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Assessing Monetary Policy in the Euro Area: a Factor-Augmented VAR Approach

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Abstract

Following the tenth anniversary of Stage III of the European Monetary Union, this study assesses the effects of monetary policy shocks in the euro area in the period during which there is a common monetary policy in Europe. In order to overcome the omitted information problem of small-scale vector autoregression (VAR) models, we combine the VAR methodology with dynamic factor analysis, a recent time-series technique for the analysis of large data sets. Using the factor-augmented vector autoregressive (FAVAR) approach of Bernanke et al. (2005), we summarise the information contained in a large set of macroeconomic time series with a small number of estimated factors and use them as regressors in recursive VARs to evaluate the impact of the non-systematic component of the ECB's actions. Overall, our results suggest that the inclusion of factors in the VAR allows us to obtain a more coherent picture of the effects of monetary policy innovations, both by achieving responses easier to understand from the theoretical point of view and by increasing the precision of such responses. Moreover, to the extent that we include in the econometric model a very wide set of variables, which we believe the ECB effectively monitors, the likelihood of obtaining a contaminated measurement of policy shocks decreases. In addition, this framework allows us to compute impulse-response functions for all the variables included in the panel, thereby providing a more complete and accurate depiction of the effects of policy disturbances. However, the extra information generated by the FAVAR also delivers some puzzling responses, in particular those relating to the components of inflation.

Keywords: Factor models, European Monetary Union, monetary policy shock, vector autoregressions, factor-augmented vector autoregressions, impulse-response functions.
JEL Classification: C32, E52, E58.

Avaliação da Política Monetária na Área do Euro: Análise VAR aumentada de Factores

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Provas concluídas em:

Resumo

Após o décimo aniversário da Fase III da União Monetária Europeia, este estudo avalia os efeitos dos choques de política monetária na área do euro no período em que existe uma política monetária comum na Europa. Com vista a superar o problema de informação omitida dos modelos vectoriais autoregressivos (VAR), este estudo combina a metodologia VAR com a análise factorial dinâmica, uma técnica recente para análise de amostras amplas. Com base na abordagem VAR aumentada de factores (FAVAR), introduzida por Bernanke et al. (2005), a informação contida num conjunto vasto de séries temporais macroeconómicas é resumida num número reduzido de factores estimados, que são depois usados como regressores em VARs recursivos, para avaliar os efeitos da componente não sistemática das acções do BCE. Em termos gerais, os resultados do estudo sugerem que a inclusão de factores nos VAR permite obter uma visão mais coerente dos efeitos das inovações de política monetária, quer pela obtenção de respostas mais facilmente interpretáveis do ponto de vista teórico, quer pelo aumento da precisão dessas respostas. Adicionalmente, na medida em que é incluído no modelo econométrico um conjunto muito amplo de variáveis, que o BCE à partida acompanha, a probabilidade de obter uma medida enviesada dos choques de política monetária diminui. Esta metodologia permite, também, calcular funções de resposta a impulso para todas as variáveis incluídas na amostra, fornecendo, deste modo, uma visão mais completa e precisa dos efeitos dos choques de política monetária. Contudo, a informação adicional gerada pelos FAVAR também revela algumas respostas inquietantes, em particular as das diferentes componentes da inflação.

Palavras-Chave: Modelos factoriais, União Monetária Europeia, choque de política monetária, vectores autoregressivos, vectores autoregressivos aumentados de factores, funções de resposta a impulso.
Classificação JEL: C32, E52, E58.

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1 Introduction

Over the last two decades, influential papers have convincingly used vector autoregression (VAR) models with recursive identification schemes (henceforth recursive VARs) to identify and assess the effects of monetary policy innovations on macroeconomic variables. The great appeal of using recursive VARs to estimate the effects of the unanticipated component of central banks' actions seems to be their ability to deliver empirical credible responses of macroeconomic variables to a monetary policy shock without imposing burdensome restrictions on the dynamic structure of the model. This is so because the policy effects can be computed as the impulse-response functions obtained by inverting the VAR representation of the data, linearly transformed to yield the moving average representation with respect to the monetary policy shock.

However, it is a fact that VAR models are small-scale models, based on a limited information set, and this is often pointed out as their major weakness for the analysis of monetary policy. Monetary policy makers actually monitor a very wide set of macroeconomic variables before deciding on the stance of their policy actions, and therefore omitting relevant information from the VAR analysis may hamper the validity of the empirical results. Additionally, impulse-response functions can only be generated for the handful of variables included in the model, which represent a very small subset of the variables of interest to monetary authorities. However, due to degrees-of-freedom problems, it is not feasible to include a large number of time series in the model, and therefore the problem of omitted variables bias cannot be solved within the standard VAR framework.

Evidence emerging from a recent strand of empirical macroeconomic literature suggests that in order to properly capture the dynamics of the economy, significant advantages arise from resorting to models specifically designed to handle a large amount of information, the so-called dynamic factor models. Such models allow us to summarise the information contained in a large number of data series in a small number of estimated factors. Currently, the estimation of dynamic factor models resorts mainly to two different methods: principal components and maximum likelihood. Regarding the principal components method, two approaches have recently emerged for extracting information from large data sets. The first is a time-domain analysis, stems from Stock and Watson (1998, 1999, 2002a, 2002b), and relies on the estimation of factors by static principal components. The second is a frequency-domain approach, was introduced by Forni et al. (2000, 2004, 2005), and relies on dynamic principal components. As regards the estimation of factors by maximum likelihood, in the domain of time, important contributions are those of Doz et at. (2006, 2007) and Reis and Watson (2007).

Bernanke et al. (2005) apply the Stock and Watson (1998, 1999, 2002a, 2002b) methodology to extract the factors that summarise the information present in a large data set and they include those factors in monetary VARs. The authors conclude that factor models are a natural solution to the degrees-of-freedom problem in the VAR analysis of monetary policy since they allow for conditioning of the VAR approach on rich information sets without giving up the statistical gains of restricting the analysis to a small number of regressors. The authors refer to their methodology as the factor-augmented VAR (FAVAR) approach. The amount of information that can be handled within the FAVAR is very large and hence the chance of misspecifying the econometric model used to assess the effects of monetary policy disturbances significantly decreases. Moreover, it makes possible to compute impulse responses of each of the variables included in the panel to the policy shock.

In this paper, we are interested in evaluating if the inclusion of factors in a VAR improves our understanding of the effects of euro area monetary policy shocks, either by changing the shape of the responses of main macroeconomic variables to those shocks, or by decreasing the uncertainty about such responses. Although there are already some applications of factor analysis to the assessment of the effects of monetary policy shocks in the euro area (e.g. Favero and Marcellino, 2005; Boivin, Giannoni and Mojon, 2009; and Blaes, 2009), none of the papers, at least to our knowledge, applies the FAVAR approach to the euro area figures as from the launch of the single monetary policy in Europe (their sample period typically begins before 1999 and, since there was not a common monetary policy at the time, some countries are used as proxies or, alternatively, the figures are obtained by aggregating the countries' individual data). After commemorating the tenth anniversary of the European Monetary Union (EMU) we believe that we are beginning to have sufficient data to assess single monetary policy in the euro area in the period in which it was truly common, and therefore we hope to contribute towards filling the gap we have found in the literature.

With the purpose in mind of assessing if the extra information included in the econometric model really matters, we follow Bernanke et al. (2005) in using the Stock and Watson (1998, 1999, 2002a, 2002b) static principal components approach to extract factors from a data set comprising 150 macroeconomic time series for the euro area and then adding those latent factors as regressors in a VAR. We proceed by comparing our results to those of a standard five-dimensional VAR and conclude that the inclusion in the model of a very large set of variables, which potentially contain information about the monetary policy shock, succeeds in delivering responses more easy to interpret from the economic point of view. In particular, we show that the small-scale VAR generates a price puzzle, i.e. a counterintuitive positive reaction of prices to an increase in the official interest rate and we also show that the decrease of real Gross Domestic Product (GDP) is very persistent, a fact which is inconsistent with long-run money neutrality. Conversely, in our FAVAR specifications the price puzzle does not appear, which seems to corroborate the explanation of Sims (1992) that the price puzzle results from imperfectly controlling within the VAR for information that the central bank may have about leading indicators of inflation. Furthermore, the output response shows a consensual hump-shaped pattern. Another useful result is that the responses delivered by the different FAVAR specifications are more precise (have lower average standard deviations) than the responses delivered by the benchmark VAR.

Taking advantage of the special features of the FAVAR methodology, we proceed by computing impulse-response functions and variance error decomposition for a wider set of variables than those typically assessed in standard VARs. Our analysis delivers three main empirical results. First, the responses of the majority of the variables to the monetary policy shock are intuitive. For instance, an unexpected tightening in monetary policy results in a gradual decrease in industrial production, capacity utilisation, consumption expenditure, retail trade, business sentiment indicators and money aggregates in the short run, before reverting to the baseline scenario as the effects of the shock fade out. Second, in line with the consensual finding in the literature that monetary policy affects the economy mostly through its systematic behaviour, we conclude that at the 6-month horizon, apart from interest rates, the contribution of the policy shock for the variables' forecast error variance decomposition is lower than 5 per cent. After 60 months this contribution increases slightly, but even then the monetary policy shock does not explain more than 20 per cent of the volatility of any variable. Third, the extra information generated by the FAVAR approach brings to light some striking results as regards the responses of exchange rates and the components of the Harmonised Index of Consumer Prices (HICP). In the first case, unless we shorten the sample period in order to exclude the most acute phase of the financial crisis in 2008, a rise in the official interest rate is associated with an initial depreciation of the euro, which is probably caused by the euro area monetary authority reacting to changes in foreign interest rates. In the second case, we find that the intuitive negative response of inflation is mainly driven by the component energy and unprocessed food.

The paper is structured as follows. Section 2 explains the reasons for the study and provides a survey on the background literature for the discussions to which we seek to contribute. Section 3 describes the main methodological aspects used as foundations for the empirical application presented in Section 4. In Section 4, the empirical implementation evolves in two main steps. First, we present the results of our analysis, based on the estimation of impulse responses to the monetary policy shock and on the assessment of the fraction of the forecast error variance of the variables that is attributable to monetary policy disturbance. Second, we check our results for robustness to changes in some of the assumptions of the model. Section 5 draws the main conclusions and discusses some possible extensions of our work for future research.

2 Brief summary of the literature

Following the seminal works of Bernanke and Blinder (1992) and Sims (1992) on the use of VAR models to identify and estimate the effects of monetary policy innovations on macroeconomic variables, a large literature has developed concentrating on the assessment of the impact of unanticipated changes in monetary authorities' actions. Indeed, since not all variations in central banks' policy can be accounted for as a reaction to the state of the economy, VAR-based approaches focus on the non-systematic component of monetary policy, rather than on the systematic one. The above-mentioned unaccounted change in central banks' policy is widely formalised in literature with the notion of a monetary policy shock.

Let us consider the following monetary policy reaction function, i.e. the function that discloses how central banks adjust short-term interest rates in response to various elements in the macroeconomy:

$$r_t = f(\Omega_t) + \eta_t \tag{1}$$

where r_t is the monetary policy variable (the official short-term interest rate), $f(\Omega_t)$ is the policy rule, i.e. the decision based on the monetary authorities' information set Ω_t, and η_t is the change in r_t not based on the information set Ω_t, i.e. that does not rely on the current or past state of the economy. The second term on the right-hand side of Equation (1) is therefore the monetary policy shock.

According to Christiano et al. (1999), there may be at least three reasons for the non-systematic change in monetary policy: (i) the shift in monetary authority's preferences between unemployment or economic growth and inflation; (ii) the central bank's desire to avoid the social costs of disappointing private agents' expectations (self-fulfilling expectations); and (iii) technical factors, in particular measurement errors, given that the data available when the central bank makes its decision is often just preliminary.

In econometric literature we can find VAR models in three different formulations: reduced-form, recursive and structural. The identification of monetary policy shocks through VAR techniques has mostly been based on recursive VARs, although some studies have alternatively chosen to rely on structural VARs. Before we proceed detailing the main differences between the three formulations, we must briefly look at the meaning of *identification* in the language of econometrics. According to Stock and Watson (2001), the identification problem relates to the need to distinguish between correlation and causation in statistical relations. Identifying monetary policy shocks correctly has important implications for macroeconomic analysis, in particular to gauge the role of monetary disturbances in the propagation of business cycles. Since policy shocks are a measure of a central bank's non-systematic action, they allow us to distinguish between the unanticipated behaviour of the monetary authority and its responses to fluctuations in output, prices and so on. Therefore the accurate distinction between the two components of the central bank's action provides the basis for understanding future changes in the monetary policy stance and for evaluating its performance.

Reduced-form VARs. A reduced-form VAR is an n-equation, n-variable linear model, in which each variable is expressed as a linear function of its own lagged values, the past values of the remaining $n-1$ variables and a serially uncorrelated error term. These equations can be estimated by ordinary least squares (OLS), where the error terms represent the innovations to the variables, after taking their past values into account. However, as the different variables are usually correlated with each other, the error terms will also be correlated across equations.

Recursive VARs. In this VAR formulation, some contemporaneous values are added as regressors, and therefore the OLS estimation delivers residuals that are uncorrelated across equations. However, the results achieved depend crucially on the order of the variables, as changing the order of the variables changes the VAR equations, the coefficients and the residuals. The recursiveness assumption makes use of the Cholesky decomposition of the variance-covariance matrix of the estimated residuals, a simple algorithm for splitting a symmetric positive-definite matrix into a lower triangular matrix multiplied by its transpose. The Cholesky decomposition implies a strict causal ordering of the variables in the VAR: the variable positioned last responds contemporaneously to all the others, while none of these variables respond contemporaneously to the variable ordered last; the next-to-last variable responds contemporaneously to all variables except the last, whereas only the last variable responds contemporaneously to it. A popular identifying assumption in VAR studies of the monetary transmission mechanism is that the monetary policy shock is orthogonal to the variables in the policy rule, in the sense that economic variables in the central bank's information set do not respond contemporaneously to realisations of the monetary policy shock. This assumption imposes the existence of a set of variables that are predetermined to the policy shock, e.g. it assumes that output and price decisions are made prior to the shock. This corresponds to ordering the monetary policy shock after output and prices in a Cholesky decomposition of disturbances estimated from a VAR on output, prices, a short-term interest rate and other policy variables, such as the level of nonborrowed reserves or the effective exchange rate. The attractiveness of the recursive identification scheme relies on the possibility of identifying the monetary policy shock without having to take a stand on any of the other shocks in the economy, i.e. the identification of the monetary policy innovation is the same, no matter how the other innovations are identified. Estimation of VARs in this way has become popular because it does not impose cross-equation restrictions on the lagged coefficient matrices that are implied by a particular structural model, which means that recursive VARs are a model-independent view of the data, i.e a data-led, atheoretical or agnostic approach.

Structural VARs. Unlike recursive VARs, structural VARs are a theory-led approach, in the sense that they require numerous restrictions in order to give the system a structural interpretation or, in other words, to achieve identification. These identifying restrictions can involve the entire VAR, so that all the causal links in the model are spelled out, or just a single equation, so that only a specific causal link is identified. Identification of monetary policy shocks in a structural VAR can be found in three main streams of literature. The first relates to the imposition of restrictions on the contemporaneous relationships between variables. In this case, economic theory is used to sort out the contemporaneous links among the variables, which means that while recursive VARs use an arbitrary mechanical method to model contemporaneous correlation in the variables, structural VARs use economic theory to associate these correlations with causal relationships (Stock and Watson, 2001). The second strategy imposes sign restrictions on the acceptable responses to shocks, for model identification (e.g. Uhlig, 2005). The third approach takes into account the longer-run properties, placing restrictions on the long-run variance-covariance matrix of the error terms, sometimes without placing restrictions on the contemporaneous relationships among the variables. For instance, Blanchard and Quah (1989) interpret fluctuations in output and unemployment as due to two type of disturbances: supply disturbances, having a permanent effect on output, and demand innovations, which do not have a permanent impact on output. We refer the reader to Christiano et al. (1999) for a critical survey on the literature on VAR identifying assumptions.

Now that we have described briefly the three VAR formulations, we think it is useful to highlight that if structural VARs can capture rich dynamic properties of multiple time series, their structural implications are only as sound as their identification schemes (in the sense that different schemes may lead to different conclusions on the effects of structural shocks). Besides this, abandoning the recursiveness assumption (a set of theory-free restrictions) has a substantial cost: a broader set of economic relationships must be identified. Therefore, given the fairly simple econometric methodology involved, the non-requirement of a complete structural model of the economy, and the reasonable assessments of the dynamic responses of key macroeconomic variables to monetary policy innovations empirically derived, VAR approach with recursive identification schemes has been a widely used tool over the last decades and will also be the approach underpinning our analysis. However, in recursive VARs, like in structural VARs, omitting variables that contain relevant information on the economic shocks may lead to a situation in which VAR innovations will not, in general, span the space of the disturbances, and therefore the shocks cannot be deduced correctly from VAR innovations. The likely solution to mitigate this problem would be to increase the amount of information in the VAR, assuming that the large quantity of variables the monetary authorities actually monitor help them to isolate the macroeconomic shocks impacting on the economy. However, increasing the number of variables in a VAR poses technical and conceptual complications, as the number of unrestricted VAR coefficients increases in direct proportion to the square of the number of variables in the system.

Taking advantage of this caveat to the VAR approach, Bernanke et al. (2005) introduce an innovative method – which they refer to as the Factor-Augmented VAR (FAVAR) approach – combining the standard VAR analysis with factor analysis for large data sets. Factor analysis seems to provide an useful way of exploiting the knowledge coming from rich data sets when estimating shocks and propagation mechanisms, since the information from a large number of data series can be summarised by a small set of latent factors. According to Stock and Watson (2005), those unobserved factors produce the observed comovements of economic time series and are driven by the macroeconomic shocks, i.e. the relevant shocks that have to be identified for the purpose of conducting policy analysis. With the FAVAR approach, Bernanke et al. (2005) claim to overcome the main drawbacks of the VAR methodology, in particular: (i) the small number of variables normally included in standard VARs is unlikely to span the information sets used by central banks, but the inclusion of additional variables is strongly limited by degrees-of-freedom problems;[1] therefore if the monetary authority has more information than that included in the VAR, the measurement of policy innovations is likely to be biased; (ii) the choice of a specific data series to represent general economic concepts such as real activity is often arbitrary; and (iii) impulse responses (a quantitative measure of the dynamic effects of policy changes on the economy) can only be computed for the few variables included in the model.

Large-dimensional dynamic factor models have become popular in empirical macroeconomics in recent years, but the literature on dynamic factor analysis in economics goes back to Geweke (1977) and Sargent and Sims (1977). In a factor model, the data generating process of each variable is the sum of a common component, driven by a small number of latent common factors, and an idiosyncratic component. Besides the aforementioned advantages of factor models, in particular the fact that they can cope with many variables without running into scarce degrees-of-freedom problems, allowing for exploitation of a "data-rich environment" (Bernanke and Boivin, 2003), and therefore leading to more precise forecasts and macroeconomic analysis, we can highlight two additional arguments in favour of these models. On the one hand, idiosyncratic movements, which may include measurement errors and local/specific shocks, can be eliminated, yielding a more reliable signal for policy makers and preventing them from reacting to idiosyncratic disturbances. On the other hand, factor modellers can remain agnostic about the structure of the economy and do not need to rely on overly tight assumptions.

[1]For instance, the well known VAR system of Bernanke and Mihov (1998) contains six variables, of which three are policy variables, i.e. variables that are potentially useful as direct indicators of the stance of the monetary policy (the fed funds rate, nonborrowed reserves and total reserves), and three are non-policy variables, i.e. economic variables the responses of which to monetary policy shocks the authors want to identify (real GDP, the GDP deflator and a spot commodity price index). Bayesian VAR models allow increasing the number of variables included, but the systems normally contain less than twenty variables (e.g. Leeper et al., 1996).

In the literature, besides the application of dynamic factor models to monetary policy analysis, the field we are interested in, we can find at least three more fields of application for factor analysis: construction of economic indicators, forecasting and international business cycles analysis. Firstly, regarding the construction of economic indicators, the most known examples are the coincident business cycle indicators constructed both for the United States (US) and the euro area, the Chicago Federal Reserve National Activity Index (CFNAI) and the EuroCOIN, respectively. The CFNAI is a weighted average of 85 monthly indicators, designed to better gauge overall economic activity and inflationary pressures. It corresponds to the first static principal component extracted from a large macroeconomic data set, and the associated methodology relies on Stock and Watson (1999). The EuroCOIN was developed by Altissimo et al. (2001) and is formally defined as the common component of the GDP growth rate, based on dynamic principal components analysis. Secondly, the underlying idea on the application of factor analysis to the forecasting exercise is to use factors estimated from a large panel of data to help forecasting the series of interest, so that information in a large number of variables can be used while keeping the dimension of the forecasting model small. In the very wide stream of literature that follows this line of research, we highlight the work of Stock and Watson (1998, 1999, 2002a, 2002b), Giannone at al. (2005) and Boivin and Ng (2005), for the US, and Angelini et al. (2001) and Marcellino et al. (2003), for the euro area. Finally, the application of factor models to international business cycles analysis has developed considerably since the creation of the EMU in 1999[2] and the abandon of an autonomous monetary policy by 16 countries, which directed considerable attention towards the study of the effects of shocks of a common monetary policy in each member's economy. Marcellino et al. (2000), Breitung and Eickmeier (2005), Eickmeier (2006) and Boivin, Giannoni and Mojon (2009), among others, evaluate the homogeneity and comovements among EMU countries by estimating

[2]More correctly, the beginning of Stage III of the EMU and the launch of the euro.

factor models for large sets of macroeconomic variables.

We now turn to the application of dynamic factor models to monetary policy analysis, the field we are focusing on. As previously mentioned, Bernanke et al. (2005) address the problem of omitted variables bias inherent in many simple small-scale VAR models through the inclusion of factors in monetary VARs. They show that the inclusion of factors ameliorates the understanding of the effects of monetary policy shocks, both through the increase in the precision of the estimates and the delivery of responses easier to interpret from the economic point of view (elimination of some puzzles empirically delivered by standard VARs). Nevertheless, this study was not the first to use factor models in the assessment of the monetary transmission mechanism. In fact, as a natural extension of the forecasting literature, Bernanke and Boivin (2003) propose to exploit the use of a dynamic factor approach in the estimation of forward-looking Taylor rules in the US, in order to mimic more closely the behaviour of central banks, whose decisions are likely to be based on a substantial amount of information. Giannone et al. (2002), in their turn, propose a new framework to analyse systematic and unsystematic monetary policy within the same econometric model. Taking into account that monetary authorities use all data available to extract information on current economic activity, they use factor analysis to show that shocks can be identified structurally and the parameters of monetary policy rules, conditional on those shocks, can be estimated. Following the same line of research, Favero et al. (2005) evaluate the role of static and dynamic principal components as instruments for the estimation of Taylor rules and conclude that the inclusion of factors in the instrument set improves in general the precision of the estimates, both for the US and the euro area. Forni et al. (2003, 2008) provide a comparison between structural factor models and structural VARs, attempting to show that factor models are better suited than VARs to provide a structural representation of the economy. They argue that dynamic factor models allow for distinguishing idiosyncratic disturbances (e.g. measurement errors), which affect almost exclusively a specific variable, from structural common/macroeconomic shocks, which are cross-sectionally pervasive, in the sense that they affect all the variables in the system. In these papers, the authors identify the main macroeconomic shocks in the US economy and estimate policy rules conditional on the shocks. Sala (2003) studies the transmission of monetary policy shocks across European countries by extracting the common European monetary shock (identified with that of Germany) and computing the country-specific responses (for eight euro area countries). Stock and Watson (2005) follow the line of investigation of Bernanke et al. (2005), also focusing on the implications of dynamic factor models for VAR analysis, but go beyond it by considering a variety of identifications schemes, such as time restrictions (the scheme adopted by Bernanke et al., 2005), long-run restrictions, restrictions on the factor loading matrixes and sign restrictions. Favero and Marcellino (2005) concentrate on European data (France, German, Italy and Spain) and use the dynamic factor model to evaluate both the determinants and the effects of monetary policy, respectively through the inclusion of the few estimated factors in the instrument set of a forward-looking Taylor rule and in the set of regressors of a structural VAR.

Finally, it is also worth mentioning that, besides the wide literature on application of factor analysis to the identification and assessment of monetary policy shocks, a more recent stream of literature begins to use factor models to help in designing an optimal monetary policy in a "data-rich environment". In some of these papers, Dynamic Stochastic General Equilibrium (DSGE) models, augmented with measurement errors, make use of the dynamic factor approach. Boivin, Giannoni and Mihov (2009) slightly change the two-step method used by Bernanke et al. (2005) to extract the common components and demonstrate, by means of the dynamic factor approach, that disaggregated prices are sticky in response to macroeconomic and monetary disturbances but flexible in response to sector-specific shocks. Boivin and Giannoni (2008) provide an evaluation of the welfare benefits associated with exploiting information beyond the handful of variables typically considered in the analysis of optimal monetary policy. The empirical framework considered consists of a fully specified DSGE model, i.e. a dynamic factor model where the structure of a DSGE model is assumed to govern the dynamics of the factors. It should be noticed, however, that in contrast to the FAVAR approach, it is not possible to estimate impulse-response functions of macroeconomic variables to policy shocks in DSGE models without imposing theory-based dynamic restrictions, since DSGE models are explicit about causal links and expectations.

In our work, we will follow Bernanke et al. (2005) and will apply the factor-augmented VAR approach to the identification and assessment of monetary policy shocks in the euro area. Since a common monetary policy in the euro area has only existed since 1999, the relevance of our work relies on the pioneering application (at least to our knowledge) of this methodology to the post-1999 data for the euro area *per se* (and not to the aggregation of individual member-states' figures or to the utilisation of some countries as proxies for the entire euro area). As a point of departure, we quote Boivin, Giannoni and Mojon (2009), who, in an interesting remark, highlight that it is not because they believe that monetary policy shocks, *per se*, constitute an important source of business cycle fluctuations that they are interested in assessing the effects of such shocks. It is because tracing the responses of variables to unanticipated changes, and assuming that the central bank will subsequently adapt its policy rule to those responses, that impulse-response functions to policy shocks provide a useful description of the *systematic* monetary policy rule.

3 Econometric framework

In this section, we describe the main methodological aspects that provide the foundations for our econometric application. Before we proceed with the description, we must first take some time clarifying the distinction between a set of concepts, some of which we have already used in the literature review without explaining exactly their meaning.

The first important distinction is between the classical/strict/exact and the approximate formulation of a dynamic factor model. The exact formulation entails three restrictive assumptions on the idiosyncratic component of the variables: they have to be cross-sectionally independent, serially independent and uncorrelated with the common factors. In its turn, the approximate factor model allows for some heteroskedasticity and limited dependence of the idiosyncratic components (serially and cross-sectionally), as well as for some moderate correlation between the latter and the factors (see, for instance, Stock and Watson (1998, 2002a) and Bai and Ng, 2002).

The second distinction to be made is between the static and the dynamic representation of a dynamic factor model. In the latter, factors are assumed to evolve according to a time series process, i.e. factors can enter with lags or leads in the data generating process of each variable. In the former, factors appear without any lags, which means that factors only have a contemporaneous effect on the variables.[3] The static approach relies on the time-domain forecasting method of Stock and Watson (1998, 1999, 2002a, 2002b), whose estimates are based on contemporaneous covariances only, meaning that they do not exploit the potential information contained in the leading-lagging relations between the elements of the panel. The authors show that when both the number of variables and the time dimension tend to infinity, the space of factors is consistently estimated by static principal components, even in an approximate factor model with factor loadings constant and idiosyncratic errors that are serially and (weakly) cross-sectionally correlated. In its turn, the dynamic method is mainly due to Forni et al. (2000, 2004, 2005) and Doz et al. (2006,

[3] In order to make this terminology clear – and it might at first seem quite misleading – it is required to note that the term static in a dynamic factor model refers to the static relationship between the common component and the variable; however, the common component itself can be a dynamic process, i.e. can capture arbitrary lags of some fundamental factors. As Forni et al. (2004) assert, when all variables are "hit" by the common shocks at the same time, the model is called static; when different variables are "hit" by different lags of the common shocks, the model is called dynamic.

2007). The latter use a time-domain approach, estimated by a Gaussian maximum likelihood method, while the former rely on a frequency-domain method, estimated by dynamic principal components, based on the dynamic covariance structure of the data.

In our study, we will follow the Stock and Watson (1998, 1999, 2002a, 2002b) principal components static approach, according to which the first principal components span the factor space even if the model is only approximate.

3.1 Time domain analysis of the dynamic factor model

Factor models represent the vector of N time series as a linear combination of two unobserved components, a common component, driven by a small number of factors, plus an idiosyncratic component, driven by N idiosyncratic factors. Let X_t be the $N \times 1$ vector of stationary zero mean variables under analysis, observed for time $t = 1, 2, ..., T$. In the general formulation of a dynamic factor model, each element of the vector $X_{it} = [X_{1t}, ..., X_{Nt}]'$, for $i = 1, 2, ..., N$, can be represented as:

$$X_{it} = \lambda_i(L) f_t + e_{it} \tag{2}$$

where f_t is the $q \times 1$ vector of common factors ($q \ll N$), whose dynamic effects on X_{it} are grouped in $\lambda_i(L) = \lambda_{i0} + \lambda_{i1} L + \lambda_{i2} L^2 + ... + \lambda_{ip} L^p$, lag polynomials in nonnegative integer powers of L (where each λ_i is a $N \times q$ matrix), and $e_t = [e_{1t}, ..., e_{Nt}]'$ is the $N \times 1$ vector of idiosyncratic disturbances. An alternative formulation of the model is:

$$X_t = \Lambda F_t + e_t \tag{3}$$

where $F_t = [f_t', f_{t-1}', ..., f_{t-p}']'$ is $r \times 1$, so that now $r = (p+1) \times q$ factors drive the variables, but the factors have only a contemporaneous effect on X_t, with loadings grouped in the $N \times r$ matrix $\Lambda = [\lambda_0, \lambda_1, ..., \lambda_p]$, the i-th row of Λ being

$\Lambda_i = [\lambda_{i0}, ...\lambda_{ip}]$. Since the association between factors and variables is only contemporaneous, the dynamic factor model is in its static formulation.

Note that we cannot estimate F_t, but instead we can estimate the common-factor space, i.e. a r-dimensional orthogonal vector whose entries span the same linear space as the entries of F_t. In fact, the factors are not identified because for any invertible $r \times r$ matrix G, Equation (3) can be rewritten as

$$X_t = \Lambda G G^{-1} F_t + e_t = \Psi P_t + e_t \quad (4)$$

where P_t is an alternative set of factors. In spite of the identification problem (which complicates the structural interpretation of the factors), P_t is just a linear transformation of F_t, and therefore both are equivalent in summarising the information contained in X_t.

In the classical or exact formulation of the factor model, the idiosyncratic components are assumed to be serially and cross-sectionally independent and the factors are assumed to be serially uncorrelated. Moreover, $E[F_t e_t'] = 0$, i.e. the factors and the idiosyncratic components are required to be mutually orthogonal. However, the assumptions of the exact model may be viewed as too restrictive and even unrealistic in economic terms. In this context, Chamberlain and Rothschild (1983) showed that a static factor model which allows for some degree of cross-sectional and temporal dependence of the idiosyncratic components, as well as for moderate correlation between the latter and the factors, still succeeds to estimate consistently the factor space. In the authors terminology, this is an approximate specification of the factor model.

Stock and Watson (1998) developed a nonparametric approach for the time domain analysis of the dynamic factor model based on the static principal components of X_t.[4] The authors show, under the finite lag assumption and some additional

[4]This means that the correlation structures and distributions of the idiosyncratic terms and the factors and the precise lag structure by which the factors enter are not specified parametrically (Stock and Watson, 1998).

technical assumptions, that the common space spanned by the dynamic factors F_t can be estimated consistently by the principal components of the $T \times T$ covariance matrix of X_t, even if some of the restrictive assumptions of the classical model are neglected. In this way, consistency of the estimators requires the factors F_t to be orthogonal, i.e. uncorrelated with each other, but they can be correlated in time and can also be weakly correlated with the idiosyncratic component. In this approximate factor model (in the terminology of Chamberlain and Rothschild, 1983) limited dependence of the idiosyncratic disturbances is allowed in both dimensions.

The starting point in the Stock and Watson (1998) approach is the estimation of the factors F_t and the loadings Λ. Let the estimators $\widehat{F}_t$ be the minimisers of the least squares criterion:

$$V_{N,T}(F,\Lambda) = (NT)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} (X_{it} - \Lambda_i F_t)^2 \tag{5}$$

where $F = [F_1, ..., F_t, ..., F_T]'$ and Λ_i is the i-th row of Λ, subject to the constraint $T^{-1}F'F = T^{-1}\sum_{t=1}^{T} F_t F_t' = I_q$.

Under the hypothesis of k common factors, Stock and Watson (1998) show that the least squares estimators of the factors $\widehat{F} = [\widehat{F}_1, ..., \widehat{F}_t, ..., \widehat{F}_T]'$ are the k eigenvectors corresponding to the k largest eigenvalues of the $T \times T$ matrix $(N)^{-1}\sum_{i=1}^{N} X_i^* X^{*\prime}_i$, where $X_i^* = [X_{i1}, ..., X_{iT}]'$. The least squares estimators of the loadings are then obtained from a linear regression (OLS) of the variables on the estimated factors. Moreover, the least squares estimators of the loadings are the k eigenvectors corresponding to the k largest eigenvalues of the $N \times N$ matrix $(T)^{-1}\sum_{t=1}^{T} X_t X_t'$. The authors prove that when the assumed number of factors, k, is equal to the true number, r, the entries of $\widehat{F}_t$ span the same linear space as the entries of F_t. When $k > r$, there are $k - r$ estimated factors that are redundant linear combinations of the elements of F_t. When $k < r$, consistent estimation of a subspace of dimension k is preserved, because of the orthogonality hypothesis.

Finally, the estimator of the common component can be obtained as $\widehat{x}_t = \widehat{\Lambda}\widehat{F}_t$ and, consequently, the estimator of the idiosyncratic component is $\widehat{e}_t = X_t - \widehat{x}_t$.

3.2 Determination of the number of (static) factors

Stock and Watson (1998) suggest determining the number of factors by minimising a particular information criterion. Nevertheless, with their simulation experiments, they conclude that more standard criteria like Akaike (AIC) or Bayes (BIC) perform better. This issue was then further developed by Bai and Ng (2002), also within the framework of large cross-section and large time dimensions, without imposing any restriction on the relation between N and T.[5] Their simulations show that the criteria they propose, which basically modify the AIC and BIC criteria in order to take into account the divergence of both N and T, have good finite sample properties and that the results hold both under heteroskedasticity in the N and T dimensions and under weak serial and cross-section dependence.

The two alternative classes of criteria proposed by Bai and Ng (2002) are the following:

$$PC(k) = V_{N,T}(\widehat{F}_{(k)}, \widehat{\Lambda}_{(k)}) + kg(N,T) \tag{6}$$

$$IC(k) = \ln\left(V_{N,T}(\widehat{F}_{(k)}, \widehat{\Lambda}_{(k)})\right) + kg(N,T) \tag{7}$$

where $V_{N,T}(\widehat{F}_{(k)}, \widehat{\Lambda}_{(k)})$ denotes the sum of squared residuals from a k-factor model, as defined in Equation (5), with $\widehat{F}_{(k)}$ and $\widehat{\Lambda}_{(k)}$ being the estimated factors and loadings. The information criteria reflect the trade-off between goodness-of-fit, on the one hand, and overfitting, on the other. The first term on right-hand side of Equations (6) and (7) shows the goodness-of-fit; if the number of factors increases, the variance of the factors also increases and the sum of squared residuals decreases. Hence, the

[5] It must be noticed that the main requirement for the consistence of factors estimated by the Stock and Watson (1998) nonparametric methodology was that N grew at a faster rate than T, a restriction that was abandoned by Bai and Ng (2002).

information criteria have to be minimised in order to determine the number of factors. The penalty of overfitting, which is the second term on the right-hand side of Equations (6) and (7), is an increasing function of N and T. Therefore, the authors define these penalty functions, $g(N,T)$, such that the criteria above allow to consistently estimate r ($\widehat{r}$ being the value of k that minimises the criteria). They show that under their hypothesis and assuming $kmax \geqslant r$, $\lim_{N,T\to\infty} p(\widehat{r}=r)=1$ if when $N\to\infty$ and $T\to\infty$, (i) $g(N,T)\to 0$ and (ii) $\min\{N,T\}g(N,T)\to\infty$. Assuming the method of principal components as the one used to estimate the factors, the authors propose three specific formulations of $g(N,T)$ applied both for $PC(k)$ and $IC(k)$: 1) $\left(\frac{N+T}{NT}\right)\ln\left(\frac{NT}{N+T}\right)$; 2) $\left(\frac{N+T}{NT}\right)\ln\left(\min\{N,T\}\right)$; and 3) $\frac{\ln(\min\{N,T\})}{\min\{N,T\}}$. The authors show, with their simulation experiments, that among the six resulting criteria, the ones that perform better and are more stable are the first and second $IC(k)$ specifications ($IC_1(k)$ and $IC_2(k)$, respectively). In the literature, the one that is commonly used for the determination of the number of factors both when US large data sets and euro area large data sets are considered, and which will similarly be the specification we will use in our empirical exercise described in Section 4, is the second $IC(k)$ specification:

$$IC_2(k)=\ln\left(V_{N,T}(\widehat{F}_{(k)},\widehat{\Lambda}_{(k)})\right)+k\left(\frac{N+T}{NT}\right)\ln\left(\min\{N,T\}\right) \tag{8}$$

3.3 The factor-augmented VAR

3.3.1 The model

Let X_t denote an $N\times1$ vector of economic time series, Y_t a vector of $M\times1$ observable macroeconomic variables that constitutes a subset of X_t and F_t a $k\times1$ vector of unobserved factors that capture most of the information contained in X_t. According to Bernanke et al. (2005), the joint dynamics of (F_t, Y_t) can be given by the following transition equation:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi^*(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + v_t \Leftrightarrow \Phi(L) \begin{bmatrix} F_t \\ Y_t \end{bmatrix} = v_t \tag{9}$$

where $\Phi(L) = I - \Phi^*(L)L = I - \Phi_1 L - ... - \Phi_d L^d$ is a conformable lag polynomial of finite order d in the lag operator L, Φ_j $(j = 1, ..., d)$ is the coefficient matrix and v_t is an error term with mean zero and covariance matrix Q. Equation (9) is a VAR model, which may contain *a priori* restrictions as in the VAR literature, but which includes both observable and unobserved variables. Bernanke et al. (2005) refer to Equation (9) as a factor-augmented vector autoregression, or FAVAR.

Since the factors are unobserved, Equation (9) cannot be estimated directly. However, we can interpret the factors, in addition to the observed variables, as the common forces driving the dynamics of the economy. For concreteness, we can assume that the relation between the "informational" time series X_t, the observed variables Y_t and the factors F_t can be summarised in the following (static) representation of a dynamic factor model:

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + e_t \tag{10}$$

where Λ^f is a $N \times k$ matrix of factor loadings, Λ^y is $N \times M$ and e_t is the vector of $N \times 1$ error terms weakly cross-sectionally and serially correlated and with mean zero. The specification of the dynamic factor model *à la* Stock and Watson (1998) implies that X_t does not depend on the lagged values of F_t, only on the current ones (static representation of the dynamic factor model). Since we assume that $M + k \ll N$, the amount of information that can be handled in a FAVAR increases significantly in comparison to standard VAR models.

3.3.2 Identification of the factors

For the estimation of the FAVAR model (9)-(10) we will follow the two-step principal components approach used in Bernanke et al. (2005), which is a nonparametric way of estimating the common space spanned by the factors of X_t, i.e. $C(F_t, Y_t)$.[6,7] In the first step, $C(F_t, Y_t)$ is estimated using the first $k + M$ principal components of X_t; in the second step, Equation (9) is estimated with F_t replaced by $\widehat{F}_t$.

We will follow the work of Bernanke et al. (2005) and will not exploit the fact that Y_t is observable in the first step. However, as shown in Stock and Watson (2002b), when N is large and the number of principal components used is at least as large as the true number of factors, the principal components consistently recover the space spanned by both F_t and Y_t. In this way, obtaining $\widehat{F}_t$ implies determining the part of $\widehat{C}(F_t, Y_t)$ that is not spanned by Y_t, i.e. by removing Y_t from the space covered by the principal components. This will be done in the second step, relying on a specific identifying assumption that exploits the different behaviour of the several variables included in X_t.[8] For concreteness, the matrix X_t is divided into slow-moving and fast-moving series. The former are those variables that are assumed to be predetermined as of the current period, i.e. that do not respond contemporaneously to unanticipated changes in monetary policy (e.g. real variables). The latter are those variables that are allowed to respond contemporaneously to policy shocks (e.g. asset prices). In order to remove the direct dependence of $\widehat{C}(F_t, Y_t)$ on Y_t, the foothold is to obtain $\widehat{C}^*(F_t)$ as an estimate of all the common components other than Y_t.

[6]Bernanke et al. (2005) also tried an alternative approach making use of Bayesian likelihood methods and Gibbs sampling to estimate the factors and the dynamics simultaneously. The authors conclude that the advantages of using this procedure (more computationally burdensome) are modest, and therefore we will only make use of the principal components approach.

[7]We will use the same terminology as in Bernanke et al. (2005) and will refer to $C(F_t, Y_t)$ as the common space spanned by the factors of X_t, i.e. both by the latent factors F_t and the observed factors Y_t. Although it might seem quite abusive to classify Y_t also as a factor, the rationale behind this terminology is that both F_t and Y_t have pervasive effects throughout the economy and are thus considered common components of all variables entering the data set.

[8]In a more recent paper, Boivin, Giannoni and Mihov (2009) impose the constraint that Y_t is one of the common components in the first step, guaranteeing that the estimated latent factors $\widehat{F}_t$ recover the common dynamics not captured by Y_t. The authors compare their methodology with that of Bernanke et al. (2005) and conclude that the results are similar.

Since slow-moving variables are assumed not to be affected contemporaneously by Y_t, $\widehat{C}^*(F_t)$ is obtained by extracting principal components from this set of variables. Afterwards, the estimated common components $\widehat{C}(F_t, Y_t)$ are regressed on the estimated slow-moving factors $\widehat{C}^*(F_t)$ and on the observed variables Y_t:

$$\widehat{C}(F_t, Y_t) = a\widehat{C}^*(F_t) + bY_t + u_t \tag{11}$$

Finally, $\widehat{F}_t$ is calculated as $\widehat{C}(F_t, Y_t) - \widehat{b}Y_t$ and the VAR in $\widehat{F}_t$ and Y_t is estimated:

$$\widehat{\Psi}(L) \begin{bmatrix} \widehat{F}_t \\ Y_t \end{bmatrix} = \varepsilon_t \tag{12}$$

where $\widehat{\Psi}(L) = \widehat{\Psi}_0 - \widehat{\Psi}_1 L - ... - \widehat{\Psi}_d L^d$ is a matrix of order d in the lag operator L, $\widehat{\Psi}_j$ $(j = 0, 1, ..., d)$ is the coefficient matrix and ε_t is the vector of structural innovations within the diagonal covariance matrix.

3.3.3 Identification of the VAR

In the FAVAR approach, as in standard VARs, the identification of the macroeconomic shocks requires identifying restrictions. We will follow Bernanke et al. (2005) assuming a recursive structure where the factors entering Equation (9) respond with a lag (i.e. do not respond within the period, here a month) to unanticipated changes on the monetary policy instrument. We will assume a Cholesky identification scheme in which the policy variable, in our case the European Central Bank (ECB) repo rate,[9] is ordered after the factors, output and prices and will treat its innovations

[9] Throughout the text, we will always refer to the policy variable as the ECB repo rate. Nevertheless it should be clarified that, in the empirical exercise, we have followed the strategy usually used in the VAR literature and have preferred to use an effective rate instead of the target rate itself. In this way, we have considered the Euro OverNight Index Average (EONIA) as a proxy for the "effective repo rate". The EONIA is the effective overnight reference rate for the euro area and is computed as a weighted average of all overnight unsecured lending transactions undertaken in the interbank market, initiated within the euro area by the banks belonging to the contributing panel. The EONIA is the interbank rate that follows more closely the ECB repo rate and one of the ECB's aims is to contribute to the smooth path of this market rate. In our sample period, the EONIA was, on average, five basis points higher than the ECB repo rate. This reduced spread

as the policy shocks. As we have mentioned in Section 2, several other identification schemes are available in VAR literature. It must be stressed that those other identification schemes (e.g. long-run restrictions and sign restrictions) can also be implemented in the FAVAR framework. Nevertheless, as we have discussed earlier, given the non-requirement of a complete structural model of the economy and the reasonable results delivered, the recursive identification scheme has become popular in the analysis of monetary policy shocks through the VAR approach, and therefore we believe it is a credible point of departure for the identification of the FAVAR.

4 Empirical analysis

4.1 The data

Our data set consists of a balanced panel of 150 monthly macroeconomic time series for the 16-country euro area from 1999:1 to 2009:3. The choice of the starting date reflects our desire to maximise the sample length while considering that the assessment of a common monetary policy in the euro area only makes real sense after the launch of the euro. The bulk of the data used in the analysis was taken from the Eurostat database, with the ECB Statistical Data Warehouse and the OECD database being alternative sources for some of the variables. The macroeconomic series were chosen from the following categories: real output and income; employment; prices; exchange rates; interest rates; stock prices; money and credit aggregates; industrial new orders and turnover; retail sales and turnover; building permits; balance of payments and external trade; confidence indicators; and some foreign variables (US, Japan and United Kingdom's GDP, inflation and interest rates). Appendix A lists all the series in the data set and their transformation.

The data were processed in five stages. First, as seasonal patterns are often so large that they may hide other characteristics of the data that are of interest for

reinforces our idea that the EONIA rate might be the best proxy for the policy variable.

the analysis of economic trends, the series were seasonally adjusted, i.e. the seasonal effects of the series were estimated and removed. The approach we used relies on a multiplicative decomposition through X-12-ARIMA, for all positive series, and on an additive decomposition for the remaining series. In the multiplicative approach the adjustment is made by dividing the original series by the seasonal factor estimates, while in the additive approach the adjusted series are the original series minus the seasonal factor estimates.

Second, as we intended to work with a balanced panel of monthly series, we had to disaggregate the quarterly series into monthly ones, using the Eurostat statistical software Ecotrim. In the econometric and statistical literature, two univariate approaches to disaggregate economic series observed at low frequency into compatible higher frequency data have been generally followed: (i) methods which do not involve the use of related series and (ii) methods which make use of the information coming from related indicators observed at the desired higher frequency (for a review of the methods, see Di Fonzo, 2003). Since the first approach only comprises purely mathematical methods, we have chosen the latter as the most interesting for our purposes. However, instead of selecting a small set of variables to help in the disaggregation of each of the quarterly variables (e.g. the GDP is usually disaggregated using as a related indicator the industrial production index), we have followed Angelini et al. (2006) in exploiting an interpolation method that makes use of the factors estimated from a large data set. For concreteness, we have modelled the large amount of information available in the monthly time series by means of a dynamic factor model (using a principal-component-based estimation procedure as described in Section 3.1) and have used the estimated factors as related indicators for the interpolation process. Angelini et al. (2006) demonstrate that this factor approach generally outperforms more standard interpolation methods if (i) there is a large number of explanatory variables for the variable to be interpolated, (ii) the variables to be used for factor extraction have a limited idiosyncratic component and

(iii) there is a limited measurement error for both the explanatory variables and the variable to be interpolated in the periods in which the latter cannot be observed. For the case when related indicators are available, several restrictions on the data generating process of the regression error have been proposed. We have followed the method proposed by Litterman (1983), according to which the model is estimated in first differences and the regression error follows an $AR(1)$ process.[10,11] The intuition behind this method is that the monthly estimates are based on two components: the first is a linear function of the monthly movements in the related indicators and the second is a distribution of the quarterly residuals so that the monthly values average to the quarterly observations.

Third, the series were transformed to account for stochastic or deterministic trends. The decision to take logarithms and/or first differences was based on unit root tests, so that the transformed series are approximately stationary. In general, first differences of logarithms were taken for all nonnegative series that were not already in rates or percentage units. The same transformation, including degree of differencing, was in general applied to all the series included in a specific group (e.g. first difference of logarithms was taken for all price indexes).

Fourth, following the common procedure in this type of analysis (e.g. Stock and Watson, 2005), the transformed seasonally adjusted series were screened for outliers and observations with deviations from the median exceeding six times the interquartile range (in absolute terms) were replaced by the median value of the preceding five observations.

[10]Alternative methods have been proposed by Chow and Lin (1971) and Fernández (1981). In the former, the regression error follows an $AR(1)$ process but the model is estimated in levels while in the latter the disturbance term follows a random walk.

[11]More specifically, we have followed the steps detailed next: first, as the theory on dynamic factor models assumes that the set of "informational" variables contains only I(0) series, we have transformed the monthly series to induce stationarity; second, as the estimated factors have mean zero and unit variance but the variables to interpolate do not, we have followed Di Fonzo (2003) in performing the following transformation to the latter: $3\ln(y_t) - 3\ln(3)$, y_t being the variable to be interpolated and 3 being the number of months in a quarter; and third, as the Litterman (1983) disaggregation method applies first differences both to the explanatory variables and the dependent variable, we have used as explanatory variables the accumulated factors and not the factors themselves.

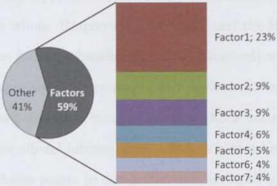
Finally, since the different scales of the time series could impair factor extraction, all "informational" series used to compute the factors were standardised to have mean zero and unit variance. The VAR/FAVAR estimation, however, was conducted using non-standardised observed variables Y_t.

4.2 Empirical implementation

As the baseline scenario of our FAVAR empirical application, we assume that the only observable variable is the policy instrument, i.e. the ECB repo rate (R_t), so that $Y_t = R_t$. However, we follow Bernanke et al. (2005) in defining an alternative specification in which the output (GDP) and the inflation (HICP) are also included in Y_t, so that $Y_t = (GDP_t, HICP_t, R_t)$. In addition, we consider a second alternative formulation in which we add a nominal effective exchange rate (NEER) to the set of observable variables, so that $Y_t = (GDP_t, HICP_t, R_t, NEER_t)$. We proceed by comparing the results of the three FAVAR specifications with those of a small-scale standard VAR model based on the ECB commodity price index, the real GDP, the HICP, the ECB repo rate and the nominal effective exchange rate.[12] Standard likelihood ratio tests are used to determine the lag-order of the models. The VAR turns out to be of order three, while the baseline FAVAR and both the two alternative FAVARs turn out to be of order two. All models are estimated with a constant and a linear trend. Finally, we set the number of factors in the FAVAR specifications as seven, based on the information criterion $IC_2(k)$ proposed in Bai and Ng (2002). Together, these seven factors explain 59 per cent of the joint-variance of the 150 variables included in our large data set (with the first factor explaining around 23 per cent of the variation on the data set and the first five factors explaining about half of the total variance, as depicted in Figure 1).

[12]In the literature we can find both VARs where the nominal effective exchange rate is used and VARs where the real effective exchange rate is preferred. We have decided to use the nominal rate, just because it would also be our choice if we would choose instead a bilateral exchange rate (e.g. *vis-à-vis* the US dollar). Nevertheless, we have compared our VAR with one including the real effective exchange rate and the results are roughly similar, both in terms of the shape and the

Figure 1: Cumulated share of variance explained by the first seven static factors



We divide the analysis of the results into three stages. First, we compare the impulse responses of the small-scale VAR with those of the FAVARs, showing that adding factors to benchmark VARs resolves the price puzzle. Second, we describe the impulse-response functions of several selected variables included in the FAVARs. Finally we look at the variance decomposition of the prediction errors. Afterwards, we check our results for robustness to changes in some of the assumptions of the model.

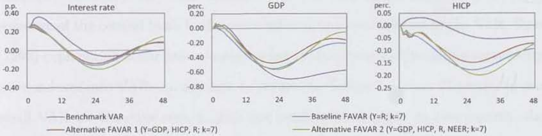
4.2.1 VARs *versus* factor-augmented VARs

Figure 2 displays the impulse-response functions computed both for the benchmark VAR model and the three FAVAR specifications. The identification of the monetary policy shock is obtained using a standard Cholesky decomposition. In the baseline and the first alternative FAVAR models, the policy interest rate is ordered last. In the benchmark VAR and in the second alternative FAVAR formulation, the policy rate is ordered before the nominal effective exchange rate, with this variable ordered last. The underlying assumption is that monetary policy shocks have no contemporaneous impact on output, prices and the factors, but they may affect the exchange rate immediately. However, the short-term key interest rate does not respond contemporaneously to changes in the nominal effective exchange rate. This is a common

magnitude of responses.

hypothesis in standard VAR literature for the EMU (e.g. Peersman and Smets, 2003) and we fully believe it is appropriate for a large and relatively closed economy such as the euro area as a whole. Responses of the GDP and the HICP are presented in percentage deviations from the baseline (i.e. non-disturbed) scenario, while interest rate responses are expressed in percentage point deviations. In the benchmark VAR model, a one-standard-deviation monetary policy shock corresponds to a 13 basis points increase in the official interest rate, which is somewhat greater than in the FAVAR models: 10 basis points in our preferred specification and 9 basis points in both alternative ones.[13] In all models, we standardise the monetary policy shock to correspond to a 25-basis-point innovation (hike) in the official interest rate.

Figure 2: Impulse responses to a monetary tightening shock



Notes: Deviations from the baseline in percentage, except for the interest rate, for which the ordinate is in percentage points. Number of months after the monetary policy shock in the abscissa.

As Figure 2 displays, the benchmark VAR model suffers from what is commonly known in the literature as a price puzzle, i.e. the counterintuitive positive reaction of prices to an increase in the official interest rate, at least in the short term. Moreover, the response of real GDP is very persistent, which is not in line with the usual finding in the literature that the output follows a hump-shaped pattern in response to a monetary policy disturbance, before slowly returning to the baseline scenario. As Bernanke et al. (2005) highlight, the persistence of the output response is inconsistent with long-run money neutrality.

[13]It must be noticed that for the benchmark VAR model, our monetary policy disturbance is well below the estimate of 30 basis points obtained by Peersman and Smets (2003) for the period 1980-1998, before the launch of the euro.

Conversely, in all FAVAR specifications the price puzzle does not appear. According to the explanation given by Sims (1992), the price puzzle might be caused by the misspecification of the monetary authority's information set, which means that the puzzle results from imperfectly controlling within the VAR for information that the central bank may have about leading indicators of inflation. In other words, the explanation for the price puzzle is that the central bank preemptively raises interest rates in anticipation of future inflation; however, in this case, what has been labelled as a non-anticipated policy shock contains, in fact, a fraction of the systematic response of the monetary authority to higher expected inflation. To the extent that the additional information processed by the central bank is not reflected in small-scale VARs, the measurement of policy innovations is likely to be "contaminated": what appears to the econometrician to be a policy shock is, in fact, the response of the central bank to the extra information not included in the VAR. Sims (1992) explanation of the price puzzle has led to the practice of including commodity price indexes into VARs, to attempt to control for future inflation. However, in our small VAR for the euro area, it does not seem to be enough. In this context, the disappearance of the price puzzle within the FAVAR approach might indicate that our estimated factors, which summarise the information contained in a large data set of macroeconomic variables, properly capture the information about prices that the central bank effectively monitors when deciding on monetary policy. Furthermore, the response of output is more in line with theory, showing a hump-shaped response and eventually returning towards zero as the effects of the shock fade out. The maximum impact on output occurs almost 22 months after the shock and is 0.55 per cent in the baseline FAVAR model and 0.48 per cent and 0.57 per cent in the two alternative versions. Also the impulse responses of the short-term interest rate are consistent with theory. The interest rate initially reflects its own shock and falls in the first 24 months and then returns to the baseline scenario.

If the FAVAR approach seems to succeed on the delivery of responses more easy to understand from the economic point of view than the standard VAR methodology, the analysis has to be completed with the comparison of the precision of responses. Table 1 presents the standard errors for the responses of interest rate, GDP and inflation to a one-standard-deviation monetary policy innovation, for each of the four models under analysis. It must be noticed that, as Bernanke et al. (2005) highlight, the two-step approach used to estimate the FAVARs suffers from "generated regressors" in the second step. In this way, the standard errors delivered by the usual econometric packages tend to underestimate the degree of uncertainty of responses, since they are computed on the assumption that the regressors included in the VAR are observed, which is not our case, as the factors are latent variables. To overcome this caveat, the standard deviations for the FAVARs (and, for comparison purposes, also for the benchmark VAR) were calculated using a standard bootstrap procedure, with 5,000 replications, which accounts for the uncertainty in the factor estimation. The results depicted in Table 1 confirm that the benchmark VAR presents the lowest precision of responses for any of the three variables (but mostly for output and inflation). The additional information delivered by the factors seems to reduce the uncertainty of responses, the first alternative FAVAR being the one showing lower standard deviations, followed by our baseline FAVAR specification.

Table 1: Uncertainty of impulse-response functions

	Interest Rate	GDP	HICP
Benchmark VAR	**0.027**	**0.073**	**0.044**
Baseline FAVAR	0.026	0.041	0.025
Alternative FAVAR 1	0.022	0.038	0.023
Alternative FAVAR 2	0.027	0.044	0.024

Notes: Standard errors for the responses to a Cholesky (degrees-of-freedom adjusted) one-standard-deviation monetary policy innovation (average over 60 periods after the shock). Figures in bold represent the highest dispersion among the four models.

4.2.2 FAVAR impulse-response functions

As previously mentioned, one advantage of the FAVAR approach is that it makes it possible to construct impulse-response functions for any element of X_t. Following Equation (12) in Section 3.3.2, the impulse responses of the estimated factors and of the variables observed included in Y_t are computed as follows:

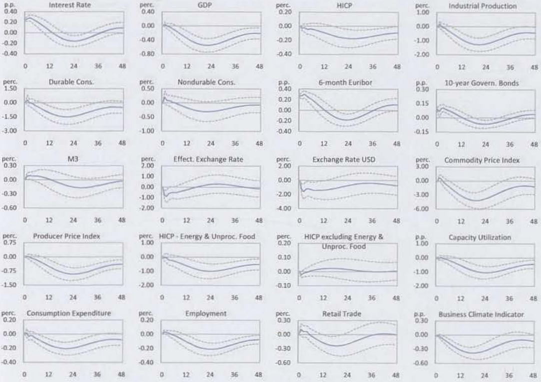
$$\begin{bmatrix} \widehat{F}_t \\ Y_t \end{bmatrix} = \widehat{\delta}(L)\varepsilon_t \tag{13}$$

where $\widehat{\delta}(L) = [\widehat{\Psi}(L)]^{-1} = \widehat{\delta}_0 - \widehat{\delta}_1 L - ... - \widehat{\delta}_h L^h$ is a matrix of polynomials in order h in the lag operator L and $\widehat{\delta}_j$ $(j = 0, 1, ..., h)$ is the coefficient matrix. Since, using Equation (10), the estimator of X_t is $\widehat{X}_t = \widehat{\Lambda}^f \widehat{F}_t + \widehat{\Lambda}^y Y_t$, impulse-response functions of each variable included in X_t can be obtained as follows:

$$X_t^{IRF} = \begin{bmatrix} \widehat{\Lambda}^f & \widehat{\Lambda}^y \end{bmatrix} \begin{bmatrix} \widehat{F}_t \\ Y_t \end{bmatrix} = \begin{bmatrix} \widehat{\Lambda}^f & \widehat{\Lambda}^y \end{bmatrix} \widehat{\delta}(L)\varepsilon_t \tag{14}$$

Figures 3 to 5 depict the impulse responses of a subset of 20 key variables to the monetary policy innovation for our baseline and the two alternative FAVARs, respectively. The corresponding 90 per cent confidence intervals (dashed lines) were calculated using a standard bootstrap procedure with 5,000 iterations, as explained earlier. It must be stressed that although we only display responses for a small subset of variables, impulse responses can be generated for all the variables included in the panel making use of Equation (14). This is so because all the variables included in the data set can be represented as linear combinations of the estimated factors ($\widehat{F}_t$ and Y_t) plus idiosyncratic noise. The responses in Figures 3 to 5 are very similar and have in general the intuitive sign and magnitude. However, there are also some counterintuitive responses for some variables. We proceed with a brief description of the responses.

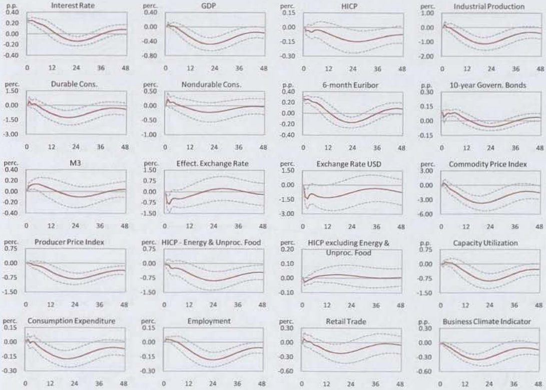
Figure 3: Impulse responses to a monetary tightening shock for the baseline FAVAR (Y_t = interest rate; seven factors)



Notes: Percentage deviations from the baseline for variables for which logarithms were taken; percentage point deviations otherwise. Number of months after the monetary policy shock in the abscissa.

An unexpected tightening in monetary policy results in a gradual decrease in industrial production, which reaches its maximum effect after around two years, before reverting to the baseline scenario. The shape of the response is similar to that of the real GDP, but the magnitude is higher, since an unexpected 25-basis-point increase in the official interest rate has a maximum impact on industrial production of more than one per cent in all the three formulations. When we split the industrial production index into durable consumer goods and nondurable consumer goods, we find out that this strong response is mainly explained by the behaviour of durable consumer goods, since the impact of the monetary policy disturbance on nondurable consumer goods is rather more modest. In its turn, capacity utilisation reaches its maximum decline roughly two years after the monetary tightening, after which it

Figure 4: Impulse responses to a monetary tightening shock for the first alternative FAVAR (Y_t = GDP, HICP, interest rate; seven factors)



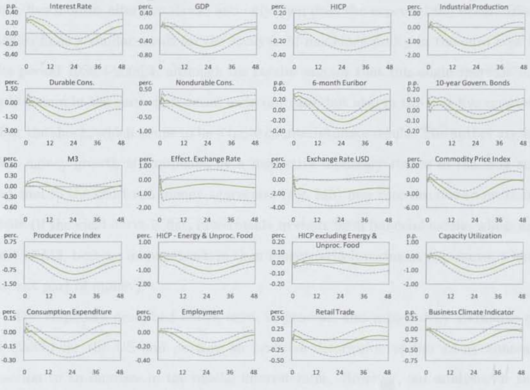
Notes: Percentage deviations from the baseline for variables for which logarithms were taken; percentage point deviations otherwise. Number of months after the monetary policy shock in the abscissa.

eventually returns towards zero. The reaction of consumption expenditure is also in line with theoretical expectations, in the sense that a higher short-term interest rate makes refinancing more expensive, leading to a decrease in private consumption, with the maximum impact (0.2 per cent, in the baseline FAVAR) being reached around 20 months after the shock.[14] Also as expected, total employment falls after the hawkish monetary policy disturbance but this movement is also not very persistent, and starts to revert two years after the shock.[15] The behaviour of retail trade and business sentiment indicators is also in line with economic theory, since a restrictive monetary policy has a negative impact on these variables, but that eventually fades

[14] Although not reported in Figures 3 to 5, the fall in consumption triggers a major reduction in consumer credit, the maximum effect being observed also around 20 months after the shock.

[15] Although not reported in Figures 3 to 5, the impulse responses of the unemployment rate also reach the maximum effect (in this case, an increase) in two years.

Figure 5: Impulse responses to a monetary tightening shock for the second alternative FAVAR (Y_t = GDP, HICP, interest rate, exchange rate; seven factors)



Notes: Percentage deviations from the baseline for variables for which logarithms were taken; percentage point deviations otherwise. Number of months after the monetary policy shock in the abscissa.

out. This is also true for two of the indicators of inflation presented, the producer price index for industry and the ECB commodity price index. Nevertheless, in spite of the expected shape of the response of the commodity price index, the magnitude of the response is much higher than expected, and therefore has to be interpreted with caution.

Short-term interest rates such as the 6-month Euribor follow the official interest rate very closely, while longer-term interest rates such as the 10-year Government bond yield, although lying closely to the path of the official rate, show responses of a minor magnitude. Money aggregates go down in the medium term subject to monetary tightening and tend towards the zero line in the long run. The decline in money aggregates reflects the decrease in demand for credit as a consequence of the higher refinancing costs resulting from higher interest rates. It should be noted, however, that all Figures 3 to 5 reveal that there is a slight increase in the first four/five months after the shock, and only then does the expected fall occur. Blaes (2009) finds a similar result for the analysis of monetary policy in the euro area in the period 1986:4-2006:4, although his results suggest that this slight increase not only occurs in the very short term, as in our case, but also in the first five quarters after the shock, which seems to be a quite counterintuitive result. The author argues that money growth is dampened by a restrictive monetary stance in the long run but that in the short run money aggregates (e.g. M3) may increase due to portfolio shifts (if the yield curve is flat, investments in short-term financial assets, which are part of M3, become more attractive than longer-term investment exposures, which are not part of money).

The responses described above were, in general, also achieved by Bernanke et al. (2005) for the US and portray an intuitive description of the macroeconomy reaction to an increase in the official interest rates. However, our analysis for the euro area also reveals some counterintuitive impulse responses for some variables. In particular, the extra information generated by the FAVAR approach brings to light a striking result as regards the responses of the components of the HICP. In fact, it seems that the intuitive negative response of inflation (total index) is mainly driven by the component energy and unprocessed food, which shows a big decrease after the policy shock. Conversely, when we look at the response of the HICP excluding energy and unprocessed food, we see that after an initial fall in the first five months following the shock, the prices start to increase. Although the magnitude of the response is not very relevant (the maximum impact is of 0.03 per cent, in the first alternative FAVAR), it constitutes a puzzle, since we were expecting core inflation to decrease after a move to monetary tightening (this supposition was based on the idea that the central bank can influence the core part of inflation with its monetary policy, but has little to say as regards the remaining components of prices).

In addition, we obtain a disappointing response of the nominal effective exchange rate and the Euro/US dollar exchange rate (both defined in indirect quotation[16]). In fact, in all FAVAR specifications, a rise in the official interest rate is associated with an initial depreciation of the euro, and this is totally against the economic rationale that a higher interest rate makes investment more attractive and therefore attracts capital inflows, causing the euro to appreciate. It is interesting to note that this against-theory result was also achieved by Laganà and Mountford (2005) for the United Kingdom and we believe that the justification they give also applies for the euro area: this result is probably caused by the euro area monetary authority reacting to changes in US (or other main trade partners) interest rates by changing the euro area official interest rate.[17] In particular, we believe that some of our results may be distorted by the fact that our sample encompasses the most acute phase of the world financial crisis (after September 2008) that was fuelled by the problems in the US subprime market. In fact, both the US Federal Reserve (FED) and the ECB started to cut their official interest rates after the beginning of the turbulence[18] and during this period the euro appreciated against the US dollar, which is in fact an intuitive response for the easing of the US monetary policy (i.e. as expected, the US dollar depreciates as a result of the decrease in US official interest rates).

It must also be noticed that, in October 2008, the ECB introduced a number of changes to its monetary policy framework. In particular, until this date, the ECB used to conduct its refinancing operations – Main Refinancing Operations and Longer-Term Refinancing Operations – in variable rate tenders in which the amount

[16]This means that the cost of one unit of local currency (the euro) is given in units of foreign currency. In the indirect quotation, an increase in the exchange rate represents an appreciation of the euro.

[17]Christiano et al. (1999) also spent some time analysing this issue. According to their conclusions, identifying monetary policy shocks in an open economy typically leads to substantial complications relative to the closed economy case, since the central bank's actions not only respond to the state of the domestic economy but also to the state of foreign economies, including foreign monetary policy decisions. In this sense, a depreciation after a tightening shock may mean that this shock is "contaminated" by the systematic reaction of the monetary authority to foreign monetary policy and expected inflation.

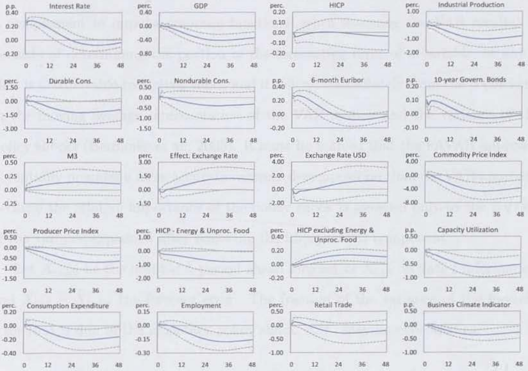
[18]The FED started first, around September 2007, with the ECB postponing the use of a restrictive monetary policy for almost one year, until October 2008.

allotted was that corresponding to the amount bid at rates equal to or above the marginal/stop-out rate. After October 2008, the ECB started to provide an unlimited amount of funds through its refinancing operations, which it began to conduct via fixed rate tenders at a rate equal to the repo rate and with full allotment. As the interbank money market practically stopped functioning during the financial crisis and as a consequence of the change in the Eurosystem's operational framework, the ECB became the "preferred counterparty", with credit institutions resorting heavily to its tenders to obtain the funds needed, and therefore short-term liquidity conditions turned out to be very ample. Consequently, the EONIA rate fell considerably and stopped mimicking so well the behaviour of the ECB repo rate. For the purposes of our analysis it is worth verifying if the exclusion of the last six observations from our sample (i.e. considering only observations until September 2008) changes in a relevant way the impulse responses of the economic variables (and in particular if it annuls the counterintuitive results of exchange rates). Figure 6 depicts the impulse responses for the same 20 variables, using our preferred FAVAR specification (interest rate as the only observed variable; seven factors) for the period 1999:1-2008:9.

As expected, the last observations of our sample (encompassing the intensification of the financial crisis and the adoption, by the ECB, of some unconventional measures within its monetary policy framework) seem to play a relevant role in the behaviour of the exchanges rates. In our reduced-sample FAVAR, the behaviour of exchange rates is more in line with economic theory, since a restrictive monetary policy stance is followed by an appreciation of the euro. It must be noticed, however, that as in Bernanke et al. (2005), for the US, or in Shibamoto (2007), for Japan, the exchange rate exhibits delayed overshooting, i.e. the exchange rate reacts to monetary policy with a delay.[19]

[19]Forni and Gambetti (2008) follow Forni et al. (2000) and use a dynamic structural factor model to analyse the effects of monetary policy in the US in the period 1973:3-2007:11. With this framework they succeed in mitigating the delayed overshooting puzzle, since in their model the maximum effect on the exchange rate is observed on impact.

Figure 6: Impulse responses to a monetary tightening shock for the baseline FAVAR – until September 2008



Notes: Percentage deviations from the baseline for variables for which logarithms were taken; percentage point deviations otherwise. Number of months after the monetary policy shock in the abscissa.

The responses of the remaining variables do not change in a significant way when we shorten the sample period. As Figure 6 shows, the maximum effect on GDP is achieved a bit latter (around two and a half years after the shock) and the response of the HICP is somewhat more sluggish, but it does not present a price puzzle. Only the response of M3 seems to change in a more visible way, with the fall in the money aggregate only occurring in the long run (almost 20 months after the shock). However, for some of the variables (e.g. HICP, M3), the precision of the responses decreases when the sample period is shorter.

4.2.3 Variance decomposition

Forecast error variance decomposition is another exercise frequently performed (as a complement to impulse-response functions) when assessing the VAR results. It consists of determining the portion of the forecasting error of a variable, at any t, that is attributable to a given shock and it follows immediately from the coefficients in the moving average representation of the VAR system and the variance of the policy shocks (Bernanke et al., 2005). It must be noticed that the FAVAR approach potentially provides a more accurate variance decomposition than the VAR approach because the relative importance of the policy shock is assessed only to the portion of the variable explained after removing the idiosyncratic component.

Let $\widehat{X}_{t+h|t}$ be the optimal h-period ahead forecast of X_{t+h} on date t information and $X_{t+h} - \widehat{X}_{t+h|t}$ the forecast error. The fraction of the variance of the forecast error that is due to the monetary policy shock, ε_t^{MP}, may be expressed as:

$$\frac{Var(X_{t+h} - \widehat{X}_{t+h|t}|\varepsilon_t^{MP})}{Var(X_{t+h} - \widehat{X}_{t+h|t})} \qquad (15)$$

Table 2 reports the results for the same 20 macroeconomic variables analysed previously for our preferred FAVAR specification, with the complete sample period. The first two columns of Table 2 report the contribution of the monetary policy shock for the variance of the forecast error of each of the variables, at the 6-month horizon and the 60-month horizon, respectively. In order to access the goodness-of-fit properties of the estimated factors, the last column of Table 2 reports the R^2 of the regression of each of the 20 variables on the common factors $\widehat{C}(F_t, Y_t)$, i.e. the fraction of each variable's variance that is explained by both $\widehat{F}_t$ and Y_t. A high R^2 indicates that the common factors nicely summarise the information contained in the variable, whereas a low R^2 means that the variable cannot be adequately explained by the common factors and implies that we must have less confidence in the impulse responses and forecast error variance decomposition computed.

Table 2: Forecast error variance explained by the monetary policy shock

Variables	Variance Decomposition		R^2
	6 months	60 months	
Interest Rate	0.193	0.053	*1.000
	(0.069)	(0.036)	
GDP	0.006	0.171	0.956
	(0.015)	(0.076)	
HICP	0.004	0.039	0.836
	(0.015)	(0.050)	
Industrial Production (IP)	0.007	0.142	0.804
	(0.018)	(0.072)	
IP - Durable Consumer Goods	0.005	0.096	0.667
	(0.016)	(0.058)	
IP - Non-Durable Consumer Goods	0.009	0.037	0.456
	(0.018)	(0.040)	
6-month EURIBOR	0.169	0.050	0.973
	(0.055)	(0.032)	
10-year Government Bond Yield	0.133	0.048	0.713
	(0.044)	(0.027)	
M3	0.019	0.013	0.289
	(0.026)	(0.037)	
Nominal Effective Exchange Rate	0.024	0.004	0.933
	(0.026)	(0.019)	
Exchange Rate (USD per EUR)	0.031	0.014	0.831
	(0.032)	(0.035)	
ECB Commodity Price Index	0.010	0.084	0.590
	(0.018)	(0.056)	
Producer Price Index - Industry	0.004	0.170	0.867
	(0.015)	(0.077)	
HICP - Energy and Unprocessed Food	0.005	0.081	0.853
	(0.017)	(0.055)	
HICP excluding Energy and Unprocessed Food	0.003	0.001	0.531
	(0.013)	(0.022)	
Capacity Utilisation	0.003	0.146	0.681
	(0.012)	(0.072)	
Consumption Expenditure	0.008	0.103	0.816
	(0.017)	(0.055)	
Employment	0.003	0.123	0.898
	(0.009)	(0.061)	
Retail Trade	0.006	0.014	0.567
	(0.015)	(0.028)	
Business Climate Indicator	0.041	0.108	0.561
	(0.046)	(0.078)	

Notes: The figures in the column under "6 months" ("60 months") report the fraction of the variance of the forecast error, at the 6(60)-month horizon, explained by the monetary policy shock. The last column reports the fraction of the variance of each variable explained by both $\widehat{F}_t$ and Y_t. Standard errors are shown in parenthesis. *This is by construction, since the interest rate is assumed to be the only variable observed.

There is an agreement in the literature that monetary policy shocks account for only a very modest percentage of the volatility of output and for even less of the movements in the price level (e.g. Christiano et al., 1999), so monetary policy affects the economy mostly through its systematic behaviour, rather than by surprising economic agents. In fact, looking at Table 2, we conclude that at the 6-month horizon, apart from interest rates, the contribution of the policy shock is lower than 5 per cent. In particular, less than 1 per cent of the variance of both GDP and HICP is accounted for by the shock. After 60 months, the monetary policy shock explains around 17 per cent and 14 per cent of the volatility of GDP and industrial production, respectively, and about 4 per cent of price volatility. In addition, the shock accounts for 10 per cent and 12 per cent of the variance of the prediction error of consumption expenditure and employment, respectively. Overall, these results surprisingly suggest a non-negligible role for the unsystematic component of monetary policy in affecting the dynamics of both real and nominal variables. Bernanke et al. (2005), in turn, find a more modest role for the policy innovations, since they conclude that apart from interest rates, the contribution of the monetary policy shock, at the 60-month horizon, ranges betwen 0 and 10 per cent. In particular, the policy shock explains 5 per cent, 4 per cent and 7 per cent of the volatility of industrial production, consumer prices and employment, respectively.

On the other hand, an analysis of the last column of Table 2 reveals that the common component explains an important portion of the variance of some variables. Specifically, we obtain an R^2 of 95.6 per cent, 80.4 per cent, 83.6 per cent, 89.8 per cent, 93.3 per cent and 97.3 per cent for the GDP, industrial production, HICP, employment, nominal effective exchange rate and 6-month Euribor, respectively. However, there are also some variables for which the R^2 is small, in particular the money aggregate M3 (28.9 per cent). It is interesting to note that very similar conclusions were reached by Bernanke et al. (2005) and Shibamoto (2007) for the US and Japan, respectively. Over and against this, Laganà and Mountford (2005) present some different conclusions for the United Kingdom, in particular they obtain only one R^2 higher than 70 per cent (other than that of the interest rate, which is 100 per cent by construction) and they conclude that the amount of variance explained by the common component is significant for monetary variables.

Before we proceed, we need to make clear that we are obviously aware of the criticism usually made of the FAVAR approach, i.e. that the static factors are identified only up to orthogonal rotations and that this is a feature that hampers their economic interpretation (see Section 3.1 above). Although the factors are not uniquely identified, from a theoretical point of view, when the sample size has a large enough N dimension (150 variables in our case), the estimated factors span the same space as the true factors, and therefore even if the estimated factors do not coincide with the driving forces of the economy, linear combinations of them do (Marcellino et al., 2000). With this caveat in mind, and stressing that this is not the main purpose of our paper, we proceed with a tentative interpretation of the estimated factors. Table 3 portrays the higher five coefficients of correlation between each of the seven factors and the variables included in our data set.

The first estimated factor mainly captures the real side of the euro area economy, as it shows a higher-than-90 per cent coefficient of correlation with real GDP and Gross Value Added (GVA) as well as with real imports and exports of goods and services. The second and the fourth latent factors mostly capture cyclical variations in inflation as displayed by the high correlation with the deflator of private consumption, the labour costs and the producer price index and with the GDP and GVA deflators, compensation per employee and some components of the HICP. The third estimated factor resembles very closely the behaviour of nominal interest rates, showing a correlation close to 75 per cent with the Euribor rates. The fifth and the seventh factors seem to mimic very closely the behaviour of exchange rates and foreign economic activity, as captured by the higher correlation with the nominal effective exchange rate, the exchange rates *vis-à-vis* the US dollar, the Japanese yen and the British pound and the US, Japan and United Kingdom real GDP. The interpretation of the sixth factor is less straightforward because it is the factor that presents lower correlation with the variables. The maximum coefficient of correlation is achieved with the variable retail trade and is of almost 59 per cent.

Table 3: Correlation between the factors and the data set

Top-5 Coefficient of Correlation		
Factor 1	Exports	0.943***
	GDP	0.942***
	Gross Value Added	0.927***
	Imports	0.922***
	Labour Productivity - Total	0.888***
Factor 2	Deflator Private Consumption	0.765***
	Labour Costs Construction	0.744***
	Labour Productivity - Construction	0.711***
	Capacity Utilisation	0.637***
	Producer Price Index - Manufacturing	0.584***
Factor 3	6-month EURIBOR	0.756***
	3-month EURIBOR	0.755***
	1-year EURIBOR	0.748***
	EONIA	0.725***
	3-year Government Bond Yield	0.647***
Factor 4	Deflator GDP	0.657***
	Deflator Gross Value Added	0.605***
	Compensation per Employee - Financials	0.523***
	HICP excluding Energy and Unprocessed Food	0.514***
	HICP excluding Food	0.469***
Factor 5	Exchange Rate (USD per EUR)	0.639***
	GDP USA	0.620***
	Nominal Effective Exchange Rate	0.607***
	Exchange Rate (JPY per EUR)	0.531***
	GDP Japan	0.504***
Factor 6	Retail Trade	0.588***
	Labour Productivity - Other Services	0.538***
	Employment - Other Services	0.509***
	HICP - Goods	0.499***
	HICP - Total	0.488***
Factor 7	Nominal Effective Exchange Rate	0.539***
	Exchange Rate (GBP per USD)	0.528***
	GDP UK	0.519***
	GDP USA	0.517***
	Exchange Rate (USD per EUR)	0.501***

*** Denote statistical significance at the 1% level.

4.2.4 Robustness check

In this section we perform a robustness test of the results described in the previous three sections for our preferred FAVAR specification. As a first step, the results presented in Figure 3 are checked for robustness to changes in the number of factors. We compute the impulse-response functions for a FAVAR specification – in which the only observable variable is the interest rate – when the number of factors is reduced to three (the number of factors used in Bernanke et al. (2005), for the US). As a second step, we treat the fed funds rate as an exogenous variable and attempt to work out if the responses change in a noteworthy way when we assume that there is no feedback from euro area variables to US monetary policy stance.

The exercise of checking the sensitivity of the results to an alternative number of factors is particularly important because, as Bernanke et al. (2005) point out, although the Bai and Ng (2002) criterion to determine the number of factors accomplishes the purpose of statistical identification, it does not necessarily determine how many factors must be included in the VAR. This means that the criterion allows us to determine the number of factors present in the data set but it does not effectively postulate how many of those factors should be included in the VAR. In this paper, we have decided to include in the VAR the optimal number of factors as given by the Bai and Ng (2002) criterion (seven). In their turn, Bernanke et al. (2005) determine the number of factors in an *ad hoc* way, using in the VAR a lower number of factors than that given by the Bai and Ng (2002) criterion.[20] Appendix B depicts the results for our robustness exercise in which we include three factors in the VAR. First, it can be seen that although we still obtain considerable R^2 for GDP, industrial production, 6-month Euribor, producer price index and employment, the number of variables increases, apart from M3, for which we obtain a low R^2. In particular, we obtain an R^2 lower than 15 per cent for the nominal effective exchange rate, the exchange

[20]The authors show that adding just one factor to the standard VAR changes the responses dramatically, and therefore it appears to be all that is needed. They conclude that adding up to seven factors does not change the FAVAR results.

rate *vis-à-vis* the US dollar, the HICP excluding energy and unprocessed food and the retail trade. In this way, lower confidence needs to be given both to impulse responses and variance decomposition computed for these variables. Second, we can see that the shape and magnitude of the responses for most of the variables does not change in a significant way. The only exception worth mentioning (apart from the counterintuitive response of M3, to which we do not give much relevance because of its low R^2) is the behaviour of the HICP. In fact, when we reduce the number of factors, the price puzzle starts to be visible. This is not a surprise, especially if we take into account that according to the tentative interpretation of the factors performed in Section 4.2.3, both the second and the fourth latent factors seem to capture cyclical variations in inflation and we are not considering the latter in this exercise.

Finally, Appendix C illustrates the results of a second check for robustness, in which we admit that the euro area macroeconomic variables do not respond to changes in US monetary policy. As in the baseline FAVAR, we obtain a high R^2 for the majority of the variables, and a low R^2 for the money aggregate. Although the magnitude of the responses does not change in a very relevant way, the shape of the responses is considerably different, as the effects are very long-lasting. This is especially visible for real variables, a fact which seems to be against theoretical expectations that the effects of the monetary policy shock eventually fade out, with variables returning to the zero line in the medium term. These results ultimately reinforce the relevance of our preferred specification and may signal that there is no need to add exogenous variables to the FAVAR (in opposition to what usually occurs with standard VARs); nevertheless, the effects of the inclusion of exogenous variables in FAVARs must be studied further in future research.

5 Conclusions

In this study, we model a large panel of macroeconomic time series with a dynamic factor model, summarise the information with a few estimated factors and use them as regressors in recursive VARs to assess the effects of monetary policy shocks in the euro area. The reason for this study comes from our awareness that policy makers base their decisions about the stance of monetary policy on a much wider information set than that included in standard VAR models.

Dynamic factor models are currently a cornerstone of macroeconometric modelling and their application to monetary policy analysis is a prominent line of research. In particular, there are many applications of the factor-augmented VAR approach for the US and also some studies for Europe, though to a minor extent. However, no attempt had yet been made (to the best of our knowledge) to explore this methodology for the post-1999 figures of the euro area *per se*. Our work is an attempt to fill this gap. Our purpose is to understand how far can we go by augmenting the small-scale VAR models with the information captured by the factors, i.e. to assess if there are gains, both economic and statistical, when we include the factors in the specification of the model.

Overall, we consider our results to be satisfactory. The impulse-response functions obtained are generally in line with the available literature and seem to make sense from an economic point of view. Moreover, more precise stylised facts on the effects of monetary policy innovations seem to be delivered. In particular, the comparison of the results of the FAVAR with those of a small-scale benchmark VAR reveals that the inclusion of the information captured by the factors into the model succeeds in mitigating the price puzzle, i.e. the counterintuitive positive response of prices to a monetary policy tightening. Furthermore, the response of GDP is also more in line with theoretical expectations, since it depicts the usual hump-shaped pattern, in opposition to the persistent decrease that is delivered by the benchmark VAR. In addition, the responses obtained in any of the FAVAR formulations have lower standard deviations than the responses delivered by the benchmark VAR. We also obtain the consensual finding that, in the short run, monetary policy shocks account for only a very modest percentage of the volatility of output and for even less of the movements in the price level, and that these percentages eventually increase slightly at longer horizons.

It must be stressed, however, that our empirical application was naturally not free from problems, with some of the impulse responses obtained being quite puzzling. In particular, we find that an unanticipated hawkish policy action is associated with a depreciation of the euro and that the intuitive response of inflation is mainly driven by the component energy and unprocessed food. As for the first case, we were already aware that identifying monetary policy shocks in the euro area with a sample period that includes several months of a worldwide financial crisis could bring us some complications. In fact, during the crisis the ECB clearly responded not only to the state of the euro area economy but also to the state of foreign economies in order to account for external demand developments, and therefore the responses to the shock may be "contaminated" by the systematic reaction of the ECB to foreign monetary policy. In the second case, the puzzling result is a consequence of the extra information provided by the FAVAR (since, typically, only the HICP is analysed, not its components) and in this sense it provides a challenging direction for further work.

On the one hand, the problems we encountered in our study reflect the difficulties we faced in the compilation and treatment of the data. On the other hand, they suggest that our work may be further improved in a number of directions.

As for the first point, we need to recognise that the treatment of the data was quite extensive and ambitious, and that alternative methodologies could probably have been used in some of the steps (e.g. seasonal adjustment, disaggregation of quarterly figures, stationarisation). Moreover, some of the conclusions would probably be more accurate if we had a longer sample period.

As for the lines for future research, we would like to start by investigating alternative estimation methods. For concreteness, we would like to depart from the Stock and Watson (1998, 1999, 2002a, 2002b) static approach and estimate our FAVAR based on the dynamic methodology of Forni et al. (2000, 2004, 2005), using a dynamic principal components method, or Doz et al. (2006, 2007), estimating the factors by maximum likelihood. Moreover, although we are quite confident of the merits of the recursive scheme, we would like to investigate the robustness of our results to alternative identification schemes, and in particular we would like to test the identification directly from imposing restrictions on the factor loadings (Stock and Watson, 2005). Furthermore, it would be interesting to develop our analysis within a pure structural factor model (Forni et al., 2008) in order to be able to assign the factors an effective economic interpretation. In addition, we would be interested in extending our approach to the assessment of the effects of common monetary policy shocks among the heterogeneous constituent countries of the euro area. The analysis of the different impacts in countries like Germany and Portugal would be of major interest. Finally, we would like to depart from the subject of monetary policy shocks identification and step into the world of optimal monetary policy rules, but still relying on dynamic factor analysis. DSGE analysis being a central piece of the *state of art* of macroeconometric modelling, we would like to venture along the line of research of Boivin and Giannoni (2008) in exploiting dynamic factor models where the structure of a DSGE model is assumed to govern the dynamics of the factors.

Appendices

A Data description and transformation

The data set is comprised of 150 macroeconomic time series for the euro area spanning the period from 1999:1 to 2009:3. By euro area we mean the 16 countries that adopted the euro up to the beginning of 2009.

It must be noticed that for the purpose of analysing monetary policy in the euro area with data for the euro area as an entity (and not with data aggregated from the different member states' data sets) we had the choice of resorting to three different kinds of samples. First, a fixed-composition sample with the 11 countries that adopted the euro at the beginning of 1999, and therefore that have belonged to the euro area in all the period under analysis. Second, a fixed-composition sample including the 16 countries that share a common monetary policy nowadays (which means that the figures for the euro area in 1999 include, for instance, the Slovakia data, although this country only adopted the euro at the beginning of 2009). Finally, a changing-composition euro area, which means that the figures for the member countries are only considered as from the moment of their entrance (in this case, the euro area figures would only include Slovakia in 2009). The third possibility was immediately discarded since we believe that the inclusion of the new countries could create a disturbance in the data at the moment of the entrance that could jeopardise our analysis. Between the two fixed-composition panels, our first choice would be the 11-country panel, since those countries actually have shared a common monetary policy since 1999. However, a great fraction of the variables was not available for this panel. Therefore, the figures used in our work are those of a fixed-composition 16-country euro area. Although the figures include five countries that did not share a common monetary policy in all the period under review, we believe that this will not impair the conclusions, given the rather low weight of these countries in the total of the euro area (on average, in the period from 1999:1 to 2009:3, the weight of the five countries' GDP in the euro area GDP was around 3 per cent; if we exclude Greece, which joined the euro area in 2001, the weight decreases to 0.9 per cent).

The format of the data description is as follows: the first column has the series number, the second the series acronym (when available, the acronym that appears in the source database), the third the series description, the fourth the transformation code and the fifth the source. As in Bernanke et al. (2005), the transformation codes are as follows: 1 – no transformation; 2 – first difference; 4 – logarithm; 5 – first difference of logarithm. An asterisk next to the acronym denotes a slow-moving variable in the estimation.

Table 4: Data description and transformation

Nr.	Acronym	Description	Tr.	Source
Real Output and Income				
1	IPIT*	Industrial Production Index - Total (2005=100, WDSA)	5	ECB SDW
2	IPICOG*	Industrial Production Index - MIG Consumer Goods (2005=100, WDSA)	5	Eurostat
3	IPIDCOG*	Industrial Production Index - MIG Durable Consumer Goods (2005=100, WDSA)	5	Eurostat
4	IPINDCOG*	Industrial Production Index - MIG non-Durable Consumer Goods (2005=100, WDSA)	5	Eurostat
5	IPIING*	Industrial Production Index - MIG Intermediate Goods (2005=100, WDSA)	5	Eurostat
6	IPINRG*	Industrial Production Index - MIG Energy (2005=100, WDSA)	5	Eurostat
7	IPICAG*	Industrial Production Index - MIG Capital Goods (2005=100, WDSA)	5	Eurostat
8	IPIC*	Industrial Production Index - Construction (2005=100, WDSA)	5	Eurostat
9	IPIM*	Industrial Production Index - Manufacturing (2005=100, WDSA)	5	Eurostat
10	LCU*	Level of Capacity Utilisation - Industry Survey (% of capacity, SA)	2	ECB SDW
11	GDP*	Gross Domestic Product at Market Prices (Chained - Mil. 2000 EUR, WDSA)	5	Eurostat
12	GVA*	Gross Value Added at Constant Prices (Chained - Mil. 2000 EUR, WDSA)	5	Eurostat

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Table 4 – Continued from previous page

Nr.	Acronym	Description	Tr.	Source
13	PCEXP*	Private Final Consumption Expenditure (Chained - Mil. 2000 EUR, WDSA)	5	Eurostat
14	GCEXP*	Government Final Consumption Expenditure (Chained - Mil. 2000 EUR, WDSA)	5	Eurostat
15	GFKF*	Investment - Gross Fixed Capital Formation (Chained - Mil. 2000 EUR, WDSA)	5	Eurostat
16	EXP*	Exports of Goods and Services (Chained - Mil. 2000 EUR, WDSA)	5	Eurostat
17	IMP*	Imports of Goods and Services (Chained - Mil. 2000 EUR, WDSA)	5	Eurostat
Employment				
18	TOTEMPL*	Total Employment (Thousands of persons, SA)	5	ECB SDW
19	EMPL*	Employees (Thousands of persons, SA)	5	ECB SDW
20	SELFEMPL*	Self-Employed (Thousands of persons, SA)	5	ECB SDW
21	TOTEMPLA*	Total Employment - Agriculture (Thousands of persons, SA)	5	ECB SDW
22	TOTEMPLI*	Total Employment - Industry (Thousands of persons, SA)	5	ECB SDW
23	TOTEMPLC*	Total Employment - Construction (Thousands of persons, SA)	5	ECB SDW
24	TOTEMPLT*	Total Employment - Trade (Thousands of persons, SA)	5	ECB SDW
25	TOTEMPLF*	Total Employment - Financials (Thousands of persons, SA)	5	ECB SDW
26	TOTEMPLO*	Total Employment - Other Services (Thousands of persons, SA)	5	ECB SDW
27	LP*	Person Based Labour Productivity - Total (2000=100, constant prices, SA)	5	ECB SDW
28	LPA*	Person Based Labour Productivity - Agriculture (2000=100, constant prices, SA)	5	ECB SDW
29	LPI*	Person Based Labour Productivity - Industry (2000=100, constant prices, SA)	5	ECB SDW
30	LPC*	Person Based Labour Productivity - Construction (2000=100, constant prices, SA)	5	ECB SDW
31	LPT*	Person Based Labour Productivity - Trade (2000=100, constant prices, SA)	5	ECB SDW
32	LPF*	Person Based Labour Productivity - Financials (2000=100, constant prices, SA)	5	ECB SDW
33	LPO*	Person Based Labour Productivity - Other Services (2000=100, constant prices, SA)	5	ECB SDW
34	TOTUNEMPL*	Standardised Unemployment Rate (%, SA)	1	ECB SDW

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Nr.	Acronym	Description	Tr.	Source
35	RUNLACO*	Real Unit Labour Costs - Total (2000=100, WDSA)	5	Eurostat
36	UNLACOA*	Unit Labour Costs, Deflator - Agriculture (2000=100, SA)	5	ECB SDW
37	UNLACOI*	Unit Labour Costs, Deflator - Industry (2000=100, SA)	5	ECB SDW
38	UNLACOC*	Unit Labour Costs, Deflator - Construction (2000=100, SA)	5	ECB SDW
39	UNLACOT*	Unit Labour Costs, Deflator - Trade (2000=100, SA)	5	ECB SDW
40	UNLACOF*	Unit Labour Costs, Deflator - Financials (2000=100, SA)	5	ECB SDW
41	UNLACOO*	Unit Labour Costs, Deflator - Other Services (2000=100, SA)	5	ECB SDW
42	COMPEMPTOT*	Compensation per Employee - Total Index (2000=100, SA)	5	ECB SDW
43	COMPEMPTOA*	Compensation per Employee - Agriculture (2000=100, SA)	5	ECB SDW
44	COMPEMPI*	Compensation per Employee - Industry (2000=100, SA)	5	ECB SDW
45	COMPEMPC*	Compensation per Employee - Construction (2000=100, SA)	5	ECB SDW
46	COMPEMPT*	Compensation per Employee - Trade (2000=100, SA)	5	ECB SDW
47	COMPEMPF*	Compensation per Employee - Financials (2000=100, SA)	5	ECB SDW
48	COMPEMPO*	Compensation per Employee - Other Services (2000=100, SA)	5	ECB SDW
Prices				
49	CP00*	HICP - All Items (2005=100, SA)	5	Eurostat
50	CP01*	HICP - Food and non-Alcoholic Beverages (2005=100, SA)	5	Eurostat
51	CP02*	HICP - Alcoholic Beverages, Tobacco and Narcotics (2005=100, SA)	5	Eurostat
52	CP03*	HICP - Clothing and Footwear (2005=100, SA)	5	Eurostat
53	CP04*	HICP - Housing Water, Electricity, Gas and other Fuels (2005=100, SA)	5	Eurostat
54	CP06*	HICP - Health (2005=100, SA)	5	Eurostat
55	CP07*	HICP - Transport (2005=100, SA)	5	Eurostat
56	GOODS*	HICP - Goods (2005=100, SA)	5	Eurostat

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Nr.	Acronym	Description	Tr.	Source
57	SERV*	HICP - Services (2005=100, SA)	5	Eurostat
58	EFOODUNP*	HICP - Energy and Unprocessed Food (2005=100, SA)	5	Eurostat
59	00XEFOOD*	HICP - Overall Index excluding Energy, Food, Alcohol and Tobacco (2005=100, SA)	5	Eurostat
60	00XEFOODUNP*	HICP - Overall Index excluding Energy and Unprocessed Food (2005=100, SA)	5	Eurostat
61	00XHOUSING*	HICP - Overall Index excluding Housing, Water, Electricity, Gas and other Fuels (2005=100, SA)	5	Eurostat
62	PPIM*	Producer Price Index - Manufacturing (2005=100, SA)	5	Eurostat
63	PPII*	Producer Price Index - Industry, Except Construction (2005=100, SA)	5	Eurostat
64	PPICAG*	Producer Price Index - MIG Capital Goods (2005=100, SA)	5	Eurostat
65	PPIING *	Producer Price Index - MIG Intermediate Goods (2005=100, SA)	5	Eurostat
66	PPINDCOG*	Producer Price Index - MIG non-Durable Consumer Goods (2005=100, SA)	5	Eurostat
67	ECBCPI	ECB Commodity Price Index Euro Denominated - Total non-Energy Commodity, use-weighted (2000=100, SA)	5	ECB SDW
68	OIL	Oil Price, Brent Crude - 1 month forward (Level - EUR, SA)	5	ECB SDW
69	DGDP*	Implicit Price Deflator - GDP (2000=100, WDSA)	5	Eurostat
70	DGVA*	Implicit Price Deflator - GVA (2000=100, WDSA)	5	Eurostat
71	DPCEXP*	Implicit Price Deflator - Private Final Consumption Expenditure (2000=100, WDSA)	5	Eurostat
72	DGCEXP*	Implicit Price Deflator - Government Final Consumption Expenditure (2000=100, WDSA)	5	Eurostat
73	DGFKF*	Implicit Price Deflator - Gross Fixed Capital Formation (2000=100, WDSA)	5	Eurostat
74	DEXP*	Implicit Price Deflator - Exports (2000=100, WDSA)	5	Eurostat
75	DIMP*	Implicit Price Deflator - Imports (2000=100, WDSA)	5	Eurostat
Exchange Rates				
76	EXRUS	Foreign Exchange Rate: United States of America (USD per EUR - monthly average)	5	Eurostat

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Nr.	Acronym	Description	Tr.	Source
77	EXRJP	Foreign Exchange Rate: Japan (JPY per EUR - monthly average)	5	Eurostat
78	EXRUK	Foreign Exchange Rate: United Kingdom (GBP per EUR - monthly average)	5	Eurostat
79	EXRSW	Foreign Exchange Rate: Switzerland (CHF per EUR - monthly average)	5	Eurostat
80	NEER	Nominal Effective Exchange Rate, 21 group of currencies (1999Q1=100)	5	ECB SDW
Interest Rates				
81	REFI	ECB Official Refinancing Operation Rate (effective, %, NSA)	1	ECB SDW
82	EURIBOR3MD	3-Month Euro Interbank Offered Rate (%, NSA)	1	ECB SDW
83	EURIBOR6MD	6-Month Euro Interbank Offered Rate (%, NSA)	1	ECB SDW
84	EURIBOR1YD	1-Year Euro Interbank Offered Rate (%, NSA)	1	ECB SDW
85	3Y.YLD	3-Year Euro Area Government Benchmark Bond Yield (%, NSA)	1	ECB SDW
86	5Y.YLD	5-Year Euro Area Government Benchmark Bond Yield (%, NSA)	1	ECB SDW
87	10Y.YLD	10-Year Euro Area Government Benchmark Bond Yield (%, NSA)	1	ECB SDW
88	S3MDREFI	Spread EURIBOR3MD - REFI	1	ECB SDW
89	S10Y.YLDREFI	Spread 10Y.YLD - REFI	1	ECB SDW
Stock Prices				
90	DJE_50	Dow Jones Euro Stoxx 50 (2001=100, NSA)	5	Eurostat
91	DJE	Dow Jones Euro Stoxx Broad (2001=100, NSA)	5	Eurostat
92	DAX30	Deutscher Aktienindex (2001=100, NSA)	5	Eurostat
93	CAC40	Compagnie des Agents de Change 40 Index (2001=100, NSA)	5	Eurostat
94	DJE_I	Dow Jones Euro Stoxx - Industrials (Points, NSA)	5	ECB SDW
95	DJE_U	Dow Jones Euro Stoxx - Utilities (Points, NSA)	5	ECB SDW
96	DJE_O	Dow Jones Euro Stoxx - Oil And Gas Energy (Points, NSA)	5	ECB SDW
97	DJE_CG	Dow Jones Euro Stoxx - Consumer Goods (Points, NSA)	5	ECB SDW
98	DJE_CS	Dow Jones Euro Stoxx - Consumer Services (Points, NSA)	5	ECB SDW
99	DJE_BM	Dow Jones Euro Stoxx - Basic Materials (Points, NSA)	5	ECB SDW
100	DJE_TECH	Dow Jones Euro Stoxx - Technology (Points, NSA)	5	ECB SDW

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Nr.	Acronym	Description	Tr.	Source
101	DJE_H	Dow Jones Euro Stoxx - Healthcare (Points, NSA)	5	ECB SDW
102	DJE_TEL	Dow Jones Euro Stoxx - Telecommunications (Points, NSA)	5	ECB SDW
103	DJE_F	Dow Jones Euro Stoxx - Financials (Points, NSA)	5	ECB SDW
Money and Credit Aggregates				
104	M1	Money Aggregate M1 (End of Period (Stocks), Mil. EUR, WDSA)	5	Eurostat
105	M2	Money Aggregate M2 (End of Period (Stocks), Mil. EUR, WDSA)	5	Eurostat
106	M3	Money Aggregate M3 (End of Period (Stocks), Mil. EUR, WDSA)	5	Eurostat
107	MFICRINTGG	Credit to General Government Granted by MFI (End of Period (Stocks), Mil. EUR, WDSA)	5	Eurostat
108	MFICRINTOR	Credit to Other Residents Granted by MFI (End of Period (Stocks), Mil. EUR, WDSA)	5	Eurostat
109	CONSCREDIT	Consumer Credit (End of Period (Stocks), Mil. EUR, SA)	5	ECB SDW
Industrial New Orders and Turnover, Retail Turnover and Sales				
110	ORDM	Industrial New Orders - Manufacturing (2005=100, SA)	5	Eurostat
111	ORDCAG	Industrial New Orders - MIG Capital Goods (2005=100, SA)	5	Eurostat
112	ORDDCOG	Industrial New Orders - MIG Durable Consumer Goods (2005=100, SA)	5	Eurostat
113	ORDING	Industrial New Orders - MIG Intermediate Goods (2005=100, SA)	5	Eurostat
114	ITIM*	Industrial Turnover Index - Manufacturing (2005=100, SA)	5	Eurostat
115	ITICAG*	Industrial Turnover Index - MIG Capital Goods (2005=100, SA)	5	Eurostat
116	ITICOG*	Industrial Turnover Index - MIG Consumer Goods (2005=100, SA)	5	Eurostat
117	ITIDCOGD*	Industrial Turnover Index - MIG Durable Consumer Goods (2005=100, SA)	5	Eurostat
118	ITIING*	Industrial Turnover Index - MIG Intermediate Goods (2005=100, SA)	5	Eurostat
119	ITINDCOG*	Industrial Turnover Index - MIG Non-Durable Consumer Goods (2005=100, SA)	5	Eurostat
120	ITINRG*	Industrial Turnover Index - MIG Energy (2005=100, SA)	5	Eurostat

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Nr.	Acronym	Description	Tr.	Source
121	RTRADE*	Total Turnover Index, Deflated, Retail Trade Excluding Fuel, Except of Motor Vehicles and Motorcycles (2005=100, WDSA)	5	ECB SDW
122	RSALESFOOD*	Total Turnover Index, Deflated, Retail Sale of Food, Beverages and Tobacco (2005=100, WDSA)	5	ECB SDW
123	RSALESNFOOD*	Total Turnover Index, Deflated, Retail Sale of Non-Food Products (2005=100, WDSA)	5	ECB SDW
124	RSALESTEX*	Total Turnover Index, Deflated, Retail Sale of Textiles, Clothing, Footwear and Leather Goods (2005=100, WDSA)	5	ECB SDW
125	RSALESHOUS*	Total Turnover Index, Deflated, Retail Sale of Household Goods (2005=100, WDSA)	5	ECB SDW
126	PCR*	Passenger Car Registrations (Absolute Value, WDSA)	5	ECB SDW
Building Permits				
127	BUILD	Building Permits - Residential Buildings (2005=100, SA)	5	Eurostat
128	BUILDCOSTI*	Construction Cost Index - Residential Buildings (2005=100, SA)	5	Eurostat
Balance of Payments (BOP) and External Trade				
129	BOPCUAC*	BOP - Current Account (Net, Mil. EUR, WDSA)	2	ECB SDW
130	BOPKAC*	BOP - Capital Account (Net, Mil. EUR, SA)	2	ECB SDW
131	BOPFAC*	BOP - Financial Account (Net, Mil. EUR, SA)	2	ECB SDW
132	EXTTRADEIMP*	External Trade - Imports - All Products, Partner: Extra-EA16 (Trade value, Mil. EUR, WDSA)	5	Eurostat
133	EXTTRADEEXP*	External Trade - Exports - All Products, Partner: Extra-EA16 (Trade value, Mil. EUR, WDSA)	5	Eurostat
134	TOTRESING*	Foreign Official Reserves - Including Gold (End of Period (Stocks), Mil. EUR, SA)	5	Eurostat
Confidence Indicators				
135	BS-BCI	EA Business Climate Indicator (SA)	2	Eurostat
136	BS-ESI-I	Economic Sentiment Indicator (SA)	2	Eurostat
137	BS-CSMCI	Consumer Confidence Indicator (SA)	2	Eurostat
138	BS-ICI	Industrial Confidence Indicator (SA)	2	Eurostat
139	BS-RCI	Retail Confidence Indicator (SA)	2	Eurostat
140	BS-CCI	Construction Confidence Indicator (SA)	2	Eurostat
141	BS-SCI	Services Confidence Indicator (SA)	2	Eurostat

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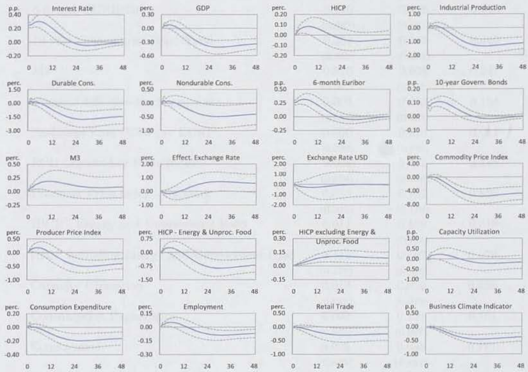
Nr.	Acronym	Description	Tr.	Source
Foreign Variables				
142	GDPUSA*	USA - GDP - Expenditure Approach (Chained Volume Estimates, Mil. EUR, SA)	5	OECD
143	GDPUK*	UK - GDP - Expenditure Approach (Chained Volume Estimates, Mil. EUR, SA)	5	OECD
144	GDPJP*	Japan - GDP - Expenditure Approach (Chained Volume Estimates, Mil. EUR, SA)	5	OECD
145	CPIUSA*	USA - CPI - All Items (2005=100)	5	OECD
146	CPIUK*	UK - CPI - All Items (2005=100)	5	OECD
147	CPIJP*	Japan - CPI - All Items (2005=100)	5	OECD
148	FFR	USA - Fed Funds Rate (Effective, %, NSA)	1	FED
149	UKOBR	UK - Official Bank Rate (Target, %, NSA)	1	BoE
150	JPCR	Japan - Call Rate (Target, %, NSA)	1	BoJ

Notes: ECB SDW - ECB Statistical Data Warehouse; MIG - Main Industrial Groups; WDSA - Working Day and Seasonally Adjusted; SA - Seasonally Adjusted; NSA - Not Seasonally Adjusted; FED - Federal Reserve System of the United States; BoE - Bank of England; BoJ - Bank of Japan.

B Robustness check: changing the number of factors

In this Appendix we list both the impulse-response functions and the forecast error variance decomposition for the FAVAR specification of our first robustness case (interest rate as the only observed variable; three factors). Standard likelihood ratio tests are used to determine the lag-order of the model, which turns out to be of order two. The model is estimated with a constant and a linear trend.

Figure 7: Impulse responses to a monetary tightening shock generated from a FAVAR with three factors and the interest rate



Notes: Percentage deviations from the baseline for variables for which logarithms were taken; percentage point deviations otherwise. Number of months after the monetary policy shock in the abscissa.

Table 5: Forecast error variance explained by the monetary policy shock – FAVAR with three factors and the interest rate

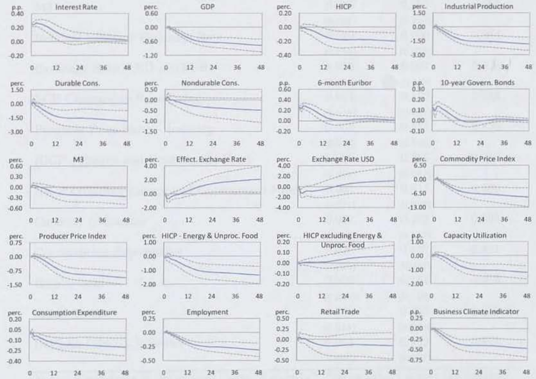
Variables	Variance Decomposition 6 months	60 months	R^2
Interest Rate	0.282 (0.089)	0.157 (0.082)	*1.000
GDP	0.008 (0.014)	0.371 (0.121)	0.927
HICP	0.028 (0.027)	0.021 (0.072)	0.540
Industrial Production (IP)	0.004 (0.013)	0.403 (0.121)	0.787
IP - Durable Consumer Goods	0.003 (0.017)	0.297 (0.119)	0.659
IP - Non-Durable Consumer Goods	0.005 (0.023)	0.213 (0.121)	0.432
6-month EURIBOR	0.276 (0.087)	0.156 (0.081)	0.919
10-year Government Bond Yield	0.282 (0.080)	0.155 (0.074)	0.649
M3	0.070 (0.052)	0.035 (0.075)	0.247
Nominal Effective Exchange Rate	0.009 (0.054)	0.253 (0.162)	0.134
Exchange Rate (USD per EUR)	0.030 (0.086)	0.013 (0.129)	0.041
ECB Commodity Price Index	0.003 (0.034)	0.412 (0.134)	0.445
Producer Price Index - Industry	0.015 (0.018)	0.167 (0.119)	0.826
HICP - Energy and Unprocessed Food	0.011 (0.017)	0.189 (0.125)	0.618
HICP excluding Energy and Unprocessed Food	0.412 (0.171)	0.167 (0.113)	0.079
Capacity Utilisation	0.019 (0.023)	0.023 (0.079)	0.535
Consumption Expenditure	0.002 (0.014)	0.221 (0.098)	0.761
Employment	0.025 (0.023)	0.098 (0.122)	0.781
Retail Trade	0.044 (0.158)	0.287 (0.146)	0.061
Business Climate Indicator	0.017 (0.050)	0.346 (0.140)	0.490

Notes: The figures in the column under "6 months" ("60 months") report the fraction of the variance of the forecast error, at the 6(60)-month horizon, explained by the monetary policy shock. The last column reports the fraction of the variance of each variable explained by both $\widehat{F}_t$ and Y_t. Standard errors are shown in parenthesis. *This is by construction, since the interest rate is assumed to be the only variable observed.

C Robustness check: treating the fed funds rate as exogenous

In this Appendix we list both the impulse-response functions and the forecast error variance decomposition for the FAVAR specification of our second robustness case (interest rate as the only observed variable; seven factors; fed funds rate as an exogenous variable). According to standard likelihood ratio tests the lag-order of the model is two. The model is estimated with a constant and a linear trend.

Figure 8: Impulse responses to a monetary tightening shock generated from a FAVAR with the fed funds rate as an exogenous variable (Y_t = interest rate; seven factors)



Notes: Percentage deviations from the baseline for variables for which logarithms were taken; percentage point deviations otherwise. Number of months after the monetary policy shock in the abscissa.

Table 6: Forecast error variance explained by the monetary policy shock – FAVAR with the the fed funds rate as an exogenous variable

Variables	Variance Decomposition 6 months	Variance Decomposition 60 months	R^2
Interest Rate	0.241	0.093	*1.000
	(0.079)	(0.066)	
GDP	0.028	0.241	0.958
	(0.035)	(0.112)	
HICP	0.002	0.129	0.842
	(0.016)	(0.107)	
Industrial Production (IP)	0.031	0.230	0.805
	(0.041)	(0.104)	
IP - Durable Consumer Goods	0.021	0.164	0.675
	(0.035)	(0.087)	
IP - Non-Durable Consumer Goods	0.008	0.085	0.441
	(0.023)	(0.069)	
6-month EURIBOR	0.206	0.082	0.975
	(0.058)	(0.050)	
10-year Government Bond Yield	0.130	0.063	0.782
	(0.041)	(0.036)	
M3	0.005	0.257	0.295
	(0.023)	(0.120)	
Nominal Effective Exchange Rate	0.010	0.036	0.934
	(0.016)	(0.035)	
Exchange Rate (USD per EUR)	0.015	0.007	0.828
	(0.023)	(0.039)	
ECB Commodity Price Index	0.064	0.123	0.623
	(0.049)	(0.081)	
Producer Price Index - Industry	0.003	0.311	0.879
	(0.015)	(0.106)	
HICP - Energy and Unprocessed Food	0.006	0.205	0.866
	(0.019)	(0.087)	
HICP excluding Energy and Unprocessed Food	0.001	0.013	0.580
	(0.011)	(0.046)	
Capacity Utilisation	0.002	0.281	0.698
	(0.010)	(0.102)	
Consumption Expenditure	0.020	0.127	0.821
	(0.025)	(0.071)	
Employment	0.026	0.194	0.910
	(0.030)	(0.110)	
Retail Trade	0.002	0.025	0.570
	(0.013)	(0.048)	
Business Climate Indicator	0.055	0.202	0.571
	(0.066)	(0.107)	

Notes: The figures in the column under "6 months" ("60 months") report the fraction of the variance of the forecast error, at the 6(60)-month horizon, explained by the monetary policy shock. The last column reports the fraction of the variance of each variable explained by both $\widehat{F}_t$ and Y_t. Standard errors are shown in parenthesis. *This is by construction, since the interest rate is assumed to be the only variable observed.

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