third, the new first k principal components are extracted from $\tilde{X}^0$, $\tilde{f}^1$. These three steps are iterated until achieving a convergence criterion.[12] The final iteration provides the estimated unobservable factors, $\hat{f}$, and the VAR in equation (4) can be estimated with $\hat{F}_t' = [\hat{f}_t, R_t']'$. Note that Boivin and Giannoni (2008) use the intervention rate as the only observable factor. However, this strategy can be generalised for multiple observable factors.

At this point, the importance of using relevant information must be emphasised as a crucial element to exploit the FAVAR approach. If one introduced many variables with similar joint behaviour, there would be a multiplicity within the information set and the space covered by the principal components would reward these variables with higher contributions to the principal components, while the remaining variables would receive lower contributions and the space spanned by the first k principal components will not cover those remaining variables. Furthermore, and as a consequence of using the variance-covariance matrix, if a group of variables has a relatively larger variance than the other, the scores could be biased. All the variables are standardised to avoid this problem, and the first k eigenvectors are selected.

As in Boivin and Giannoni (2008), the ECB refinancing rate is added, what implies that there are no observational errors in the monetary policy instrument. Thus, given the data $X_{i,t}$, with $i = 1, ..., N$, and $t = 1, ..., T$, the unobservable factors are estimated using the iterative strategy, enabling the estimation of transition matrix Λ.

[11] Using the Gram–Schmidt process could be an interesting strategy to estimate the unobservable factors. This process is a method for orthonommalising a set of vectors and it starts with an initial vector, which could be the intervention rate, followed by the computation of orthonormal vectors from the remaining vectors, which could be the principal components. However, the econometric properties need to be investigated.

[12] I use as convergence criterion that the maximum absolute difference between the first k principal components of two consecutive iterations is smaller that 10^{-6}, i.e., $\max\left(\max\left(\tilde{f}^{s-1} - \tilde{f}^{s}\right)\right) < 10^{-6}$.

The loading matrix is estimated by OLS, $\hat{\Lambda}_{OLS} = (\hat{F}'\hat{F})^{-1}\hat{F}'X$.

One of the inconveniences at this stage is the selection of the optimal number of factors because the degrees of freedom can change during the second step since the factors are used to estimate a VAR. Hannan and Quinn (1979) and Bai and Ng (2002) suggest a set of information criteria (IC) that is used in the FAVAR framework. Table A.2 reports the results for these criteria using up to eight factors.[13] Following Ahn and Horenstein (2013) IC, the model is specified with $k = 2$ unobservable factors. However, a model with $k = 5$ unobservable factors is used as a robustness check to the model fitted, in line with Bernanke et al. (2005).[14]

The second step consists in estimating a standard VAR model of order p with the fitted factors from previous step. The VAR model is estimated using the companion form as in equation (4) by OLS, $\hat{\Theta}_{OLS} = (Z'_{t-1}Z_{t-1})^{-1}Z'_{t-1}Z_t$. The coefficients of interest are located in the sub-matrix $\hat{\Theta}_{r\times(p\times r)}$. Here, an analogous question as in the previous step arises: what the optimal number of lags is. The IC are calculated for up to twelve lags, and they determine $p = 4$ lags.[15] The estimation process can be summarised as follows:

1. Estimation of the factors, $\hat{f}$, with the iterative method from $s = 1$ until $\max\left(\max\left(\tilde{f}^{s-1} - \tilde{f}^{s}\right)\right) < 10^{-6}$:
   (a) $\tilde{f}^0 = PCA_k(XX') \rightarrow X_t = \beta_f \tilde{f}^0_t + \beta_R R_t + e_t \rightarrow \hat{\beta}^R_{OLS}$;
   (b) $\tilde{X}^0 = X - \hat{\beta}^R_{OLS} R$;
   (c) $\tilde{f}^1 = PCA_k\left(\tilde{X}^0 \tilde{X}'^0\right)$.
2. Estimation of the system (3)-(4) given the factors:
   (a) Output eq.: $\hat{\Lambda}_{OLS} = (\hat{F}'\hat{F})^{-1}\hat{F}'X$, with $\hat{F}' = [\hat{f}', Y']$.
   (b) State eq.: $\hat{\Theta}_{OLS} = (Z'_{t-1}Z_{t-1})^{-1}Z'_{t-1}Z_t$, with $Z'_t = \left[F'_t, F'_{t-1}, \ldots, F'_{t-p+1}\right]$.

[13] Note that Bai and Ng (2002) (BNC) criteria, type 1, determines that the model requires the same number of factors than the eigenvalue criteria described in Ahn and Horenstein (2013).

[14] Appendix B shows this robustness check.

[15] Hannan-Quinn (HQC) criteria have proved to be the best behaved among the three most common IC: Akaike (AIC) and the Schwarz criteria (BIC). This is due to the specification penalty function which penalises additional lags with a negligible weight and therefore does not allow to observe the optimal number of lags. The AIC criteria asymptotically overestimates the order of a VAR, while BIC and HQC criteria are consistent estimators of the lag/factor order. Then, the use of HQC is justified.

2.2.2 Structural analysis

The structural analysis estimates the impulse response functions (IRFs) of the variables of interest to monetary policy shocks. To that end, an identification is made using the Cholesky decomposition of the variance-covariance matrix of the error term. IRFs are the result of combining the dynamic of the VAR model and the factor loadings, and more specifically:

$$IRF_{i,t} = \hat{\Lambda}_i'(\hat{\Theta}^t)_{1:r,1:rp}\hat{S} \tag{5}$$

where $\hat{S}$ denotes the Cholesky orthogonalisation of the fitted error term $\hat{\upsilon}_t$ in equation (4) under the assumption of no contemporaneous effects of the monetary policy.[16] Therefore, the order of the factors is important and the intervention rate is located in the last place.

However, the structural analysis implies the presence of generated regressors and bootstrapping is required to get accurate confidence intervals. The confidence intervals are á la Gonçalves and Perron (2014), which implements factor estimations in the bootstrap repetitions. Note that the bootstrap is extended, as in Bernanke et al. (2005), by accounting for the uncertainty in the factor estimation due to a small sample and a bias-corrected bootstrap is used as proposed by Kilian (1998).

2.3 The data

The data used in the analysis has a monthly frequency for the period Jan. 2000 - May 2013. A large data set is compiled with 177 variables from different sources - Eurostat, OECD and World Bank. It includes data from the EA, Germany, France, Finland, Spain, Italy, Portugal and Greece, as the group of countries in which it is expected to find heterogeneous effects.[17]

In terms of the variables, two types of variables can be distinguished. On the one hand, we have country-level variables, representing the real economy and national

[16] Notice that the subindex $(1 : r, 1 : rp)$ of $\hat{\Theta}^t$ in equation (5) denotes the first r raws from the resulting matrix.

[17] Initially, Ireland, Belgium and the Netherlands were considered. However, they were left out because of a trade-off between the number of common variables and the length of the sample. The number of common variables at a national level is vast, but the starting period significantly differs across countries. Therefore, the inclusion of these countries would reduce the already short sample. However, this omission has a relatively small impact in the currency area, in terms of the GDP or the possible slipover effects and interactions within financial markets or trade.

financial markets. On the other hand, the same variables for the whole euro-area are included and extended with EA monetary and financial variables, such us money aggregates or balance sheet items of the banking system. Appendix B shows a detailed list of the different variables used in the estimation and the transformations - to induce stationarity. In particular, two transformations are made: first log-differences and first differences. Variables that have a first order of integration, $I(1)$, use first log-differences transformation is used into, such as the Industrial Production Index (IPI). Indicators and variables that admit a moving average representation, $I(0)$, use first differences transformation, such as the Consumer Confidence Index. All series are corrected of the seasonal effects, if necessary, using TRAMO-SEATS software.[18]

From a wide range of variables, there are three relevant variables for this analysis: IPI, unemployment and the Harmonised Index of Consumer Prices; (HICP) and the ECB interest rate is used as the monetary policy tool. The rest of variables are classified in: a) money and financial variables such as money, credit aggregates or interest rates; b) real activity variables, such as electricity consumption or car registration; and c) opinion polls and surveys, such as the industrial climate or consumer confidence indicator.

3 Empirical results

This section presents the main results obtained from estimating a FAVAR model with 4 factors, 2 unobservable and 1 observable, and 3 lags according to the respective information criteria. The IRFs show the signs and persistence of the effect of an increment of 1% in the intervention rate on the set of macroeconomic variables.

3.1 Cross-country heterogeneous responses

Responses of the Industrial Production

Figure 1a (pp. 15) shows the IRFs of the IPI to a monetary shock. The first conclusion that one can extract is that there are no substantial differences in response to a monetary sock, suggesting that there are homogenous responses in the industry

[18] TRAMO stands for *Time series Regression with ARIMA noise, Missing values and Outliers*; and SEATS stands for *Signal Extraction in ARIMA Time Series*. See Maravall et al. (1996) for more details.

to the common monetary shock. This result is in line with the findings of Boivin et al. (2008). Furthermore, a little overreaction in such responses arises during the second year, being more evident in the case of Germany, France, Spain and Italy, as we can see in figure 1b (pp. 15).

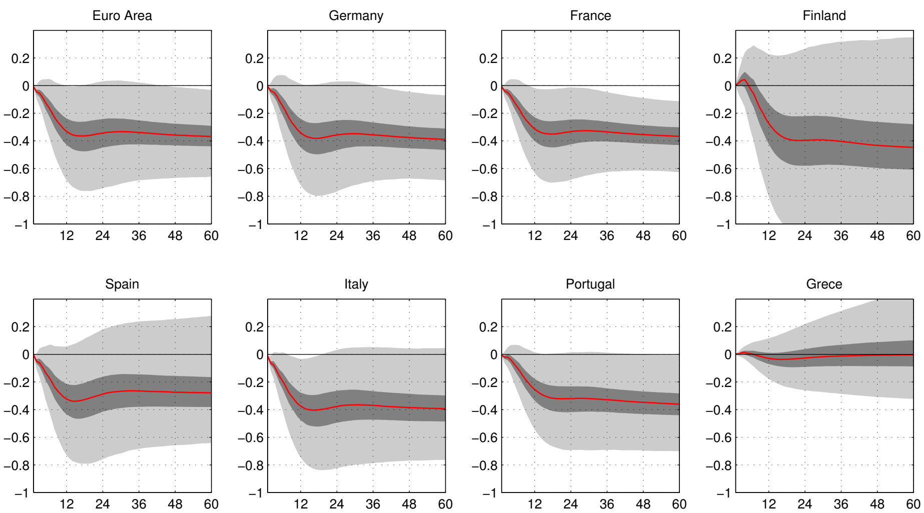
In almost all economies, the dynamic effects of a monetary shock are permanent, showing a significant and non-transitory reduction of industrial production after an interest-rate hike, except for the Greek case. However, two big groups can be identified in terms of their long-term performance.

On the one hand, Germany, France and Italy exhibit a similar performance in terms of industrial production. These countries suffer a reduction in industrial production close to 0.4% and lead the EA in the same direction as a consequence of their weight in the area. On the other hand, Spain and Portugal suffer a smaller reduction close to 0.3%, attenuating the EA performance from the German, French and Italian contributions. In particular, Spain is less volatile than its neighbours and the contractionary monetary shock results in a reduction of 0.3%. This small difference may be as a consequence of the short time horizon of the data in which close to 40% of the sample is under the financial and sovereign debt crises.

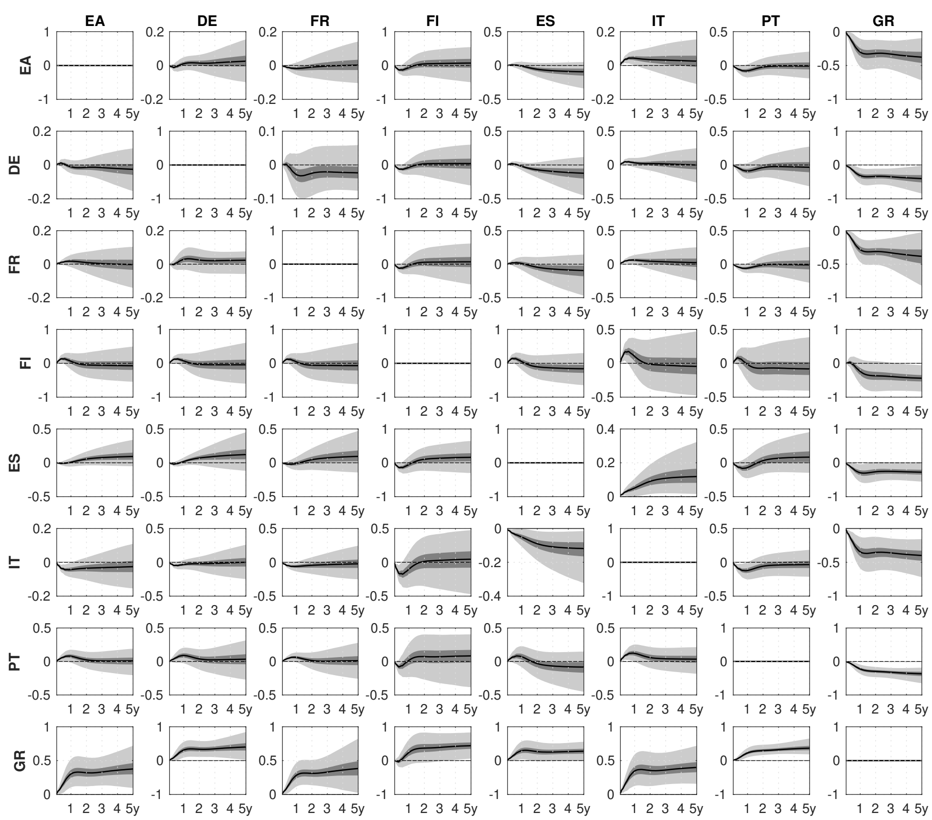
Finland is the only country that shows a very volatile behaviour. However, and based on the confidence bands, the degree of uncertainty is the greatest among all the selected countries, so this result is probably not significant.[19] By contrast, Greece shows neutral effects in its response to the monetary shock and, as in the case of Spain, this could be as a consequence of the weight of the crisis in the observations. This fact would explain the slow recuperation of the country since public-debt woes forced Greece to seek a bail-out from the eurozone and the International Monetary Found In 2009.

From a more abstract point of view, these results suggest that business cycles across EA countries have synchronised except for the Greek one, which has the most different response with respect to its neighbours. This result is against the initial hypothesis of this paper, but the use of the IPI as an indicator of the real activity of the whole economy is limited, and any extrapolated conclusion to the GDP must be carried out with precaution. Indeed, the empirical evidence suggests that the

[19] As it can be seen in the in table 1 (pp. 28), the variance decomposition shows an R^2 related to the Finnish industrial production is close to 15%, the third lowest value, but still not too far from the big countries.



(a) EA (selected countries): IRF of the IPI to an increment of 1% in the interest rates.



(b) EA (selected countries): Test for difference between pairs of IPI-IRFs.

Figure 1: Structural Analysis of the Industrial Production Index

The red line shows the median IRF calculated with 10000-iteration bootstrap with 68% and 95% confidence intervals denoted by dark grey and grey, respectively.

industrial sector is homogeneous across EA countries and any heterogeneity in output responses should be explained by the different sectoral composition of the aggregate production.[20] For example, Germany has an industrial sectoral specialisation, and it is very different from the Greek one, based on retail trade.

The economic intuition behind these results suggests that the industry has specific funding features that do not depend on country-specific characteristics. We find that the industrial sector in the selected countries, except for Greece, have homogenous responses to the common monetary policy shock and this should be as a consequence of similar industry funding patterns across them. Following Siedschlag et al. (2015), the fact that the industry is a more capital intensive sector would imply a higher dependency on external funding provided by the banking system than some other sources.[21] Therefore, any heterogeneity in the response of a country's industry to a monetary policy shock would be as a result of a miss-alignment of the national banking system with the rest of domestic banking systems.

In this regard, Carlino and Defina (1998) find heterogeneities among the responses across states in the US and explain that industry mix is one of the elements which can explain the cross-state heterogeneity. Two reasons can explain this fact. First, the authors use a regional approach, and the asymmetries in the industry are stronger at a regional level than at a country level. The EA does not behave as a federal state, as the industrialisation process took place before the establishment of the EA and the regional forces allocating the different sectors took place within the countries instead of across countries. Second, their approach uses the sectoral weights to identify the source of heterogeneity, while in this case the industry responses are used to test for heterogeneity. However, the empirical evidence suggests that industry plays a significant role in the transmission of the monetary policy shocks to the real economy in both cases.[22]

Responses of Unemployment

[20] Such as, Altavilla (2002) and Caporale and Soliman (2009), which find strong size heterogeneities; while Mandler et al. (2016) and Clausen and Hayo (2006) find soft size heterogeneities.

[21] Note that the authors find by fitting an empirical model to EA microdata that different external funding sources are relevant or used by enterprises, controlling by sector and other enterprise characteristics.

[22] Farès and Srour (2001) finds that manufactures has a stronger response than any other sector to a monetary shock and this result is supported by Carlino and Defina (1998), which describes how manufactures play a crucial role while explanting the cross-state heterogeneity in transmitting the monetary policy shock, more than the average company size or even number of banks.

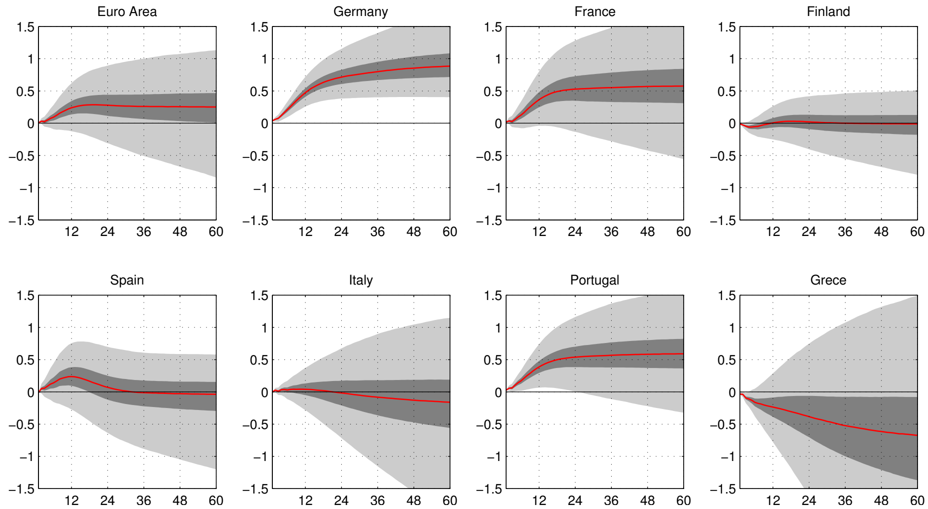
Unlike the industrial production, the responses of the unemployment rate to a common monetary shock are heterogeneous across EA countries, as figure 2a (pp. 18) shows. The unemployment rate increases in a fraction of the countries, while it decreases in the other. The two big groups in terms of the industrial production IRFs do not show a joint performance in terms of the unemployment, as we can see in figure 2b (pp. 18).

On the one hand, the unemployment rate shows similar performance in Germany, France and Portugal. These countries undergo a permanent increment above 0.5% in unemployment after the contractionary shock. In particular, the response of Germany is the largest among those countries, while France and Portugal show a more moderate but not insignificant increment. The EA exhibits a similar performance but less intense than those countries, due to the considerable weight of Germany and France in the currency area.

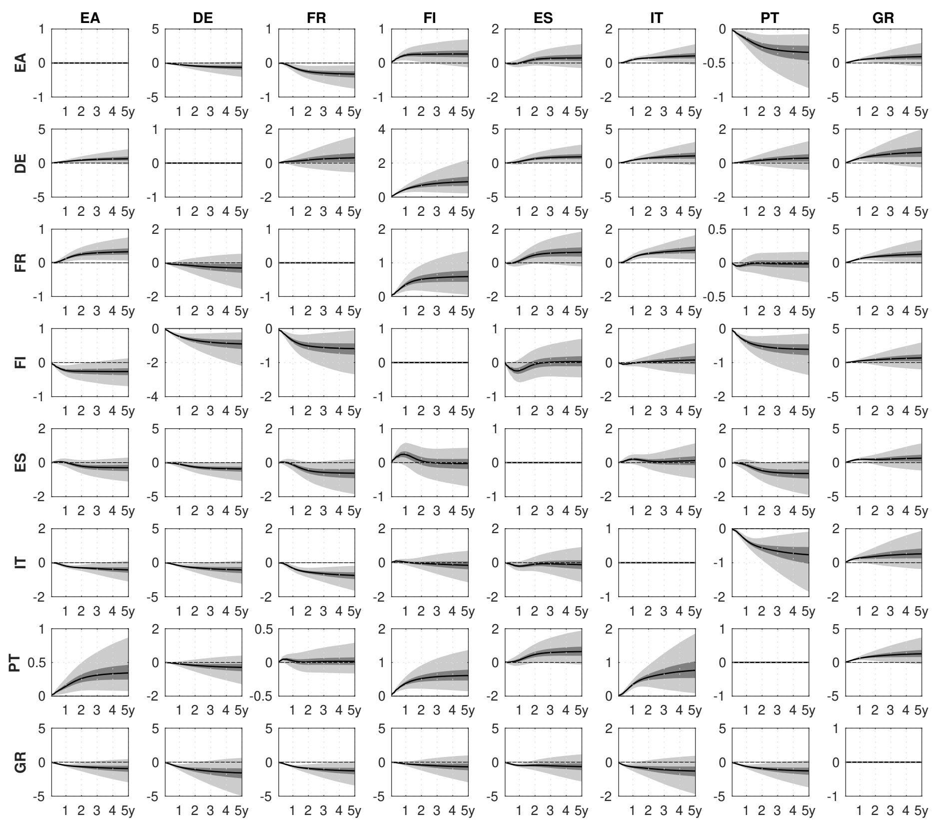
On the other hand, Spain, Italy and Finland do show non-permanent effects in the long-term. The unemployment rate increases during the first year and afterwards declines to zero. Italy and Finland responses are not statistically significant, indicating the neutrality of the policy. In the case of Italy, the In the case of Finland, there is a mirror effect to the case of Italy: a slight initial reduction in the number of unemployed and a subsequent sine-convergence to zero. By contrast in Greece, the unemployment rate exhibits a significant and persistent reduction as a consequence of a contractionary monetary shock.

Italy, Finland and Greece are clear examples opposite to what the economic theory dictates: neutrality or increment of the unemployment after a contractionary shock. However, again the explanation may be in the weight of the crisis in the dataset since Greece experienced significant difficulties during this period. However, Greece is the country that has the highest uncertainty, provided by its confidence interval, and therefore one should be sceptical with this specific result. Hence, the data suggest that Spain, Italy and Finland do not significantly respond to monetary policy shocks, and that is why the financial crisis had profound consequences in these countries, and the low-interest environment seemed to be sterile.

Summing up, heterogeneous effects are found in terms of unemployment responses, which is the mirror image of employment. This finding added to the homogeneity on production, suggesting that labour productivity plays a vital role in the adjustment of the real economy to monetary shocks. The EA has a high heterogeneity in the



(a) EA (selected countries): IRF of Unemployment to an increment of 1% in the interest rates.



(b) EA (selected countries): Test for difference between pairs of Unemployment IRFs.

Figure 2: Structural Analysis of Unemployment

The red line shows the median IRF calculated with 10000-iteration bootstrap with 68% and 95% confidence intervals denoted by dark grey and grey, respectively.

sectorial structures across countries and regions, and therefore, countries with a higher or lower degree of industrial specialisation will have heterogeneous effects, mainly due to different processes of sectoral adjustment. Thus, the relative importance of the sector in each country influences the analysis of the industrial production as an indicator to analyse heterogeneities, and this fact must be considered when drawing conclusions from that variable.

Another source of labour asymmetries can be found in the lack of a common regulatory framework for labour markets in the EA. Thus, countries with more flexible labour markets would adjust further to a shock, while on the contrary countries with labour rigidities would show less-dynamic behaviours in the labour market. At this point, the quantity- vs price-adjustment debate gains importance, since the quantity strategy dominates the response against wage adjustment in some countries, and suggests wage rigidities in others. According to these results, the empirical evidence suggests that Spain, Italy and Finland have some rigidities in the adjustment via quantities, while Germany and France are more dynamic. However, the lack of monthly wages series or labour costs does not allow this to deepen in this field.

Thus, and according to the results, Germany, followed by France and Portugal are the most dynamic economies in terms of their labour markets in response to monetary shocks, since they show a clear and steady path in their responses. By contrast, Spain, Italy and Finland are not affected by monetary shocks in terms of unemployment. Then, the implementation of a common regulatory framework, in this case, would facilitate the transition to a unique European Business Cycle.

Responses of Prices

Figure 3a (pp. 21) shows the IRF of the harmonised prices to a contractionary monetary policy shock. In all the economies a temporary "price puzzle" appears, which vanishes after approximately one year. The puzzle was more significative in previous estimations, but it has reduced with the introduction of international commodity prices. Boivin et al. (2008) explains that it could be due to the real exchange rate depreciation. According to figure 3b (pp. 21), small heterogeneity is found in response to the monetary shock with the exemption of Finland. After the first year and the price puzzle effect, countries perform a permanent reduction in the level of prices, consistent with the medium-term target of the ECB. However, this reduction is not very significant.

EA countries experience a decline in the price level following a contractionary policy impulse, but it is weaker than in the case of the IPI. Unlike the rest of the countries, Finland experiences a more drastic and significant reduction in the price level, which may indicate greater price flexibility.

Two prominent groups can be distinguished for the HICP responses, as we can see in figure (3b). On the one hand, a big group formed by France, Spain, Portugal and Greece, which exhibits a non-significant change in prices in the long-run and they undergo a reduction by about 2% in average. On the other hand, Germany and Italy remain at a lower level than the original one before the shock and the responses are somewhat more significant than the first group. These two countries undergo a reduction by about 2.5% and 1% respectively.

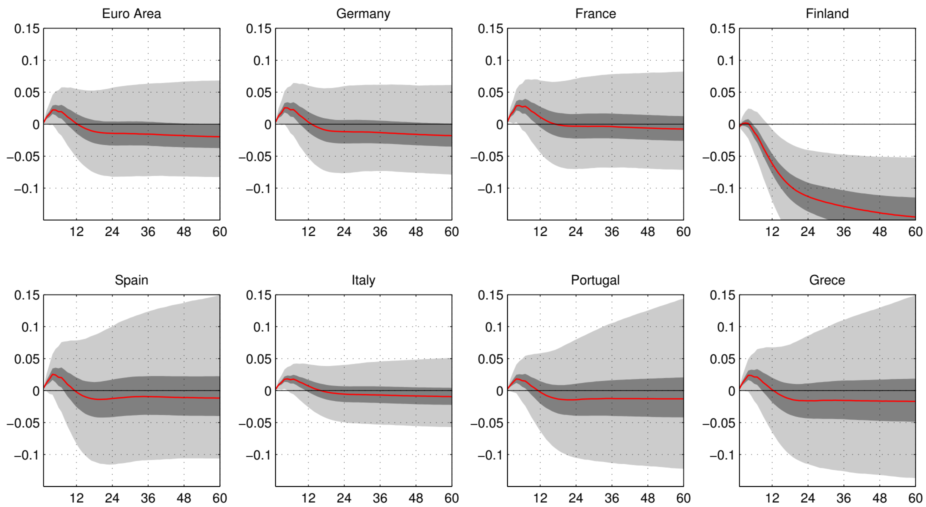
Although the price puzzle implies a problem from a theoretical point of view, it is a common result in the literature.[23] However, it allows us to do a quick analysis of the found differences in terms of the speed of the adjustment of prices. In this case, France and Italy present a slower adjustment, in the long run, needing between three and four months more than the rest of the countries to achieve the initial price level. This performance implies that French and Italian consumer prices are stickier than in the rest of the countries, leading to a slower adjustment process. By contrast, Spain and Portugal show a greater ability to adjust prices, resulting in less than two months than in the EA. Therefore, heterogeneities in terms of the speed of the adjustment are found, result in line with Altavilla (2002) findings.

However, the found price heterogeneities are still weaker than those obtained in the industrial production, and in this regard, it may be inferred that the ECB performs well in its price stability target, attempting to homogenise the impact of its interventions across EA countries. However, this result must be complemented by the variance decomposition analysis.

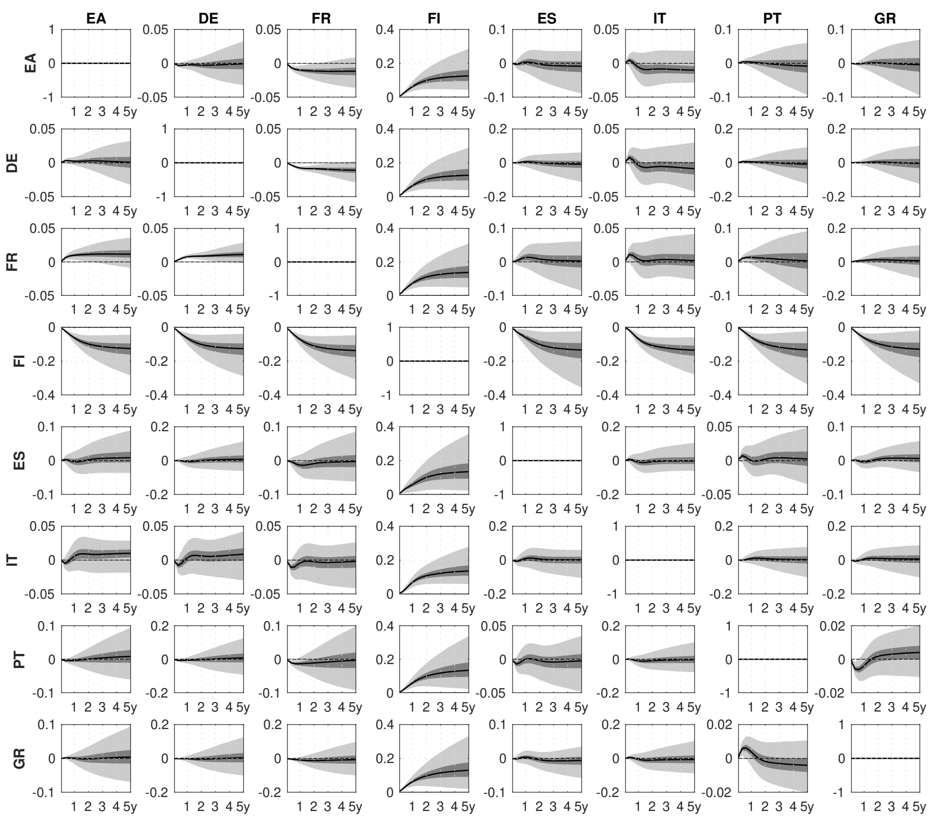
3.2 Variance Decomposition Analysis

Another exercise typically practised in the VAR framework is variance decomposition analysis. This exercise determines the fraction of the forecasting error of a variable, at a given horizon, that is attributable to a particular shock. Table 1 (pp. 28), reports the results for the macroeconomic variables of interest, and among them,

[23] For example, Boivin and Giannoni (2008), Boivin et al. (2008) and Boivin et al. (2010)



(a) EA (selected countries): HICP-IRF to an increment of 1% in the interest rates.



(b) EA (selected countries): Test for difference between pairs of HICP-IRFs.

Figure 3: Structural Analysis of the Harmonized Index of Consumer Prices (HICP)

The red line shows the median IRF calculated with 10000-iteration bootstrap with 68% and 95% confidence intervals denoted by dark grey and grey, respectively.

those analysed in the previous section.

The first column shows the contribution of the monetary policy shock to the variance of the forecast of such variables, at the sixty-month horizon (5 years). The second column contains the R^2 for each of these variables, and it helps us to assess the results provided by IRFs. However, the bottom line of this analysis is that the results in this exercise are less significant than those obtained in Bernanke et al. (2004), but still, brief reflection can be considered.

If one looks at industrial production results, it is noticeable that the contribution of the monetary shock is between 7.4% and 24.5%, and this is a significant value across countries. The average is 14.2%, while in terms of the EA increases to 18.94%. In particular, monetary shock significantly contributes to Germany, France, Italy and Portugal. However, it shows a lower contribution in Finland, Spain and Greece. This result can be read as if monetary policy stimulus affects big countries' production while it does not exert a significant influence in the rest. After Spain and Greece were affected by the crisis, the monetary policy implemented by the ECB was not as effective as expected.

In terms of the R^2, the results across countries are similar, except for Spain that has a higher explanation of the variance. The percentage explained is close to the 17% on average, reaching a 34% for the whole EA. The Spanish result is particularly interesting since it confirms the conclusion drawn in the previous paragraph.

Moving to analyse the results of the unemployment rates, the average significance is better than the one obtained in terms of the industrial production but worse than the one in terms of prices. In terms of unemployment, the contribution of the policy shock is between 0.1% and 48.0%, and this fact reflects the presence of high heterogeneity across labour markets again. The sample average is 9.8%, while in terms of Eurozone it falls to 2.3%. Germany gets special attention, as monetary shocks have a more significant contribution to the variability of unemployment, and specifically 48.2%. However, for the rest of countries small but essential contributions are found. Italy and Portugal show the lowest significance, while the rest of the countries obtain an R^2 above 16%.

Thus, the heterogeneities observed through the IRF appear to be consistent, even if the signs of the responses were not clear. Therefore, the ECB should not consider the labour market when it is implementing monetary policy since the effects on that market would be small and heterogeneous. The idea of a common regulatory framework must be emphasised, as it would allow the implementation of specific monetary policies to stimulate this market.

Finally, the analysis of prices shows a higher significance than the one found in production and employment, but it explains a lower fraction of variance. The contribution of the policy shock is between 0.15% and 0.85%, except for Finland that obtains 32%. The sample average is 4.4%, while in terms of Eurozone it falls to 0.85%.

This result can be explained for two reasons. Firstly, once again the weight of the years of crisis in the dataset is very high. During these years, the balance sheet of the ECB has tripled, interest rates have drastically fallen, while the inflation has remained close to 1.5%. Thus, and contrary to the predictions like the Quantity Theory of Money, the model cannot reproduce the expected inflation - maybe as a consequence of lack of correlations.

Secondly, the principal unobserved factor explains the most substantial fraction of price variance. The FAVAR specification, under a scheme of non-contemporary effects, could be identified with the one which captures the dynamics of interbank and money markets, i.e., the first level of the credit channel of MTM.

4 Conclusions

This paper shows that a common monetary policy does not necessarily have homogeneous effects in different fundamental macroeconomic variables across EA member countries and the degree of heterogeneity depends on the intrinsic characteristics of each of the economies.

In terms of industrial production, homogeneous responses are found. This homogeneity may be explained by the funding patterns that the industry exhibits, depending on external funding from the banking system. However, the use of the IPI as a proxy of the economic activity may not be optimal as a consequence of the different sectoral composition across EA countries. This variable omits a part of the aggregate-production behaviour, which is affected by different sectoral productivities and different relative sectoral weights. Therefore, the heterogeneity on GDP responses identified by the literature could be stronger than those obtained in this paper.

For the case of the labour market, clear heterogeneities across EA countries emerge as a response of a monetary shock. This result may be mainly due to different productivities and a lack of a common regulatory framework in the EA labour market. The existence of a common regulatory labour framework would allow more effective implementation of the monetary policy in terms of unemployment and would improve the synchronisation of business cycles in Europe, resulting in a single European Economic Cycle. The empirical evidence suggests that there are two widely divergent zones within Europe in terms of the nominal-wage rigidities.

The effects on prices are relatively homogeneous in the long run, fact explained by the membership of a common currency area, which facilitates adjustments via prices. However, in the short and medium-run slight heterogeneities appear in terms of the speed of the adjustment across countries.

Some brief reflections on the assumptions behind the methodology should be highlighted. The specification chosen for this exercise, the methodology FAVAR, could be extended. Its current specification with common cross-country factors assumes that the same underlying forces drive all countries. One way to improve the specification of this model would be by determining a common underlying factor to all countries, which would be extracted from the European financial system and money markets, and country-specific underlying factors in each country. However, its implementation would be more complicated.

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Table 1: Variance Decomposition Analysis

	Var. decomp.	R^2
IPI Eurozone	0.1894	0.3398
IPI Germany	0.1917	0.2128
IPI France	0.2453	0.1899
IPI Finland	0.0673	0.1519
IPI Spain	0.0735	0.2149
IPI Italy	0.1752	0.1957
IPI Portugal	0.1924	0.0406
IPI Greece	0.0010	0.0061
Unemployment Eurozone	0.0227	0.3475
Unemployment Germany	0.4802	0.1629
Unemployment France	0.0771	0.2686
Unemployment Finland	0.0010	0.2407
Unemployment Spain	0.0058	0.2313
Unemployment Italy	0.0026	0.0561
Unemployment Portugal	0.1191	0.0681
Unemployment Greece	0.0180	0.1532
HICP Eurozone	0.0085	0.4765
HICP Germany	0.0076	0.3249
HICP France	0.0040	0.4125
HICP Finland	0.3213	0.2508
HICP Spain	0.0015	0.3505
HICP Italy	0.0059	0.1398
HICP Portugal	0.0020	0.1520
HICP Greece	0.0029	0.1878
Share prices Eurozone	0.0120	0.5507
Crude Oil Price	0.1357	0.3791
M1	0.0102	0.1195
M2	0.0101	0.1655
M3	0.0101	0.2030
Loans ECB	0.0024	0.3045
Overnight deposits	0.0398	0.1344
Exchange rate Pound	0.1403	0.0801
Exchange rate Dollar	0.0316	0.1093
Eonia	0.0146	0.5003
Long term interest rate Eurozone	0.0295	0.3920
Public debt yield 3 years Eurozone	0.0300	0.2980
Euribor 1 year	0.0090	0.5209
Euribor 3 month	0.0108	0.5234
Main refinancing operations Interest Rate	0.1176	1.0000

Table 2: Information criteria for FAVAR(k,p)

Factor IC	***k= 1***	***k= 2***	***k= 3***	***k= 4***	***k= 5***	***k= 6***	***k= 7***	***k= 8***	***k= 9***	***k= 10***
AIC 1	0.926	0.890	0.867	0.842	0.819	0.797	0.776	0.759	0.745	0.730
AIC 2	0.925	0.887	0.864	0.838	0.814	0.791	0.770	0.752	0.738	0.723
AIC 3	0.947	0.919	0.905	0.887	0.870	0.855	0.839	0.828	0.819	0.810
BIC 1	0.961	0.940	0.932	0.920	0.909	0.899	0.888	0.882	0.878	0.873
BIC 2	0.958	0.934	0.925	0.911	0.899	0.888	0.876	0.869	0.864	0.858
BIC 3	1.125	1.173	1.232	1.280	1.326	1.367	1.405	1.445	1.486	1.522
BNC 1	0.004	0.004*	0.018	0.029	0.041	0.054	0.068	0.086	0.107	0.128
BNC 2	0.019	0.027	0.049	0.067	0.088	0.108	0.130	0.155	0.185	0.213
BNC 3	-0.038	-0.060	-0.066	-0.077	-0.086	-0.094	-0.102	-0.105	-0.105	-0.105
EVC[A]	2.293	2.654*	1.233	1.102	1.058	1.064	1.174	1.208	1.134	1.063
GEVC[A]	1.014	1.102*	1.022	1.008	1.001	1.003	1.008	1.008	1.013	1.001
Lags AIC										
p=1	-5.695	-7.270	-7.678	-7.784	-8.294	-8.834	-9.163	-9.393	-9.401	-9.485
p=2	-5.857	-7.347	-7.664	-7.737	-8.143	-8.582	-7.296	-7.385	-7.035	-6.649
p=3	-5.760	-7.127	-7.530	-7.236	-7.271	-6.908	-7.748	-8.028	-7.931	-7.578
p=4	-5.860	-7.092	-7.041	-6.569	-6.733	-6.227	-5.713	-6.182	-5.316	-6.071
p=5	-5.872	-7.251	-7.434	-7.300	-7.313	-7.408	-6.953	-6.591	-2.847	-3.291
p=6	-5.844	-7.158	-7.217	-7.013	-6.878	-6.719	-5.869	-2.808	-1.294	0.343
p=7	-5.768	-7.041	-7.048	-6.773	-6.562	-6.210	-5.445	-4.603	-1.786	2.291
p=8	-5.717	-6.983	-6.903	-6.504	-6.033	-5.570	-5.014	-4.079	-2.224	1.168
p=9	-5.669	-6.906	-6.678	-6.272	-5.801	-5.250	-4.537	-3.236	-1.908	0.627
p=10	-5.599	-6.764	-6.442	-5.891	-5.326	-4.716	-3.645	-2.204	-0.672	5.075
p=11	-5.494	-6.816	-6.870	-6.523	-6.477	-6.361	-5.933	-5.306	-4.355	-3.379
p=12	-5.454	-6.439	-6.049	-5.213	-4.510	-3.636	-0.837	0.790	3.058	5.564
Lags BIC										
p=1	-5.155	-5.765	-5.108	-3.451	-1.821	0.511	1.942	4.235	7.209	10.741
p=2	-5.052	-5.275	-3.811	-1.523	0.534	3.665	7.206	10.168	14.870	18.354
p=3	-4.863	-4.980	-3.397	-0.992	1.770	4.956	9.195	13.847	22.385	27.239
p=4	-4.633	-4.433	-2.372	0.557	4.022	8.117	13.509	21.718	28.985	36.980
p=5	-4.355	-3.862	-1.396	2.059	6.155	11.100	17.163	24.011	33.539	45.034
p=6	-4.102	-3.350	-0.443	3.589	8.501	14.212	20.824	28.622	38.147	50.017
p=7	-3.852	-2.819	0.589	5.083	10.550	17.005	24.530	33.553	43.510	55.582
p=8	-3.581	-2.222	1.632	6.725	12.842	20.011	28.652	38.672	49.792	66.137
p=9	-5.665	-7.200	-7.554	-7.591	-8.016	-8.454	-8.668	-8.766	-8.628	-8.549
p=10	-5.795	-7.208	-7.416	-7.350	-7.586	-7.823	-6.305	-6.131	-5.487	-4.776
p=11	-5.667	-6.918	-7.159	-6.655	-6.436	-5.770	-6.262	-6.148	-5.609	-4.769
p=12	-5.736	-6.813	-6.546	-5.795	-5.618	-4.710	-3.732	-3.675	-2.221	-2.326
Lags HQC										
p=1	-5.72	-6.90	-6.81	-6.33	-5.92	-5.51	-4.48	-3.46	1.02	1.39
p=2	-5.66	-6.74	-6.47	-5.85	-5.21	-4.44	-2.90	0.95	3.35	5.96
p=3	-5.55	-6.55	-6.18	-5.42	-4.61	-3.56	-1.98	-0.21	3.63	8.84
p=4	-5.47	-6.43	-5.91	-4.96	-3.80	-2.54	-1.05	0.94	3.97	8.66
p=5	-5.39	-6.28	-5.56	-4.53	-3.29	-1.84	-0.08	2.41	5.06	9.05
p=6	-5.29	-6.07	-5.20	-3.96	-2.54	-0.92	1.31	4.06	7.07	14.44
p=7	-26.30	-47.71	-67.80	-87.49	-107.22	-127.18	-146.05	-164.85	-183.23	-201.26
p=8	-26.23	-47.55	-67.49	-86.94	-106.35	-126.09	-144.85	-163.34	-181.26	-198.97
p=9	-26.15	-47.44	-67.28	-86.57	-105.84	-125.41	-143.86	-161.98	-179.81	-197.29
p=10	-26.04	-47.22	-67.01	-86.08	-105.15	-124.60	-142.69	-160.46	-177.89	-195.12
p=11	-25.95	-47.02	-66.66	-85.61	-104.49	-123.67	-141.43	-159.00	-176.21	-193.11
p=12	-25.87	-46.84	-66.37	-85.28	-103.98	-122.96	-140.61	-157.70	-174.87	-192.67

[A] *This information criterion estimates the number of factors according to the maximum value.*