Essays in Applied Monetary and Financial Economics

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To my parents and sisters without whom my dreams would have not come true.
To my love who has believed in me.
To Stefan Niemann without his support and help I would not have been completed this book.
To Luis Puch without whom I would not have started my journey.
To caffeine and sugar, my companions through many long nights of writing.

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this thesis are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements. This dissertation contains fewer than 30,000 words excluding appendices and bibliography, and has 16 figures and 10 tables.

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Abstract

This thesis presents three applied researches on monetary and financial economics. Using new advances in multivariate time-series models, I investigate in the effects of monetary policy in a) the real economy and b) the credit channel of monetary policy transmission. However, this methodology, in particular the factor augmented vector autoregression, is very flexible. It can be used to analyse dynamic systems, allowing researchers to analyze micro-markets and extract conclusions about their agents. This thesis presents (i) a quantitative assessment of the heterogeneous effects of the monetary policy across countries in a currency area, (ii) evidence of the time variation of the credit channel and (iii) the effects of the interactions among banks in a payment system on funding patterns.

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Introduction

Applied Research to social science has increased exponentially in the last decades as a consequence of the consolidation of information technologies (IT). In the field of Economics, this means that researchers can access to more and better data, but also that we can apply a more extensive set of quantitative models based on numerical methods to answer new questions. For example, the proliferation of time-varying parameters[1] since the early 1950s or Bayesian approaches[2] in econometrics since the 1960s have extended the limits of the applied research to a new horizon.

Moreover, the volume of information available to researches has increased to a new level where the new advances in Big Data question the traditional analysis and challenges researches about implementing new models in a data-rich framework. In this scenario, we have the examples of Stock and Watson (1999), which uses factor models based on over a hundred series to forecast inflation, and Bernanke, Boivin and Elias (2005), which develops the factor-augmented vector autoregression (FAVAR) framework based on earlier factor literature. In both cases, we have a practical example of economic analysis using large datasets.

This thesis provides three examples of applied research in the field of monetary and financial economics based on the FAVAR methodology. Within the new advances on macro-econometric modelling, FAVAR model and its variants are designed to work with a large number of variables, allowing researchers to analyse complex dynamics among macroeconomic variables in a simple way. These models were initially designed to make quantitative assessments of macroeconomic policies, and more

[1]For example, Klein (1953) states that "*Individuals differ greatly in, and it may not be possible to obtain observations on a sufficiently large number of variables so that each unit may be considered to behave according to the same structural equation*" (pp. 216).

[2]For example, W. D. Fisher, Jacques Dréze and Clifford Hildreth.

specifically the dynamic effects of the monetary policy. However, the methodology has more potential and applications than that. It can be used to analyse dynamic systems from a microeconomic perspective since it accepts a state space representation. This advantage lets researchers estimate the differences among agents or the interactions among them, and it is not used in other fields as often as in the assessment of the monetary policy.

This thesis is structured in 3 chapters. The first chapter presents and assesses the heterogeneous effects that a common monetary policy shock exerts on different economies in a currency area, the Eurozone. To this end, a structural FAVAR (SFAVAR) model is used to show that the effects on both industrial production and inflation are relatively homogeneous among countries. FAVAR family is the common denominator of the three chapters. In that chapter, I find that the industrial sector is homogenous across countries and responds very similar to monetary policy shocks. However, significant differences are found in employment responses, which suggests that the lack of a common regulatory framework has prevented the integration of the labour markets in the Eurozone. Therefore, a common labour market regulation would improve the synchronisation of the business cycles among euro area countries.

The second chapter extends the static framework with time-varying parameters FAVAR (TVP-FAVAR) model to test for changes in the dynamic effects of the monetary policy through the credit channel. The European Central Bank has injected massive amounts of liquidity into the banking system due to the 2007 Great Recession, but the credit channel has not been reactivated. The double directionality of the liquidity provided by the ECB, between the central bank and commercial banks, has hindered the interbank market's performance as a consequence of a high-risk context. I find that the credit channel has been misspecified because of this dynamic, and they can show different performances during tight money periods. Reserves do not play a crucial role in the MTMs, but it helps to the good performance of the credit channel.

The third chapter identifies the determinants behind the dynamics of the real-time settlement payment system in Mexico, SPEI, during the period January 2005-December 2015. To that end, we use a two-step econometric strategy. First, we estimate a TVC-FAVAR model to identify the underlying dynamic factors. Second, we regress the fitted dynamic factors on SPEI's network metrics, such as centrality, distance and bilateral relationships. These metrics capture different market aspects and help us to understand banks' strategy patterns. We find that five factors are driving the dynamics of the Mexican payment system, and linear combinations of the network metrics explain changes in these dynamics. The two main forces are: (*i*) the trend, affected by most of the metrics; and (*ii*) the stability of the system, affected by centrality and the bilateral relationships.

Chapter 1

Heterogenous effects of monetary policy in the Euro Area: a FAVAR approach

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 chapter 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 chapter is twofold. First, the present study 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 research 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 essential to address its effects on the effectiveness of the 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 chapter is organised as follows. Section 1.1 presents a literature review of selected papers related to this field, differentiating between the concepts of asymmetric and heterogeneous effects. Section 1.2 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 1.3, considering the impulse response functions and a variance decomposition analysis. Section 1.4 concludes presenting the conclusions.

1.1 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 chapter defines heterogeneity as the different responses of production, employment and inflation rate 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 general 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

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

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 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 and 2011. Unlike Boivin et al. (2008), the authors find significant and heterogeneous

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

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 substantial 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 chapter 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.

1.2 The FAVAR framework, estimation and data

As mentioned, this chapter 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 broad set of macroeconomic variables.

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

1.2.1 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 initial set-up of the FAVAR model:

$$X_t = \Lambda F_t + \varepsilon_t \quad , \quad \varepsilon_t \sim WN(0, \Sigma_\varepsilon) \tag{1.1}$$

$$F_t = \sum_{h=1}^{p} \phi_h F_{t-h} + \upsilon_t \quad , \quad \upsilon_t \sim WN(0, \Sigma_\upsilon) \tag{1.2}$$

Equation (1.1) 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 (1.2) 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 (1.1) becomes:

$$X_t = \Lambda^f f_t + \Lambda^Y Y_t + \varepsilon_t \tag{1.3}$$

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 (1.1) and (1.3) imply that $F_t = [f_t', Y_t']'$ and $\Lambda = [\Lambda^f, \Lambda^Y]$.

Using the companion form, equation (1.2) by can be written as a $VAR(1)$:

$$Z_t = \Theta Z_{t-1} + \mathrm{v}_t \quad , \quad \mathrm{v}_t \sim WN(0, \Sigma_{\mathrm{v}}) \tag{1.4}$$

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

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

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 (1.2) are located in the first r rows of Θ. Σ_{v} is a $(rp \times rp)$ matrix, which contains Σ_υ in the first r rows and r columns.

The system of equations conformed by equations (1.3) and (1.4) 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 1.1 (pp. 5). 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-

[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).

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.

1.2.2 Estimation

This chapter uses a two-step principal components analysis (PCA) approach as proposed in Stock and Watson (1998) to estimate (1.3)-(1.4), 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 estimation by principal components 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.

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 (1.3) and (1.4) 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

[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.

[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 $\tilde{f} = X'\tilde{\Lambda}/N$.

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 (1.4) 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 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 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 $X_t = \beta_f \tilde{f}^0_t + \beta_R R_t + e_t$ 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 (1.4) can be estimated with $\hat{F}'_t = [\hat{f}_t, R'_t]'$. Note that Boivin and Giannoni (2008) use

[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 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 more considerable 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. 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 B.1 in Appendix B (pp. 90) reports the results for these criteria using up to eight factors.[13] Following Ahn and Horenstein (2013) IC, the model is specified with $\hat{k} = 2$ unobservable factors. The second step consists in estimating a standard VAR model

of order p with the fitted factors from the previous step. The VAR model is estimated using the companion form as in equation (1.4) 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, a similar 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 $hat p = 3$ lags.[14] However, a model with $\hat{p}5$ unobservable factors is used as a robustness check to the model fitted, in line with Bernanke et al. (2005).[15]

[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] 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 fact 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.

[15] Figures C.1, C.2 and C.3 in Appendix C (pp. 95-96) show this robustness checks.

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 (1.3)-(1.4) 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 $Z'_t = \left[F'_t, F'_{t-1}, \ldots, F'_{t-p+1}\right]$.

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:

$$IRF_{i,t} = \hat{\Lambda}'_i(\hat{\Theta}^t)_{1:rp,1:rp}\hat{S} \tag{1.5}$$

where $\hat{S}$ denotes the Cholesky orthogonalisation of the fitted error term $\hat{\upsilon}_t$ in equation (1.4) 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).

1.2.3 The data

The data used in the analysis has a monthly frequency for the period Jan. 1990 - May 2013. A large data set is compiled with 177 variables from different sources -

[16] Notice that the subindex $(1:rp, 1:rp)$ of $\hat{\Theta}^t$ in equation (1.5) denotes the first r rows from the resulting matrix.

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 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. Table A.1 in Appendix A (pp. 84) 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 an order of integration one, $I(1)$, 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, the monthly inflation (month-over-month percentage change of 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.

1.3 Empirical results

This section presents the main results obtained from estimating a FAVAR model with $\hat{r} = 4$ factors, $\hat{k} = 2$ unobservable and $\hat{m} = 2$ observable, and $\hat{p} = 3$ lags according to the respective information criteria. The observable factors are ECB's main refinancing operation rate, as aforementioned; but also, and in line with Miranda-Agrippino and Rey (2015), VIX indicator is included to account for the for the global financial cycle

[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.

[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.

and isolate the effects of the monetary policy shock. While the authors find empirical evidence of the FED's influence in the global financial cycle, there have been periods when FEDs interventions did not have major effects in the global economy - such as after the dot-com crisis. Thus, the model uses the VIX indicator as a proxy of international financial conditions. Without this variable, the model would not properly identify the effects of the monetary shocks in the economy. 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.[19]

1.3.1 Cross-country heterogeneous responses

Responses of the Industrial Production

Figure 1.1a (pp. 16) 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 terms of the signs, in response to a monetary sock, suggesting that there are homogenous responses in the industry to the common monetary shock. This result is in line with the findings of Boivin et al. (2008). Furthermore, a slight overreaction in such responses arises after the first year, being more evident in the case of Germany, France, Spain and Italy, as we can see in Figure 1.1b (pp. 16).

In almost all economies, the dynamic effects of a monetary shock last around 18 months, showing a significant and non-transitory reduction of industrial production after an interest-rate hike. However, two big groups can be identified in terms of the size of the reaction.

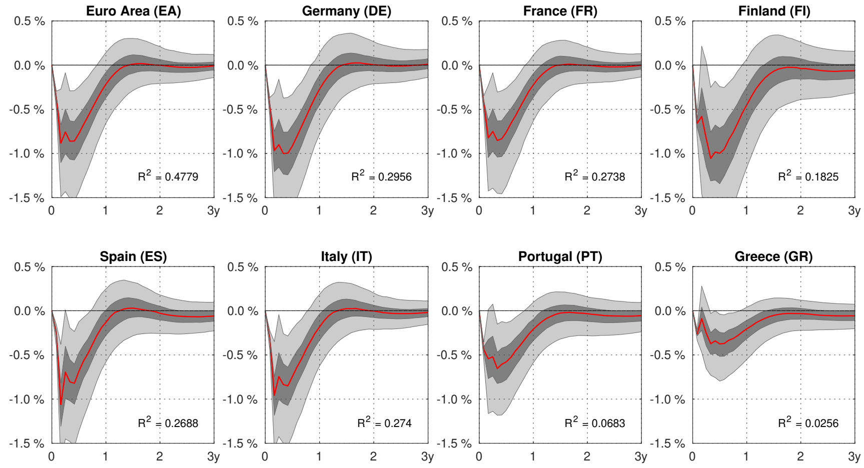
On the one hand, Germany, France, Spain and Italy exhibit similar performance in terms of industrial production. These countries suffer a reduction in industrial production close to 1% and lead the EA in the same direction as a consequence of their weights in the area. On the other hand, Portugal and Greece suffer a smaller reduction close to 0.5%, without affecting the EA performance as a consequence of the lower weights. In particular, Spain is a little more volatile than its neighbours and the contractionary monetary shock results in a reduction of up to 1.3%. 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 the highest uncertainty. Based on the confidence bands, the degree of uncertainty is the greatest among all the selected countries,

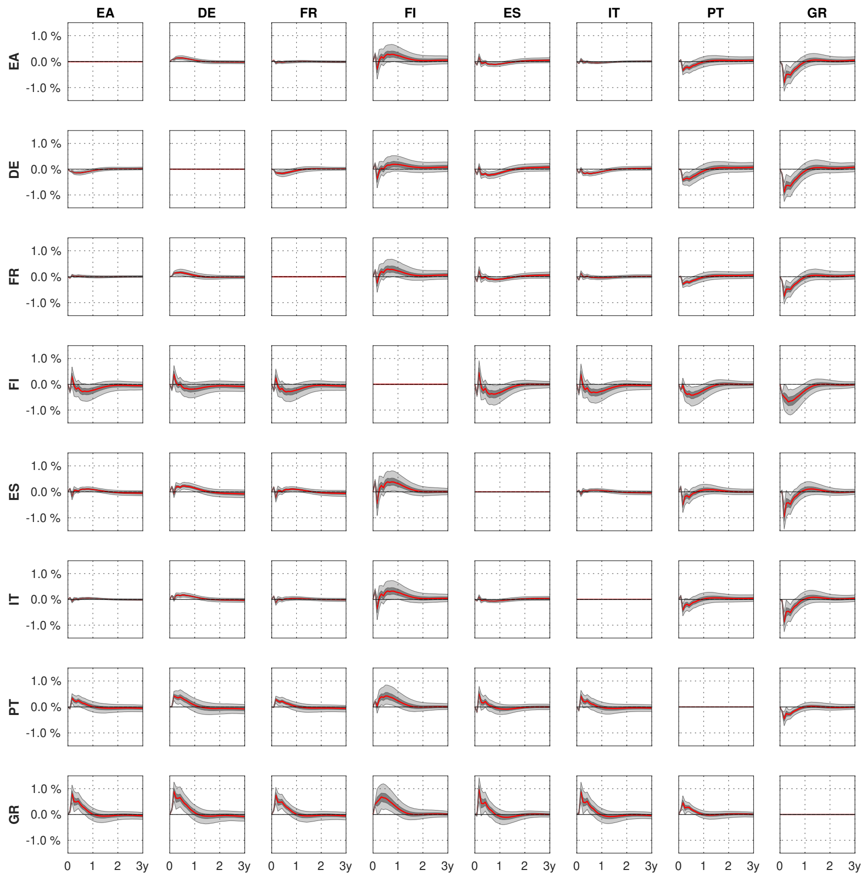
[19] Section B.2 in Appendix B (pp. 91) show the estimates of the smaller VAR(3) for the four factors, as well as different specification tests and the roots of the estimated VAR polynomial.

Fig. 1.1 Structural Analysis of the Industrial Production Index

(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.



Note: the red line shows the median IRF calculated with 2000-iteration bootstrap with 68% and 95% confidence intervals represented by dark and bright grey areas respectively.

so this result is probably not significant.[20] By contrast, Greece shows almost a neutral effect in its response to the monetary shock and, as in the case of Spain, this result 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 chapter, 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 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.[21] 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.[22] 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

[20] As it can be seen in the in Table 1.1 (pp. 24), the variance decomposition shows an R^2 related to the Finnish industrial production is close to above 15%, the third lowest value, but still not too far from the big countries.

[21] 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.

[22] 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.

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.[23]

Responses of Unemployment

Unlike the industrial production, the responses of the unemployment rate to a common monetary shock are heterogeneous across EA countries, as Figure 1.2a (pp. 19) shows. The unemployment rate increases in a fraction of the countries, while it decreases in the other. The two big groups in terms of industrial production almost show a joint performance in terms of unemployment, as we can see in Figure 1.2b (pp. 19).

On the one hand, the unemployment rate shows similar performance in Germany, France, Finland and Portugal. These countries undergo a temporary increment above 0.05% in unemployment after the contractionary shock. In particular, the response of Germany is the most significant among those countries, while France, Finland and Portugal show a more moderate but not insignificant increment. The EA exhibits a similar performance but with more uncertainty than those countries, due to the considerable weight of Germany and France in the currency area.

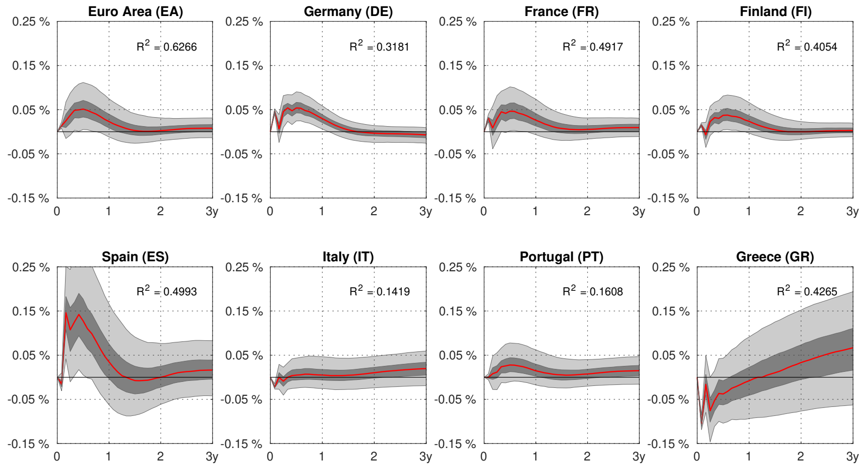
On the other hand, Spain shows the most considerable reaction in terms of unemployment. The unemployment rate increases during the first year three times more than in the previous group, and afterwards declines to zero. Italian responses are not statistically significant, indicating the neutrality of the policy. By contrast in Greece, the unemployment rate exhibits a significant reduction as a consequence of a contractionary monetary shock in the short run.

Italy and Greece are clear examples opposite to what the economic theory dictates: neutrality or reduction of 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

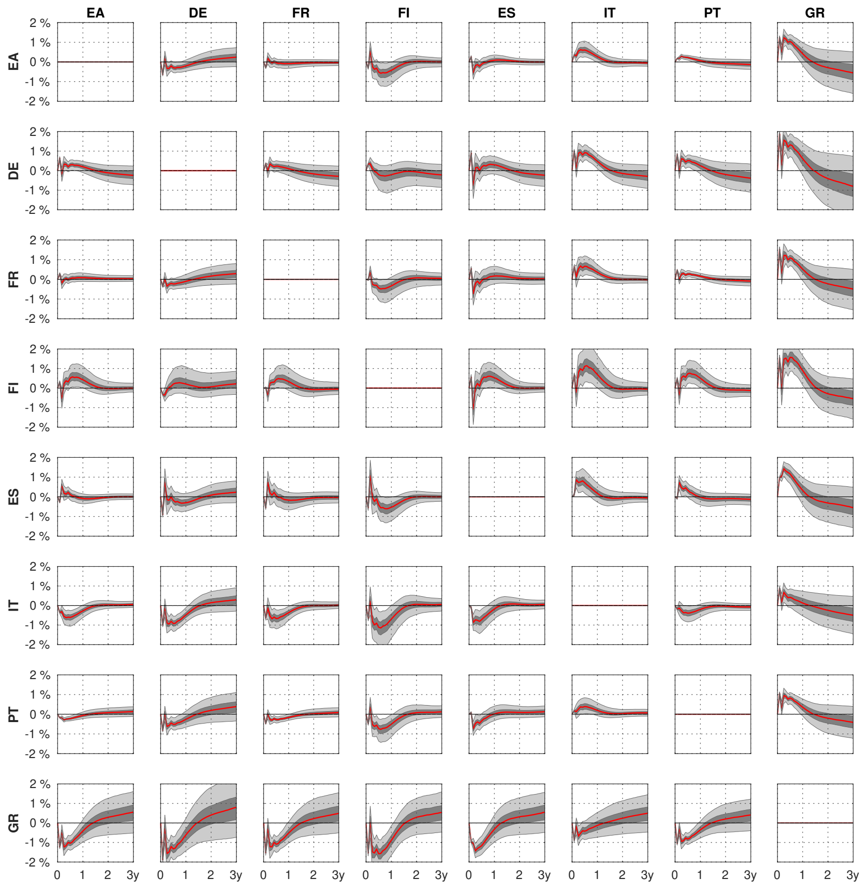
[23] Farès and Srour (2001) finds that manufactures has a stronger response than any other sector to a monetary shock and this result is supported by Carlino and Defina (1998), which describes how manufactures play a crucial role while explanting the cross-state heterogeneity in transmitting the monetary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

Fig. 1.2 Structural Analysis of Unemployment

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



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



Note: the red line shows the median IRF calculated with 2000-iteration bootstrap with 68% and 95% confidence intervals represented by dark and bright grey areas respectively.

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 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 Germany, France, Finland, Portugal and Italy have some rigidities in the adjustment via quantities, while Spain and Greece are less rigid. However, the lack of monthly wages series or labour costs does not allow to deepen in this field.

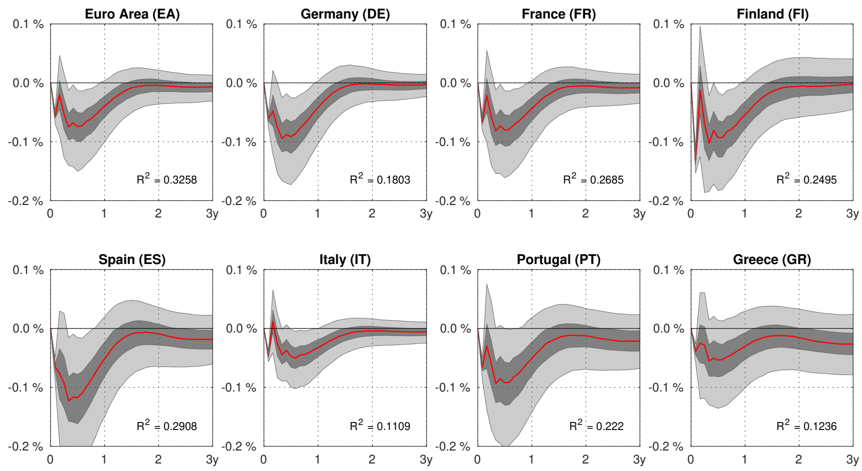
Thus, and according to the results, Germany, followed by France, Finland and Portugal are the less dynamic economies in terms of their labour markets in response to monetary shocks, since they show clear and small reactions in their responses, and Spain also has a great reaction. By contrast, Italy is not affected by monetary shocks in terms of unemployment, and Greece reacts in the opposite direction. Then, the implementation of a common regulatory framework, in this case, would facilitate the transition to a unique European Business Cycle.

Responses of Inflation

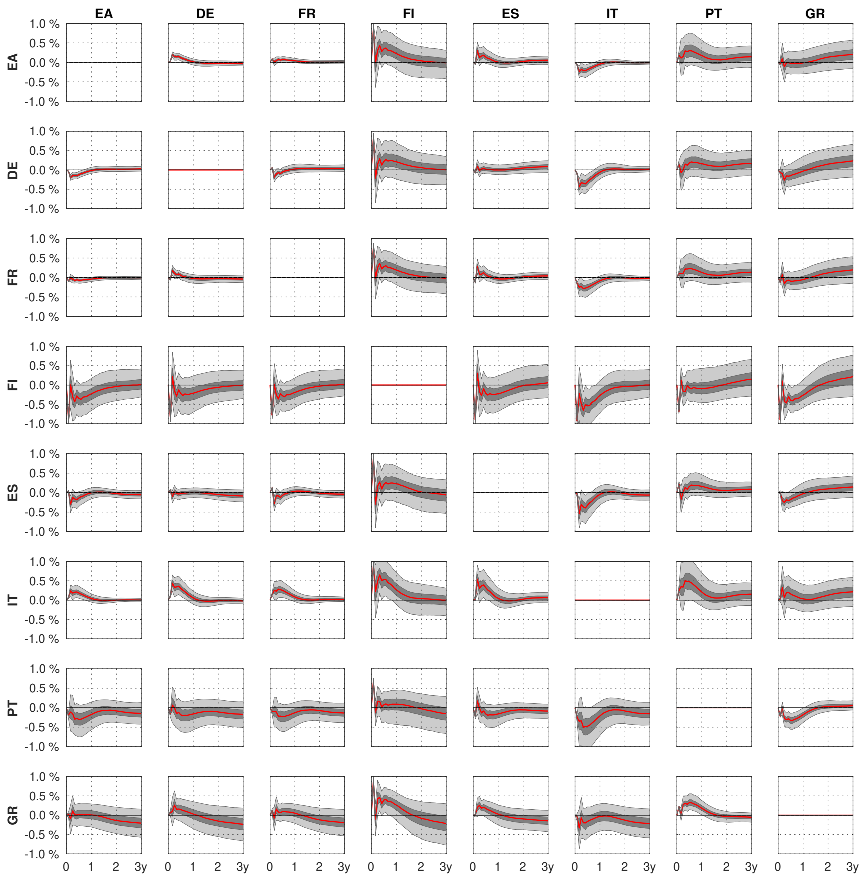
Figure 1.3a (pp. 21) shows the IRF of the inflation to a contractionary monetary policy shock. In almost all the economies a temporary "price puzzle" appears in the second period, which vanishes after that. The puzzle was more significative in previous estimations, but it has reduced with the introduction of international commodity prices. Boivin et al. (2008) explains that it could be due to the real

Fig. 1.3 Structural Analysis of the Inflation (m-o-m)

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



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



Note: the red line shows the median IRF calculated with 2000-iteration bootstrap with 68% and 95% confidence intervals represented by dark and bright grey areas respectively.

exchange rate depreciation. According to Figure 1.3b (pp. 21), sign heterogeneities are found in response to the monetary shock. After the price puzzle effect, countries perform a temporary reduction in inflation, consistent with the medium-term target of the ECB. However, this reduction is not very significant in most of the cases.

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. Finland, Spain and Portugal experience a more drastic and significant reduction in the price level, which may indicate greater price flexibility.

According to Figure (1.3b), two prominent groups can be distinguished for the inflation responses. On the one hand, Italy, Portugal and Greece exhibit non-significant changes in inflation in the short run. On the other hand, Germany, France, Spain and Finland suffers a depreciation above 0.1%, and their responses are somehow more significant than in the first group. Note that Spain exhibits a more volatile reaction, similar to Finland.

Although the price puzzle implies a problem from a theoretical point of view, it is a typical result in the literature.[24] 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 inflations 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.

1.3.2 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 1.1 (pp. 24), reports the results for the macroeconomic variables of interest, and among them, those analysed in the previous section.

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

The first six columns show the contribution of the monetary policy shock to the variance of the forecast error of these variables at different horizons. The last column contains the R^2 for each of these variables, and it helps us to assess the results provided by the IRFs. However, the bottom line of this analysis is that the results in this exercise are as significant as those obtained in Bernanke et al. (2005).

If one looks at industrial production results, it is noticeable that the contribution of the monetary shock is between 7% and 25%, and this is a significant value across countries. The average is 14.2%, while in terms of the EA falls to 7%. In particular, monetary shock significantly contributes to most of the countries in the short run, except for Greece and Portugal. However, it shows a more considerable contribution in Germany and Italy. This result can be read as if monetary policy stimulus affects big countries' production while it does not exert a strong influence in the rest.

In terms of the R^2, the results across countries are similar, except for Portugal and Greece that has a higher explanation of the variance. The percentage explained is close to 25% on average, reaching 48% for the whole EA.

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 obtained in terms of inflation. In terms of unemployment, the contribution of the policy shock is between 39% and 58% in the short run, and this fact reflects the presence of heterogeneity across labour markets again. The sample average is 50%, while in terms of Eurozone is 51%. Spain gets special attention, as monetary shocks have a more significant contribution to the variability of unemployment, and more specifically almost 60%. However, smaller but significant contributions are found for the rest of the countries. Italy and Portugal show the lowest significance, while the rest of the countries obtain an R^2 above 50%.

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 inflation 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 0.05% and 12% in the long run. The sample average is around 7%, while in terms of Eurozone it increases to almost 10%.

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

Table 1.1 Variance Decomposition Analysis

Variable	*3 months*	*1 year*	*2 years*	*3 years*	*4 years*	*5 years*	R^2
Main Refinancing Operations Rate	25.96%	22.78%	8.56%	8.09%	7.12%	6.80%	1.00†
VIX Indicator	65.68%	2.64%	0.00%	0.03%	4.06%	5.05%	1.00†
Eonia	2.39%	13.21%	3.74%	6.51%	6.51%	6.55%	0.85
Euribor 1 month	7.30%	12.89%	3.29%	6.34%	6.46%	6.53%	0.85
Euribor 3 months	10.39%	11.93%	2.82%	6.15%	6.38%	6.49%	0.82
Euribor 1 year	7.18%	11.20%	1.94%	6.01%	6.25%	6.45%	0.77
ECB Overnight deposits	2.00%	17.06%	14.53%	5.09%	6.98%	6.66%	0.05
Money aggregate 1	6.62%	1.64%	14.80%	6.03%	7.23%	6.75%	0.06
Money aggregate 2	26.01%	30.72%	8.80%	9.36%	7.42%	6.91%	0.23
Money aggregate 3	20.58%	27.27%	6.48%	8.96%	7.18%	6.84%	0.32
Euro Area Loans to HH	18.90%	16.88%	5.47%	7.48%	6.76%	6.68%	0.75
Euro Area Loans to MFI	39.27%	18.92%	4.48%	6.66%	6.75%	6.59%	0.37
Exchange Rate EUR/GBP	52.76%	28.08%	8.04%	6.34%	7.48%	6.64%	0.09
Exchange Rate EUR/USD	51.11%	43.73%	21.90%	2.45%	6.08%	6.70%	0.16
Shares' Prices Euro Area	54.80%	35.74%	56.22%	8.96%	6.97%	5.26%	0.60
Shares' Prices Germany	55.32%	32.70%	66.27%	6.64%	6.51%	5.87%	0.53
Shares' Prices France	54.63%	36.17%	55.05%	9.76%	7.25%	5.53%	0.58
Shares' Prices Finland	53.36%	42.59%	28.83%	26.81%	12.18%	6.95%	0.36
Shares' Prices Spain	53.13%	30.68%	57.24%	0.06%	26.73%	16.00%	0.54
Shares' Prices Italy	53.70%	36.84%	31.57%	5.08%	7.37%	7.29%	0.55
Shares' Prices Portugal	54.72%	40.03%	34.33%	0.26%	4.47%	7.74%	0.57
Shares' Prices Greece	55.31%	31.58%	44.28%	7.39%	9.18%	8.29%	0.47
IPI Euro Area	50.33%	48.88%	10.46%	8.95%	9.83%	7.02%	0.48
IPI Germany	51.25%	40.05%	10.09%	7.07%	8.65%	6.80%	0.30
IPI France	48.31%	51.70%	13.10%	9.70%	9.56%	7.10%	0.27
IPI Finland	43.29%	55.08%	21.45%	11.22%	14.14%	7.86%	0.18
IPI Spain	50.41%	64.12%	0.48%	17.13%	41.27%	25.80%	0.27
IPI Italy	51.57%	50.46%	6.34%	10.06%	10.97%	7.10%	0.27
IPI Portugal	37.63%	86.78%	19.02%	38.04%	20.83%	10.07%	0.07
IPI Greece	38.41%	26.63%	20.25%	3.68%	0.03%	4.69%	0.03
Unemployment Euro Area	51.43%	0.61%	0.19%	11.48%	5.65%	6.99%	0.63
Unemployment Germany	43.91%	6.03%	12.34%	5.53%	7.29%	6.65%	0.32
Unemployment France	38.72%	13.03%	10.77%	5.41%	2.69%	5.83%	0.49
Unemployment Finland	50.30%	7.77%	13.66%	26.41%	6.39%	8.48%	0.41
Unemployment Spain	58.74%	3.50%	17.77%	12.76%	7.14%	7.38%	0.50
Unemployment Italy	45.03%	5.54%	6.13%	7.19%	6.56%	6.67%	0.14
Unemployment Portugal	45.81%	0.82%	3.15%	7.43%	6.14%	6.63%	0.16
Unemployment Greece	38.99%	7.44%	7.18%	6.93%	6.69%	6.67%	0.43
HICP Euro Area	38.15%	42.92%	27.11%	10.96%	22.42%	9.66%	0.33
HICP Germany	43.79%	43.68%	20.76%	7.90%	10.88%	7.27%	0.18
HICP France	35.44%	57.78%	28.46%	18.90%	22.64%	10.04%	0.27
HICP Finland	9.65%	79.18%	30.24%	14.74%	10.66%	7.79%	0.25
HICP Spain	43.24%	67.43%	6.96%	3.61%	1.21%	5.45%	0.29
HICP Italy	28.21%	7.56%	35.44%	4.71%	29.16%	11.79%	0.11
HICP Portugal	35.48%	41.25%	7.87%	3.38%	2.51%	5.57%	0.22
HICP Greece	0.2849	0.3077	0.0017	0.0348	0.0433	0.0595	0.12

† By construction.

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.

1.4 Conclusions

This chapter 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 chapter.

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 different zones within Europe in terms of the nominal-wage rigidities.

The effects on the inflation rate are relatively homogeneous in the long run, fact explained by the membership of a common currency area, which facilitates adjustments via inflation. 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.

Chapter 2

Assessing the credit channel in the Euro Area: a time-varying FAVAR approach

Introduction

Monetary Policy has not been as effective as it should have been in the course of the 2007 Great Recession. Models describing the Monetary Policy Transmission Mechanisms (MTM) have underestimated the directionality and causality of the linkages into the different transmission channels. Thus, the final effects on the real economy become undetermined, and the Central Banks are therefore unable to stabilise output and inflation. This research provides empirical evidence of the performance of the MTMs in the Eurozone, emphasising the role of banks' reserves in the Credit Channel.

To be more specific, the Credit Channel of the MTM has not been properly introduced into the DSGE models. This channel has two conduits. On the one hand, there is the traditional balance-sheet subchannel, which operates through the net worth of business firms. Thus, Bank's financial position, measured in terms of leverage or debt-to-equity ratio, determines the borrowing capacity of a bank. On the other hand, there exists the bank-lending subchannel, and it is based on the unique role that banks play in the financial system. Such role regards the banks as financial intermediaries, which try to mitigate transaction costs. Therefore, it focuses on lending flows.

Under a FAVAR model with time-varying coefficients, this research aims to asses the quantitative effects of the monetary policy in high-risk conditions. We expect to prove that bank reserves play a crucial role in the MTMs. Bank reserves are one of the essential factors in money creation. Thus, a high-risk scenario changes the composition of the banks' balance sheets and they hoard more substantial reserves.

This situation ends in a tightening in the granting of loans and credits even under an expansionary monetary policy. Therefore, Monetary Policy turns out to be less effective.

On this subject, Mumtaz et al. (2011) and Eickmeier et al. (2011), for example, using a TV-FAVAR model for testing the effectiveness of the monetary policy. As we will discuss in Section 2.3, both approaches find time-varying effects of the monetary policy. However, we are going to introduce long-run stability in the empirical model and apply it in the Eurozone. Basing on Eickmeier et al. (2011), this method will attempt to capture the dynamics and linkages in the bank lending, capital investment decisions and money creation in the Eurozone.

The remainder of this draft is structured as follows. In Section 2.1, this chapter is motivated by showing empirical evidence in favour of the hypothesis. Section 2.2 discusses the literature in this field to point out the last advances in this matter. The empirical framework used to test the hypothesis is reported in section 2.2. Section 2.4 provides the results from the time-varying framework. Finally, the conclusions are presented in section 2.6.

2.1 Motivation and hypothesis

Some authors[1] have criticized the performance of the ECB since the 2007 Financial Crisis. Most of them state that the ECB intervention was erratic mainly due to the lack of a coherent strategy, which attended to price stability. Using the conventional tools of interest rates and open market operations, the package of preventative measures was designed to provide the financial system with enough liquidity to attain the desired price stability. Indeed, Krugman (2012) pointed out that ECB might say *"Price stability is the mandate, but it is not defined. So the reality is we're going to need to see 3-plus per cent inflation over the next five years. [...] If anything, cut interest rates. Open-ended lending to governments and banks"* (interview). This assessment shows that ECB has actively pursued an inflation-targeting policy instead of making a direct intervention in the banking system to reactivate the credit.

In response to the economic tensions, the ECB's balance sheet had practically doubled in size between 2007 and 2009, and almost trebled between 2007 and 2012. Despite such liquidity injections, a high-risk aversion left the interbank market almost paralysed. The banking system was unable to perform the role of financial

[1] See Durré and Pill (2012), Hetzel (2013) or Wessel (2014) for a wider discussion.

intermediaries, and the real economy was, therefore, gravely affected by this absence of funding liquidity[2].

As suggested in the previous section, this credit crunch raises doubts on the credit channel's effectiveness as part of the monetary transmission mechanism. In particular, the performance of the bank-lending subchannel. Then, a natural question emerges, what has failed in the credit channel? Alternatively, where is the liquidity provided by the ECB?

The hypothesis is that the credit channel, specifically the bank-lending subchannel, has not taken into account the double directionality of the liquidity flows. This double directionality lies in how the commercial banks get liquidity from the central bank but also can leave deposits in it. According to Figure 2.1 (pp. 30), the empirical evidence suggests that a high-risk aversion in the interbank market has diverted liquidity from wholesale banks to the ECB. Wholesale banks place a fraction of their liquidity as voluntary reserves and deposits in the ECB, as it guaranteed lower but risk-free returns.

In this regard, the conventional view of the MTM is based on the fact that Monetary Policy has constant effects along the time. However, the market's circumstances must be taken into account to implement a more effective monetary policy, or in other words, monetary policy effects could have different effects along the time depending on financial market conditions. Figure 2.2 and 2.3 (pp. 31 and 33) show these structural instabilities.

Following FAVAR methodology[3] described in the previous chapter, Figure 2.2 shows the empirical IRF functions for the period 2001:01-2007-12 in the Eurozone. According to the graphs, the credit channel of the MTM works as it has been conventionally described.

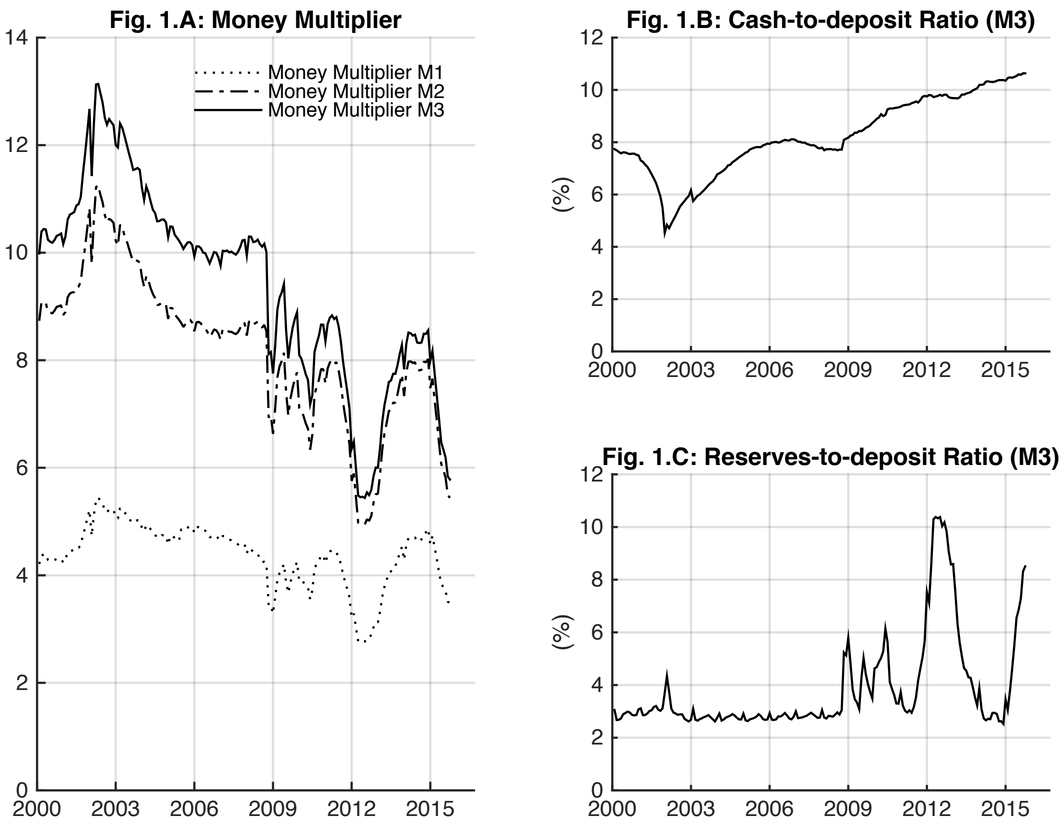
We can observe that after a100 basis-points reduction on the main refinancing operations (MRO) rate, financial markets react with optimism. On the one hand, the monetary base (B) raises and the cash-to-deposits ratio increases because of the relative rise in alternative asset prices - as we can deduce when the EuroStoxx turns bullish. On the other hand, the reserves-to-deposits ratio temporarily falls to adjust to new interest rates.

The volume of loans to financial corporations also increases, what denotes that the interbank market is working correctly and providing enough liquidity to the entire

[2] The credit crunch firstly affects investment and consumption via the production of durable goods, and lately employment and output. This fact denotes a contraction of domestic demand.

[3] FAVAR methodology combines the standard structural VAR analysis with recent developments in factor analysis for large data sets, and it is indeed essential to properly identify the monetary transmission mechanism.

Fig. 2.1 Euro Area: the Money multiplier and its decomposition



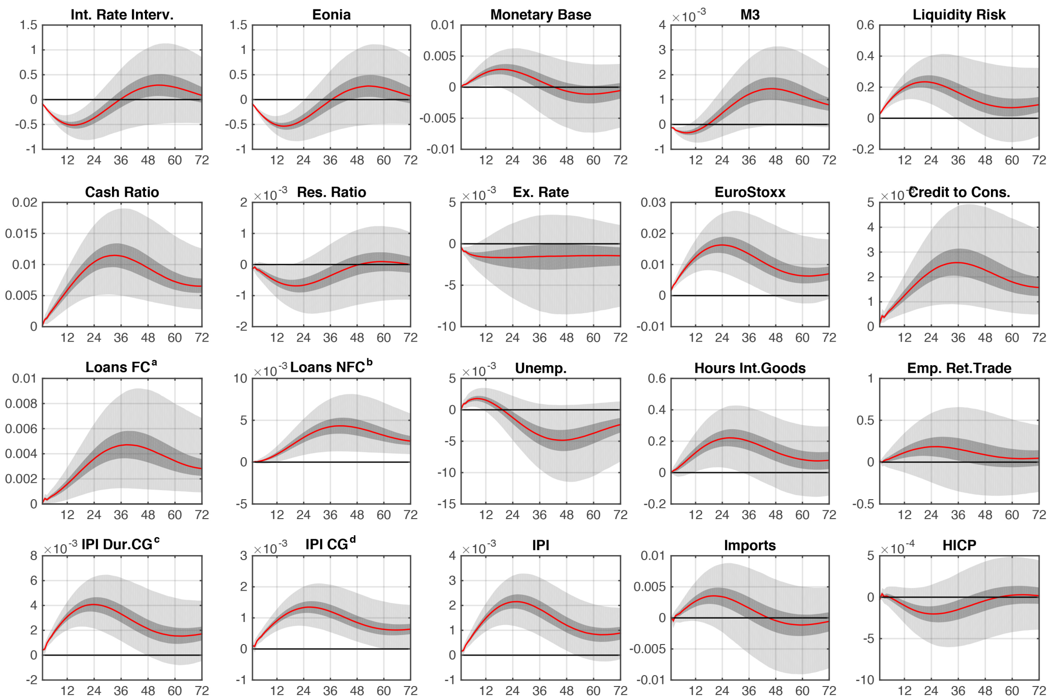
banking system. Both effects make the money supply (M3) increase. Therefore, the liquidity risk[4] in the system is reduced. This fact is reflected by a positive value in the chart. This result suggests that deposits are rising because of a) the cash-to-deposits ratio is rising, b) the reserves-to-deposits ratio is declining, and c) the volume of loans to non-financial corporations is increasing.

Such dynamic suggests that the M3 money multiplier is probably remaining constant or increasing in the medium and long term. All the effects and dynamics into the financial system suggest that the multiple expansion of credit is correctly working through the banking system. Therefore, the real economy has enough liquidity to build its activity up.

In this regard, in terms of the link with the real economy, we observe that the volume of loans to non-financial corporations is increasing. Considering the positive effect on the production of durable consumer goods, this result suggests

[4] This index summarises into a single composite indicator the Funding liquidity risk, if a firm is not able to meet its cash-flow needs, and Market liquidity risk if a firm cannot quickly eliminate a position.

Fig. 2.2 Impulse response functions before 2007 Great Recession



Note: *a* and *b* denotes loans to financial corporations and non-financial corporations respectively, *c* is Industrial Production Index (IPI) of Durable Consumer Goods, and *d* is IPI of Consumer Goods. Clear and dark grey shaded areas denote 95% and 68% confidence intervals respectively.

that investment is increasing. Then, unemployment goes down and the number of working hours increases, remaining the average labour productivity undetermined.

Finally, output increases, but a weaker trade balance mitigates such growth. This fact can be seen by an increase in imports as a consequence of the appreciation of the Euro and a probable decrease in exports. This result also shows part of the exchange-rate channel of the MTM. Finally, the results suggest that domestic demand is growing because of consumption, investment and imports.

In such a way, the performance of the credit channel of the MTM before the financial crisis was as previously described. However, the results completely change in the period after the crisis.

On the other hand, Figure 2.3 shows the empirical IRF functions for the period 2008:01-2014-09 in the Eurozone. According to the graphs, the credit channel of the MTM has failed in terms of what has been conventionally described.

After a 100 basis-points reduction on the MRO rate, now financial markets react with uncertainty mainly due to a high-risk environment. The monetary base is reduced and the cash-to-deposits ratio increases because of the relative rise in alternative asset prices - see that EuroStoxx turns bullish -. Notice that such performance of the monetary base is against a good sense. It can be explained as the strong correlation between B and M, and as a consequence of such correlation this method is not able to identify the linkages with B. However, the reserves-to-deposits ratio reaches a new level. This effect would be the result of the aforementioned high-risk scenario and a reduction in the level of deposits.

The volume of loans to financial corporations therefore falls, which denotes that the interbank market is neither correctly working nor providing enough liquidity to the entire banking system. Both effects make the money supply decline. Therefore, the liquidity risk in the system is higher than in previous periods, and it is reflected by a negative value in the chart. This result suggests that deposits are shrinking because of a) the cash to-deposits and the reserves-to-deposits ratios are increasing, and b) the volume of loans to non-financial corporations has significantly fallen.

Such dynamic performance suggests that the M3 money multiplier is probably decreasing in the medium and long term. In this case, the effects and dynamics into the financial system suggest quite strongly that the interbank market was frozen through the crisis and thereby the multiple expansion of credit through the banking system did not efficiently work. Therefore, the real economy has not enough liquidity to confront its activity.

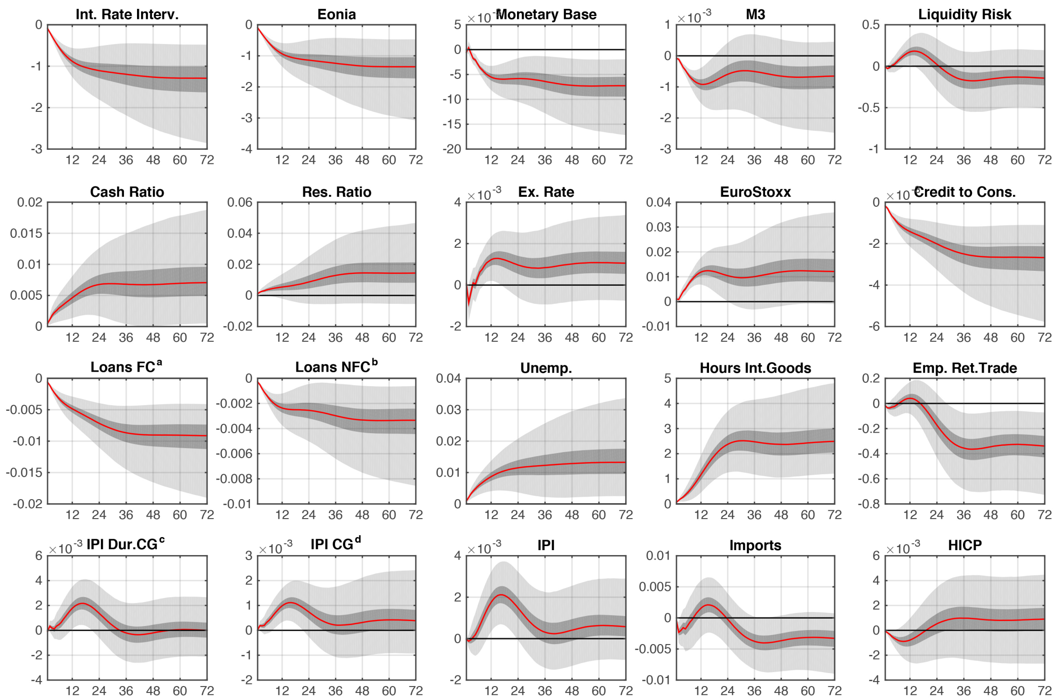
In terms of the real economy, we observe that the volume of loans to non-financial corporations is declining. Considering the neutral effect on the production of durable consumer goods in the long term, the result suggests that investment is falling. Then, unemployment and the number of working hours go up. These effects imply that the average labour productivity increases, showing a countercyclical performance.

The final effects on the output are opaque[5]. The output seems to increase slightly, but such growth is mainly due to a favourable trade balance. This fact is reflected by a reduction in imports as a consequence of a weaker Euro and a likely increase in exports. Again, it shows part of the exchange rate channel of the MTM. Furthermore, the estimation suggests that production is growing due to the external demand, while domestic consumption and investment are falling. Notice that the results also suggest that there is a substitution effect between durable and non-durable goods.

Finally, the performance of the credit channel of the MTM after the financial crisis was not as it has been described by the conventional view of the MTM. This simple exercise motivates to use a more flexible empirical model that fits in better with the current context, where monetary policy can affect in different ways to a

[5] Notice that also the final effects on HICP are ambiguous since the econometric model provides a price puzzle. Using a specific factor for all prices could mitigate this problem.

Fig. 2.3 Impulse response functions after 2007 Great Recession



Note: *a* and *b* denotes loans to financial corporations and non-financial corporations respectively, *c* is Industrial Production Index (IPI) of Durable Consumer Goods, and *d* is IPI of Consumer Goods. Clear and dark grey shaded areas denote 95% and 68% confidence intervals respectively.

subset of variables subject to different market conditions. The new empirical model should be able to incorporate these contrary dynamics in the MTMs.

The following section presents a literature review of the papers which have tested the existence of the MTMs and the effects of the monetary policy.

2.2 Brief literature review

There exists an extensive literature regarding the MTM. However, it is necessary to define and limit the theme. According to Ireland (2005), the MTM "*describes how policy-induced changes in the nominal money stock or the short-term nominal interest rate impact real variables such as aggregate output and employment*" (pp. 1). The MTM identifies the links and causal effects between agents and markets.

The MTM comprises different channels. According to Mishkin (1995) and Ireland (2005), there are four channels: to wit, the interest rate or Keynesian interest rate, the exchange rate, asset price channels, and the credit channel. Both authors make a similar description and give similar conclusions for these mechanisms.

This section discusses a summary of the literature, and assess the different empirical studies that have tested these theories.

Empirical studies

There exists an extensive literature about the evidence of the credit channel and its both components. However, we are going to focus on recent empirical researches.

Kashyap and Stein (1994) use disaggregate data on bank balance-sheets to provide a test of the lending view of monetary policy transmission in the United States during the 1980s. They argue that if the lending view is correct, one should expect the loan and security portfolios of large and small banks to respond differentially to a contraction in monetary policy. Using a set of different regressions, the authors verify such view.

Mishkin (1995) remarks that the importance of bank lending has diminished since World War II. In the same line, Perez (1998) provides an empirical examination to the Bank lending channel for the United States in the period between World War II and the late 1990s. The author uses the causal-order methodology and focuses on the real gross national product and real commercial-industrial loans. He finds that the bank lending subchannel has been effective up to the Oil Crisis of the 1970s. Since then, a structural change arises, and such effects have continuously been reduced mainly as a consequence of financial innovation.

However, the results of Kashyap and Stein (1994) and Perez (1998) cannot be understood as an existence test of the bank lending channel. In both cases, the authors use variables from both the bank lending and balance-sheet subchannels. Then, their results would test the credit channel as a whole.

By contrast, Kishan and Opiela (2000) give evidence of a credit channel and a bank-lending channel in the United States from 1980 to 1995. These authors test for bank-loan supply shifts by segregating banks according to asset size and capital-to-leverage ratio. They stress the importance of the bank capital to leverage ratio in explaining the effect of policy on bank loan growth and argue that bank-asset size and bank capital affect the ability of banks to raise funds and maintain loan growth under a contractionary policy. Their results support this hypothesis. However, this assessment should take into account the double directionality between banks and the central bank, since it is not able to explain the performance of the channel in the Euro Area during the 2007 Great Recession.

More recently, Gambacorta et al. (2011) and Santis et al. (2013) base their analysis on the methodology applied in Kashyap and Stein (1994). By contrast, both articles use disaggregated data, including banks' characteristics such as size, liquidity and capital. However, both exclude interbank positions, what creates, serious omitted-variable problems, that underestimate the effects on the credit channel. Gambacorta et al. (2011) show that new factors, such as changes in banks' business models and market funding patterns, had modified the monetary transmission mechanism in Europe and the US before the crisis. They find an important result: the type of funding is a key element in assessing banks' ability to withstand adverse shocks: short-term funding and securitisation activity seem to be particularly important in this respect.

Dave et al. (2013) test for empirical evidence of the credit channel using a Factor-Augmented Vector Autoregression model (FAVAR) for the United States from 1976 to 2005. The authors implement the methodology suggested by Bernanke et al. (2005)[6] for a detailed description. but taking into account microdata and focusing on the bank-lending subchannel. They find that the existence of the bank lending channel is prevalent and not only in retail banks. This result casts doubt on previous notion and components of the channel. Banks are affected due to their ability to substitute between different sources of funding. However, they are also differently affected by the types of loans due to their relative risk aversion ant the term structure of the loans. This result is consistent with Gambacorta et al. (2011).

Finally, a new variety into the FAVAR models has gained importance in the last years. The time-varying FAVAR models (TV-FAVAR) have incorporated larger flexibility in analysing the MTMs than previous models. We find the main contributions in Mumtaz et al. (2011) and Eickmeier et al. (2011). In the first paper, the authors implement a TV-FAVAR model in order to test the changes in the effectiveness of monetary policy using quarterly UK data from 1975 to 2005. They introduce time-varying coefficients in what is called the dynamic equation[7]. Their conclusions show that time-variation should be taken seriously, as it has clear implications for structural economic models. More specifically, they show that around the beginning of the nineties, monetary policy shocks started having a bigger impact on prices and began contributing more to overall volatility.

By contrast, Eickmeier et al. (2011) implement a FAVAR with time-varying parameters (TVP-FAVAR) with quarterly US data from 1972 to 2007. Furthermore, they implement a time-varying structure more flexible than in Mumtaz et al. (2011). In particular, they also allow for time-varying in the observation equations and their volatilities, giving the most significant time-varying framework for the TVP-

[6] This technique measures the effects of monetary policy. See the previous chapter for a more detailed explanation.

[7] In particular, the authors incorporate time-varying coefficients and volatility in the VAR equation.

FAVAR models[8]. Their results, in line with Gambacorta et al. (2011), suggest that the volatility of monetary policy shocks has changed in the US, and the reaction of GDP, the GDP deflator, inflation expectations and long-term interest rates to an equally-sized monetary policy shock has decreased since the early-1980s.

Next section shows empirical results that test for time variation of the credit channel in the Euro Area.

2.3 The empirical model

Following the current lines of research on the empirical effects of Monetary Policy, this section presents a discussion of the empirical model used to test the initial hypothesis. In particular, a TVP-FAVAR model is used, based on the findings from the analysis of Figure 2.2 and 2.3 - a fixed-parameter FAVAR for two different periods. Although fixed-parameters models are rational in some sense, most of them ignore underlying dynamics that may exist in the data set. However, the main disadvantage of a time-varying framework in the parameters is that it can lead to more complex analysis.

2.3.1 The TVP-FAVAR approach

As proposed in Bernanke et al. (2005), FAVAR models and all its variants have been quickly included in the empirical analysis of the effects of Monetary Policy. The main advantage of this methodology is based on the fact that it exploits a broad set of economic information. This data-rich environment results in a more extensive analysis, as it allows study the effects of a single shock on a vast number of different variables at the same time. Thus, FAVAR estimation and its variants, such as the TVF-FAVAR, represent a suitable framework for analysing empirical micro-effects of monetary policy shocks.

The family of FAVAR models is based on a system of two blocks of equations. On the one hand, the first block is called the Observation Equation, (2.1), and it is composed of N sub-equations where all variables are singly regressed on the factors. On the other hand, the second block is known as the Dynamic Equation, (2.2), and it is composed of the G sub-equations capturing the comovement of the factors. Thus,

[8] This framework will be used as a baseline empirical model. The authors assume random walks for the coefficients, while in our case we will introduce stable process.

the FAVAR in its matrix form is given by:

$$X_t = \Lambda F_t + u_t \tag{2.1}$$

$$F_t = \sum_{h=1}^{p} \phi_h F_{t-h} + \varepsilon_t \tag{2.2}$$

In equation (2.1), $X_t = [x_{1,t}, \ldots, x_{N,t}]'$ (for $t = 1, \ldots, T$) is a $(N \times 1)$ vector that represents the total set of variables in time t and it is assumed to depend on the factors, $F_t = [f_{1,t}, \ldots, f_{G,t}]'$ - a $(G \times 1)$ vector that represents the underlying forces driving the economy. Λ is the loading factor, an $n \times G$ matrix, and allows to decompose the effects of several factors on the set of observation. In equation (2.2), ϕ_h represents an autoregressive coefficient, and more specifically, the specification assumes that the factors follow a VAR process of finite order p. The vectors u_t and ε_t have $(N \times 1)$ and $(G \times 1)$ elements respectively and they denote error terms in both equations, with some statistical properties as discussed further in the next part. The system integrated by equations (2.1) and (2.2) reflects an implicit joint dynamic within the information set that follows a specific dynamic process. Then, we could identify that joint dynamic as the monetary transmission mechanisms (MTMs), and therefore FAVAR methodology is enough flexible to identify the different levels and channels into the MTMs.

Regarding the factors, the reader could argue that this methodology has some difficulties for interpreting the underlying factors or the possible bias in their estimation due to an unbalanced data structure. However, their economic meanings are not critical in this analysis. The estimation of the factors is done by principal components analysis, which seeks the most relevant directions of comovement in the dataset and simultaneously minimises the overall variability. Thus, although the economic meaning of the factors is not clear, they represent and capture the dynamic inertia within the overall system. Respect to the possible bias, the same argument can be applied. The dynamic of a dataset dominated by a specific subset of variables would be dominated by the inertia of such type of variables. Thus, these issues are minor problems.

Let us use an analogy to understand how FAVAR models work. We must understand the overall economy as a dynamic system, similar to the motion of a liquid through a pipe. In this example, the economic variables would be identified with the different components of the liquid, such as molecules, while the underlying factors or forces that drive the economy would be identified with specific characteristics of the pipe and the fluid, such as the diameter or the gravity.

Moreover, the system described by equations (2.1) and (2.2) is a dynamic framework with fixed parameters that can be modified to allow more flexibility into the system. Thus, as introduced by Negro and Otrok (2008), a time-varying coefficients model is used since it allows the effects of the factors to change over time, or in other words, the dynamic effects of the MTMs. This flexible framework, but mathematically more complex, modifies the system (2.1-2.2). Thus, the extended system is given by:

$$X_t = \Lambda_t F_t + u_t, \qquad u_t \sim N(0, V_t) \tag{2.3}$$

$$F_t = \sum_{h=1}^{p} \phi_{t,h} F_{t-h} + \varepsilon_t, \qquad \varepsilon_t \sim N(0, Q_t) \tag{2.4}$$

where the time-varying coefficients are assumed to follow an autoregressive processes of order 1:

$$\Lambda_t = A(L)\Lambda_{t-1} + \upsilon_t, \qquad \text{vec}(\upsilon_t) \sim N(0, W_t) \tag{2.5}$$

$$\Phi_t = B(L)\Phi_{t-1} + \eta_t, \qquad \text{vec}(\eta_t) \sim N(0, R_t) \tag{2.6}$$

Λ_t denotes the time-varying factor loading in time t, $\Lambda_t = [\Lambda_{1,t}, \Lambda_{2,t}, \ldots, \Lambda_{G,t}]$ with $\Lambda_{g,t} = [\lambda_{1,g,t}, \lambda_{2,g,t}, \ldots, \lambda_{n,g,t}]'$ for $g = 1, 2, \ldots, G$. Φ_t denotes the time-varying parameters in time t, $\Phi_t = [\Phi_{1,t}, \Phi_{2,t}, \ldots, \Phi_{p,t}]$ with $\Phi_{k,t} = [\phi_{1,k,t}, \phi_{2,k,t}, \ldots, \phi_{G,k,t}]'$ for $k = 1, 2, \ldots, p$. $\phi_{g,k,t} = [\phi_{[f_g, f_1],k,t}, \phi_{[f_g, f_2],k,t}, \ldots, \phi_{[f_g, f_G],k,t}]$ is a $(1 \times G)$ vector with the kth-order autoregressive coefficients of factor g, $F_{g,t}$, with respect to all factors, F_{t-k}. $A(L)$ and $B(L)$ are polynomials of the lag operator and define the persistence of the time-varying parameters processes. Finally, the error terms u_t, ε_t, $\text{vec}(\upsilon_t)$ and $\text{vec}(\eta_t)$ are now assumed to follow multivariate normal distributions with time-varying variances, and they are discussed further in next part.

Let us conclude by finishing the previous analogy of the pipe to illustrate the time-varying framework. Now the relationships among the characteristics of the pipe are dynamic, and the underlying factors, such us the gravity or the density, can also change over time. Thus, the effects on a single molecule of the fluid, an economic variable in our case, are determined by the characteristics of the system and the changes in the system properties.

2.3.2 Estimation

Several authors have used TVP-FAVAR to estimate the time variation on the MTMs. However, the literature uses three different methods: rolling window, Bayesian and classical estimation. Regarding the rolling-windows analysis, Bagzibagli (2012) estimates fixed-parameters FAVARs over fixed length samples rolled by twelve, six and three months. However, the argument that the author provides to support this method, based on the short history of the third stage of the EMU, is contradictory to the length of the windows. Also, that analysis does not allow for all of error covariance matrices to be time-varying, or at least, it is not clearly stated.

Mumtaz et al. (2011), Koop and Korobilis (2014) and Molteni and Pappa (2017), among some others, use Bayesian methods for the analysis of different economies. However, such Bayesian simulation methods, traditionally based on Markov Chain Monte Carlo (MCMC) methods, are computationally expensive when the researcher is estimating a single TVP-FAVAR, and there is some uncertainty when it comes to the convergence of the model. Finally, Eickmeier et al. (2011) and Abbate et al. (2016) use classical TVP-FAVAR based on Kalman filter and Kalman smoother. These estimations result computationally simple, and they have a straight forward reading.

Thus, this chapter uses classical estimation because it presents some advantages over the other two methods in this particular case. On the one hand, classical estimation is not as time exhaustive as most of the Bayesian TVP-FAVAR, and its benefits in using short samples are offset by using monthly data. On the other hand, rolling-window estimation has some advantages and is computationally more simple. It is mainly used to test the forecast accuracy of a model and its stability over time. However, it is unclear the optimal length of the window, it assumes equal weights for every observation and could ignore long-run relationships in the data. Following Petrova (2019), the rolling window procedure is as a particular case of a kernel-type estimation with a flat kernel weights. However, Kapetanios et al. (2014) point that exponential kernels tend to perform better, but they are computationally more exhaustive.

Factor models aim to reduce a dimensionality problem and uncovering latent relationships among the elements of a large dataset. The literature combines unobservable and observable factors, which are related with policy tools, to make quantitative policy analysis. In particular, I add an observable factor, $\mathfrak{i}_t$, that represents the the interest rate on the main refinancing operations and assume $A(L)$ and $B(L)$ to be all-ones matrices - $A = 1_{N\times G}$ and $B = 1_{G\times pG}$, implying that the parameters follow random walks. Therefore, the system formed from equation (2.3) to (2.6) can be written in equation-by-equation form as:

$$x_{i,t} = \sum_{g=1}^{G} \lambda_{i,g,t} f_{g,t} + \lambda_{i,\mathrm{i},t} \mathrm{i}_t + u_{i,t} \tag{2.7}$$

$$f_{g,t} = \sum_{h=1}^{p} \sum_{j=1}^{G} \phi_{[f_g,f_j],h,t} f_{j,t-h} + \sum_{h=1}^{p} \sum_{j=1}^{G} \phi_{[f_g,\mathrm{i}],h,t} \mathrm{i}_{t-h} + \varepsilon_{g,t} \tag{2.8}$$

$$\lambda_{i,g,t} = \lambda_{i,g,t-1} + \upsilon_{i,g,t} \tag{2.9}$$

$$\phi_{[f_g,f_1],k,t} = \phi_{[f_g,f_1],k,t-1} + \eta_{[f_g,f_1],k,t-1} \tag{2.10}$$

and this TVP-FAVAR specification (equations (2.7) to (2.10)) can be estimated using Kalman techniques. This chapter extends the method in Koop and Korobilis (2014). The authors estimate the TVP-FAVAR using updating schemes based on the one-sided exponentially weighted moving average (EWMA) filters combined with Kalman filter recursions.[9] The selection of EWMA specification is due to the serial correlation problem that usually performs equations (2.7) and (2.8). The origin of this problem lies in misspecification of the model or an omitted variable. However, by definition, the factors should capture the effects of an omitted variable. Therefore, the EWMA method should avoid any possible serial correlation.

The standard estimation procedure is divided into three steps. First, the static unobservable factors are estimated. Second, the time-varying parameters are estimated given the static factors. Third and final, the dynamic factors are estimated given the rest of the parameters.

The procedure begins with the estimation of the factors. According to Bai and Ng (2006), principal components analysis (PCA) can consistently estimate the static unobservable factors[10] as the number of variables n increases faster than the time frame T. Therefore, they can be considered as observable, $\hat{F}^U_{PCA}$. When the number of variables quickly increases, the correlation between an individual variable and the entire system tend to be small, what results in a more accurate estimation of the joint rotation of the factors and factor loading[11]. Thus, assuming observable factors simplify the estimation of the system. Koop and Korobilis (2014) uses PCA estimator as a proxy for the unobservable factors, and the dynamic factors are estimated in the last step and as the result of the Kalman smoother in the last stage of the procedure.

[9] By contrast, Eickmeier et al. (2011) specify a moving average process through the idiosyncratic component of the equation (2.2), ε_t.

[10] The number of factors is chosen according to Ahn and Horenstein (2013) and the Eigenvalue Growth-Ratio Criteria (EGRC), as it showed the best performance among eleven different information criteria. Table B.3 and B.4 in Appendix B.3 (pp. 93-94), the information criteria are reported.

[11] According to Bai and Ng (2013) this method is usually not able to separately identify the factors and factor loadings but it can identify their joint rotations.

However, Bai and Ng (2006) proves consistency in the context of static parameters. As mentioned before, Polynomials $A(L)$ and $B(L)$ in equations (2.5) and (2.6) are assumed to be the identity matrix, and it implies that the time-varying parameters follow a random walk, keeping unchanged consistency property of PCA estimator.[12]

I modify the procedure in Koop and Korobilis (2014) by taking the proxies for the unobservable factors from the residuals after an auxiliary regression, as in Bernanke et al. (2005), since it avoids collinearity problems in the system. This regression,

$$\hat{F}^U_{PCA,t} = \beta \mathrm{i}_t + e_t \tag{2.11}$$

is estimated and the unobservable factors constructed as $\tilde{F}^U_{PCA,t} = \hat{F}^U_{PCA,t} - \hat{\beta}_{OLS}\mathrm{i}_t$. $\tilde{F}^U_{PCA,t}$ represents the uncorrelated part of $\hat{F}^U_{PCA,t}$ with the interest rate. Thus, the static factors are given by $\tilde{F}_t = [\tilde{F}^U_{PCA,t}, \mathrm{i}_t]'$. Once the factors have been estimated, we continue with the procedure as in Koop and Korobilis (2014).

The second and third step estimate the time-varying parameters and the dynamic factors using Kalman filter recursions respectively, and this chapter follows the algorithm proposed by Koop and Korobilis (2014) [13]. The authors extend the procedure proposed by Doz et al. (2011) by adding a step that draws the time-varying coefficients using the Kalman filter.

In the second step, the algorithm estimates the time-varying parameters given the static factors[14]. To that end, a FAVAR model is used to initialise the estimation by using the results of the FAVAR. Then, the set of time-varying variances $\{V_t, Q_t, W_t, R_t\}$ is estimated using variance discounting methods. These methods, introduced by Harrison and West (1987) and generalised in Quintana and West (1988), allow for slow-random changes in the variances that can capture structural changes. V_t and Q_t are estimated using EWMA methods which respectively depend on decay factors κ_1 and κ_2, while for W_t and R_t are estimated using the forgetting factor methods described in Koop and Korobilis (2012) and Koop and Korobilis (2013) which respectively

[12] Notice that Bates et al. (2013) characterise the type of instabilities under which the PCA estimator of the factors is consistent. To that end, the authors identify three sources of instabilities: white noise, random walks and single large breaks. They find that PCA estimator is consistent in all of them. However, the authors do not study the properties of an autoregressive process, and it could be an exciting extension to TVP-FAVAR models since it gives to the coefficients certain long-run stability.

[13] The authors provide a remarkable description, and pre-published versions offer technical appendix with all functions.

[14] The number of factors and lags is determined using eleven different information criteria. Those can be classified into four groups: Ahn and Horenstein (2013) Eigen-value-based Information Criteria (ICs), Akaike ICs, Bayesian ICs and Bai and Ng (2002) ICs. Appendix B.3 (pp. 93) reports all of them.

depend on forgetting factors κ_3 and κ_4.[15] This step finishes by estimating Λ_t and Φ_t, using Kalman filter and smoother.

The dynamic factors are estimated, $\hat{\tilde{F}}_t$, in the third and last step given the time-varying coefficients, Λ_t and Φ_t, using Kalman filter and smoother.

2.3.3 Structural analysis and dynamic impulse response functions

The impulse responses are presented based on the TVP-VAR for $[\mathrm{i}_t, \tilde{F}_t^U]'$, i.e. equations (2.7) to (2.10). To identify the structural monetary shocks, a Cholesky factorization of Q_t is used - see, e.g., Primiceri (2005) and Koop and Korobilis (2014). This identification scheme implies that the unobservable factors respond with at least one lag to changes in the official interest rates, or in other words, the structural restrictions are implemented assuming that monetary policy shocks are not contemporaneously affected by the rest of factors. In this way, the variance-covariance matrix in the system is that in which the main refinancing operations rate is ordered last, and the last column of the impulse response functions is the column of the monetary policy shock.

Let us consider the time-varying matrix Ω_t. The Cholesky dynamic factor, S_t, of is defined as the unique lower triangular matrix such that $S_t S'_t = \Omega_t$. This implies that we can rewrite the VAR in terms of orthogonal shocks $\omega_t = S_t^{-1} \varepsilon_t$ with identity covariance matrix

$$\Theta_t(L) F_t = S_t \omega_t \tag{2.12}$$

where $\Theta_t(L) = (1 - \Phi_{t,1} L - \dots - \Phi_{t,p} L^p)$ and the impulse response to orthogonalised shocks are found from the moving average (MA) representation:

$$F_t = C_t(L) S_t \omega_t = \sum_{j=0}^{\infty} C_{j,t} S_t \omega_{t-j} \tag{2.13}$$

with $C_t(L) = (\Theta_t(L))^{-1}$. Thus, $C_{j,t} S_t$ has the interpretation the marginal change in the factors to orthogonalised shocks. This identification involves an ordering of the variables in the TVP-VAR given by $[\mathrm{i}_t, \tilde{F}_t^U]'$. We use the time-varying estimated VAR coefficients and error covariance matrix at time t to calculate the impulse responses at time t and they are assumed to remain unchanged over the horizon of 12 months for which we calculate impulse responses.

[15] An interesting extension to this procedure would be to endogenise the decay and forgetting factors using a heuristic algorithm to find the optimal values.

Summing up, the model is estimated by a two-step Kalman restricted estimation, based on the procedure in Koop and Korobilis (2014). The algorithm is as follows:

1. Initial values:
   (a) obtain the principal components estimates of the factors $\hat{F}^U_{PCA,t}$.
   (b) obtain the estimates of the factors by subtracting the projection of the interest rates to the the principal components: $\tilde{F}^U_{PCA,t} = \hat{F}^U_{PCA,t} - \hat{\beta}_{OLS}\mathrm{i}_t$.
   (c) initialize all parameters from the ordinary least squares FAVAR estimation $\{\Lambda_0, \Phi_0, V_0, Q_0, R_0, W_0\}$.
2. Estimate the time varying parameters $\{\Lambda_t, \Phi_t, V_t, Q_t, R_t, W_t\}$ given $\tilde{F}_t = [\tilde{F}^U_{PCA,t}, \mathrm{i}_t]'$:
   (a) estimate $\{V_t, Q_t, R_t, W_t\}$ using variance discounting procedure.
   (b) estimate $\{\Lambda_t, \Phi_t\}$, given $\{V_t, Q_t, R_t, W_t\}$, using the Kalman filter and smoother.
3. Estimate the dynamic factors $\tilde{F}_t$ given $\{\Lambda_t, \Phi_t, V_t, Q_t, R_t, W_t\}$ using the Kalman filter and smoother.

2.4 Results in the Euro Area

The TVP-FAVAR model is estimated for the Euro Area (EA). The dataset is composed of 137 macroeconomic variables from January 2001 to September 2014 - monthly frequency. Those macroeconomic variables are representing:[16] *i*) economics activity with demand and supply indicators such as industrial production indexes (IPIs), economics climate indicators and purchasing managers' index (PMI); *ii*) labour market, such as unemployment rate, vacancies and working hours;[17] *iii*) consumption and production prices; *iv*) exchange rates, stocks and money market variables; and *v*) interest rates, such as official interest rates, Euro OverNight Index Average (EONIA) and other spreads.

According to the information criteria, a TVP-FAVAR model is estimated using six unobservable factors, $\hat{G} = 5$, the ECB's MRO rate as the only observable factor, i_t, and seven lags, $\hat{P} = 8$.[18] However, the decay and forgetting factors are set following Koop and Korobilis (2014): $\kappa_1 = 0.95$, $\kappa_2 = 0.95$, $\kappa_3 = 0.85$ and $\kappa_4 = 0.99$.[19]

[16] See Appendix A.2 (pp. 85) for a description of the variables and their transformations.
[17] Vacancies are used at a country level. While the rest of labour macro-variables are at an EA level.
[18] The different information criteria calculated are reported in Appendix B.3 (pp. 93).
[19] Appendix C.2 (pp. 97) shows a different specification as a robustness check.

2.4.1 Evolution of the credit channel in the Euro Area

Figure 2.4 and 2.5 (pp. 45 and 46 respectively) show the Dynamic Impulse Response Functions (DIRF) of the main macroeconomic variables after applying an expansionary monetary policy reducing the MRO rates by 1%. The figures show the dynamic iso-horizon DIRFs. This representation shows what the response of each variable would be with respect to its actual value in each period. The responses are vertically represented, and they show how a monetary shock would shift the variable at any time and different selected horizons - showing that they are stationary in the medium and long run.[20]

Let us start with Figure 2.4, which shows the performance in the money markets. We find that the effects of an expansionary monetary shock have a different size over time. Three periods can be identified: before the crisis, the transition period and after the crisis.

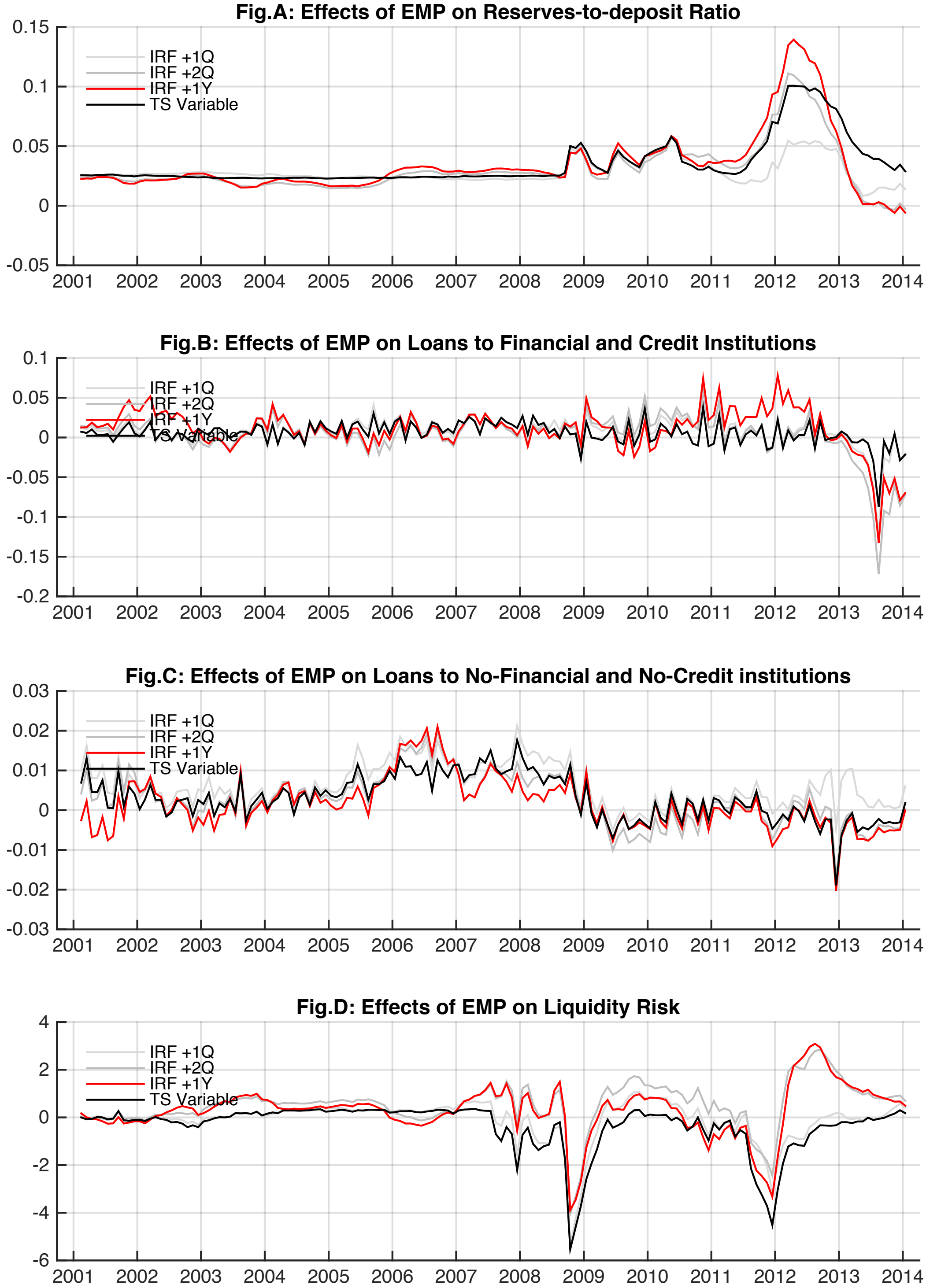
The pre-crisis period is characterised for having modest effects as a consequence of a monetary shock. The empirical evidence suggests that conventional monetary policy did not have substantial effects on the reserve-to-deposit ratio and lending activity. The sign of the effects was fluctuating, not showing a clear pattern. However, this behaviour changes during the transition period, and it consolidated after August 2008 in terms of the size, while the sign also changes.

In terms of the reserves-to-deposit ratio, Figure 2.4.A, the empirical evidence suggests that monetary policy did not have effects on this ratio until late 2010. Since then, the reduction in the interest rates would result in a reduction of the response of the ratio during the first quarter, followed by a raise until the first year. This reduction in the short run is offset in the long run, but it changes after the third quarter of 2012 when the interest rate reduction decreases the reserves ratio in the short and long term. This change coincides with the ECB's interventions of a) extension of full allotment with the fixed/indexed rate (FRFA) for MROs, b) the special-term in refinancing operations and c) three-month LTROs. Thus, these unconventional measures helped to change the performance of the reserves-to-deposit ratio.

If we look at Figure 2.4.D, we can observe the effects of the expansionary policy on the liquidity risk index. The overall performance is similar to the reserves-to-deposit ratio before the crisis. However, after the crisis, a reduction in the interest rates has resulted in a reduction of liquidity risks. This fact means that the expansion

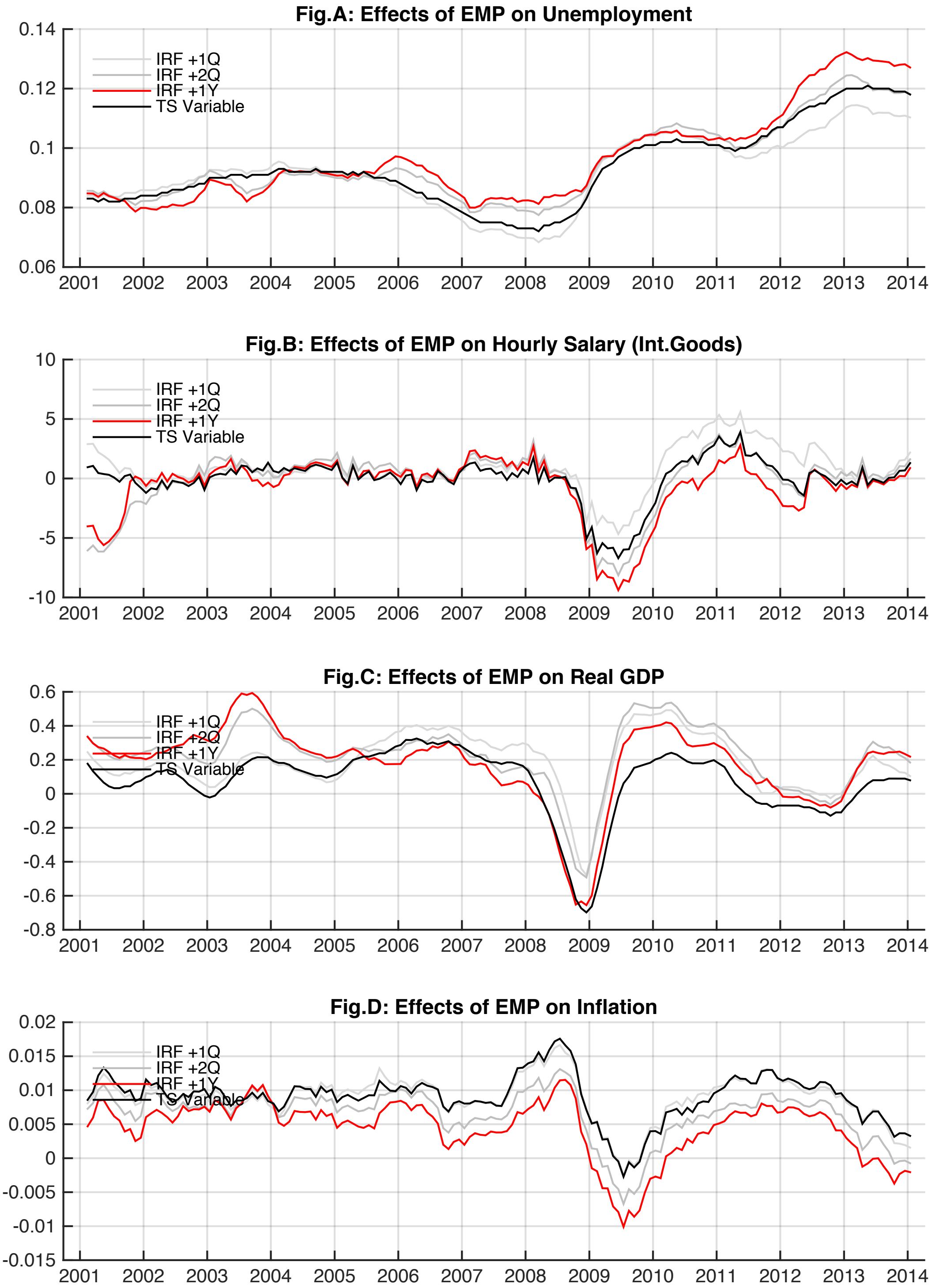
[20] In this case, the DIRF for a single variable has two dimensions: the horizon of the response and the period t at which the shock is applied. This multidimensionality suppose a problem when computing the confidence intervals since they are three-dimensional point clouds, and the results are not as illustrative as in the case of a fixed-parameters FAVAR framework.

Fig. 2.4 DIRF in Money and Financial Markets to a 1% MRO rate reduction



Note: EMP denotes expansionary monetary policy IRF +1Q represents the response of the variable to a reduction of 1% in the MRO rate after one quarter (red line). IRF +2Q and IRF +1Y represent the response after two quarters and after one year respectively.

Fig. 2.5 DIRF in the real economy to a 1% MRO rate reduction



Note: EMP denotes expansionary monetary policy IRF +1Q represents the response of the variable to a reduction of 1% in the MRO rate after one quarter (red line). IRF +2Q and IRF +1Y represent the response after two quarters and after one year respectively.

of the money supply, as a consequence of lower rates, met its mission. Between August 2007 and late 2012, the liquidity risk was reacting more in the short term than in the long term, but after 2012 the response remains unchanged in after one year.

Thus, combining the responses of both variables, we find that during the first wave of the crisis, dated between August 2008 and mid-2012, the expansionary monetary policy did help to reduce banks' incentives to accumulate reserves in the short run, but it did not in the long run, which resulted in moderate effects on the liquidity risk. However, after mid-2012, the new rate reduction made banks start to reduce the volume of reserves and releasing liquidity into the system, and the liquidity risk improved, especially in the long run. Although, did this new liquidity increase the lending performance?

In terms of the lending activity, financial and credit institutions (FCI) do not seem to respond to monetary policy strongly. The loans to financial and credit institutions (FCI) seem to positively react to the central bank intervention during the sovereign crisis. However, this effect could be related to the unconventional monetary policy and asset purchase programmes (bonds, securities, public and corporate sector). By contrast, loans to non-FCI show how the monetary policy can have ambiguous effects. Before 2007 an increment the lending activity was followed after a reduction in the interest rates. From 2007 to 2009, 2007 great recession, loans to non-FCI were negatively reacting to the monetary expansion, and since 2009 does not seem to have effects. This response during the great recession is one of the transmission channels to the real economy since this variable is capturing loans to non-financial firms and households.

Regarding the liquidity risk, monetary policy is effective by reducing the risk in tight money times. However, and as stated before, it could be affected by the unconventional monetary policy, since it overreacts during the sobering debt crisis.

Figure 2.5 (pp. 46) shows the effects of an expansionary policy, a reduction of 1% in the MRO rate, on the real economy. The effects on the labour market are apparent, Figure 2.5.A, and an expansionary monetary policy would increase unemployment since 2006. This result explains the effects on wages, which has been pushed down since 2009 - see Figure Figure 2.5.B. This dynamics in the labour market would be related to the performance of non-FCI and investments. Given that both variables were negatively affected in this period, firms' capacity to open new vacancies or demand of new worker has been reduced in recent years. However, the effects on the nominal adjustment via salaries have recovered in the short run since mid-2012, becoming neutral in the long run.

Regarding the aggregate production, the effects on the GDP before mid-2005 and after 2009 of an expansionary monetary shock has the predicted sign by the models in any macroeconomic textbook. However, it produced adverse effects on the aggregate production from mid-2005 until the most profound moment of the great crisis. Indeed, interest rates have not had effects on the GDP since 2007. This fact is related, but not as an effect, with the dynamics in the labour market. However, after 2009 the effects have turned positive and even stronger than in the period before mid-2005, becoming again weaker during the sobering crisis.

The empirical evidence suggests that unemployment increases and GDP decreases during the expansionary monetary policy after the crisis. The result is a consequence of the lousy performance of the MTMs during the crisis. First, the interest rate channel might not have been responding as good as in low-risk environments. We would expect an overall reduction in all interests rates following a reduction of the MRO rate. However, in a context of financial risk, financial and credit institutions adjust less than proportionally their rates, creating a larger gap for profits. Second, in the context of the bank lending channel, uncertainty and liquidity risk reduce the incentives that banks have to perform lending activities. Both effects, via interest rates and lending activities, sharply reduce the level of investments and results in very low aggregate demand with: *i*) high unemployment, *ii*) low output and *iii*) lower prices. Thus, financial conditions determine the effectiveness of monetary policy (in terms of output and price stabilisation). This explanation should not be understood as if the effects of the monetary policy are offset by a deep contraction of the privet sector, but as rupture of the relationship between a central bank and the financial markets that has severe consequences in the real economy.

Finally, in term of inflation, Figure 2.5.D shows that the DIRF suggest a price-puzzle. It could be due to a misspecification of the empirical model or that there are not enough variables capturing the dynamics of prices. However, inflation has been reacting in the same direction since mid-2003, changing its intensity, in terms of the size, of the effects. Note that this result suggests that the ECB is unable to control inflation, result in line with some studies. However, as we anticipated in the previous paragraph, the rupture of the link central bank - financial markets would explain this result.

2.5 Conclusions

In this chapter, I provided empirical evidence that suggests that the MTMs, and in particular the credit channel, changes over time. Some rigidities emerge in the effects of the traditional monetary policy on the economy, due to financial stress. Unlike the conventional and static view of the MTMs, I find that the credit channel is more complex and exhibits complex dynamics that must be considered by policymakers. These results are in line with those found by other authors examining the same question in other countries, such as the United States, the United Kingdom or Germany.

As this chapter shows, monetary policy interventions can have different effects over time, and this ambiguity can lead to non-optimal interventions by the ECB. While ECB's motivation is price stability after the great recession different packages were implemented to rescue the real economy. More specifically, and as a derivation from the results in Chapter 1 and 2, the decreasing trend of the monetary policy effects could be explained as a consequence the servitisation. In this chapter, I find that the effects of the monetary policy change over time, and it seems that they have a decreasing trend. If we complement these findings with those obtained in chapter 1, we could extrapolate that the servitisation is changing the sectoral structure of the EA, and given that this growing sector has a weak link with conventional monetary policy, the effects of conventional monetary policy on the real economy would be expected to be less significant over time - in terms of output and unemployment stabilization. This hypothesis is supported in this chapter, and it is in line with similar studies in the field of time variation of the monetary policy effects, opening the door to a new policy debate about the effectiveness of a central bank in the context of sectoral structural changes. However, this also motivates the research on new monetary policy tools to offset this no-new trend.

Concerning this analysis, an interesting debate arises: *the ceteris paribus analysis* and its implications in policy design. While central banking in the Eurozone has been driven by VARs analysis, the assumption of *ceteris paribus* implies that the European Central Bank is assuming constant the effectiveness of its policy. However, we provided empirical evidence against this idea, showing the existence of different performance of the MTMs.

An interesting way to improve this analysis would be introducing the unconventional monetary policy, such as the APP programme by the ECB, as a second tool of the monetary policy. However, this is a complex task, since the identification scheme of the effects would be more complicated.

Chapter 3

SPEI's diary: econometric analysis of a dynamic network

This chapter is coauthored with Biliana Alexandrova-Kabadjova, from Banco de Mexico, and has been published as Gavilan-Rubio, M.A. and Alexandrova-Kabadjova, B. (2018): "SPEI's diary: econometric analysis of a dynamic network", Journal of Financial Market Infrastructures, vol. 3, No. 2/3, pp. 93-119.

Introduction

Financial market infrastructures (FMIs) constantly evolve into more complex dynamic systems. Globalization, financial innovation and new means-of-payment adoption push the day-to-day performance of payment systems to their limits, with the result that all are continually seeking new ways to assist consumers and businesses in how to make financial transactions. For instance, our once cash-based society is crossing a digital frontier of mobile platforms (eg, Apple Pay, Android Pay), and new players are similarly performing traditional functions (eg, PayPal, Square). In the latter case, systems such as bitcoin are attempting to find alternatives to the existing payment arrangement. Beyond these examples, the market of payment services is more dynamic than ever.

The dynamics present a constant challenge to central banks in their exercise of liquidity provision. As these systems have grown and incorporated new technologies, the rules and standards governing them must evolve to accommodate such advances. In this way, understanding the determinants behind these dynamics helps policy makers to design better policies that ensure payment-system integrity as well as identify any effect among participants. This ensures that all participants have the same incentives and prevents anomalies as a result of government policies that apply to some players but not others.

The real-time settlement payment system in Mexico, known by its Spanish acronym SPEI, has experienced important changes since its birth in August 2004. It grew at an average of 9.8% per year in nominal volume and at an average of 47.4% per year in number of payments between 2005 and 2015. The number of participants has increased from 24 to 130, and it now spans not only credit institutions but also brokerages, nonbank financial institutions and other FMIs. All of these changes affect the dynamics of the system as well as participants' intraday liquidity management. The dynamics prompt the correct operation of the payment system, while the intraday liquidity management determines liquidity pressure.

These elements are just some of the challenges that FMI authorities have to deal with in order to ensure the stability of the system. A retrospective assessment of the dynamic network and its effects on intraday liquidity management must be carried out to help policy makers understand the implications of their decisions. A question arises: what forces drive the dynamics in SPEI?

This chapter seeks to pin down the determinants of SPEI's dynamics between 2005 and 2015. Our hypothesis is that network metrics are behind it. As we have said, payment systems are affected by globalization, financial innovation and means-of-payment incorporation, and changes to those three elements embody changes to the value and number of payments traded in those infrastructures. In this way, values and quantities are a result of market forces, and network metrics can be read as indicators of these forces. Let us give an example using the degree centrality in a three-participant payment system. This metric is defined as the number of links incident upon a node. In the case that one participant, say A, implements a new successful means of payment, we expect that it increases the number of payments toward the other two participants, B and C. A's degree centrality would increase along with the system's centrality. However, we also expect a weaker competitive system as a result of A's new comparative advantage, and effects on system growth are uncertain given the effects on other metrics. Thus, network metrics mirror market structure in a payment system and affect its dynamics.

We use a time-varying coefficients factor-augmented vector autoregressive model (TVC-FAVAR) to test our hypothesis and answer our question. A FAVAR model and its variants describe dynamic systems based on the underlying forces driving a system, which are known as the factors that explain the behavior of a system. The time-varying specification also allows testing for structural changes, which are the conditions that occur when a market changes how it functions.

We follow a two-step strategy to test our hypothesis. First, we fit the TVC-FAVAR model to the empirical data, obtaining the underlying dynamic factors and the loadings (participants' reactions to the factors). The data set contains the daily network of payments in SPEI between August 14, 2004 and June 30, 2016, but we present the results for the period January 2005-December 2015. The second step is factor identification, in which we regress the dynamic factors on the network metrics. Significant coefficients in this step imply that network metrics explain the performance of the forces driving the dynamics, which supports our hypothesis.

The main contribution of this chapter is to apply, for the first time, econometric methods in order to identify the network metrics as forces driving a payment system. This approach expands the concept of controllability introduced by Galbiati et al. (2013) and implemented in Galbiati and Stanciu-Vizeteuz (2015). While both papers identify the relevant nodes as a set with the ability to influence all other nodes, leading the network to a particular configuration or state, we alternatively propose that the network metrics of the whole system are the forces driving such dynamics.

The second innovation of this chapter is to show the behavioral implications of our approach for liquidity management. This novelty seeks changes in the use of two funding resources as a response to changes in the forces driving the system. These funds are identified following the algorithm introduced by Alexandrova-Kabadjova et al. (2015) and are defined as (i) reused payments, incoming payments used for covering new outgoing payments; and (ii) external funds, participants' funds received from liquidity-provision channels outside the large-value payment system (LVPS). Thus, we show the changes in the composition of both resources as a result of changes in the network metrics.

We find that five factors drive the (Mexican) payment system, two of them most significantly, and that their performance is explained by network metrics. Factor 1 measures the system trend and is affected by market structure conditions. Factor 2 is an indicator of system stability (the inverse of liquidity pressure). Moreover, we verify changes in the performance of the system and the response of the participants to such changes.

The remainder of this chapter is structured as follows. Section 3.1 presents a brief literature review. Section 3.2 describes the evolution of the overall dynamics in SPEI, taking into account the external funds and reused payments. In Section 3.3, we present the methodology to answer our research question and identify the determinants driving the dynamics in SPEI. Section 3.4 shows the factor identification results and the behavioral implications for liquidity management. Finally, in Section 3.5, we present our conclusions and some potential future extensions of this line of research.

3.1 Literature Review

The aim of this chapter is to identify the forces that are driving SPEI. This question is intrinsically related to the concept of controllability. This section provides an overview of the main studies dedicated to analyzing the concept. We also extend this section with the main studies dedicated to analyzing bank-funding patterns in liquidity management, since we show the implications of the driving forces in reused payments and external funds. Finally, given our transactional analysis, we also discuss topics related to FMI (data) analysis.

According to control theory, a dynamical system is controllable if, with a suitable choice of inputs, it can be driven from any initial state to any desired final state with infinite time - see Kalman (1963), Luenberger (1979) and Slotine and Li (1991).

Liu et al. (2011) develop analytical tools, based on nodes' weight identification, to study the controllability of an arbitrary complex directed network, identifying the set of driver nodes with time-dependent control that can guide the system's entire dynamics.

The authors find that the number of driver nodes is determined mainly by the network's degree distribution and show that sparse inhomogeneous networks, which emerge in many real complex systems, are the most difficult to control. However, they can be controlled using a few driver nodes; counterintuitively, Liu et al. (2011) discover that in both model and real systems the driver nodes tend to avoid the high-degree nodes.

While these authors set the analytical framework using the characteristics of real networks, such as trust in college students and prison inmates, Galbiati et al. (2013) suggest the same analytical framework in payment systems and interbank lending markets. Galbiati et al. (2013) describe TARGET2 (T2) by means of classic network measures and apply these methods to uncover two additional features of T2: driver nodes and communities.

By looking at T2 drivers, Galbiati et al. (2013) were able to single out banks that might have a dominant influence on systemic liquidity flow. These authors focus on the largest eighty-nine banks in the system, and they are able to single out thirteen banks, which would not have all been detected by looking at bank size or other centrality measures.

While previous papers identify the controllability of the system through driver nodes, we propose a different approach. We use network metrics as external regressors of the underlying forces, which are first estimated using econometric methods. Thus, the definition of driver nodes is not excluded in our approach, since system network metrics are driven by participant weights.

Our study also examines the implications of network metrics changes in liquidity management and funding patterns. The concept of reused payments, and external funds as its complement, is based on the liquidity game among banks. Bech and Garratt (2003) examined banks' intraday behaviors in a game theoretic framework for the case of two players. Their paper models intraday settlements as two-stage games in which each player basically determines whether to make a payment early or late. Under a different regime, these authors find that both early and delayed payments are possible equilibriums. However, for certain levels of delay and liquidity costs, participants might be in a prisoner's dilemma, in which the dominant strategy for both is to delay payments.

Becher et al. (2008) investigate the factors influencing the timing and funding of payments in the CHAPS sterling system. Their results show that participants in CHAPS sterling often use incoming funds to make payments, a process known as liquidity recycling.

The authors explain that liquidity recycling can be problematic if participants delay their outgoing payments in anticipation of incoming funds. Their analysis of CHAPS payment activity shows that the level of liquidity recycling, though high, is stable throughout the day. This is a consequence of (i) the settlement of time-critical payments in CHAPS supplies liquidity early in the day, (ii) the sterling system throughput guidelines providing a centralized coordination mechanism that essentially limits any tendency toward payment delay, and (iii) the relatively small direct membership of the system facilitating coordination, enabling members to maintain a constant flux of payments during the day.

Diehl (2013) addresses the question of how free-riding in LVPSs should be measured properly. He developed several measures for identifying free-riding. His study shows that a combination of at least two measures is recommended for capturing the effects of free-riding. Based on nine important banks in the German part of T2, free- riding was measured at the single bank level. The evaluated measures show stable payment behavior of most of the participants over time. However, some remarkable regime shifts were observed.

Massarenti et al. (2012) studied the intraday patterns and timing of all T2 interbank payments. They provide insight into the intraday patterns of T2 payments and into the evolution of settlement delay. Their analysis provides a system-wide view and can be used by operators and overseers of central banks. One of their results indicates that in terms of the numbers of payments processed, the first hour and a half is the most critical time during the system's operating hours, whereas the last hour is crucial in terms of value of payments.

Heijmans and Heuver (2014) study the T2 transaction data in order to identify different liquidity elements. They develop a method to identify liquidity stress in the market as a whole and at the individual bank level. The stress indicators look at liquidity provided by the central bank (monetary loans), unsecured interbank loans (value and interest rate), the use of collateral and payments on behalf of their own business and that of their clients. In the case of Mexico, two simulation studies have been conducted by Alexandrova-Kabadjova and Solís-Robleda (2012) and Alexandrova-Kabadjova and Solís-Robleda (2013) to analyze the settlement rules of SPEI and the liquidity management of commercial banks that are direct participants.

These authors study the behavior of the selected financial institutions related to the reuse of incoming payments. They find that despite the growing volume of low-value payments processed in real time through SPEI, settlement is performed efficiently. Further, the authors argue that, according to the observed patterns in commercial banks' intraday behavior, there are particular hours in which low-value payments are preferably sent.

What these papers have in common is that they use transaction-level data from a payment system, FMI or real-time gross settlement (RTGS) system. However, they do not look at operational level per type of direct participant.

In the next section, we present a description of SPEI performance, in aggregate and at the level of funding patterns.

3.2 SPEI's diary: dynamic evolution

As mentioned, SPEI has experienced significant growth since its birth in August 2004. It grew at an average of 9.8% per year in nominal volume between 2005 and 2015, 5.8% in real terms, assuming the consumer price index as a proxy to the deflator of payment services.[1] The value of total payments in 2005 was 247.5% of the Mexican gross domestic product (GDP), increasing to 335% in 2015.

[1] We exclude 2004 in the calculation of the rate because SPEI was not operating the whole year.

The change in the size of the infrastructure is the result of different elements, such as more direct participants operating in the system and the inclusion of new types of participants. These elements, among some others, have been affected by changes in the regulatory framework, changing the SPEI ecosystem and liquidity management. In this section, we present the changes in the organizational scheme of SPEI and the main dynamics in the funding patterns of liquidity management.

3.2.1 SPEI organizational scheme

The present study focuses on identifying the dynamics of SPEI. This system, alongside the Swiss interbank clearing (SIC) and Turkish RTGS (TIC-RTGS) systems, is among the few examples worldwide of RTGS systems being used to simultaneously settle both large- and low-value payments. The SPEI organizational scheme refers to three aspects of the system's connectivity: direct participants, FMIs and the liquidity provision mechanism.

SPEI started operations on August 13, 2004 and was meant to substitute SPEUA, a Mexican RTGS system that had been processing large-value payments since 1994.[2] Since August 19, 2005, SPEI has been the only system settling all-size direct credit electronic payment transactions in real time. This condition has led to the development of new intraday-liquidity-management skills required to deal with the challenge of settling low-value payments in real time. Parts (a) and (b) of Figure 3.1 (pp. 58) show the organizational scheme of SPEI in 2005 and 2015, respectively.

Banco de Mexico (BdM) uses two channels to provide liquidity to commercial banks, development banks and brokerage houses. The first channel is via collateralized overdrafts and is available to participants with accounts in SIAC.[3] The second is through repurchase agreement (repo) transactions using a computational module known as RSP, which is specifically designed for settling these operations.[4]

Several changes in the regulatory framework of the Mexican FMIs took place in 2008. The Mexican peso (MXN) was incorporated into the set of currencies that the continuous linked settlement (CLS) system operates in on foreign exchange markets.[5] A direct connection was established between SPEI and CLS. Later, the authorities

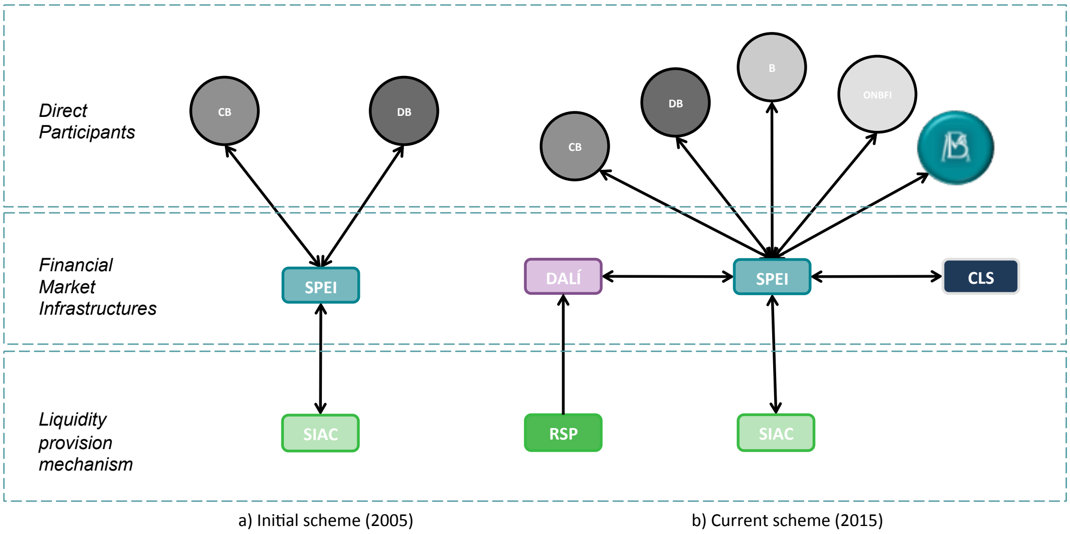
[2] "SPEUA" is the Spanish acronym for the extended-use electronic payments system.

[3] SIAC is the system in charge of managing the accounts of commercial and development banks, brokerages and government entities that by law should have an account at BdM. This system is operated by the central bank and provides liquidity to the FMIs in Mexico.

[4] Repos and overdrafts should be fully collateralized. The rules applying to commercial banks are established in numeral M.73 of circular 2019/95 (repealed by circular 3/2011); the rules followed by development banks are given in numeral BD.51 of circular 1/2006, whereas numeral CB.2 of circular 115/2002 establishes the rules on brokerage houses.

[5] CLS operates under the payment versus payment (PvP) scheme.

Fig. 3.1 Organizational scheme of SPEI.



introduced a new security settlement system, known as the DALÍ, which operates under the delivery versus payment (DvP) scheme.[6] Since then, participants that have access to DALÍ and SPEI have been allowed to transfer funds to their own accounts from one system to the other. Finally, nonbank financial institutions were allowed direct access to SPEI but with no access to the intraday liquidity provided by the central bank.

Regarding the participants, they are allowed to make fund transfers and payment obligations on their own behalf or on behalf of a third party (clients). In 2005, direct participants in SPEI were only private multiple-purpose banks (CBs) and public development banks (DBs). Both groups are credit institutions and have current accounts in the SIAC. However, since 2008, four groups of direct participants in SPEI have been identified:

i) private multiple-purpose banks (CBs),

ii) public development banks (DBs),

iii) brokerage houses (Bs), and

iv) other nonbank financial institutions (ONBFI).

Further, DALÍ and the CLS system are FMIs connected to SPEI.

[6] This FMI replaced the interactive system for securities depository (SIDV) in November 2008.

3.2.2 Funding patterns and liquidity management in SPEI

he changes in the organizational scheme of SPEI affect the funding patterns and the liquidity management of the participants in the system. Over 90% of the overall volume processed is considered to be low-value payments, and given that the system operates as an RTGS scheme, low-value payments push up the liquidity pressure.[7] Participants with direct access to BdM liquidity assess the funds needed to settle their obligations throughout the day in advance. Then, based on their pre-assessment, they transfer funds from their accounts in SIAC to their accounts in SPEI, and they use their accounts in SPEI to settle payments during the day.

Following the algorithm proposed in Alexandrova-Kabadjova et al. (2015) and using transactional data from SPEI, we can distinguish between two funding resources: (i) reused payments, or incoming payments used for covering new outgoing payments; and (ii) external funds, or participants' funds received from liquidity-provision channels outside the LVPS. The settlement process in SPEI is organized through cycles, and the authors develop an algorithm based on the date of these settlement cycles.

The algorithm works as follows. Let $\mathscr{L}$ be the set of participants in the system, and let $\mathscr{T}$ be the set of cycles in one day. We denote the sum of the incoming payments as $P^{rec}_{i,t}$ and the sum of the outgoing payments as $P^{sent}_{i,t}$ by each $i \in \mathscr{L}$ and in each cycle $t \in \mathscr{T}$, respectively. We define the difference between these two amounts by participant in each cycle $t \in \mathscr{T}$ as:

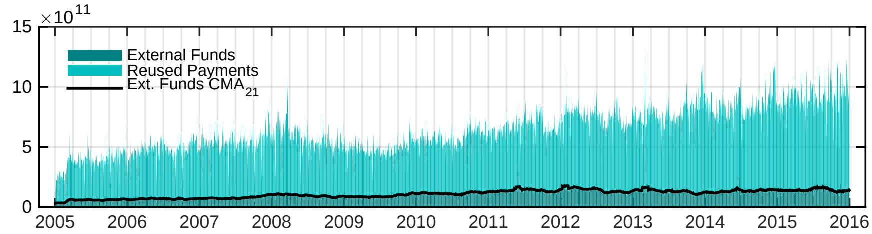
$$A_{i,t} = P^{rec}_{i,t} - P^{sent}_{i,t} \tag{3.1}$$

Let S_i be the positive balance resulting from aggregating the value of $A_{i,t}$ for each $t \in \mathscr{T}$, given that $S_i = 0$ for all $i \in t_1$. We denote F_i as the sum of funds each $i \in \mathscr{L}$ has to spend in those cycles, in which $S_i \leq 0$, given that $F_i = 0$ for all $i \in t_1$. And in this way, thanks to the register of the cycles, both resources can be observed.

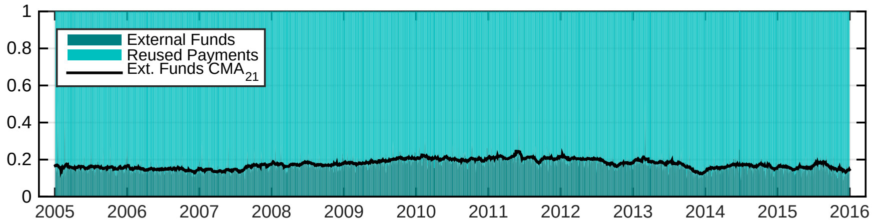
Figure 3.2 (pp. 60) illustrates the use of external funds and reused payments for commercial and development banks in SPEI. Figure 3.2(a) shows the levels of external funds, reused payments and a twenty-one-day moving average of the external funds. Figure 3.2(b) shows the performance of the same funds as a ratio. In aggregate terms, the external funds ratio has followed a relatively stable path. It has been fluctuating around 20%. We observe that in the first period between 2005 and 2007, external funds are stable. This fact is related to the stable growth of the number of payments. We also observe that the external-funds-to-total-payments ratio is around 15%. After this period, we observe a reduction in the number of payment transactions,

[7] If we compare that scheme with a deferred net settlement scheme (DNS).

Fig. 3.2 SPEI 2005-15: funding patterns.



(a) Total payments in the banking system (Mexican new pesos).



(b) Proportion of funds (with respect to 1).

without significant changes on the level of external funds. During this period (2008 to mid-2010), the external funds ratio was around 19%. Between July 2010 and August 2011, we observe strong growth of the payments and an increment in the level of external funds used to cover participants' obligations. Consequently, the proportion of external funds on average during this period is 21%. In the period between September 2011 and June 2013, the volume of payments remained at the same level, and the external funds ratio was 19%. Finally, for the period between July 2013 and December 2015, a new rise in the volume of payments is observed. Nevertheless, the average proportion of extra funds used has fallen to 16%.

3.3 Methodology: Econometric Analysis

As stated, we attempt to identify the underlying forces driving SPEI, and we point to network metrics as the driver of the dynamics in this system. We use a two-step strategy to test this hypothesis. In the first step, we estimate the underlying dynamic factors driving the system. To this end, we estimate a TVC-FAVAR model with the time series of participant payments. As a result, we obtain an unbiased estimation of the dynamic factors and the participant responses to the factors (these are known as loadings).

In the second step, we regress the estimated dynamic factors on eight different network metrics. We use a variant of a time series regression, a seasonal autoregressive integrated moving average with exogenous variables (SARIMAX) model. If the coefficients in these regressions were significant, network metrics would explain the behavior of the estimated dynamic factors, supporting our initial hypothesis.

In this section, we present a detailed description of the data set and methodology implemented to test our hypothesis.

3.3.1 The data

The payment system data is constructed in the following way. The initial database contains the daily transactional payments from August 13, 2004 to June 30, 2016. First, we create an aggregate daily network of payments. This network compounds the bilateral transactions among sixty-four participants over 2983 days. With this network, we calculate the network metrics of the system as a time series.

Second, we aggregate the daily network of payments by participants, ie, we create a panel with the total sent payments by participant over 2983 days (190912 observations). We use this panel to estimate the TVC-FAVAR model and obtain the dynamic underlying factors.

As mentioned, we are interested in showing the implications of this factor analysis in liquidity management. To that end, following Alexandrova-Kabadjova et al. (2015), the external funds and reused payments are distinguished from the initial database (the transactional data). Therefore, and as a result of the algorithm, we finally have three panels: the total payments, the external funds and the reused payments, for sixty-four participants over 2983 days (in Mexican pesos).

The three panels as well as the daily networks have the same participants. There are sixty-two direct participants, of which fifty-seven are commercial banks, four are development banks and one is BdM. There are also two FMIs with accounts in SPEI: DALÍ and the CLS system.

3.3.2 Step 1: econometric framework of the dynamic factors

SPEI can be assumed to be a dynamic system. This is based on the idea that there exists a relationship that describes a time dependence in the set of participants, or, alternatively, a network whose status changes over time. These changes refer to the evolution of the payments among participants, the ability to create subgroups and the structure of connections among them. SPEI as a dynamic system accepts the following state space representation:

$$X_t = \Lambda F_t + \varepsilon_t. \tag{3.2}$$

$$F_t = \Phi(L) F_t + \nu_t \tag{3.3}$$

Equation (3.2) states that X_t, a vector with N total payments[8] at time t, is a linear combination of F_t, the underlying factors at the same time t. The factors represent the state of the world, and they fully describe the system and its response to any given change.[9] Thus, they behave like an engine driving SPEI. Λ is the loading factor and reflects the response of the payments to the unknown factors. Equation (3.3) represents the dynamics of the underlying factors as difference equations.[10] $\Phi(L)$ denotes a polynomial of a lag operator of order L, ie, it produces the Lth previous elements of F_t.[11] Note that this specification assumes linearity.[12]

FAVAR models can be used to estimate dynamic systems. The main advantage is based on the fact that it exploits a large set of economic information, and particularly for this case, a large number of participants. This data-rich environment results in a more extensive analysis, as it allows us to isolate the effects of the factors on a vast number of different variables at the same time. The model results in a consistent estimation of the dynamic factors and loadings when N grows faster than $T^{0.5}$ - see Bai and Ng (2006).[13] As argued by Stock and Watson (2002) and Banerjee et al. (2008), the factors are still estimated consistently even if there is some time variation in the loading parameters. Thus, TVC-FAVAR represents a suitable framework for estimating the dynamic system and analyzing empirical micro-effects.

The reader could argue against this methodology due to the difficulties in understanding the meaningless factors or the possible bias as a result of unbalanced panels. The meanings are not crucial from the perspective of a dynamic system that is mainly focused on predicting the performance of the system. Despite this advantage, we carry out a factor-identification in the second step of our strategy. The effects of unbalanced panels are mitigated under the assumption of large data sets: as stated, we work with panels with 2983 periods of observations.

[8] One for every participant.

[9] The data contained in X_t is usually transformed to induce stationarity. However, we only standarize the data. Barigozzi et al. (2016) and Barigozzi and Luciani (2017) show that under some mild conditions and with N and T going to infinity, a dynamic factor model following Stock and Watson (2002) methodology is consistent.

[10] In our case, it follows a vector-autoregressive process.

[11] We can expand this polynomial as $\Phi(L)F_t = \Phi_1 F_{t-1} + \Phi_2 F_{t-2} + \ldots + \Phi_L F_{t-L}$.

[12] Nonlinear dynamic systems are known as chaotic systems. They are ruled by chaos theory and are highly sensitive to initial conditions.

[13] In our case, $N = 64$ and $T^{0.5} = 54.62$.

Moreover, we introduce the time-varying coefficients, which implies that the effects of the factors may change across time. In other words, the dynamic system can evolve over time, which allows testing for structural changes to the system. The TVC-FAVAR model accepts an equation-by-equation (for every participant) representation and is given by

$$x_{i,t} = \lambda_{i,t} F_t + \varepsilon_{i,t}, \qquad \varepsilon_t \sim N(0, V_t) \tag{3.4}$$

$$f_{g,t} = \sum_{h=1}^{p} \phi_{g,h,t} F_{t-h} + \nu_{g,t}, \quad \nu_t \sim N(0, Q_t) \tag{3.5}$$

$$\lambda_{i,t} = \lambda_{i,t-1} + \omega_{i,t}, \qquad \mathrm{vec}(\omega_t) \sim N(0, W_t) \tag{3.6}$$

$$\phi_{g,t} = \phi_{g,t-1} + \eta_{g,t}, \qquad \mathrm{vec}(\eta_t) \sim N(0, R_t) \tag{3.7}$$

where the subindex i denotes each participant in SPEI; $x_{i,t}$ is the observable time series of participant i - total payments, external funds and reused payments - at period t; $\lambda_{i,t} = [\lambda_{1,i,t}, \lambda_{2,i,t}, ..., \lambda_{G,i,t}]$ denotes the factor loading; and $F_t = [f_{1,t}, f_{2,t}, ..., f_{G,t}]'$ denotes the underlying G factors driving the dynamic into the system at period t. Equations (3.6) and (3.7) show that the dynamics of the coefficients follow random walks, and they model the evolution of the responses to factors or changes in the behavior of the participants.[14]

Regarding the error terms, they are assumed to be Gaussian and are estimated recursively using simulation-free variance matrix discounting methods (see, for example, Quintana and West (1988)). We use exponentially weighted moving average (EWMA) estimators. These depend on two decay factors. Such recursive estimators are trivial computationally. In addition, the EWMA is an accurate approximation to an integrated generalized autoregressive conditional heteroscedasticity (GARCH) model. All variance-covariance matrixes are assumed to be diagonal.

The model is estimated by a two-step Kalman restricted estimation, following the procedure in Koop and Korobilis (2014). The algorithm is as follows.

1. Initial values:
   (a) obtain the principal components estimates of the factors $\hat{F}_t$.
   (b) initialize all parameters from the ordinary least squares static estimation of $\{\Lambda_0, \Phi_0, V_0, Q_0, R_0, W_0\}$.
2. Estimate the time varying parameters $\{\Lambda_t, \Phi_t, V_t, Q_t, R_t, W_t\}$ given $\hat{F}_t$:

[14] Thanks to this specification, one can analyze the causes of behavioral changes across time, for example, by regressing the dynamic slopes to the economic and financial characteristics of each institution.

(a) estimate $\{V_t, Q_t, R_t, W_t\}$ using variance discounting procedure.

(b) estimate $\{\Lambda_t, \Phi_t\}$, given $\{V_t, Q_t, R_t, W_t\}$, using the Kalman filter and smoother.

3. Estimate the dynamic factors $\tilde{F}_t$ given $\{\Lambda_t, \Phi_t, V_t, Q_t, R_t, W_t\}$ using the Kalman filter and smoother.

Note that $\Lambda_t = [\lambda_{1,t}, \lambda_{2,t}, ..., \lambda_{N,t}]'$ is a N-by-G matrix.

This empirical model is fitted for three SPEI unbalanced dynamic panels. First, we estimate the model for the total payments, keeping the factor loadings Λ_t and the dynamic factors $\tilde{F}_t$. Given that the total payments can be decomposed into the sum of external funds and reused payments, we estimate the model for both resources to analyze the implications for liquidity management using the dynamic factors from the total-payment model.

3.3.3 Step 2: network measurements and factor identification

Our hypothesis is that network metrics are driving the dynamics of the system. The underlying factors represent the engines driving the system, and as engines they need fuel to accelerate. However, they can slow down as a consequence of erosion and frictions. In order to identify the factors, we estimate a Seasonal Auto Regressive Integrated Moving Average with exogenous regressors (SARIMAX $(p,d,q)(P,D,Q)_s$) model for every underlying factor:

$$\nabla^d \nabla_s^D f_{g,t} = c_g + \sum_{k_1=1}^{p} \phi_{g,k_1} F_{t-k_1} + \sum_{m_1=1\times s}^{P} \Phi_{g,m_1} F_{t-m_1} + \gamma_g NM_t + \mu_{g,t} \tag{3.8}$$

$$\mu_{g,t} = \sum_{k_2=1}^{P} \theta_{g,k_2} \mu_{t-k_2} + \sum_{m_2=1\times s}^{Q} \Theta_{g,m_2} \mu_{t-m_2} + \zeta_{g,t}, \quad \zeta_{g,t} \sim WN(0, \sigma_g) \tag{3.9}$$

where subindex g denotes the g^{th}-factor, $f_{g,t}$ with $g = 1, 2, \ldots, G$; subindex s denotes the seasonal frequency and in this case $s = 5$ working days; ∇^d denotes the d^{th}-difference operator; ∇_s^D denotes the seasonal D^{th}-difference operator; c_g is a constant term; NM_t is a vector with external regressors and we include eight different network metrics at period t; and $\mu_{g,t}$ is an error term. Thus, the significance and sign of the coefficients show the effects in the dynamic of the system. Positive signs reflect earnings or acceleration, while negative signs represent losses or deceleration.

Regarding the external regressors, we calculate different network related with three concepts: centrality, structure and bilateral relationships within the network.[15]

We use three different centrality measurements (out-degree centrality, out- eigenvector centrality and harmonic distance) that capture the involvement in the cohesiveness of the network as a system. A highly centralized network is dominated by one participant who sends or receive more payments, while a less centralised network has most participants interconnected. Thus, centrality should capture market structures related with the competition, where a high centrality represents an oligopolistic competition, and a low centrality represents a more competitive market. While out-degree centrality measures the direct links each participant has to others, out-eigenvector centrality measures how connected a participant is and the direct influence it might have over other connected participants in the network. The harmonic distance captures how close a participant is to all the other participants in the system.

Regarding the structure, we use two different metrics to measure the structure of the network, community structure and clustering coefficient, that capture the degree to which participants in a network tend to congregate together. While the community structure measures if the participants of the network can be grouped into sets of participants such that each set is densely connected internally, the clustering coefficient measures how participants tend to cluster together. Both metrics have a similar tone, but they differ in the level of aggregation. While the community structure focuses on the system as a whole community, the cluster clustering coefficient tries to find the number of small cohesive communities in the system.

Finally, we use three metrics to measure bilateral relationships in the system. In particular, we use reciprocity and propose two new metrics, relative net-trade value and reactivity, to provide a measure of the quality of the bilateral relationships and its relative importance in the network. Reciprocity measures the likelihood of participants to be mutually connected in the system. Relative net-trade value attempts to measure how asymmetric the bilateral relationship is, considering the value of the flows. Also, we develop a new measurement, called apparent reactivity, which attempts to capture the responsiveness of sent payments to incoming payments. More specifically, we define apparent reactivity as the incoming payment elasticity of sent payments.

In the next section, we explain the results of the factor identification and their implications for liquidity management.

[15] See Appendix D (pp. 99) for a detailed description of the metrics and their calculations.

3.4 Empirical results

We fit a TVC-FAVAR model with five factors and six lags.[16] That specification explains more than 95% of the system variance, ie, any linear combination of the five dynamic factors explains above 95% of the variability of the participants in the system.

3.4.1 Network measurements as engines of the dynamic

The dynamic factors represent the common trends in the system. The main factor reflects the aggregate dynamic in the system, as we can see in Figure 3.3.[17] However, the rest of the factors identify complex interrelationships among participants that are part of different concepts. The interpretation of these concepts can be abstract because of the topology behind the factor method. For example, they can mean simple concepts, such as weight or length, as well as more complex measurements, such as the moment of inertia. In our case, we can state that network metrics explain a large fraction of factor behavior.

We select eight out of eighteen different network measurements to identify the underlying factors of the system. On the one hand, we drop ten measures because they are strongly correlated with the selected ones. They would create multicollinearity problems in the identification of the contributions. Thus, the other ten network measurements do not provide substantial new information. On the other hand, the eight selected measurements capture different properties of the network. In particular, they measure centrality, distance, clustering and bilateral relationship. Table 3.1 (pp. 69) shows the results of the factor identification made with an equation-by-equation SARIMAX $(1,1,1)(2,0,1)_{5\text{ days}}$ model.

Factor 1 identifies the common stochastic trend driving the nonstationary series of payments. This implies that SPEI has an evolutionary direction. It could be understood as the aggregate trend of the system. The empirical evidence suggests that changes in centrality, network structure and bilateral relative net-trades drive the changes in the dynamics. Thus, changes in the trend are the result of changes in the market structure's conditions.

According to Table 3.1, centrality negatively affects the aggregate dynamics. Let us think in terms of two extreme cases: a fully connected payment system versus a

[16] We determine the number of factors with the eigenvalue ratio test, as in Ahn and Horenstein (2013). We estimate the factors using principal component (PC) analysis. We calculate the PC on the covariance matrix of the standardized and seasonal-adjusted series. We determine the number of lags equal to 6 using the Bayesian information criterion (BIC); see Schwarz (1978).

[17] See Appendix D (pp. 99) for a detailed description of the measures and their evolutions.

star-structured one. In the first case, every participant can send and receive payments from every participant. The star structure forces the participants to use the central participant as intermediary. The velocity of the payments would increase in the fully connected system, and it would drop in the star structure. Thus, SPEI would maximize the velocity of transactions under a cohesive system, ie, with no intermediaries.

Both the community-structure probability and clustering coefficient also support this result. They have a negative sign in their contributions to the inertia. The existence of microsystems slows down the aggregate dynamic of the system. In the context of payment systems, clusters prompt the members to face higher risk. If they are close to the rest of the system, they become more vulnerable, since codependent relationships can lead to liquidity constraints. Cluster banks trade less with non-cluster banks, and vice versa. Therefore, liquidity pressure increases, since access to reused payments is limited.

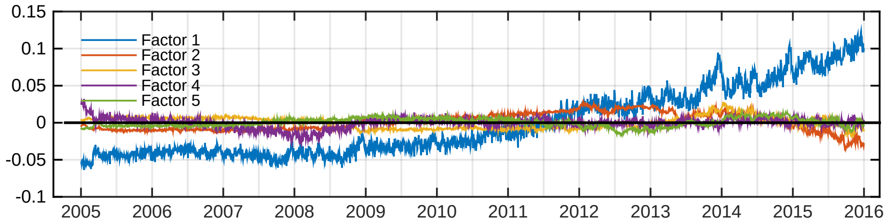
Moreover, the relative net-trade value (RNTV) shows a negative effect. This fact suggests that asymmetric bilateral relationships create resistance in the dynamics. A higher RNTV implies that participants do not send proportional payments with respect to those received. This creates asymmetries in the trade of payments. Funding problems arise when there are unbalanced relationships. For example, a small participant would require large use of external funds to meet its obligations. This slows down the liquidity flows, and therefore reduces the inertia of the entire system.

To sum up, changes in factor 1 are a result of adjustments to the market structure's conditions. Centrality, structure and RNTV capture the market positions on the network. As a result, the dynamics of the system can shift. Thus, the maximal growth rate of total payments would be achievable under a perfect competition scheme.

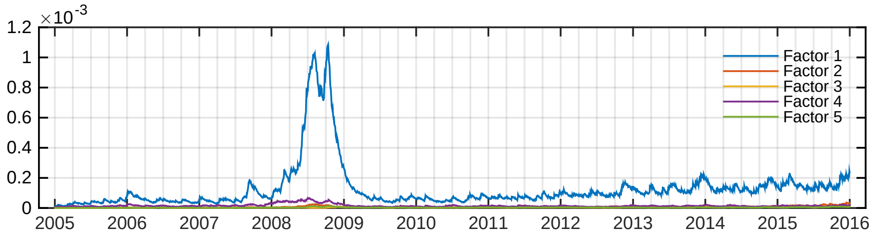
According to Table 3.1, factor 2 accelerates because of increments in centrality. In addition, bilateral relationships make it decelerate. Thus, factor 2 seems to be a measure of stability in the network structure. Well-connected and big participants give persistence and cohesiveness to the network. Removing any of these participants would increase demand for liquidity from the whole system.

By contrast, RNTV and reactivity erode the centrality effects. An asymmetric and very reactive payment system becomes less stable. This fact is due to the funding capacity and dependence on payments. On the one hand, asymmetric trade defines a structure of classes among participants. A participant with a large deficient trade faces self-liquidity pressure and needs external funds; but this is the mirror image of a surplus participant. Thus, there would be classes in terms of funding capacity. On the other hand, a reactive participant responds by changing outgoing payments in a way that is more than proportional to changes in incoming payments. However,

Fig. 3.3 SPEI 2005-15: dynamic factors.



(a) Evolution of dynamic factors ($\tilde{F}_t$).



(b) Evolution of dynamic factors volatility ($\tilde{Q}_t$).

this also implies a higher dependency, since incoming payments can represent an important fraction of the funds. More than proportional responses lead the system in explosive growth that is not adjusted for liquidity. This results in liquidity constraints and higher risk. The opposite is also true, however: less than proportional responses slow the system, resulting in excess liquidity.

Let us illustrate the performance of network stability measurement (NSM) with an example. Say participant A gets an advantage with respect to the rest, and it becomes more important than the rest in its centrality. It would start to exhibit a larger surplus trade, and the total system could grow. However, some other participants would react to this asymmetry. If the response is more than proportional, the system could explode or collapse. So, the only way to compensate for the centrality advantage and to control the system would be by reducing the reactivity. Thus, the stability of the payment system is driven by a fragile equilibrium between the centrality, asymmetry and reactivity of its participants.

The remaining factors have a less straightforward identification. Factor 3 seems to be capturing interactions among participants. It is affected by centrality, community structure, harmonic distance, reciprocity and reactivity. This cocktail of measurements could be capturing the system strength of participants' relationships. This measure would be an alternative approach and bring new meaning to the weighted network. Factor 3 would refer to a more abstract concept, the interconnectivity strength of the network. There can be inactive participants in the day-to-day trading

Table 3.1 Factor Identification in SPEI: SARIMAX $(1,1,1)(2,0,1)_{5\text{ days}}$

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Constant	-0.2273***	-0.0101	-0.0002	0.1195***	-0.0156***
	(0.04)	(0.01)	(0.00)	(0.01)	(0.00)
Out-Eigenvector	-0.1720***	0.0392***	0.0474***	0.0798***	-0.0184*
	(0.05)	(0.01)	(0.01)	(0.03)	(0.01)
Out-Degree	-3.5579***	0.2764***	0.2019***	1.2091***	-0.0808
	(0.24)	(0.07)	(0.06)	(0.13)	(0.05)
Harm. Distance	0.4586	0.0040	-0.0077*	-0.2067***	0.0254***
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)
Community	-1.4321***	0.0591	0.1310**	0.2680**	-0.0325
	(0.24)	(0.06)	(0.06)	(0.13)	(0.06)
Clustering	-0.0350***	0.0014	-0.0008	0.0161**	0.0004
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)
Reciprocity	0.0036	0.0007	0.0036***	-0.0085***	-0.0005
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RNTV	-0.0885***	-0.0130***	0.0017	0.0423***	-0.0054***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Reactivity	-0.0016	-0.0012**	-0.0016***	0.0003	-0.0002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Factor 1 (t-1)	0.9876***	-0.0057	-0.0008	0.0182**	-0.0074
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Factor 2 (t-1)	-0.0970	0.9858***	-0.0024	0.0712**	0.0462***
	(0.07)	(0.00)	(0.02)	(0.03)	(0.01)
Factor 3 (t-1)	-0.3106***	0.0545**	0.9679***	-0.0055	0.0657***
	(0.07)	(0.02)	(0.00)	(0.03)	(0.02)
Factor 4 (t-1)	-0.0504	0.0013	0.0474***	0.9613***	-0.0118
	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)
Factor 5 (t-1)	-0.0794	0.0470**	0.0651***	0.0077	0.9617***
	(0.07)	(0.02)	(0.02)	(0.04)	(0.01)
θ_1 (MA1)	-0.5691***	-0.3295***	-0.2278***	-0.5663***	-0.1964***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
Φ_1 (SAR1)	1.0746***	1.0869***	1.0664***	1.0568***	1.1006***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Φ_2 (SAR2)	-0.0757***	-0.0947***	-0.0887***	-0.0611***	-0.1163***
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Θ_1 (SMA1)	-0.9719***	-0.9574***	-0.9182***	-0.9587***	-0.9336***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)

Note: standard deviations between brackets. * represents significance at 10%, ** at 5% and *** at 1%. RNTV denotes relative net-trade value; $MA1$ denotes the moving average component of order 1; $SAR1$ and $SAR1$ denote the seasonal autoregressive component of order 1 and 2 respectively; and $MA1$ denotes the seasonal moving average component of order 1.

of a payment system. Factor 3 could measure whether participants were actively using the system with most of the rest of the participants.

Factor 4 seems to be the effect of most measurements in the payment system business cycle. It could measure the business cycle of the system. Note that it is not affected by reactivity, but it is affected by the trend of the system as well as the stability of the system (factors 1 and 2). Centrality, distance and RNTV affect factor 5. This suggests that it could be reflecting the evolution in the rate of change of payment velocity.

Thus, factor identification is crucial and moves network analysis to a new step. We find that the trend of the system is driven by network positions, that factor 2 measures the stability of the network and that factor 3 captures a sort of interconnectivity strength. Factors 4 and 5 have a more complex meaning. Once we know the meaning of the main factors, we can also analyze the structural changes in SPEI and the implications for liquidity management.

3.4.2 Behavioral implications and liquidity management

The TVC-FAVAR model allows us to check structural changes in the system. We differentiate between two kinds of changes. On the one hand, we have changes to the conditions of the system, measured through changes in the performance of the factors. We consider big changes in levels and volatilities. On the other hand, we have changes in the loadings or reactions to the factors, which are reflected by changes in $\lambda_{r,i,t}$. Given the large number of participants, we analyze the average participant's response and the funding breakdown, ie, the adjustment via external funds and reused payments.

Changes on the conditions of SPEI

We focus on factors 1 and 2, since they have the clearest meaning. As seen in Figure 3.3(a), we do not observe big changes in the levels of factor 1. However, its volatility reveals two clear structural breaks, as shown in Figure 3.3(b).

The first change captures the effect of new participants in the system. In particular, DALÍ, the securities settlement system in Mexico, experienced a change in performance in 2008. This affected the volatility of the trend. We could read this finding in two different ways. First, the increased volatility may be related to higher risk: in

this case, the risk would be associated with the uncertainty of a new "big" participant in the system and its impact on liquidity pressure. Following Barvell (2002), new participants should encourage competition among old participants in order to promote efficient and low-cost payment services. However, there could be a cost if these participants are other FMIs (DALÍs case). The introduction of a big FMI could result in excessive legal, financial or operational risks. In addition, as we extract from the volatility of factor 1, old participants perceived higher risk with the introduction of DALÍ.

Second, this break may be interpreted as an increase in the system's heterogeneity. Originally, there were commercial and development banks participating in the system. However, after some reforms in the regulatory framework in 2008, the heterogeneity of the participants increased: brokerages, other nonbank financial institutions, two infrastructures and BdM started to operate in SPEI. This change in the typology of participants resulted in a rise in system heterogeneity.

The second structural change reflects the effects of the 2007 financial crisis, which affected the Mexican economy one year later. It is represented by the highest peak in factor 1's volatility. Analogously to DALÍ's introduction, the financial crisis increased uncertainty in the financial market. Participants were unable to know for certain the quality of other participants' balance sheets. Thus, there were some tensions, which resulted in a convulsed period.

A third change in performance is shown by the constant growth in volatility that factor 1 exhibits from mid-2010 onward. The management of governmental payments through SPEI explains this trend. Payments to suppliers, transfers and taxes, for example, started to be executed in SPEI. Given their nature of nonregularity and volume, volatility has been increasing since then.

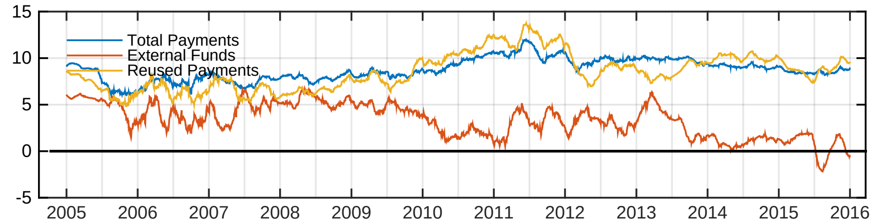
Thus, we find that the conditions of the system, measured by the volatility of the trend, change across time. The system is sensitive to diverse changes, and these affect the total system.

Responses to the factors

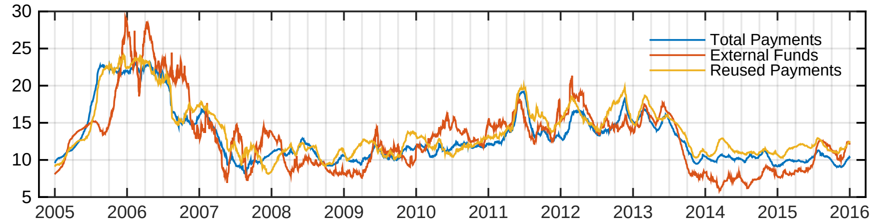
As we explained in Section 4, the empirical model estimates loadings or factor responses assuming time-varying coefficients: the evolution of $\lambda_{r,i,t}$. Under this specification, the response to a change in the factors is different across time. This means, for example, that an increase in the total volume of payments has different effects in the system today than it will tomorrow. In addition, as we segregate these effects by funding origin, we can analyze the adjustment process between external funds and reused payments.

We define "system effects" as the changes in the responses to factor 1, which reflect the main inertia of the system. We can observe these changes in parts (a) and (b) of Figure 3.4 (pp. 72). The first change we identify is the learning process during the early years of SPEI. We define this process as a transition period with a high heterogeneity in the response among participants to changes in the dynamics

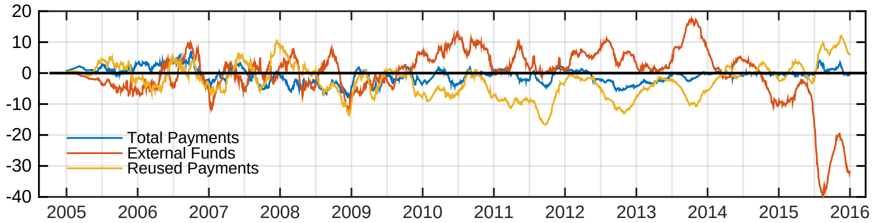
Fig. 3.4 SPEI 2005-15: responses to the factors.



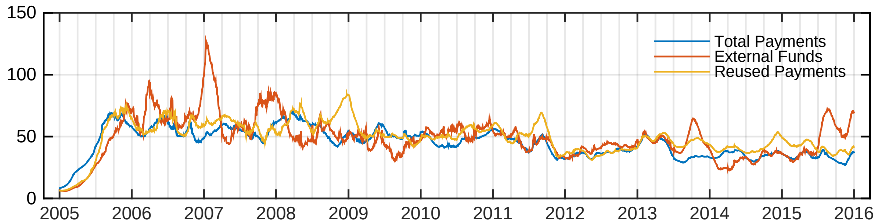
(a) Average response to factor 1 ($\tilde{\bar{\lambda}}_{1,i,t}$).



(b) Standard deviation among participants in response to Factor 1 ($s.d.(\tilde{\lambda}_{1,i,t})$).



(c) Average response to factor 2 ($\tilde{\bar{\lambda}}_{2,i,t}$).



(d) Standard deviation among participants in response to Factor 2 ($s.d.(\tilde{\lambda}_{2,i,t})$).

of the system. We establish this fact as the increment in the standard deviation of the responses in Figure 3.4(b); this reflects the diversity of the responses among the participants to factor 1. Thus, there is no common performance among the participants.

This pattern is also reflected in the evolution of external and reused funds. It implies that (i) the learning process did not only affect the decision to use one kind of fund and (ii) the participants were adjusting to each other. We can observe that external funds behave in a more unstable fashion than reused payments. This suggests that the use of external funds broadly responds to participants' decisions and not to adjustments to the system. Thus, participants are surer about the evolution of incoming payments and make excessive use of external funds.

However, reused payments behave in a more stable manner and are more synchronized with the system. Participants improve the expectation mechanism of incoming payments during the learning process. Thus, there is a trade-off between both funds: in other words, participants learn how to replace external funds with reused payments. This trade-off not only defines their individual strategies, but also affects liquidity pressure. An intensive use of reused payments can increase liquidity pressure, but it reduces the underlying cost of the external funds. Pricing policy in the payment system must ensure self-sufficiency via reused payments, financing payments without having to resort excessively to external funding sources. Participants learn this mechanism during the learning process.

After the learning process, the system remains stable until mid-2008. From mid-2008 until 2012, the variability in the responses to the trend grows. This reflects the adjustment of the banking system to the entrance of new participants. After this period of new participant proliferation, participants homogenize their responses, and the system remains stable. However, we observe that the responses of the external funds stabilize. This fact implies that participants become more efficient in their intraday liquidity management. They have a prior strategy in the use of incoming payments. The use of external funds responds less to changes in the dynamics. Thus, the empirical evidence suggests an improvement in the efficiency of SPEI.

System effects show that participants have learned to cover their intraday liquidity needs. As a result, participants have made their responses uniform. In addition, they have improved the use of external funds versus reused payments. Therefore, the system has become more efficient regarding liquidity pressure.

Stability effects are defined as the changes in the responses to factor 2, which reflect the stability of the network. The heterogeneity in responses has been decreasing since SPEI began, as we can see in parts (c) and (d) of Figure 3.4 (pp. 72). External funds and reused payments follow the same pattern: responses are becoming homogenous. This indicates that responses to changes in the stability of the system are relatively similar among participants, and their asymmetries, in terms of their responses, are lessening.

However, if we look at the funding components, we observe different behaviors. External funds and reused payments respond differently to changes in stability. Before mid-2009, both resources follow a nondeterministic trend, and there is no clear adjustment between them. After mid-2009, there is a long-run trade-off between them that goes on until mid-2014. As we saw in Figure 3.3(a) (pp. 68), factor 2 indicates high stability of the network during this period. High stability in the network makes reused payments decline and external funds increase. This reduces liquidity pressure. If liquidity pressure decreases, the system becomes more stable. However, given the opportunity cost of the external funds, the dynamics could slow down. There is feedback, though, between both elements: the funding adjustment reflects cause and effect. For this reason, we observe that the responses of total payments to system stability follow a random walk. But its evolution depends on which effect dominates: velocity of payments or system stability.

Note that this effect is strongly related to the reactivity and the RNTV. As we saw in the factor identification, the reactivity of the system helps to stabilize the network. There is a negative relationship between reactivity and network stability. This indicates that a reduction in the dependency on incoming payments leads to an improvement in stability. The response of funding resources to factor 2 shows this mechanism of adjustment.

Since mid-2014, the dynamics of the system have changed, and the funding patterns have experienced a period of less stability. Now, reused payments react positively, but the opposite is true for the external funds. This would accelerate the system, but it would become less stable. Again, the evolution depends on which effect dominates. Reused payments are a larger fraction of the payments, so the final effect is based on them.

To sum up, the responses to factor 2 show the mechanism of adjustment between the funding resources and the stability of the system. At the same time, its interactions with the dynamics and the velocity of payments are also visible. For this reason, we can consider factor 2 as an inverse measurement of the liquidity pressure.

3.5 Final remarks and conclusions

The research presented in this chapter seeks to identify the determinants of the dynamics in SPEI and their effects on liquidity management. We also give some implications for participants' funding performance. Given this methodology, we identify the changes in the structure of the system. Thus, we analyze the controllability of a payment system.

We find that five forces are driving SPEI. The two main forces determining its performance are the trend and the network stability. The trend measures the growth of the payment system, and it has inertia, but this inertia changes as a consequence of the market structure conditions. The more competitive the payment system, the faster it grows. Thus, market structure conditions in a payment system are a function of centrality, grouping and trading. Changes in the dynamics reflect adjustments in the competitiveness of the system. Network stability refers to the notion of a system that exhibits controllable or uncontrollable changes. These changes may be detrimental to the performance of the system. The stability of the network results from a fragile equilibrium between centrality and bilateral interactions. It determines the liquidity pressure. This is the result of two forces with opposite directions: earnings from big participants' persistence and the cost of asymmetry. Therefore, the interaction between both forces explains the two-faced problem in a payment system: velocity of payments versus liquidity pressure.

Thus, the main conclusion from these results is that network metrics are the representation of the underlying factors in a different reference system (both are expressed using different bases for the same vector space). Knowing the dynamic performance of the networks metrics will help us to understand the policy effects in a payment system.

Moreover, we also find changes in the responses to the forces, and we are able to state different processes. Responses to the trend are different among participants. We identify a learning process, which explains the ability of participants to mix external funds and reused payments. We assess the effect of a new FMI in the market. It increases the risk and entropy among participants' behavior. The financial crisis also contributed to this effect.

The responses to the stability are diverse as well. However, they have been converging since the creation of SPEI. External funds increase during stable periods, providing more stability at the same time. Reused payments increase during unstable periods, but they reduce stability. Thus, there is feedback between stability and funding composition. Both results suggest that the system tends to converge. This implies that there exists an underlying optimal equilibrium.

Finally, we confirm an improvement in efficiency of the participants operating in SPEI. This result suggests that for more than a decade the liquidity settlement mechanism of SPEI has been able to deal with a continuous increase in the volume of payments, without creating extra pressure regarding the level of external funds needed to cover the new payment obligations.

This chapter opens the door to new lines of research. On the one hand, optimal pricing policy must ensure the least liquidity cost. This chapter could motivate a theoretical analysis in this regard. On the other hand, the idea of underlying optimal equilibrium suggests optimality in payments. The residuals of the model could be meant as error expectations. Thus, optimality in payment systems is the next step.

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Appendix A

Description of the datasets

A.1 Chapter I: Euro Area and selected countries

The following table shows the list of variables used in the empirical model in chapter 1. Note that three transformations were made: "1" denotes first-logarithmic differences, "2" first differences and "3" seasonal adjustment. The symbol $*$ represents a variable available for the Eurozone, Germany, France, Finland, Spain, Italy, Portugal and Greece.

Table A.1 Variables and transformations

Variable	Type	Variable	Type
Real Activity		**Monetary and Financial Markets**	
- Industrial Production *	1	- lEuroStoxx 50	1
- Constructtion Activity *	2	- Credit cons. 1-5 years	1
- Retail Trade *	2	- Credit cons. 1 year	1
- Economic situation *	2	- Loans Money Market	1
- Stock in manufactures *	2	- Money Market Funds	1
- Electricity consumption *	2	- Reserve Assets *	1
- Car registration *	2	- Securities Money Market	1
- Confidence indicators	2	- Overnight deposits	1
		- Deposits ECB	1
Labour Market		- Loans ECB	1
- Unemp. Eurozone *	1	- M1	1
- Emp. in manufacture sector *	2	- M2	1
- Emp in retail sector *	2	- M3	1
- Emp in service sector *	2		
		Interest and Exchange Rates	
Prices		- MRO Interest Rate	0
- Harmonised CPI *	1,3	- Long term interest rate *	0
- Crude Oil Price	1	- Sov. bond yield 3y	0
- Crude Oil Europe	1	- Eonia	0
- Gasoil Price	1	- Euribor	0
- Copper Price	1	- Eurbor 1 year	0
- Natural Gas Prrice	1	- Eurbor 1 month	0
- Nickel Price	1	- Eurbor 3 month	0
- Olive Oil Price	1	- Interbank 6 month	0
- Zinc Price	1	- Exchange rate Pound	0
- Share prices *	1	- Exchange rate Dollar	0

A.2 Chapter II: Credit channel in the Euro Area

All series were directly taken from different sources and are seasonal adjusted. Format is following Bernanke et al. (2005)'s papers: variable number; transformation code; source; and series description as appears in the database. The transformation codes are 1-no transformation; 2-standarized; 3-first difference of logarithm. An asterisk *, next to the transformation, denotes a variable assumed to be slow-moving in the estimation.

Table A.2 List of Variables in TVP-FAVAR model

Var. No.	*Transf.*	*Source*	*Description*
Production and Demand			
1	3*	Eurostat	Industrial Production Index (IPI)
2	3*	Eurostat	MIG - Intermediate and capital goods
3	3*	Eurostat	MIG - Intermediate goods
4	3*	Eurostat	MIG - Energy (except D and E)
5	3*	Eurostat	MIG - Capital goods
6	3*	Eurostat	MIG - Consumer goods
7	3*	Eurostat	MIG - Consumer goods (except food, beverages and tobacco)
8	3*	Eurostat	MIG - Durable consumer goods
9	3*	Eurostat	MIG - Non-durable consumer goods
10	3*	Eurostat	IPI Mining and quarrying
11	3*	Eurostat	IPI Manufacturing
12	3*	Eurostat	IPI Manufacture of food, beverages and tobacco products
13	3*	Eurostat	IPI Manufacture of textiles, wearing apparel, leather and related products
14	3*	Eurostat	IPI Manufacture of wood, paper, printing and reproduction
15	3*	Eurostat	IPI Manufacture of chemical, basic pharm. and pharm. preparations products
16	3*	Eurostat	IPI Electricity, gas, steam and air conditioning supply
17	3*	OECD	Consumer Confidence in Manufacturing Index
18	3*	OECD	Manufacturing Orders
19	3*	OECD	Consumer Confidence in Retail Services Index
20	3*	OECD	Construction Orders
21	3*	OECD	Consumer Confidence Index
22	3*	OECD	Consumer Confidence in Construction Index
23	2*	Markit	PMI Manufacturing
24	2*	Markit	PMP Services
25	2*	Markit	PMI Total
26	3*	OECD	Consumer Confidence in Services Index
27	3*	OECD	Indicator Total Construction
28	3*	OECD	Indicator Retail sales
29	3*	Eurostat	Car registration
30	3*	OECD	GDP (Trend)
31	3*	Eurostat	Imports
32	3*	OECD	Retail Trade
33	3*	Eurostat	Electric Consumption
94	3*	Eurostat	Construction
95	3*	Eurostat	Residential buildings
96	3*	Eurostat	Non-residential buildings
97	3*	Eurostat	Building Permissions - Residential
98	3*	Eurostat	Building Permits - One dwelling residential buildings
99	3*	Eurostat	Building Permits - Two or more dwelling residential buildings

Table A.2 List of Variables in TVP-FAVAR model

Var. No.	*Transf.*	*Source*	*Description*
Employment			
34	1*	Eurostat	Unemployment rate (%)
35	1*	Eurostat	Unemployment rate. Under 24 years old (%)
36	1*	Eurostat	Unemployment rate. Between 24 and 78 years old (%)
37	2*	OECD	Employment in Manufacturing - Future tendency
38	2*	OECD	Employment in Construction - Future tendency
39	2*	OECD	Employment in Retail Trade - Future tendency
40	2*	OECD	Employment in Service - Future tendency
41	3*	OECD	Vacancies in Austria
42	3*	OECD	Vacancies in Germany
43	3*	OECD	Vacancies in Luxemburg
44	3*	OECD	Vacancies in Norway
45	3*	OECD	Vacancies in Portugal
46	2*	Eurostat	Employment in Intermediates Goods
47	2*	Eurostat	Employment in Capital Goods
48	2*	Eurostat	Employment in Durable Consumer Goods
49	2*	Eurostat	Employment in Non-durable Consumer Goods
50	2*	Eurostat	Working hours in Intermediates Goods
51	2*	Eurostat	Working hours in Capita Goods
52	2*	Eurostat	Working hours in Durable Consumer Goods
53	2*	Eurostat	Working hours in Non-durable Consumer Goods
54	2*	Eurostat	Wages in Intermediates Goods
55	2*	Eurostat	Wages in Capita Goods
56	2*	Eurostat	Wages in Durable Consumer Goods
57	2*	Eurostat	Wages in Non-durable Consumer Goods
Prices			
58	3*	Eurostat	Harmonized Index of Consumer Prices (HICP)
59	3*	Eurostat	HICP - Clothing & footwear
60	3*	Eurostat	HICP - Health
61	3*	Eurostat	HICP - Transport
62	3*	Eurostat	HICP - Non-energy. Industrial durable goods
63	3*	Eurostat	HICP - Services
64	3*	Eurostat	HICP - Food Excluded
65	3*	Eurostat	HICP - Underlying
66	3*	Eurostat	HICP - Social Expenditures Excluded
67	3*	Eurostat	HICP - Industry
68	3*	Eurostat	HICP - Intermediate goods
69	3*	Eurostat	HICP - Consumer goods
70	3*	Eurostat	HICP - Mining & quarrying
71	3*	Eurostat	HICP - Energy
72	3*	World Bank	Commodity Price: Palatine
73	3*	World Bank	Commodity Price: Copper
74	3*	World Bank	Commodity Price: Aluminium
75	3*	World Bank	Commodity Price: Oil
76	3*	World Bank	Commodity Price: Corn
77	3*	World Bank	Commodity Price Index
78	3*	World Bank	Commodity Price: Oil - Brend
79	3*	World Bank	Commodity Price: Rubber
80	3*	World Bank	Commodity Price: Sugar
81	3*	World Bank	Commodity Price: Zinc
100	3*	OECD	Commodity Price Index (OECD)
101	3*	OECD	Industrial CommoditIES Price Index (OECD)
102	3*	OECD	Oil Price Index (OECD)

Table A.2 List of Variables in TVP-FAVAR model

Var. No.	*Transf.*	*Source*	*Description*
Exchange Rates, Stock and Money Market			
82	3	ECB	Exchange rate: Dollar-Euro
83	3	ECB	Exchange rate: Yen-Euro
84	3	ECB	Exchange rate: British Pound-Euro
85	3	ECB	Exchange rate: Swiss franc-Euro
86	3	ECB	Exchange rate: Canadian Dollar-Euro
87	3	EuroStoxx	Eurostoxx Euro Area
88	3	EuroStoxx	EuroStoxx Electrical Companies - Euro Area
89	3	EuroStoxx	EuroStoxx Finance Corporations - Euro Area
90	3	EuroStoxx	EuroStoxx General Industry - Euro Area
91	3	EuroStoxx	EuroStoxx General Retailers - Euro Area
92	3	EuroStoxx	EuroStoxx Personal Goods - Euro Area
93	3	EuroStoxx	EuroStoxx Technology, Hardware & Equipment - Euro Area
103	3	ECB	Monetary Aggregate 1
104	3	ECB	Monetary Aggregate 2
105	3	ECB	Monetary Aggregate 3
106	3	ECB	Monetary Base
107	1	ECB	Reserve-to-Deposits Ratio
108	1	ECB	Cash-to-Deposits Ratio
109	1	ECB	Financial Market Indicator - Liquidity Risk
110	1	ECB	Money Market Risk Indicator
111	3	ECB	Loans to Financial Corporations
112	3	ECB	Loans to Insurance Corporations
113	3	ECB	Loans to Non-financial Corporations
114	3	ECB	Loans to Households
115	3	ECB	Loans to Non-financial Corporations. Maturity less than 1 year.
116	3	ECB	Credit to Consumption - Households
117	3	ECB	Loans to Mortgage - Households
118	3	ECB	Other Loans to Households
135	3	ECB	Marginal Facility Deposits
136	3	ECB	Marginal Facility Credits
Interest Rates			
137	1	ECB	Main Refinancing Operations (MRO) Rate (%)
119	1	ECB	Interest Rate Marginal Credit Facility (%)
120	1	ECB	Interest Rate Marginal Deposit Facility (%)
121	1	ECB	Interest Rate - EE.UU (%)
122	1	ECB	Interest Rate - EONIA (%)
123	1	ECB	Interest Rate Deposits 1 month (%)
124	1	ECB	Interest Rate Deposits 3 month (%)
125	1	ECB	Interest Rate Deposits 6 month (%)
126	1	ECB	Interest Rate Deposits 12 month (%)
127	1	ECB	Interest Rate - Credit Corporations to Households 1 year (%)
128	1	ECB	Interest Rate - Credit Corporations to Households 1-2 year (%)
129	1	ECB	Interest Rate - Credit Corporations to Non-financial Corporations up to 5 year (%)
130	1	ECB	Spread MRO Rate - FED (%)
131	1	ECB	Spread MRO Rate - EONIA (%)
132	1	ECB	Spread MRO Rate - Interest Rate Deposits 6 month (%)
133	1	ECB	Spread MRO Rate - Interest Rate: C.Corp to Households 1 year (%)
134	1	ECB	Spread MRO Rate - Interest Rate C.Corp. to NFC up to 5 year (%)

Appendix B

Information criteria and estimations

B.1 Information Criteria in Chapter I:

Table B.1 Information Criteria FAVAR(k-factors,p-lags,$m = 2$)

Factor IC	*k= 1*	*k= 2*	*k= 3*	*k= 4*	*k= 5*	*k= 6*	*k= 7*	*k= 8*	*k= 9*	*k= 10*
AIC 1	0.9233	0.8870	0.8637	0.8399	0.8167	0.7955	0.7739	0.7601	0.7463	0.7320
AIC 2	0.9206	0.8836	0.8595	0.8351	0.8112	0.7894	0.7674	0.7530	0.7387	0.7239
AIC 3	0.9538	0.9256	0.9101	0.8934	0.8766	0.8613	0.8451	0.8368	0.8281	0.8185
BIC 1	0.9753	0.9532	0.9438	0.9329	0.9215	0.9115	0.9002	0.8971	0.8934	0.8885
BIC 2	0.9697	0.9462	0.9353	0.9230	0.9103	0.8991	0.8867	0.8824	0.8776	0.8717
BIC 3	1.2188	1.2620	1.3158	1.3626	1.4041	1.4433	1.4765	1.5196	1.5591	1.5936
BNC 1	0.0414	0.04	0.0554	0.0679	0.0802	0.0942	0.1072	0.1295	0.1515	0.1725
BNC 2	0.0647	0.07	0.0943	0.1146	0.1347	0.1565	0.1772	0.2073	0.2371	0.2659
BNC 3	-0.0224	-0.0434	-0.0509	-0.0596	-0.0686	-0.0758	-0.0841	-0.0831	-0.0823	-0.0826
***EVC**[A]*	2.4254	2.6324	1.3476	1.1507	1.0986	1.0318	1.3414	1.2817	1.2077	1.0479
***GEVC**[A]*	1.0146	1.0975	1.0243	1.0122	1.0052	0.9975	1.0035	1.0078	1.0218	1.0002
Lags AIC										
p=1	-29.00	-51.21	-72.09	-92.74	-113.43	-134.41	-155.17	-176.15	-197.18	-217.71
p=2	-29.10	-51.21	-72.02	-92.68	-113.31	-134.12	-154.69	-175.47	-196.25	-216.43
p=3	-29.30	-51.38	-72.19	-92.76	-113.36	-133.86	-154.29	-174.78	-195.36	-215.44
p=4	-29.28	-51.35	-72.07	-92.50	-112.96	-133.30	-153.49	-173.90	-194.15	-213.94
p=5	-29.42	-51.44	-72.05	-92.42	-112.79	-132.99	-152.96	-173.09	-193.07	-212.51
p=6	-29.37	-51.30	-71.81	-92.02	-112.16	-132.15	-152.00	-171.98	-191.99	-211.21
p=7	-29.27	-51.07	-71.53	-91.66	-111.63	-131.41	-151.04	-170.77	-190.43	-209.48
p=8	-29.13	-50.87	-71.26	-91.22	-110.97	-130.54	-150.10	-169.51	-189.19	-207.87
p=9	-28.96	-50.76	-71.11	-90.98	-110.53	-129.89	-149.43	-168.72	-188.10	-206.70
p=10	-28.82	-50.55	-70.75	-90.53	-109.88	-129.08	-148.31	-167.30	-186.69	-205.15
Lags BIC										
p=1	-28.54	-50.40	-70.82	-90.92	-110.94	-131.16	-151.06	-171.08	-191.04	-210.40
p=2	-28.19	-49.59	-69.48	-89.02	-108.34	-127.63	-146.48	-165.33	-183.98	-201.83
p=3	-27.93	-48.94	-68.39	-87.29	-105.90	-124.13	-141.97	-159.57	-176.96	-193.54
p=4	-27.46	-48.10	-67.00	-85.20	-103.02	-120.32	-137.06	-153.62	-169.61	-184.74
p=5	-27.14	-47.39	-65.71	-83.29	-100.37	-116.77	-132.43	-147.74	-162.40	-176.00
p=6	-26.64	-46.43	-64.20	-81.07	-97.25	-112.69	-127.36	-141.56	-155.18	-167.41
p=7	-26.07	-45.39	-62.66	-78.88	-94.24	-108.69	-122.29	-135.28	-147.49	-158.38
p=8	-25.48	-44.38	-61.12	-76.62	-91.09	-104.58	-117.25	-128.95	-140.11	-149.47
p=9	-24.85	-43.46	-59.70	-74.56	-88.17	-100.69	-112.47	-123.09	-132.88	-140.99
p=10	-24.25	-42.44	-58.08	-72.27	-85.04	-96.63	-107.24	-116.60	-125.34	-132.15
Lags HQC										
p=1	-28.93	-51.09	-71.90	-92.46	-113.05	-133.91	-154.54	-175.37	-196.24	-216.59
p=2	-28.96	-50.96	-71.63	-92.12	-112.55	-133.13	-153.44	-173.92	-194.37	-214.19
p=3	-29.09	-51.00	-71.61	-91.92	-112.21	-132.37	-152.40	-172.45	-192.54	-212.08
p=4	-29.00	-50.85	-71.30	-91.38	-111.44	-131.31	-150.97	-170.80	-190.38	-209.47
p=5	-29.07	-50.82	-71.07	-91.02	-110.89	-130.51	-149.81	-169.21	-188.37	-206.91
p=6	-28.95	-50.55	-70.64	-90.34	-109.87	-129.17	-148.23	-167.32	-186.35	-204.50
p=7	-28.78	-50.20	-70.17	-89.70	-108.97	-127.92	-146.63	-165.33	-183.85	-201.65
p=8	-28.57	-49.88	-69.71	-88.98	-107.92	-126.56	-145.07	-163.29	-181.66	-198.92
p=9	-28.33	-49.64	-69.36	-88.46	-107.10	-125.42	-143.77	-161.72	-179.63	-196.63
p=10	-28.12	-49.31	-68.81	-87.73	-106.07	-124.11	-142.01	-159.53	-177.28	-193.96

Note: dark grey denotes global minimum (maximum in case of EVC and GEVC), while bright grey denotes local. Factors IC are chosen horizontally, for each IC, while lags IC are chosen vertically, conditional to the number of unobservable factors.
[A] This information criterion estimates the number of factors according to the maximum value.

B.2 Estimations in Chapter 1:

Table B.2 Results of estimation VAR($p = 3$) in Chapter I

Variable	***Factor 1***	***Factor 2***	***VIX***	i_{ECB}
Constant	1.60E-08***	1.22E-06***	-3.74E-05***	-0.0072***
	(0.00)	(0.00)	(0.02)	(0.01)
Factor 1 (t-1)	0.3903	-0.3485	-1861.1***	-807.45*
	(0.08)	(0.12)	(1,539.80)	(337.57)
Factor 2 (t-1)	0.0858***	0.3223	1662.3***	-771.52
	(0.06)	(0.08)	(1,043.90)	(228.85)
VIX (t-1)	1.79E-06***	2.28E-05	1.0932	-0.0402*
	(0.00)	(0.00)	(0.09)	(0.02)
i_{ECB} (t-1)	-0.0001	0.0001	0.6966*	0.9732
	(0.00)	(0.00)	(0.34)	(0.08)
Factor 1 (t-2)	0.062***	0.4014	4887.1	-481.13***
	(0.09)	(0.13)	(1,656.50)	(363.16)
Factor 2 (t-2)	0.0341***	0.0912***	715.18***	-166.63***
	(0.06)	(0.09)	(1,108.20)	(242.95)
VIX (t-2)	-4.05E-06***	5.25E-06***	-0.0481***	-0.0247***
	(0.00)	(0.00)	(0.13)	(0.03)
i_{ECB} (t-2)	4.00E-05***	-0.0001*	-0.5639***	0.1108***
	(0.00)	(0.00)	(0.50)	(0.11)
Factor 1 (t-3)	0.2990	-0.1299***	-4750.3	25.043***
	(0.08)	(0.12)	(1,519.00)	(333.02)
Factor 2 (t-3)	0.0052***	0.2929	-574.37***	-312.4***
	(0.06)	(0.08)	(1,040.10)	(228.02)
VIX (t-3)	2.79E-06***	-2.74E-05	-0.1329***	0.0551
	(0.00)	(0.00)	(0.09)	(0.02)
i_{ECB} (t-3)	9.15E-06***	1.97E-05***	-0.1361***	-0.1236**
	(0.00)	(0.00)	(0.33)	(0.07)
Tests (p-values)				
- Breusch-Pagan test	0.2843	0.8251	0.2652	0.1607
- Engle ARCH test	0.4659	0.5319	0.9602	0.2430
- AR1 Ljung-Box Q-test	0.4531	0.5103	0.7602	0.9509
- AR2 Ljung-Box Q-test	0.5156	0.3303	0.5366	0.7853
Stability Eigenvalues:				
- Largest modulus root		0.9885		

Note: standard deviations between brackets. * represents significance at 10%, ** at 5% and *** at 1%. Breusch-Pagan test is calculated Koenker style, and it tests the null hypothesis of non heteroskedastic errors; Engle ARCH test, and it tests the null hypothesis of non ARCH errors; AR1 and AR2 Ljung-Box Q-test test the null hypothesis that the residuals are not autocorrelated with order 1 and 2 respectively.

Fig. B.1 Fitted and Actual Factors:

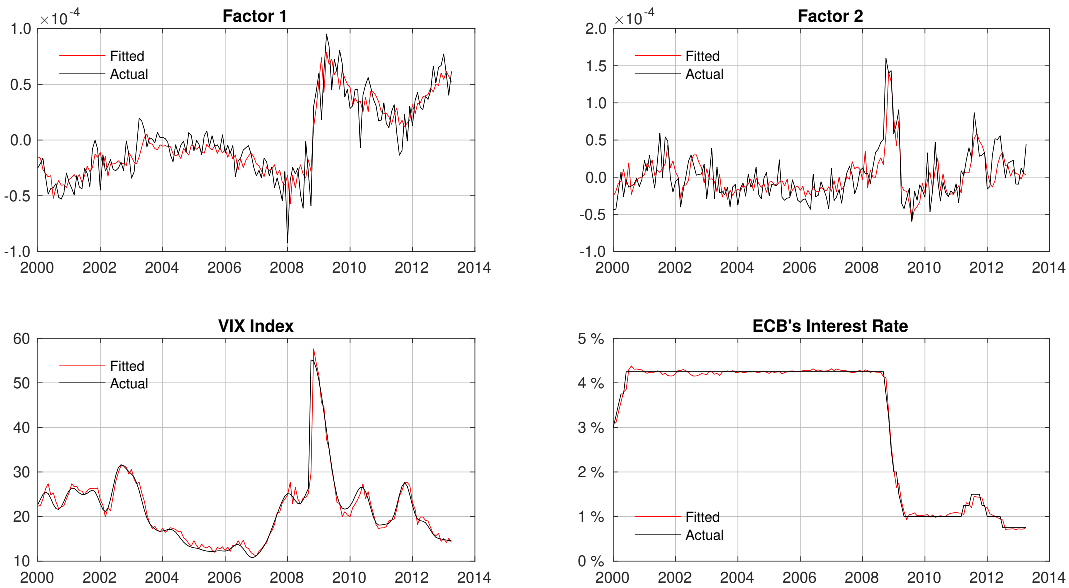
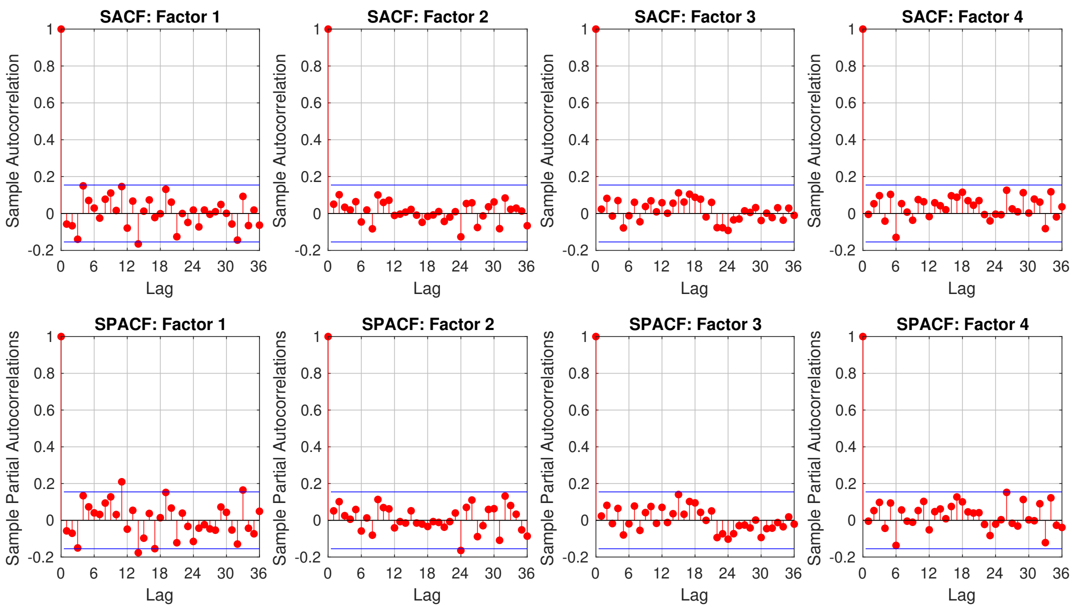


Fig. B.2 White Noise test of Residuals:



B.3 Information Criteria in Chapter II

Table B.3 Information Criteria TVP-FAVAR (1/2)

IC	*Lags \ Factors*	*k = 1*	*k = 2*	*k = 3*	*k = 4*	*k = 5*	*k = 6*	*k = 7*	*k = 8*	*k = 9*	*k = 10*
BNC1	*p = 1*	10.059	9.605	9.345	9.181	8.961	8.831	8.639	8.458	8.323	8.195
	p = 2	10.063	9.612	9.352	9.182	8.967	8.854	8.683	8.540	8.456	8.380
	p = 3	10.062	9.603	9.341	9.166	8.954	8.856	8.697	8.639	8.598	8.568
	p = 4	10.056	9.590	9.332	9.156	8.933	8.839	8.717	8.799	8.716	8.727
	p = 5	10.052	9.582	9.328	9.156	8.933	8.846	8.773	8.871	8.841	8.981
	p = 6	10.045	9.577	9.323	9.149	8.930	8.884	8.902	8.829	8.969	9.035
	p = 7	10.041	9.559	9.305	9.145	8.934	8.973	9.046	8.983	9.060	9.000
	p = 8	10.029	9.554	9.306	9.135	8.930	8.970	9.083	8.941	9.094	9.172
	p = 9	10.023	9.547	9.290	9.134	8.991	9.042	9.247	9.149	9.271	9.378
	p = 10	10.019	9.540	9.279	9.121	9.026	9.103	9.361	9.231	9.263	9.353
BNC2	*p = 1*	10.180	9.785	9.586	9.482	9.323	9.253	9.122	9.001	8.927	8.859
	p = 2	10.184	9.794	9.594	9.484	9.330	9.277	9.167	9.084	9.060	9.045
	p = 3	10.183	9.785	9.583	9.469	9.317	9.280	9.182	9.184	9.203	9.235
	p = 4	10.178	9.772	9.575	9.459	9.297	9.264	9.202	9.345	9.323	9.395
	p = 5	10.173	9.764	9.571	9.460	9.298	9.272	9.259	9.418	9.449	9.650
	p = 6	10.167	9.759	9.566	9.454	9.295	9.311	9.390	9.377	9.578	9.705
	p = 7	10.163	9.742	9.550	9.451	9.301	9.401	9.535	9.532	9.670	9.672
	p = 8	10.152	9.737	9.550	9.441	9.297	9.398	9.573	9.491	9.706	9.845
	p = 9	10.146	9.731	9.535	9.440	9.359	9.471	9.738	9.701	9.884	10.052
	p = 10	10.142	9.725	9.525	9.429	9.395	9.533	9.852	9.784	9.878	10.029
BNC3	*p = 1*	10.131	9.713	9.490	9.361	9.178	9.083	8.928	8.783	8.685	8.592
	p = 2	10.135	9.721	9.497	9.362	9.184	9.107	8.972	8.866	8.817	8.778
	p = 3	10.134	9.711	9.486	9.347	9.170	9.109	8.986	8.964	8.959	8.966
	p = 4	10.129	9.698	9.477	9.337	9.150	9.092	9.005	9.124	9.078	9.125
	p = 5	10.124	9.690	9.472	9.337	9.150	9.099	9.062	9.196	9.202	9.378
	p = 6	10.117	9.685	9.467	9.330	9.147	9.137	9.191	9.154	9.330	9.432
	p = 7	10.113	9.667	9.450	9.326	9.151	9.226	9.335	9.308	9.421	9.398
	p = 8	10.102	9.662	9.450	9.316	9.147	9.223	9.372	9.266	9.455	9.570
	p = 9	10.095	9.655	9.434	9.314	9.207	9.295	9.536	9.474	9.632	9.775
	p = 10	10.091	9.649	9.424	9.302	9.243	9.356	9.650	9.556	9.624	9.751
EVC[A]	*p = 1*	1.607	1.284	1.491	1.149	1.183	1.011	1.260	1.140	1.033	1.171
	p = 2	1.607	1.284	1.491	1.149	1.183	1.011	1.260	1.140	1.033	1.171
	p = 3	1.607	1.284	1.491	1.149	1.183	1.011	1.260	1.140	1.033	1.171
	p = 4	1.607	1.284	1.491	1.149	1.183	1.011	1.260	1.140	1.033	1.171
	p = 5	1.607	1.284	1.491	1.149	1.183	1.011	1.260	1.140	1.033	1.171
	p = 6	1.607	1.284	1.491	1.149	1.183	1.011	1.260	1.140	1.033	1.171
	p = 7	1.607	1.284	1.491	1.149	1.183	1.011	1.260	1.140	1.033	1.171
	p = 8	1.607	1.284	1.491	1.149	1.183	1.011	1.260	1.140	1.033	1.171
	p = 9	1.607	1.284	1.491	1.149	1.183	1.011	1.260	1.140	1.033	1.171
	p = 10	1.607	1.284	1.491	1.149	1.183	1.011	1.260	1.140	1.033	1.171
GEVC[A]	*p = 1*	1.002	0.999	1.029	0.990	1.005	0.978	1.006	1.000	0.989	1.003
	p = 2	1.003	0.999	1.028	0.991	1.007	0.981	1.011	1.006	0.995	1.026
	p = 3	1.002	0.999	1.028	0.991	1.009	0.982	1.021	1.011	1.000	1.021
	p = 4	1.001	0.999	1.027	0.990	1.009	0.987	1.039	1.006	1.006	1.024
	p = 5	1.001	0.999	1.028	0.990	1.010	0.992	1.042	1.013	1.023	1.028
	p = 6	1.001	1.000	1.028	0.990	1.015	1.004	1.020	1.036	1.013	1.051
	p = 7	0.999	1.000	1.029	0.991	1.026	1.011	1.022	1.028	0.996	1.062
	p = 8	1.000	1.000	1.028	0.992	1.026	1.016	1.011	1.038	1.015	1.047
	p = 9	1.000	0.999	1.030	0.999	1.028	1.028	1.018	1.035	1.019	1.086
	p = 10	0.999	0.999	1.030	1.005	1.031	1.035	1.014	1.022	1.017	1.078

Note: Factors IC are chosen horizontally, for each IC, while lags IC are chosen vertically, conditional to the number of unobservable factors.
[A] This information criterion estimates the number of factors according to the maximum value.

Table B.4 Information Criteria TVP-FAVAR (2/2)

IC	*Lags \ Factors*	*k = 1*	*k = 2*	*k = 3*	*k = 4*	*k = 5*	*k = 6*	*k = 7*	*k = 8*	*k = 9*	*k = 10*
AIC1	*p = 1*	10.079	9.634	9.385	9.230	9.020	8.899	8.718	8.547	8.422	8.303
	p = 2	10.083	9.642	9.392	9.231	9.027	8.923	8.762	8.630	8.555	8.489
	p = 3	10.082	9.633	9.381	9.216	9.013	8.925	8.777	8.729	8.697	8.678
	p = 4	10.076	9.620	9.372	9.206	8.993	8.909	8.797	8.889	8.816	8.837
	p = 5	10.072	9.612	9.368	9.206	8.994	8.917	8.853	8.961	8.941	9.092
	p = 6	10.065	9.607	9.363	9.199	8.990	8.955	8.983	8.920	9.070	9.146
	p = 7	10.061	9.589	9.346	9.196	8.995	9.044	9.128	9.074	9.161	9.112
	p = 8	10.050	9.584	9.347	9.186	8.992	9.042	9.165	9.033	9.196	9.285
	p = 9	10.044	9.578	9.331	9.185	9.052	9.114	9.329	9.241	9.373	9.490
	p = 10	10.039	9.571	9.321	9.173	9.088	9.175	9.443	9.324	9.366	9.467
AIC2	*p = 1*	10.089	9.649	9.404	9.254	9.050	8.933	8.757	8.590	8.470	8.357
	p = 2	10.092	9.657	9.411	9.255	9.055	8.957	8.801	8.673	8.603	8.542
	p = 3	10.091	9.647	9.400	9.239	9.042	8.959	8.815	8.772	8.745	8.730
	p = 4	10.086	9.634	9.391	9.229	9.021	8.942	8.834	8.931	8.863	8.889
	p = 5	10.081	9.626	9.387	9.230	9.022	8.949	8.890	9.003	8.988	9.143
	p = 6	10.074	9.621	9.382	9.222	9.018	8.987	9.020	8.961	9.116	9.196
	p = 7	10.070	9.603	9.364	9.219	9.023	9.076	9.164	9.115	9.207	9.162
	p = 8	10.059	9.598	9.365	9.209	9.019	9.073	9.201	9.073	9.241	9.334
	p = 9	10.053	9.591	9.349	9.207	9.079	9.145	9.365	9.281	9.418	9.539
	p = 10	10.048	9.584	9.338	9.195	9.115	9.206	9.478	9.364	9.410	9.515
AIC3	*p = 1*	10.108	9.678	9.442	9.302	9.106	8.999	8.831	8.673	8.562	8.456
	p = 2	10.112	9.686	9.450	9.303	9.112	9.023	8.875	8.756	8.694	8.642
	p = 3	10.111	9.676	9.439	9.287	9.099	9.025	8.890	8.855	8.837	8.831
	p = 4	10.106	9.663	9.430	9.278	9.078	9.008	8.909	9.015	8.956	8.990
	p = 5	10.101	9.656	9.426	9.278	9.079	9.016	8.966	9.088	9.081	9.244
	p = 6	10.094	9.650	9.421	9.271	9.076	9.054	9.096	9.046	9.210	9.299
	p = 7	10.090	9.633	9.404	9.268	9.081	9.144	9.240	9.201	9.301	9.265
	p = 8	10.079	9.628	9.404	9.258	9.077	9.141	9.278	9.159	9.336	9.437
	p = 9	10.073	9.621	9.389	9.257	9.138	9.213	9.442	9.367	9.513	9.643
	p = 10	10.068	9.615	9.378	9.245	9.174	9.274	9.556	9.450	9.506	9.619
BIC1	*p = 1*	10.112	9.683	9.450	9.311	9.118	9.014	8.849	8.694	8.585	8.483
	p = 2	10.115	9.691	9.457	9.313	9.125	9.038	8.893	8.777	8.718	8.669
	p = 3	10.115	9.682	9.447	9.298	9.112	9.040	8.908	8.877	8.862	8.859
	p = 4	10.109	9.669	9.438	9.288	9.092	9.025	8.928	9.037	8.981	9.019
	p = 5	10.105	9.662	9.434	9.289	9.093	9.032	8.986	9.110	9.107	9.274
	p = 6	10.098	9.657	9.430	9.282	9.090	9.071	9.116	9.069	9.236	9.328
	p = 7	10.094	9.639	9.413	9.279	9.095	9.161	9.261	9.224	9.328	9.295
	p = 8	10.083	9.634	9.413	9.270	9.092	9.159	9.299	9.183	9.363	9.469
	p = 9	10.077	9.628	9.398	9.269	9.153	9.231	9.464	9.392	9.541	9.675
	p = 10	10.073	9.622	9.388	9.257	9.189	9.293	9.578	9.476	9.535	9.652
BIC2	*p = 1*	10.131	9.713	9.490	9.361	9.178	9.083	8.928	8.783	8.685	8.592
	p = 2	10.135	9.721	9.497	9.362	9.184	9.107	8.972	8.866	8.817	8.778
	p = 3	10.134	9.711	9.486	9.347	9.170	9.109	8.986	8.964	8.959	8.966
	p = 4	10.129	9.698	9.477	9.337	9.150	9.092	9.005	9.124	9.078	9.125
	p = 5	10.124	9.690	9.472	9.337	9.150	9.099	9.062	9.196	9.202	9.378
	p = 6	10.117	9.685	9.467	9.330	9.147	9.137	9.191	9.154	9.330	9.432
	p = 7	10.113	9.667	9.450	9.326	9.151	9.226	9.335	9.308	9.421	9.398
	p = 8	10.102	9.662	9.450	9.316	9.147	9.223	9.372	9.266	9.455	9.570
	p = 9	10.095	9.655	9.434	9.314	9.207	9.295	9.536	9.474	9.632	9.775
	p = 10	10.091	9.649	9.424	9.302	9.243	9.356	9.650	9.556	9.624	9.751
BIC3	*p = 1*	10.309	9.978	9.841	9.799	9.701	9.691	9.620	9.558	9.542	9.531
	p = 2	10.313	9.986	9.849	9.801	9.708	9.716	9.665	9.642	9.676	9.719
	p = 3	10.312	9.977	9.839	9.786	9.696	9.719	9.681	9.743	9.820	9.909
	p = 4	10.307	9.965	9.831	9.777	9.676	9.704	9.702	9.904	9.940	10.069
	p = 5	10.303	9.958	9.827	9.778	9.678	9.712	9.759	9.977	10.066	10.325
	p = 6	10.296	9.953	9.823	9.772	9.675	9.752	9.890	9.937	10.196	10.381
	p = 7	10.293	9.935	9.806	9.769	9.681	9.842	10.036	10.093	10.289	10.348
	p = 8	10.282	9.931	9.807	9.760	9.678	9.840	10.074	10.052	10.325	10.522
	p = 9	10.276	9.925	9.792	9.760	9.740	9.913	10.240	10.262	10.504	10.729
	p = 10	10.272	9.919	9.783	9.748	9.777	9.975	10.355	10.346	10.498	10.707

Note: Factors IC are chosen horizontally, for each IC, while lags IC are chosen vertically, conditional to the number of unobservable factors.

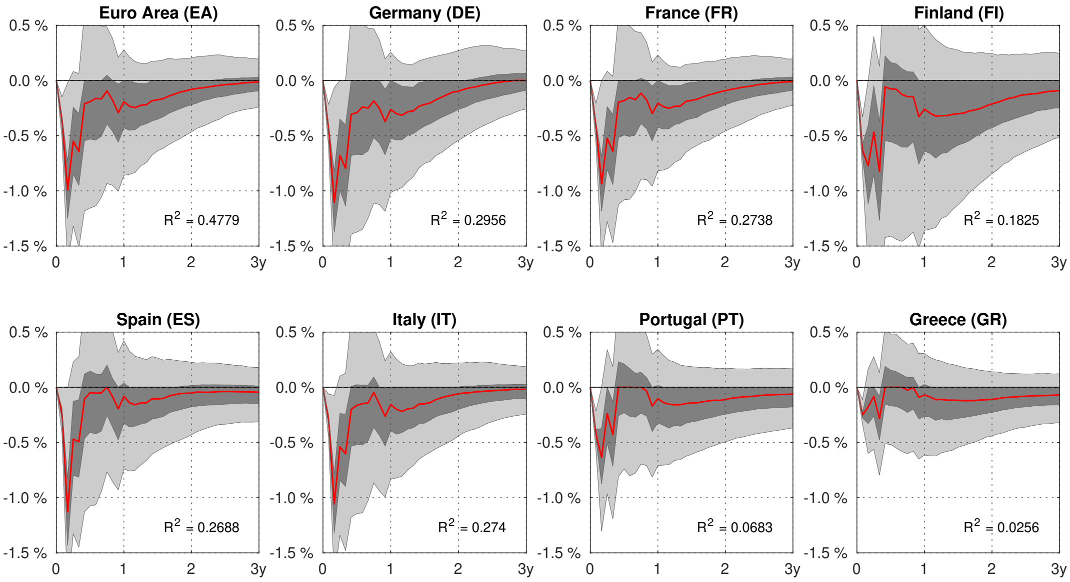
Appendix C

Robustness checks

C.1 Chapter I: Impulse response functions with 4 factors and 5 lags

This section present a robustness check specifying different number of lags. In particular, it is shown the results for $\hat{p} = 5$, which according to Table B.1 in Appendix A (pp. 90) could be other optimal combination. Notice that the signs of the IRFs are similar to the IRFs presented in the Chapter 1. However, the introduction of 2 extra lags increases the noice of the IRFs.

Fig. C.1 Robustness check: IRF of the IPI with 5 lags



Note: the red line shows the median IRF calculated with 2000-iteration bootstrap with 68% and 95% confidence intervals represented by dark and bright grey areas.

Fig. C.2 Robustness check: IRF of the Unemployment Rate with 5 lags

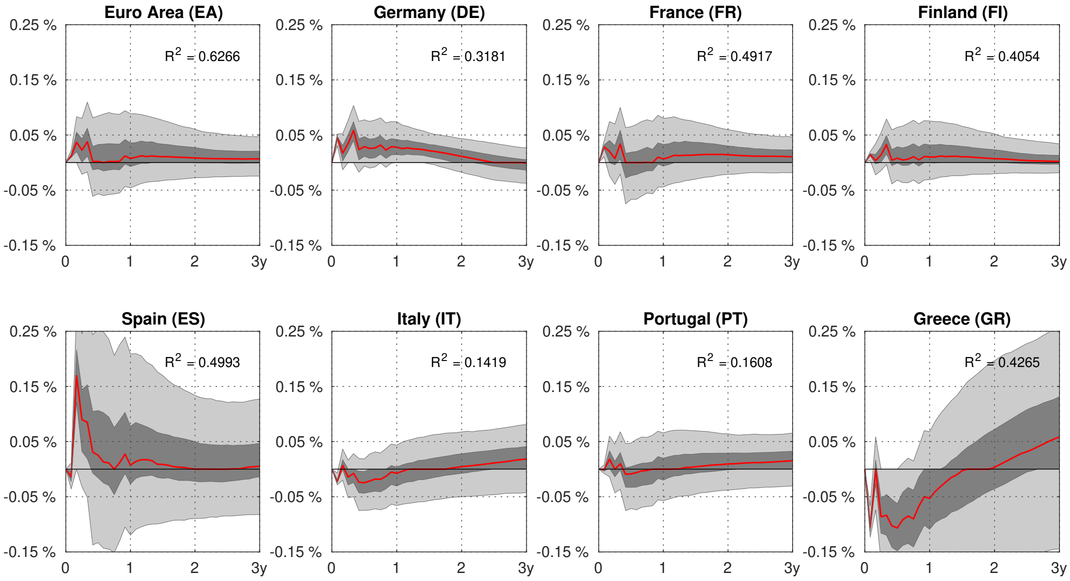
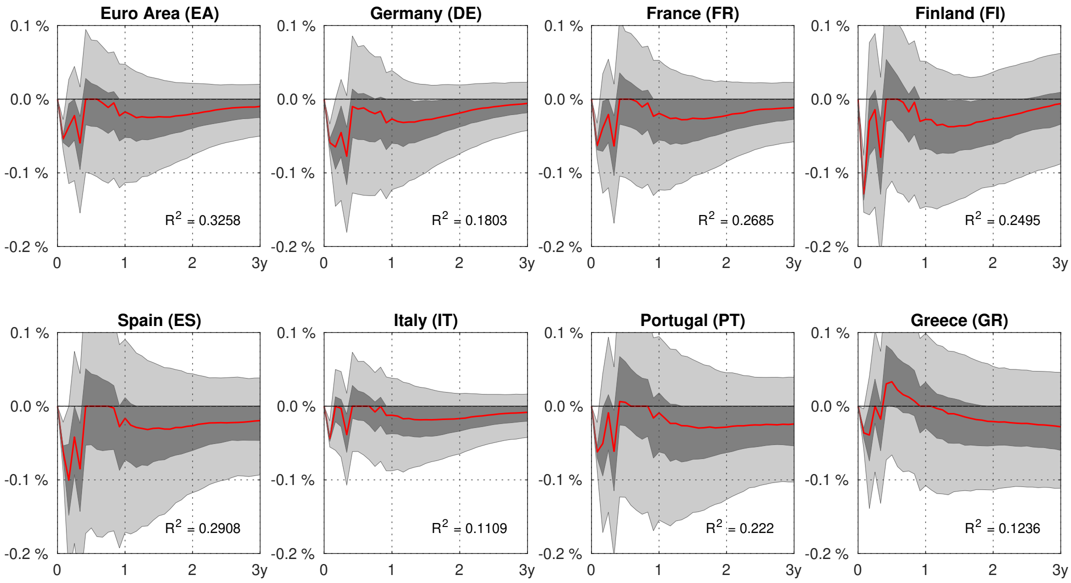


Fig. C.3 Robustness check: IRF of the Inflation with 5 lags



Note: the red line shows the median IRF calculated with 2000-iteration bootstrap with 68% and 95% confidence intervals represented by dark and bright grey areas.

C.2 Chapter II: Dynamic Impulse Response Functions with 6 factors and different lags

This section present a robustness check specifying different number of lags for selected variables.

Fig. C.4 Robustness check: DIRF with 4 lags

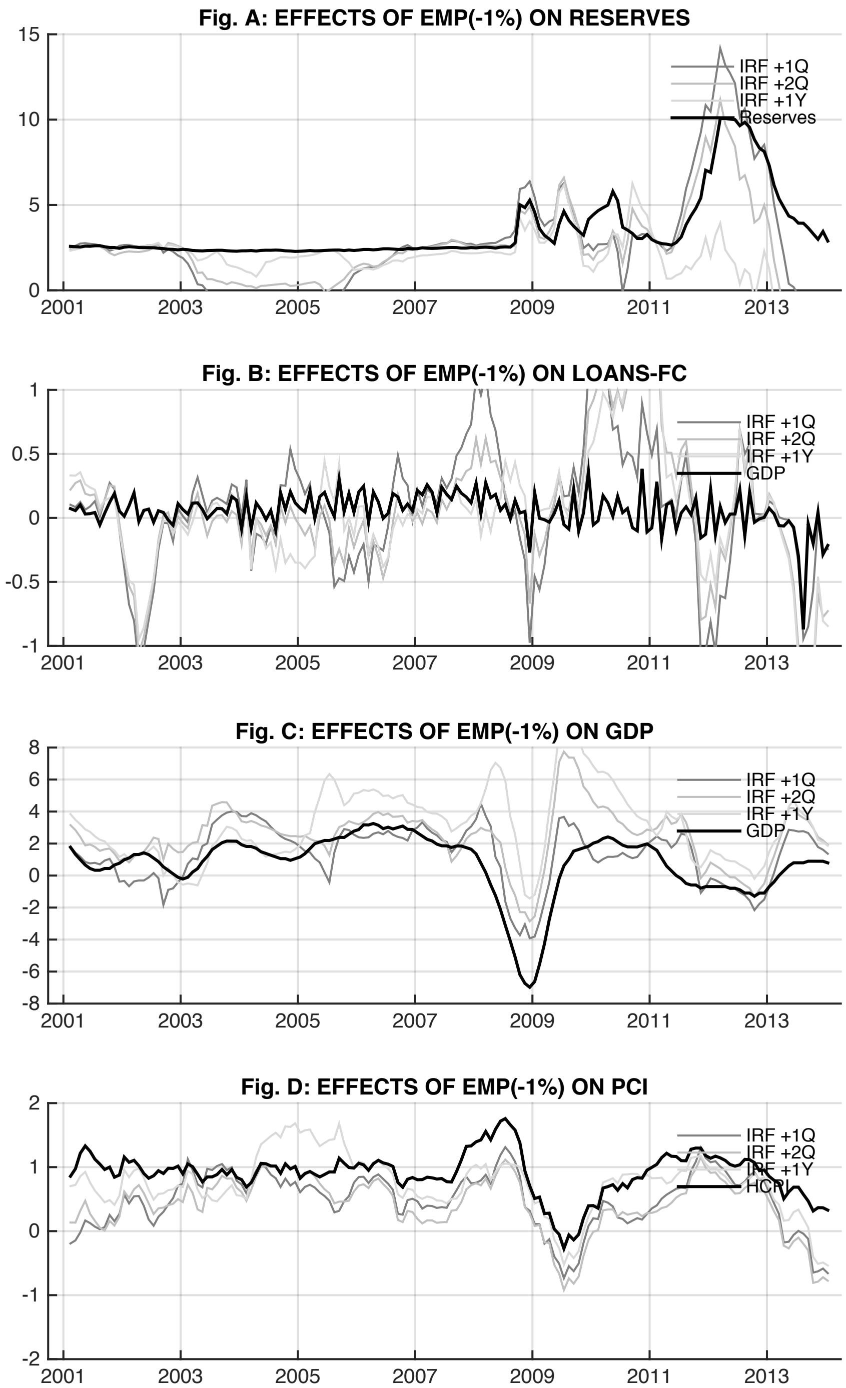
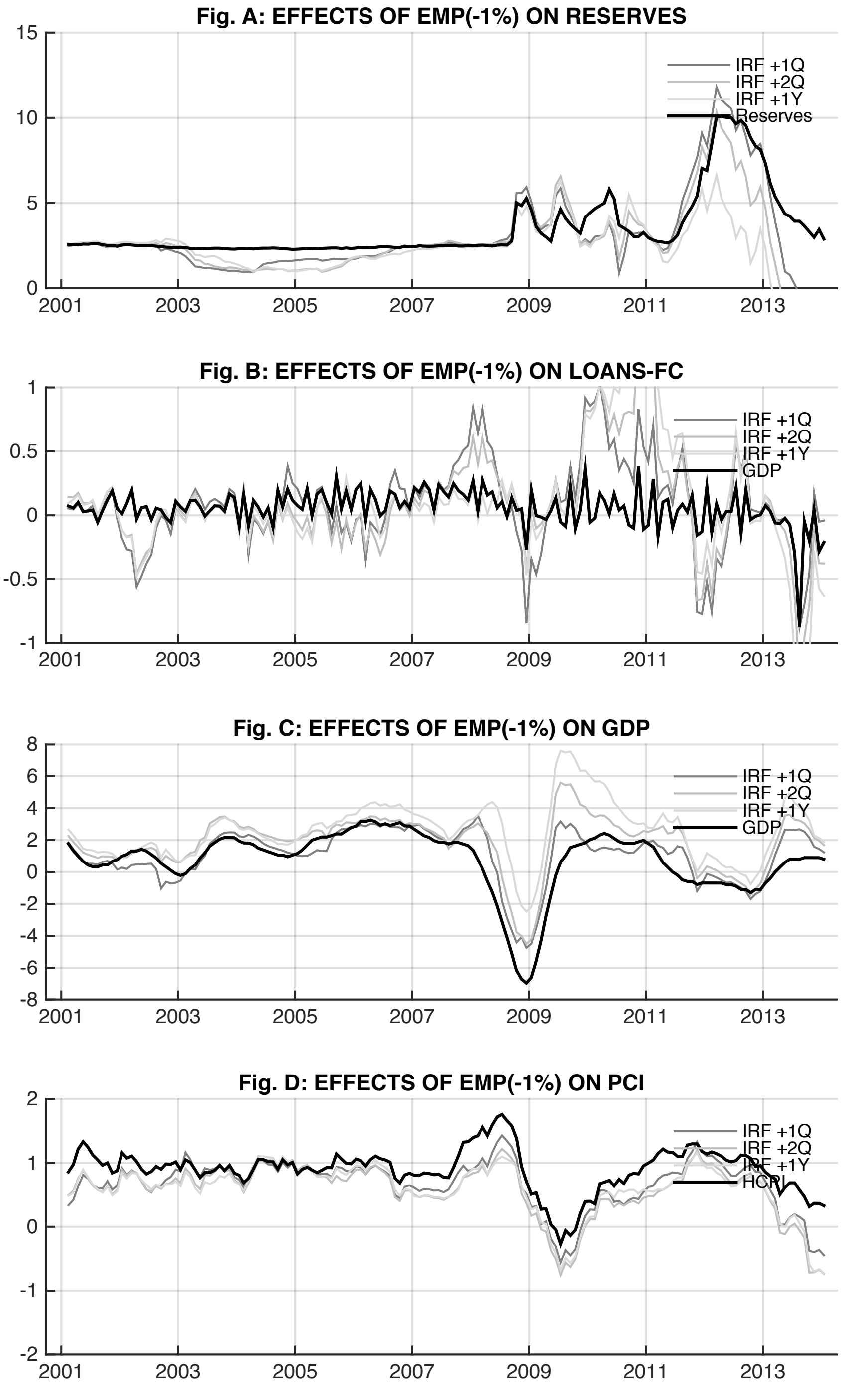


Fig. C.5 Robustness check: DIRF with 12 lags



Appendix D

Networks Measurements

We calculate the Network Measurements for the 2983 periods of the sample. Mathematically, the adjacency matrix $A \in \mathfrak{M}_{NxN}$ can represent a network. The adjacency matrix A has elements:

$$A_{ij} = \begin{cases} 1, & \text{if there is an edge from vertex } i \text{ to } j, \\ 0, & \text{otherwise.} \end{cases}$$

A denotes the adjacency matrix for out-flows in a directed network; A^T, the transpose of A, denotes the adjacency matrix for in-flows in a directed network. $\bar{A}$ is a symmetric matrix that represents the adjacency matrix in a undirected network:

$$\bar{A}_{ij} = \bar{A}_{ji} = \begin{cases} 1, & \text{if there is an edge between vertex } i \text{ and } j, \\ 0, & \text{otherwise.} \end{cases}$$

N, the number of vertex, can change across time as a consequence of new participants or participants leaving the structure.

D.1 Eigenvector Centrality in A, A^T and $\bar{A}$:

Following Newman (2006), for a given graph $G := (N, E)$ with $|N|$ vertex let A, A^T and $\bar{A}$ be previous adjacency matrices. The relative centrality score of vertex n can be defined as:

$$x_n = \frac{1}{\delta} \sum_{q \in M(n)} x_q = \frac{1}{\delta} \sum_{q \in G} A_{n,q} x_q$$

where $M(n)$ is a set of the neighbours of n and δ is a constant. With a small rearrangement this can be rewritten in vector notation as the eigenvector equation:

$\mathbf{Ax} = \delta\mathbf{x}$. The module of the main eigenvector is normalised, $\tilde{x}$, at every period t to keep cohesiveness across time. The eigenvector centrality of the graph G is given by the average of the components of the normalised eigenvector:

$$EV(G) = \frac{1}{N}\sum_{n\in N}\tilde{x}_n$$

D.2 Degree Centrality in A, A^T and $\bar{A}$:

The degree of a vertex in a network is the number of edges attached to it. In mathematical terms, the degree k_n of a vertex n is:

$$k_n = \sum_{j=1}^{N} A_{n,j}$$

Following Freeman (1978), the degree centralisation of the graph G is as follows:

$$DC(G) = \frac{\sum_{i=1}^{|N|}[k_{n^*} - k_i]}{N^2 + 3N + 2}$$

where k_{n^*} is the node with highest degree centrality of G.

D.3 Community Structure:

Following Nadakuditi and Newman (2012), a network is said to have community structure if the nodes of the network can be easily grouped into (potentially overlapping) sets of nodes such that each set of nodes is densely connected internally. We define the probability of a community structure as the difference between the density inside the groups and outside the groups. However, given the difficulty of this measurement, we approximate it by the difference between in-degree centrality and out-degree centrality:

$$CS(G) = IDC(G) - ODC(G)$$

D.4 Clustering Coefficient in A, A^T and $\bar{A}$:

According to Watts and Strogatz (1998), the local clustering coefficient for directed graphs is given as:

$$C_i = \frac{|\{e_{jk} : v_j, v_k \in N_i, e_{jk} \in E\}|}{k_i(k_i - 1)}.$$

where e_{ij} denotes an edge connecting vertex n_i with n_j, and the neighbourhood N_i for a vertex v_i is defined as its immediately connected neighbours as $N_i = \{n_j : e_{ij} \in E \bigvee e_{ji} \in E\}$. The overall level of clustering in G is the average of the local clustering coefficients of all the vertices:

$$C(G) = \frac{1}{N}\sum_{i=1}^{N} C_i$$

D.5 Harmonic Distance and Diameter in A, A^T and $\bar{A}$:

Harmonic Distance was proposed by Dekker (2005), as the reverse of the sum and reciprocal operations in the topological distance, $d(n_i, n_j)$, defined as the shortest path between vertex n_i and n_j:

$$HD(G) = \frac{1}{N}\sum_{j \neq i} \frac{1}{d(n_i, n_j)}$$

Analogously, we define the Network's Diameter as the largest finite distance in the network:

$$D(G) = \max\{d(n_i, n_j)\}$$

D.6 Reciprocity:

A traditional way to define the reciprocity, according to Newman et al. (2002), r is using the ratio of the number of reciprocal edges, $E^{+,+}$, to the total number of edges, E:

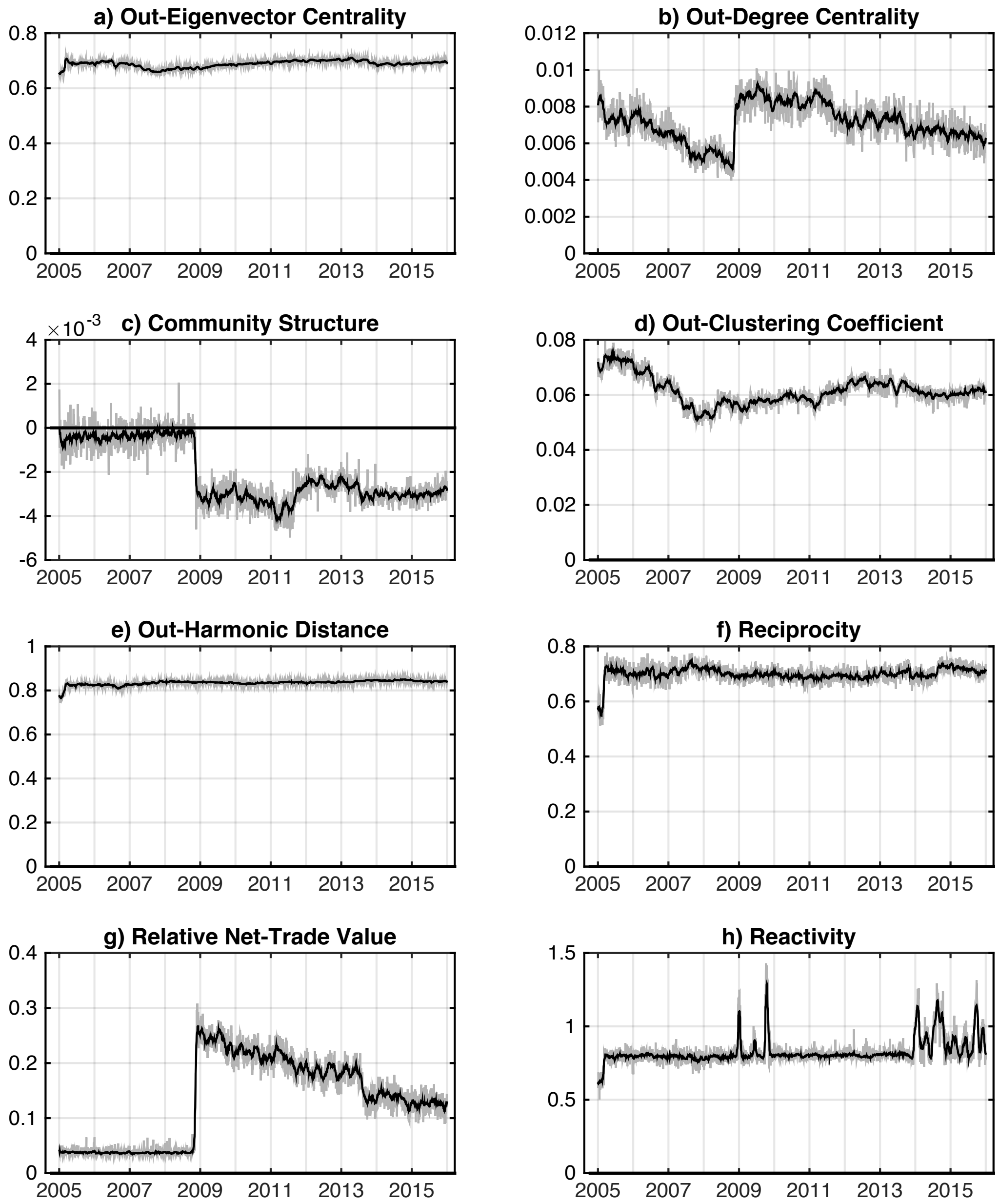
$$r = \frac{E^{+,+}}{E}$$

But also, following Garlaschelli and Loffredo (2004) reciprocity is calculated as the correlation coefficient between the entries of the adjacency matrix of a directed graph. It can be written as:

$$\rho = \frac{r - \bar{a}}{1 - \bar{a}} \quad ; \quad \bar{a} = \frac{\sum_{i \neq j} a_{ij}}{N(N-1)}$$

where $\bar{a}$ denotes the ratio of observed to possible directed links.

Fig. D.1 SPEI 2005-2015: Evolution of Network Measurements.



D.7 Relative Net-Trade Value (RNTV):

The Relative Net-Trade Value is an index used in International Trade Analysis, and we can use it for a payment system. The matrix $W \in \mathfrak{M}_{NxN}$ represents a payment network. RNTV captures the value of the net commerce between two participants respect to the total volume. It is given by weighted average:

$$RNTV(G) = \sum_{i=1}^{N} \omega_i RNTV(n_i) = \sum_{i=1}^{N} \omega_i \sum_{j=1}^{N} \frac{1}{N-1} \frac{W_{i,j} - W_{j,i}}{W_{i,j} + W_{j,i}}$$

where ω_i denotes the weight of n_i-payments respect the total payments in the system:

$$\omega_i = \frac{\sum_{i=1}^{N} W_{i,j}}{\sum_{i=1}^{N} \sum_{j=1}^{N} W_{i,j}}$$

D.8 Reactivity:

Let us define Reactivity as the incoming-payment elasticity of payments. This means the relative change in the payments sent by participant n_i to n_j when participant n_j changes by 1% the payments sent to n_i. Thus, this is a measure of how sensitive n_i-payments are. We can define the Apparent Reactivity of the payment system as the following weighted average:

$$AR(G) = \sum_{i=1}^{N} \omega_i AR(n_i) = \sum_{i=1}^{N} \omega_i \sum_{j=1}^{N} \frac{1}{N-1} \frac{\sinh^{-1}(W_{i,j})}{\sinh^{-1}(W_{j,i})}$$

where ω_i denotes the weight of n_i-payments respect the total payments in the system, as in RNTV. $\sinh^{-1}$ denotes the inverse hyperbolic sine, which keeps natural logarithm properties but maps in 0.