A Dynamic Economic and Monetary Union

ADEMU WORKING PAPER SERIES

One Money, Many Markets

A Factor Model Approach to Monetary Policy in the Euro Area with High-Frequency Identification

Giancarlo Corsetti[ⱡ]

Joao B. Duarte[ǂ]

Samuel Mann[Ŧ]

March 2018

WP 2017/087

www.ademu-project.eu/publications/working-papers

Abstract

We reconsider the effects of common monetary policy shocks across countries in the euro area, using a data-rich factor model and identifying shocks with high-frequency surprises around policy announcements. We show that the degree of heterogeneity in the response to shocks, while being low in _nancial variables and output, is significant in consumption, consumer prices and macro variables related to the labour and housing markets. Mirroring country-specific institutional and market differences, we find that home ownership rates are significantly correlated with the strength of the housing channel in monetary policy transmission. We document a high dispersion in the response to shocks of house prices and rents and show that, similar to responses in the US, these variables tend to move in different directions.

JEL Codes: E21, E31, E44, E52, F44 and F45
Keywords: Monetary Policy, High-Frequency Identification, Monetary Union, Labour Market, Housing Market.

[ⱡ] University of Cambridge. Email: gc422@cam.ac.uk.

[ǂ] Nova School of Business and Economics and University of Cambridge. Email: joao.duarte@novasbe.pt.

[Ŧ] University of Cambridge. Email: sm959@cam.ac.uk.

Horizon 2020
The Framework Programme
for Research and Innovation

ADEMU

A Dynamic Economic and Monetary Union

Acknowledgments

We thank Alexei Onatski, Peter Karadi, Luca Dedola, Pontus Rendahl, Vasco Carvalho, Petra Geraats, Simon Lloyd, and all the participants of the Macro Lunch Seminar at the University of Cambridge for their useful comments and suggestions. Joao B. Duarte also acknowledges the financial support from the ADEMU project, the Cambridge-INET Institute and the Keynes Fund under the grant JHOH. Even though our work has greatly benefitted from several discussions and detailed comments, we are solely responsible for any errors and omissions.

This project is related to the research agenda of the ADEMU project, “A Dynamic Economic and Monetary Union". ADEMU is funded by the European Union's Horizon 2020 Program under grant agreement N° 649396 (ADEMU).

The ADEMU Working Paper Series is being supported by the European Commission Horizon 2020 European Union funding for Research & Innovation, grant agreement No 649396.

1 Introduction

Monetary policy in the euro area has long been challenged by financial, economic and institutional heterogeneity among member countries. Although over time there has been some convergence in financial markets, the convergence process has slowed down markedly since the financial crisis (see ECB, 2017). Other markets have remained remarkably different across member countries. Most notably, the institutional backgrounds in labour and housing are highly dissimilar across the currency block.

Two longstanding questions are to which extent these differences in institutional backgrounds imply a heterogeneous transmission of the European Central Bank's (ECB) common monetary policy and, in particular, which specific institutional characteristics drive the observed heterogeneity. These questions are of first-order importance from a policy perspective.[1] Naturally, the ECB would benefit from knowing how national policies and reforms of the institutional framework in a particular economy affect monetary transmission. At the same time, national policy makers would gain from understanding the implications of their policies and reforms for the transmission of monetary policy.

In this paper, we investigate heterogeneity in the transmission of monetary policy across the euro area (EA) using a dynamic factor model (DFM), and take a first step towards relating the observed heterogeneity to cross-border differences in institutions and markets. We assemble a large dataset including economic and financial time series for the EA as a block and for the 11 original member countries, spanning the years from 1999 to 2016. The high dimensionality of the data allows us to carry out a formal comparison of the degree of heterogeneity among responses to monetary policy shocks across different dimensions of the economy, such as output and asset prices, as well as housing and labour markets. To identify monetary policy shocks, we construct an external instrument using high-frequency changes in asset prices around ECB policy announcements, following the contributions by Gurkaynak et al. (2005) and Gertler and Karadi (2015). Comparing country-specific institutional characteristics in national housing markets as a case study, we show that these characteristics are strongly correlated to the strength of the housing channel in monetary policy transmission.

Our main results are as follows. First, at the aggregate EA level, we find that the factor model results are in line with theory and, notably, that the transmission of monetary shocks does not suffer from the price puzzle. Second, we show that the estimated country-level effects are significantly heterogeneous in prices and variables related to labour and housing markets—some of the least integrated markets in the euro area. The degree of heterogeneity

[1] The early policy and empirical debate on this issue is summarized by Angeloni et al. (2003), see also Berben et al. (2004).

among responses to policy is instead low in financial variables and output. Third, we use our comparative analysis of European housing markets to show that the strength of the housing channel is correlated with differences in home ownership rates, which, as we argue, reflect different institutional characteristics across euro area countries.

On methodological ground, the paper's main contribution lies in the construction of the external instrument series, which we base on changes in the 1-year Euro Overnight Index Average (EONIA) swap rate (i.e. the Overnight Index Swap (OIS) rate for the euro area) around policy announcements. In doing so, we overcome major data availability issues by combining intraday data with end-of-day data from different timezones, creating de-facto intraday series where actual intraday data is unavailable.[2] This solution for the construction of our instrument is not only mechanically feasible, but also economically meaningful, as it highlights the implications of using various means of policy communication—press releases, press statements and Q&A sessions—for the transmission of current and expected future policy. The approach helps us to create a broad measure of monetary policy surprises that incorporates all of the communication channels above. Finally, we test for the relevance of the series in a small VAR, confirming its validity as an external instrument. At the time of writing and to the best of our knowledge, there are very few attempts to construct an external instrument for EA monetary policy.[3] A notable exception is Jarocinski and Karadi (2018). In contemporaneous work, these authors use the high-frequency co-movement of interest rates and stock prices around a narrow window of the policy announcement to disentangle policy from information shocks. Notably, the effects of the monetary shocks we identify in this paper are close to the effects of policy shocks (as opposed to information shocks) documented by these authors.

Our second contribution is motivated by the need to test heterogeneity in the responses of economic variables to a common shock. For each set of impulse responses (e.g. GDP across member countries), we calculate the coefficient of variation statistic, also known as relative standard deviation. The coefficient of variation for a variable is defined as the standard deviation of responses across countries with respect to the EA response, normalised by the size of the EA response. This yields a statistical measure of the dispersion of impulse

[2]Intraday data on EONIA swaps is only available for recent years. However, we were able to combine end-of-day data from Tokyo and London to create a de-facto intraday series that goes back to the introduction of the euro. We then compared a narrowly constructed instrument over a sub-sample for which we had complete intraday data with our proposed de-facto intraday series. We find that the series are not significantly different for the sub-sample. See Section 2.3.1 for details.

[3]Limitations on the availability of data are a strict constraint to construct this instrument for the euro area. Some work, such as Kim and Other (2017), resorts to daily data. However, as the resulting windows around policy announcements become very large, they are more likely contaminated by shocks other than those stemming from monetary policy. Notably, European data is frequently released on the morning of a policy meeting, leading to a systematic disturbance of instruments that rely on daily data.

responses which allows us to carry out comparisons across variables. We employ a bootstrapping procedure to obtain error bands for the coefficient of variation of each variable as well as pairwise differences across variables.

In specifying our empirical model, we build on two strands of the literature. The first is factor modelling, which has emerged as early as the 1970s[4] and was more recently popularised for monetary policy analysis by Bernanke et al. (2005). These authors model macroeconomic interaction with a factor-augmented VAR (FAVAR) that combines factors and perfectly observable series, typically interest rates, in one dynamic system. As a special case of FAVARs, dynamic factor models (DFMs) only contain unobservable factors. Among other applications of DFMs, Stock and Watson (2012) use this approach to disentangle the channels of the 2007-09 recession.

From an applied perspective, the prime advantage of a factor approach[5] is its ability to keep track of individual country-level responses to a common monetary policy shock without heavy parameterisation. Looking at the alternatives, country-by-country VARs incur the cost of heavy parameterisation, while a large panel VAR (PVAR) with all countries imposes restrictions on the individual dynamics. The dynamic factor model solves both problems and provides dynamic effects on the individual countries—including net spillovers—while keeping the parameter space small. In addition, the assumptions on the information structure in the dynamic factor model naturally fit the EA setting. The ECB follows not only a large number of euro-wide series but also series in individual member countries. Hence, an empirical model with a small number of variables that does not include country-level data is unlikely to span the information set used by the ECB.[6]

While we closely follow the methodology of Stock and Watson (2012) when we construct our DFM, we bridge the approach with developments from the literature on high-frequency identification and external instruments. As is well known, estimations of monetary policy transmission suffer from an identification problem. One common way to overcome this problem and identify monetary policy shocks is to impose additional internal structure on the VAR, such as timing or sign restrictions. Alternatively, one can add information from outside of the VAR, termed an external instrument approach. We make use of the latter. The two leading examples of existing external instruments for monetary policy shocks in the US are the Romer and Romer (2002) instrument based on a narrative approach, and the

[4]see Stock and Watson (2016) for a comprehensive exposition of factor models, including their early history.

[5]see e.g. Giannone et al. (2005), Bernanke et al. (2005), Stock and Watson (2005) and Forni and Gambetti (2010).

[6]Other seminal contributions on dynamic factor modelling include Sargent and Sims (1977), Sargent (1989), Giannone et al. (2005) and Boivin and Giannoni (2007).

high-frequency approach by Gurkaynak et al. (2005). For the second, the key idea is that by choosing a narrow time window around policy announcements, any surprises occurring within the window are most likely only associated with monetary policy shocks. The idea to use high-frequency changes in asset prices, specifically interest rate derivatives, has also been developed by Kuttner (2001), Hamilton (2008) and Campbell et al. (2012).[7] Building on these contributions, Gertler and Karadi (2015) identify monetary policy shocks in a VAR using high frequency changes in Fed funds futures. This paper builds a hybrid between the high-frequency identification proposed by Gertler and Karadi (2015) and the dynamic factor model of Stock and Watson (2012).

The analysis of the housing channel conducted in our paper is related to Calza et al. (2013), who studied how heterogeneity in the structure of housing finance across member countries in the euro area can affect the transmission of monetary policy to house prices. Differently from their work, we take a more comprehensive approach and, specifically, document how differences in home ownership rates are closely linked to asymmetries in house price responses. Moreover, we investigate the role of rents in the housing channel and show that together with house prices, they have a strong link to responses in consumption. More generally, our work is related to the large body of policy and academic research that, given the importance of the topic, has been devoted to the heterogeneous transmission of monetary policy across EA member states. Among the leading examples are Ciccarelli et al. (2013), who look at heterogeneity from the perspective of financial fragility, as well as Barigozzi et al. (2014) who, similar to the methodology followed in this paper, rely on a factor model, although identifying shocks with sign restrictions and pursuing a less comprehensive study, both in the number of variable included and the methodological and empirical questions addressed.

In the next section, we describe the methodology used in the empirical analysis and provide details on the external instrument used for the identification of monetary policy shocks. In Section 3, we present our results, tracing out the effects of monetary policy on the EA as a whole, as well as on individual member countries. Section 4 uses the housing market as a case-study to uncover how institutional differences are affecting the monetary transmission across the euro area. Section 5 concludes.

[7]Further applications of high-frequency identification in the context of monetary policy can be found in Hanson and Stein (2015), Nakamura and Steinsson (2013), Bagliano and Favero (1999), Cochrane and Piazzesi (2002), Faust et al. (2004) and Barakchian and Crowe (2013), among others.

2 A Dynamic Factor Model for the EA

We begin by motivating the use of a dynamic factor model for the EA and laying out the empirical framework. Later in this section we provide details about the external instrument we construct to identify monetary policy shocks. At the end of the section, we discuss the large data set and estimation.

2.1 Motivation

Given the EA setting, we are fundamentally interested in studying the effects of a common monetary policy shock on the EA as a block and on its individual member countries.[8] Recovering both the effects on the block and on member countries imposes some empirical challenges and trade-offs. On the one hand, fully recovering the effects of monetary policy on each individual member country comes with heavy parameterisation. On the other hand, reducing the parameter space by imposing restrictions prevents us from studying the full width of heterogeneous effects. In addition, a small data sample in the time dimension, as encountered in the context of the EA, further increases the acuteness and relevance of this trade-off.

We propose a dynamic factor model for the EA as a parsimonious way to avoid heavy parameterisation while keeping track of individual country responses to the common monetary policy shock. The dynamic factor model allows us to capture dynamic effects on individual countries through unobservable common components. The dimensionality reduction achieved through the factor model allows us to get statistically robust dynamic effects on the individual countries while keeping the parameter space small.

The dynamic factor model has another set of appealing features for the EA. Firstly, we can relax the informational assumption that both the ECB and the econometrician perfectly observe all relevant economic variables. Secondly, as the ECB monitors a large number of indicators in the process of policy formulation, including on country level, it is necessary for the econometrician to take account of the same information set. The DFM achieves this. Finally, the dynamic factor model provides a format that is consistent with economic theory. We next address each of these points.

In using a dynamic factor model we do not have to take a stand on specific observable measures corresponding to theoretical concepts. This point was convincingly put forward by Bernanke et al. (2005). In the EA context, this relaxation becomes more relevant as it is harder to find observable Eurowide variables—often weighted averages of individual member

[8] A similar setting would appear if one was simultaneously interested in the effects of monetary policy on the U.S. as a whole and at the individual State level.

countries—that correspond to concepts of economic theory. For example, the concept of *economic activity* in the EA may not be perfectly measured by taking a weighted average of real GDP across countries, given compositional changes that cannot be captured by treating the EA as a single economy in a theoretical model.

The European Central Bank follows not only a large number of eurowide series but also a large number of individual member countries' series. Hence, an empirical model with a small number of variables that does not include country data is unlikely to span the information set used by the ECB. This naturally motivates the inclusion of country-level series in our analysis.

The state-space representation of the dynamic factor model also provides a clear link with economic theory, which creates the opportunity to formally test different mechanisms aimed at explaining the dynamic effects found in this paper. Moreover, given the large size of dynamic effects found in observables, it is possible to test interactions of different mechanisms using the same model and dataset.

There are alternatives to the DFM approach chosen by us—notably Panel VAR and Global VAR models. Both of these approaches involve restricting or explicitly modelling the dynamics through which variables in different units affect each other. These restrictions come at a cost of higher parameterisation relative to the dynamic factor model. Given that we are not explicitly interested in these interaction at the cross-sectional level, but rather in the final net effect, we choose the dynamic factor model for efficiency gains. Ciccarelli et al. (2013) provide a further insightful discussion of the differences between these three approaches.

2.2 Empirical Framework

We consequently use the DFM to model macroeconomic interaction. In doing so, we largely follow the methodology proposed by Stock and Watson (2012).

Given a vector of n macroeconomic series $X_t = (X_{1t}, ..., X_{nt})'$ we first model each series as a combination of factors and idiosyncratic disturbances:

$$X_t = \Lambda F_t + e_t, \tag{1}$$

where F_t is a vector of unobserved factors, Λ is an $n \times r$ matrix of factor loadings and $e_t = (e_{1t}, ..., e_{nt})'$ denotes a vector of n disturbances. We can interpret ΛF_t as the 'common component' of X_t, whilst e_t is the 'idiosyncratic component'. The evolution of factors is characterised by the following VAR:

$$F_t = \Phi_1 F_{t-1} + \Phi_2 F_{t-2} + ... + \Phi_s F_{t-s} + \eta_t, \tag{2}$$

which can be rewritten with lag-operator notation as

$$\Phi(L) F_t = \eta_t, \tag{3}$$

where $\Phi(L)$ is a $p \times r$ matrix of lag polynomials and η_t a vector of r innovations. This equation characterises all dynamics in the model. As it stems solely from the interaction of factors, there is no need to model the co-movement of observed variables, hence avoiding the curse of dimensionality.

The static factors can be estimated by suitable cross-sectional averaging. Whilst a setup with multiple factors and general factor loadings does not allow for simple cross-sectional averaging to produce a consistent estimate of the factors, the idea can be generalised using principal components analysis. Given large n and T, the principal components approach estimates the space spanned by the factors, even though the factors themselves are not estimated consistently. Put differently, F_t is estimated consistently up to premultiplication by an arbitrary nonsingular $r \times r$ matrix. The resulting normalisation problem can be resolved by imposing the restriction that $\Lambda'\Lambda = I_r$. Given that this restriction is chosen arbitrarily, the factors cannot be directly interpreted in an economic sense. For most parts, we will work with the reduced-form DFM, making the normalisation inconsequential.

More generally, principal component analysis provides the factors that explain the most variation in the data, while at the same time avoiding an information overlap between the factors as they are orthogonal to each other.

2.3 Identification

This section turns to the identification of the monetary policy shocks in the DFM. As is well known, estimations of monetary policy suffer from an identification problem, as monetary policy contemporaneously reacts to other variables in the model. To find the part of the variation in monetary policy that is orthogonal to other variables, various approaches have been proposed in the literature. In traditional VAR-type models, researchers have typically imposed some internal structure on the coefficients in the VAR, such as timing restrictions or sign restrictions. More recently, Montiel Olea et al. (2012) as well as others have proposed an additional method, where information from outside the VAR is used to identify monetary policy. In the so-called external instrument approach, an instrument is employed that is correlated with the structural shock that the researcher tries to uncover, while being uncorrelated with all other shocks in the system. This corresponds to the standard assumptions of relevance and exogeneity in the instrumental variables literature.

The main concept behind using an external instrument is that when regressing the VAR innovations η_t on the instrument Z_t, the fitted value of the regression identifies the structural shock—up to sign and scale. In fact, as this approach uncovers the covariance between η_t and Z_t, a regression of the instrument on the VAR innovations would equally uncover the structural shock.

Following the VAR literature and the notation in Stock and Watson (2012), we model a linear relationship between the VAR innovations η_t and the structural shocks ϵ_t:

$$\eta_t = H\epsilon_t = [H_1 \cdots H_r] \begin{pmatrix} \epsilon_{1t} \\ \vdots \\ \epsilon_{rt} \end{pmatrix}, \tag{4}$$

where H is a matrix of coefficients and H_1 is the first column of H. It follows that $\Sigma_{\eta\eta} = H\Sigma_{\epsilon\epsilon}H'$, with $\Sigma_{\eta\eta} = E(\eta_t\eta_t')$ and $\Sigma_{\epsilon\epsilon} = E(\epsilon_t\epsilon_t')$. If the system is invertible—a standard assumption in the VAR literature—structural shocks can be expressed as linear combinations of innovations:

$$\epsilon_t = H^{-1}\eta_t. \tag{5}$$

The main interest in the DFM, as in other VAR-type models, lies in uncovering impulse response functions (IRFs) to a specific shock. To find the impulse response function of X_t with respect to the i^{th} structural shock, we can use equations 3 and 5 to get

$$F_t = \Phi(L)^{-1}H\epsilon_t. \tag{6}$$

Substituting 6 into 1, we find that

$$X_t = \Lambda\Phi(L)^{-1}H\epsilon_t + e_t. \tag{7}$$

where the IRF is $\Lambda\Phi(L)^{-1}H$. Λ and $\Phi(L)$ are already identified from the reduced form, equation 2, which we can estimate via ordinary least squares. However, this leaves the identification of H_t, which is dealt with in the next section.

As mentioned above, we identify the shock of interest, say ϵ_{1t}, using the instrumental variable Z_t. The necessary conditions are:

1. Relevance: $E(\epsilon_{1t} Z_t) = \alpha \neq 0$

2. Exogeneity: $E(\epsilon_{jt} Z_t) = 0$, $j = 2, ..., r$

3. Uncorrelated shocks: $\Sigma_{\epsilon\epsilon} = D = diag(\sigma^2_{\epsilon_1}, ..., \sigma^2_{\epsilon_r})$,

where D is an $r \times r$ matrix. The last condition is the standard structural VAR assumption that structural shocks are uncorrelated. This assumption does not fix the variance of shocks. From equation 4 we get

$$E(\eta_t Z_t) = E(H\epsilon_t Z_t) = (H_1 \cdots H_r) \begin{pmatrix} E(\epsilon_{1t} Z_t) \\ \vdots \\ E(\epsilon_{rt} Z_t) \end{pmatrix} = H_1 \alpha, \tag{8}$$

where the last identity follows from the relevance and exogeneity conditions. It follows that H_1 is identified up to scale and sign by the covariance between the VAR innovations and the instrument. To identify the shocks themselves, we need the third condition on uncorrelated shocks. It implies that we can rewrite the varianance-covariance matrix of η_t as

$$\Sigma_{\eta\eta} = H \Sigma_{\epsilon\epsilon} H' = HDH'. \tag{9}$$

Moreover, defining by Π the matrix of coefficients from the population regression of Z_t on η_t, the fitted value of this regression is

$$\Pi \eta_t = E(Z_t \eta_t') \Sigma^{-1}_{\eta\eta} \eta_t, \tag{10}$$

which, using equation 8 and 9, can be written as

$$E(Z_t \eta_t') \Sigma^{-1}_{\eta\eta} \eta_t = \alpha H_1' (HDH')^{-1} \eta_t. \tag{11}$$

By simplifying and using equation 5, we obtain

$$\alpha H_1' (HDH')^{-1} \eta_t = \alpha (H_1' (H')^{-1}) D^{-1} \epsilon_t. \tag{12}$$

Finally, we note that $H^{-1} H_1 = e_1$, where $e_1 = (1, 0, ..., 0)'$, which implies that

$$\alpha (H_1' (H')^{-1}) D^{-1} \epsilon_t = (\alpha / \sigma^2_{\epsilon_1}) \epsilon_{1t} = \Pi \eta_t. \tag{13}$$

This conforms with the original statement that the fitted value of a regression of the instrument on the innovations, i.e. $\Pi \eta_t$, identifies the structural shock ϵ_{1t} up to a constant.

For additional intuition, Stock and Watson (2012) point out that if the structural shocks ϵ_t were observable and we could hence regress the instrument on the structural shocks, the predicted value would again uncover the shock ϵ_{1t}, up to scale, as the coefficients on all other elements of ϵ_t would be zero. This follows from the relevance and exogeneity conditions of the instrument. Equation 13 shows that the projection of Z_t on η_t provides the exact same result, uncovering ϵ_{1t}. Note that to estimate the structural shock, we use the sample analogue of the above equation.

2.3.1 Instrument - "Scripta Volant, Verba Manent"[9]

To obtain an instrument that fulfills the necessary requirement of only being correlated with the monetary policy shock, we build a new series of high frequency surprises around ECB policy announcements. A similar approach has previously been proposed for US monetary policy by Gertler and Karadi (2015). The key idea is that by choosing a narrow time window around policy announcements, any surprises occurring within the window are most likely only associated with monetary policy shocks. Put differently, the assumption is that no other major structural shocks occur during the chosen window around the policy announcement. Correspondingly, all endogenous monetary policy, i.e. all expected monetary policy, is assumed to already have been priced in before the window starts. Consequently, endogenous monetary policy would not cause a change in the instrument at the time of the announcement.

For the instrument we choose changes in the 1-year Euro Overnight Index Average (EONIA) swap rate. The logic goes that while expectations about future policy rate changes are already priced in, unexpected policy shocks will cause the swap to appreciate or depreciate instantly. If market participants, for example, expect a hike in the policy rate by a certain amount, the announcement of such a hike will not cause the 1-year EONIA swap rate to move. However, should a hike or cut be out of line with expectations, the swap rate will adjust as soon as the announcement is made. Similarly, any policy action that changes expectations about future rate movements—often termed 'forward guidance'—will have an impact on the swap. Lloyd (2017a) and Lloyd (2017b) demonstrates that 1 to 24-month Overnight Indexed Swap (OIS) rates accurately measure interest rate expectations. As our chosen EONIA swap rate is the corresponding OIS rate for the euro area, this finding is directly applicable to our instrument, allowing us to capture not only current monetary policy, but also expectations about the future path of monetary policy.

[9]The original quotation (*Verba volant, scripta manent*), attributed to Caius Titus, roughly translates as "spoken words fly away, written words remain." We find that, on the contrary, it is often the spoken word of the ECB President during the press conference and Q&A session, which has a larger impact on markets than the written word of the monetary policy press release.

When deciding on the tenor of the EONIA swap, two considerations have to be taken into account. Firstly, to capture how a monetary policy shock affects interest rates across the whole yield curve, a longer dated swap is better suited compared to one with a shorter tenor. On the other hand, however, term premia play a larger role at longer horizons, potentially contaminating the information about future short rates. In dealing with this trade-off, we choose the 1-year rate, based on the observation that 1-year rates are highly sensitive to monetary policy, while still remaining relatively unaffected by term premia. That said, we also construct instruments based on 3-month, 6-month and 2-year EONIA swaps and do not find a significant difference in our results.

For their high frequency analysis of US monetary policy, Gertler and Karadi (2015) choose a window of 30 minutes around the policy announcement (starting 10 minutes before the Federal Open Market Committee (FOMC) announcement and ending 20 minutes after). The main policy announcement of the FOMC contains a large amount of information about the decision as well as the view of the committee about the state of the economy and expectations of future policy action. This means that within the 30 minute window, the market can fully integrate recent policy changes and adjust the price of the instrument. The procedure of policy releases is somewhat different at the ECB. The release of the monetary policy decision at 13:45 CET only contains a limited amount of information on the latest policy actions. A significant amount of information is disseminated to the market at a later stage, through the press conference and Q&A with the President, starting at 14:30 CET. For this reason, we decided to extend the window for our analysis to cover not only the prime release, but also the press conference. Specifically, we choose a 6-hour window from 13:00 to 19:00 CET.[10]

Figures 1 and 2 show examples of characteristic movements in the 1-year EONIA swap on ECB meeting days, highlighting the importance of including the Q&A in the high-frequency window. On 5 June 2008, the Governing Council of the ECB decided that policy rates will remain unchanged. As this was in line with market expectations, the 1-year EONIA swap rate did not move much in reaction to the press release at 13:45 CET. During the press conference however, the president expressed concern about increased risks to price stability,

[10] The press conference typically lasts for only one hour, implying that the window could be more narrowly defined, ending, e.g. at 16:00 CET. We chose not to do so due to data availability issues. Specifically, intraday data on swap prices on Bloomberg are available only from January 2008 onwards. In other words, we would have been able to create an instrument only from 2008 using intraday data. For a window from 13:00 to 19:00 CET, however, this problem does not arise as these times correspond to the closing times of the Tokyo and London stock exchanges, respectively. Hence it is possible to obtain end-of-day data, which is available from 2001, and create a *de-facto* intraday window from 13:00 to 19:00 CET. For the subsample of overlapping observations (2008-2016) we tested for the difference in using the window ending with the press conference vs. later the same afternoon and found it to be statistically insignificant.

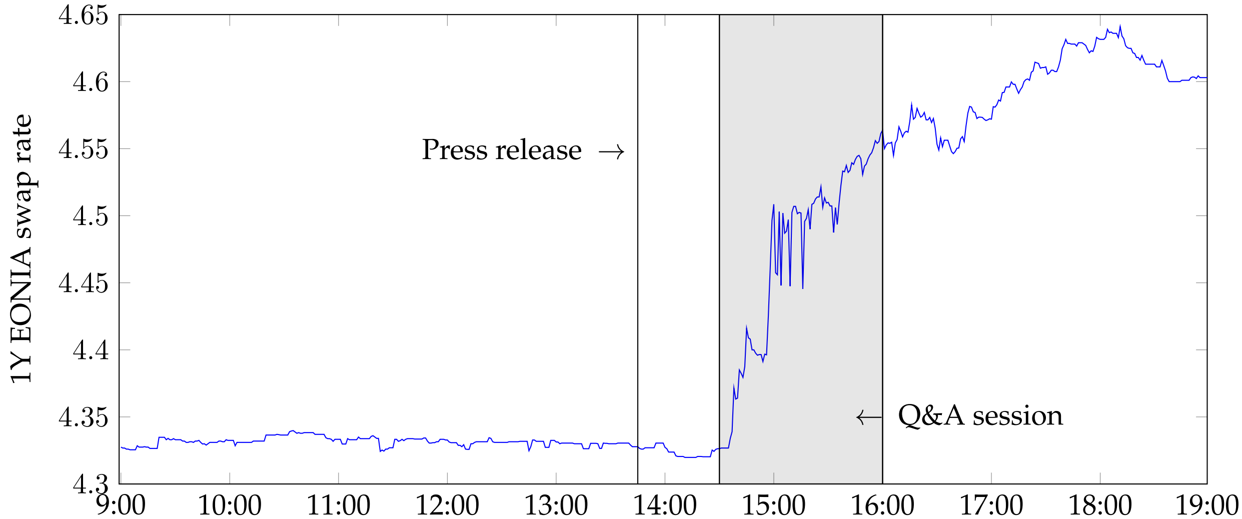

Figure 1: 1-year EONIA swap rate on 5 June 2008. Horizontal axis shows Central European Time (CET). Source: Bloomberg, authors' calculations.

setting expectations of rate hikes in the near future. In reaction to this information, the swap rate immediately jumped higher and over the afternoon increased by 27 basis points. This example clearly demonstrates that information about ECB policy information can to a large degree be contained in the press conference, compared to the policy announcement. An example where both the original announcement, as well as the press conference convey substantial information to market participants is the meeting on 6 October 2011. The press release once again stated that rates would remain unchanged. However, this was not in line with market expectations for a cut and hence created a tightening surprise that led to an immediate increase in the 1-year EONIA swap rate. During the press conference, the then ECB President Jean-Claude Trichet re-emphasised that inflation rates had remained at elevated levels. This in turn pushed market expectations towards tighter monetary policy and caused a further jump in the swap rate. Naturally, there are also examples where the press conference does not convey a significant amount of information to the market, but the above cases highlight the need to include the press release in the high-frequency window.

The above discussion raises the question to which degree the various forms of information dissemination could be used to develop a more differentiated understanding of the nature of policy shocks. Previous contributions have suggested a separation of monetary policy *instrument* shocks from monetary policy *communication* shocks, sometimes also termed *target* and *path* shocks. For the euro area, work on this distinction is being pursued by Jarocinski and Karadi (2018). For the purpose of our paper, we want to use a broad measure of monetary policy shocks that encompasses all forms of surprises, whether they are to the instrument or

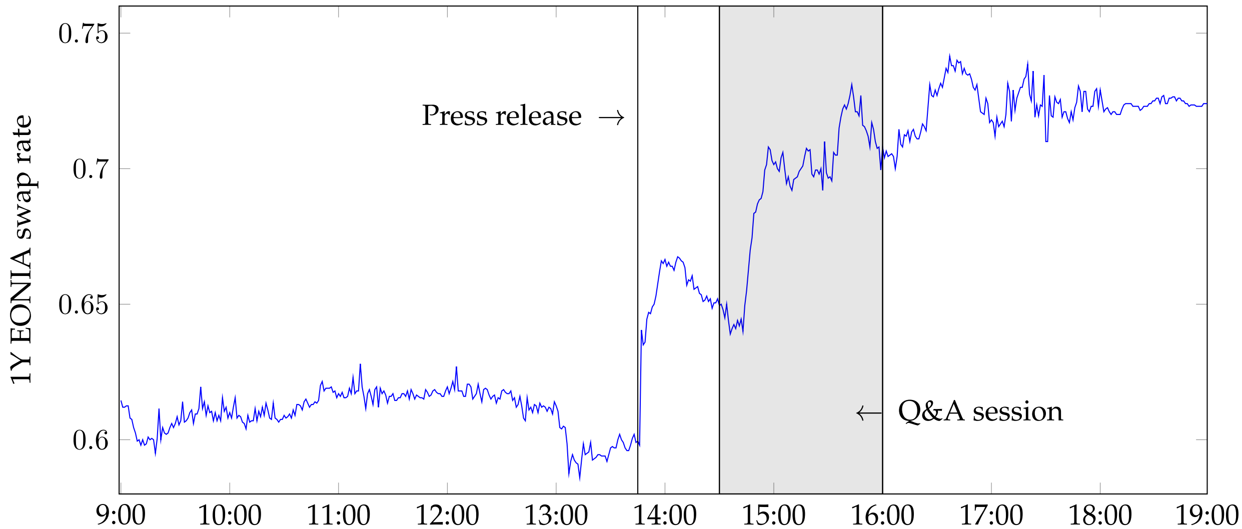

Figure 2: 1-year EONIA swap rate on 6 October 2011. Horizontal axis shows Central European Time (CET). Source: Bloomberg, authors' calculations.

expectations. That said, we hope that the development of our instrument is informative for future research on the manifold nature of monetary policy shocks within the euro area.

As we estimate a quarterly VAR, we have to turn the surprises on ECB meeting days into quarterly average surprises. In practice, we first calculate the cumulative daily surprise over the past quarter (93 days) for each day in our sample. In the next step we take the average of this daily cumulative series over each quarter. In doing so, we incorporate the information that some meetings happen early within a quarter while others happen later. Our averaging procedure makes sure that a surprise happening late in the quarter has less influence on the quarterly average than a surprise at the beginning of the quarter.[11]

To get a better understanding of the instrument, we plot its values in Figure 3. In particular, we want to point out events that led to particularly large positive or negative values in the instrument to develop an intuition regarding the behaviour of the series. Proceeding chronologically, the earliest of the four largest surprises happened in the fourth quarter of 2001, with a value of -0.15. This data point is driven by the aggressive interest rate cut on 17 September 2001, in response to the 9/11 terrorist attacks.[12] The ECB cut all three interest rates by 50bp leading to a drop in 1-year EONIA swaps of 20bp during our window. Another particularly large negative shock appears in the fourth quarter of 2008. The value of -0.17 is mostly driven by the monetary policy decision on 2 October 2008. Interest rates were kept

[11] A similar approach was taking by Gertler and Karadi (2015) to create monthly FOMC surprises.

[12] Note that the surprise actually happened in the third quarter of 2001. However, because our averaging approach takes into account whether a shock appears early or late in a quarter—and consequently, whether it has a larger influence on the current or the next quarter—the policy decision from 17 September 2001 mostly affects our instrument during Q4 2001.

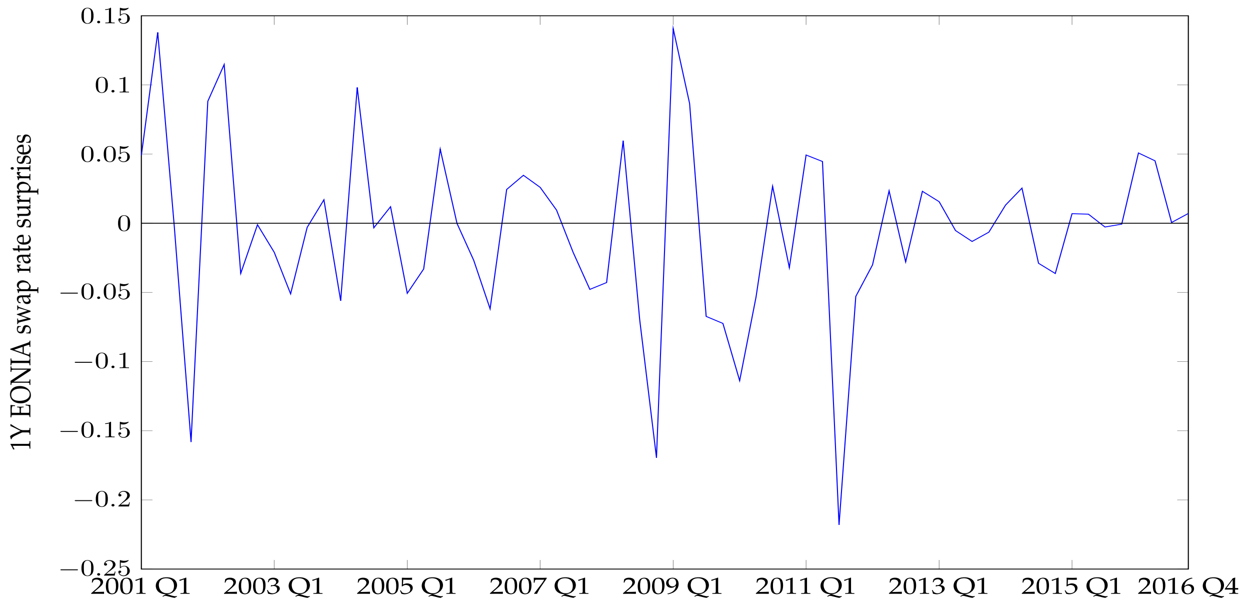

Figure 3: Instrument - Quarterly 1-year EONIA swap rate surprises from 2001Q1 to 2016Q4

unchanged on the day, in line with expectations. However, President Trichet highlighted financial market turmoil and weakness in the EA economy during his statement, leading to a large drop in the swap rate between 14:30 and 15:30 CET as markets priced in future cuts to the policy rate. In the following quarter, Q1 2009, our instrument records a particularly high reading of 0.14. This goes back in large part to a contractionary monetary policy surprise during the meeting of 4 December 2008, but also to a surprise during the meeting of 15 January 2009. Interestingly, during both meetings, which happened at the height of the financial crisis, interest rates were cut—by 75bp and 50bp, respectively. While this led to momentarily lower swap rates on both occasions, rhetoric during the press conference led to further increases in the rate. In fact, on both occasions, the President's various dovish and hawkish comments led to the rate moving up and down, but the contractionary sentiment dominated overall. Finally, we investigate the events driving our instrument during Q3 2011. The negative value of -0.22—the largest value in absolute terms during our sample period—mainly goes back to the policy decision on 4 August 2011. After an interest rate hike at the previous meeting, policymakers left interest rates unchanged on the day. As this was in line with expectations, the swap rate did not move at 13:45 CET. During the press conference, however, the ECB announced the decision to conduct a liquidity-providing supplementary longer-term refinancing operation (LTRO), based on observed tensions in financial markets within the euro area. This policy action amounted to a large dovish surprise and 1-year EONIA swaps fell by about 18bp between 14:30 and 15:30 CET.

Finally, we test the strength of our instrument. We do so in a small VAR containing only three variables: output, consumer prices and a policy indicator. The model is specified both at monthly and quarterly frequency and is identified using high-frequency instruments based on 3, 6 and 12-month EONIA swaps. We report further details and all results in Appendix B, but note here that in our baseline specification the instrument is strong, with a first-stage F-test statistic of 19.45. This confirms the relevance of our external instrument.

2.4 Data and Estimation

Our data set consists of quarterly observations from 1999 Q4 to 2016 Q4 on 90 area-wide measures such as prices, output, investment, employment and housing, as well as 342 individual country time series for the 11 early adopters of the Euro: Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain. The vintage of the data is June 2017. Appendix C lists all data series with detailed descriptions and notes on the completeness and length of the individual series.

All data series are transformed to induce stationarity. Depending on the nature of the data, this was done either by taking the first difference in logs or levels. Details on transformations can also be found in Appendix C. As we lose one observation by differencing, our working dataset starts in 2000 Q1.

Principal component analysis is sensitive to double-counting[13] and we consequently only use a subset of our data for factor extraction. In practice, we avoid double-counting along two dimensions. Firstly, we do not include euro area aggregates for indicators where we have included all individual country series. Secondly, we do not include category aggregates, such as GDP, when we have included its components, such as the components of GDP. Where possible, we avoid using high-level aggregate series altogether and instead include disaggregate series. In total, we use 179 series for factor extraction.

We rely on a number of specific tests and information criteria to determine the number of common factors r. Specifically, we estimate them by means of the test proposed by Onatski (2009), which suggests $r \in 2, 3$ (Table 1), the eigenvalue difference method proposed by Onatski (2010) suggesting $r = 2$, the criterion by Bai and Ng (2002) suggesting $r = 5$, and the bi-cross-validation method proposed by Owen and Wang (2015)[14] suggesting $r = 8$. We choose as our baseline specification $r = 5$, that is, the average of these results. Figure 13 in Appendix A shows the variance of the data explained by each additional factor. Five factors account for 80% of the total data variance.[15]

[13] see e.g. Stock and Watson (2012).

[14] see Figure 12 in Appendix A.

[15] As can be seen in Figure 13, the bulk of the variance in the data is explained by the first two factors.

Table 1: Determining the number of common factors: Onatski (2009) test. The Table shows p-values of the null of q_0 common shocks against $r_0 < r \leq r_1$ common shocks.

r_0 **vs** $r_0 < r \leq r_1$	1	2	3	4	5	6	7
0	0.727	0.089	0.122	0.153	0.18	0.209	0.232
1	0	0.05	0.089	0.122	0.153	0.18	0.209
2	0	0	0.521	0.414	0.539	0.632	0.705
3	0	0	0	0.229	0.414	0.539	0.632
4	0	0	0	0	0.794	0.595	0.746
5	0	0	0	0	0	0.336	0.595
6	0	0	0	0	0	0	0.561

On the basis of Akaike and Bayes Information Criteria we include one lag for the baseline of the DFM.

To get a better understanding of how well the extracted factors characterise the data, Table 2 shows the variation in the data explained by the five factors. The second column shows the fraction of explained variation for a selection of aggregate area-wide series. The third column shows the corresponding average across series from individual member countries. In particular, two observations stand out. Firstly, the variation in most aggregate series is remarkably well explained by the five factors. With a few exceptions, notably the exchange rate, the R-squared ranges between 70% and 99%. Secondly, despite the granularity of the individual country series, the factors on average still explain more than half of all variation. In some cases, such as HICP inflation, government spending and, most notably, long-term interest rates, they explain considerably more. Columns 4 and 5 show the same information as column 3, but differentiate between the size of the countries. In particular, we separate the 5 countries in our sample with the largest economies (by nominal GDP) from the 6 countries with the smallest economies. As expected, the factors pick up information from the large economies to a much greater extent than for smaller economies. With the exception of exports, imports and rents, data from larger economies is consistently explained better by the factors. This difference is particularly strong for GDP (70% vs. 45%) and unemployment (68% vs. 36%). As concrete examples of the above, Figure 17 in Appendix E plots fitted series on the basis of the 5 extracted factors against actual (transformed) series for GDP and HICP in the euro area, Germany and Luxembourg.

In line with this observation and the test results from Onatski (2009) and (2010), we re-estimate the DFM with only two factors. We find that all main results of the 5-factor model hold. While the smaller amount of factors allow for greater precision, the larger amount of factors gives us more explanatory power for the observable series. We prefer the latter effect over the former and hence select 5 factors for our baseline specification.

Table 2: R-squared for regression of data series on five principal components. *Germany, France, Italy, Spain, Netherlands. **Belgium, Austria, Ireland, Finland, Portugal, Luxembourg.

	EA aggregate	Average across individual country series	Average across large* countries	Average across small** countries
Gross Domestic Product	0.85	0.56	0.70	0.45
Harmonised Index of Consumer Prices	0.81	0.64	0.71	0.59
House Prices	0.71	0.46	0.52	0.40
Exports	0.76	0.54	0.49	0.58
Imports	0.75	0.58	0.45	0.69
Government Spending	0.18	0.68	0.77	0.59
Gross Fixed Capital Formation	0.76	0.33	0.51	0.19
Consumption	0.61	0.30	0.34	0.27
Unemployment	0.72	0.51	0.68	0.36
Long-term Rates	0.99	0.98	0.98	0.98
Rents	0.41	0.35	0.32	0.38
Share Prices	0.65	0.58	0.59	0.57
Producer Prices in Industry	0.87	-	-	-
Wages	0.75	-	-	-
Employment	0.74	-	-	-
GER 2Y yield	0.98	-	-	-
Cost of Borrowing indicator	0.91	-	-	-
EONIA	0.99	-	-	-
Nominal Effective Exchange Rate	0.12	-	-	-

3 Empirical Results

This section gives an overview of our empirical findings, starting at the euro area aggregate level and subsequently exploring results on the country level.

3.1 Euro-wide Dynamic Effects of Monetary Policy

We start our description of the results with an overview of a selection of aggregate series across the euro area. Figure 4 shows percentage responses to a contractionary monetary policy shock of 25 basis points (bp). As discussed in Section 2.3, the external instrument approach identifies the shock only up to sign and scale. Using the response of EONIA as a policy indicator, we scale the system to a 25bp contraction in EONIA. The shaded area around the point estimates signify confidence intervals of one standard deviation, obtained from a wild bootstrapping procedure with a simple (Rademacher) distribution. Given a strong instrument, the confidence intervals obtained under this approach are valid despite the presence of heterogeneity. Because both stages of the regression are incorporated in the bootstrapping procedure, the error from the external instrument regression is accounted for. A similar approach has been followed by Mertens and Ravn (2013) and Gertler and Karadi (2015).

Notably, our results do not suffer from the prize puzzle—the occurrence of rising prices in reaction to a contractionary monetary policy shock. In fact, while the harmonised index of consumer prices (HICP) does not have any significant reaction, our producer prices fall significantly, in line with economic theory. Given the longstanding struggle of VAR-type models to get rid of the price puzzle, we interpret these findings as an indication of the ability of the model to accurately characterise economic dynamics. In particular, we attribute the non-existence of the price puzzle to the combination of correctly capturing information about prices in the economy (via the DFM) and precisely identifying monetary policy shocks (via the high frequency instrument).[16] The remainder of the series in Figure 4 also behave as suggested by theory. GDP contracts overall, as do all components with the exception of Government Spending, which increases in reaction to a contractionary shock. In line with theory, investment (GFCF) is a lot more volatile than consumption, as are imports and exports. The reaction of the German 2-year sovereign yield closely follows EONIA. The aggregate indicator for mortgage interest rates in the euro area as compiled by the ECB also rises in reaction to a shock, but displays imperfect pass-through as a significant number of mortgages are characterised by fixed rates that do not adapt to changes in policy. In the

[16] We also applied the FAVAR approach proposed by Bernanke et al. (2005) using EONIA as the only observable factor and found that the price puzzle was still present

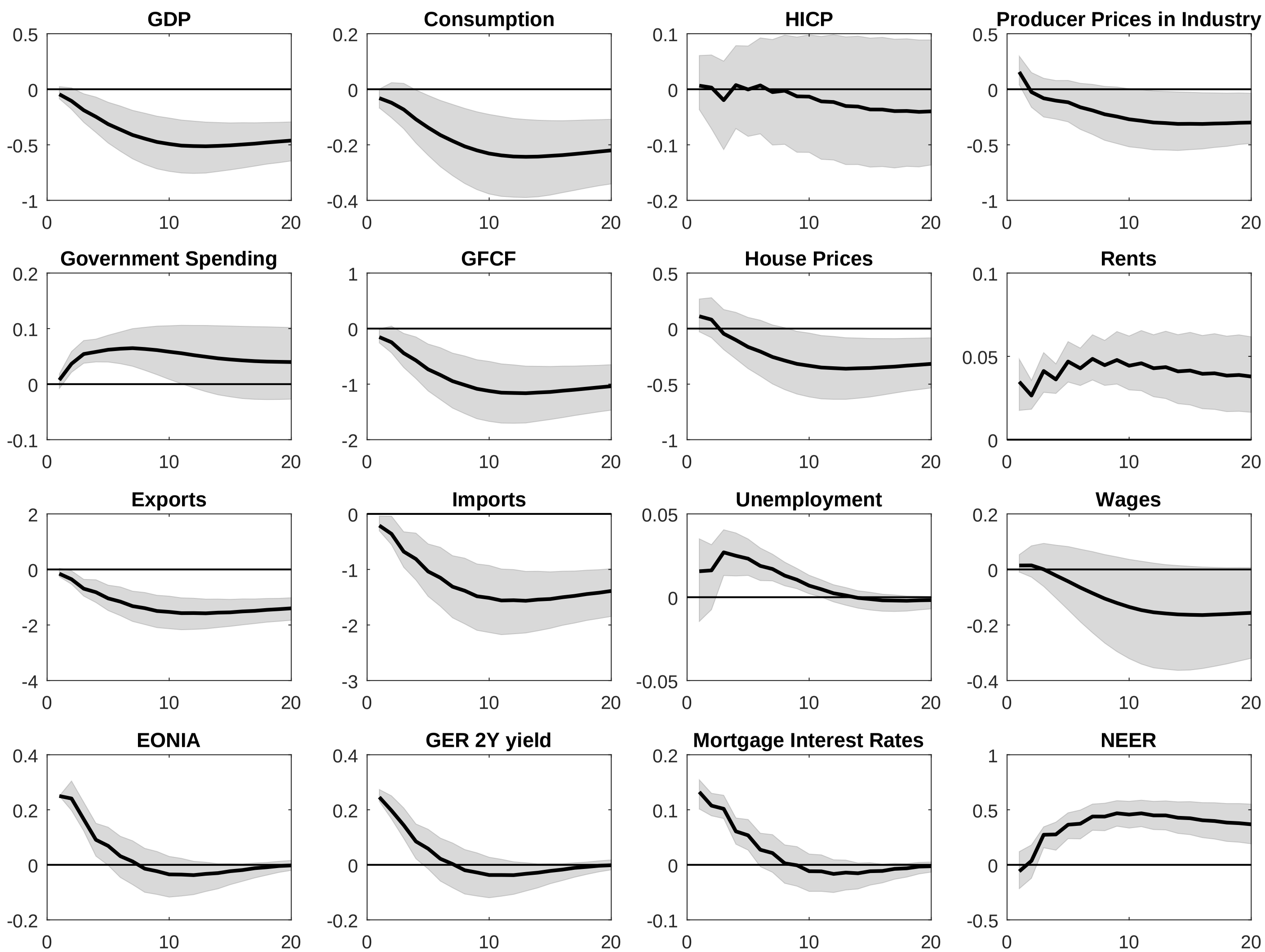

Figure 4: Percentage responses of selected euro-wide variables to a 25bp contractionary policy shock. Note: Confidence intervals are obtained from a wild bootstrap procedure with a simple (Rademacher) distribution.

labour market, unemployment rises, while wages fall. Interestingly, the reaction in wages is not significant, hinting at a large degree of nominal wage stickiness. In the housing market, house prices fall significantly after a contraction, following economic theory that higher policy rates make mortgages more expensive and consequently suppress demand for houses. Rents, on the other hand, increase in reaction to a shock. Recent research (see e.g. Duarte and Dias, 2016) suggests that a worsening of conditions in the mortgage market leads agents to substitute house purchase with renting, thus exerting pressure on rental prices. Motivated by this result, Section 4 will take a closer look at the housing markets in the euro area and explore potential avenues for connecting the results to economic theory.

3.2 Cross-Country Dynamic Effects of Monetary Policy

Moving on to results at the country level, we start to uncover the full potential of the DFM when it comes to providing results for a large number of series. Of the 342 individual country series in our data set, we have selected a representative sub-sample for Figures 5-7. In particular, this section takes a closer look at the responses of GDP, the components of GDP, interest rates, equities, housing prices and housing rents. We point out, however, that the model produces impulse response functions for all series in our sample.

Figure 5 shows responses for real GDP and HICP across the 11 euro area countries in our sample. While we omitted error bands for ease of presentation, it is noteworthy that reactions of GDP across countries are significantly heterogeneous. At one end of the spectrum, the reaction of Irish GDP clearly differs from the five countries with the weakest reaction. That said, even the reactions of Finland and Luxembourg are statistically different from France and Spain, having non-overlapping confidence intervals from the 10th step onward. This heterogeneity is in itself noteworthy, but also raises the question which parts of the economy are particularly prone to asymmetric reactions.

For a first pass at this question, Figure 6 contains the reactions of the components of GDP. A look at the IRFs offers two main conclusions. Firstly, some series, such as private consumption and gross fixed capital formation tend to move in the same direction, or with similar patterns, despite heterogeneity across countries. This compares to series such as government spending and net exports, which in some instances even move in opposite directions. In part, these differences in the general nature of responses can be explained by the determinants of the individual series. Government spending, for example, is notoriously idiosyncratic, varying in degrees of pro- and countercyclicality both across countries as well as within a country over time.

Secondly, we observe that even among series where responses across countries move in

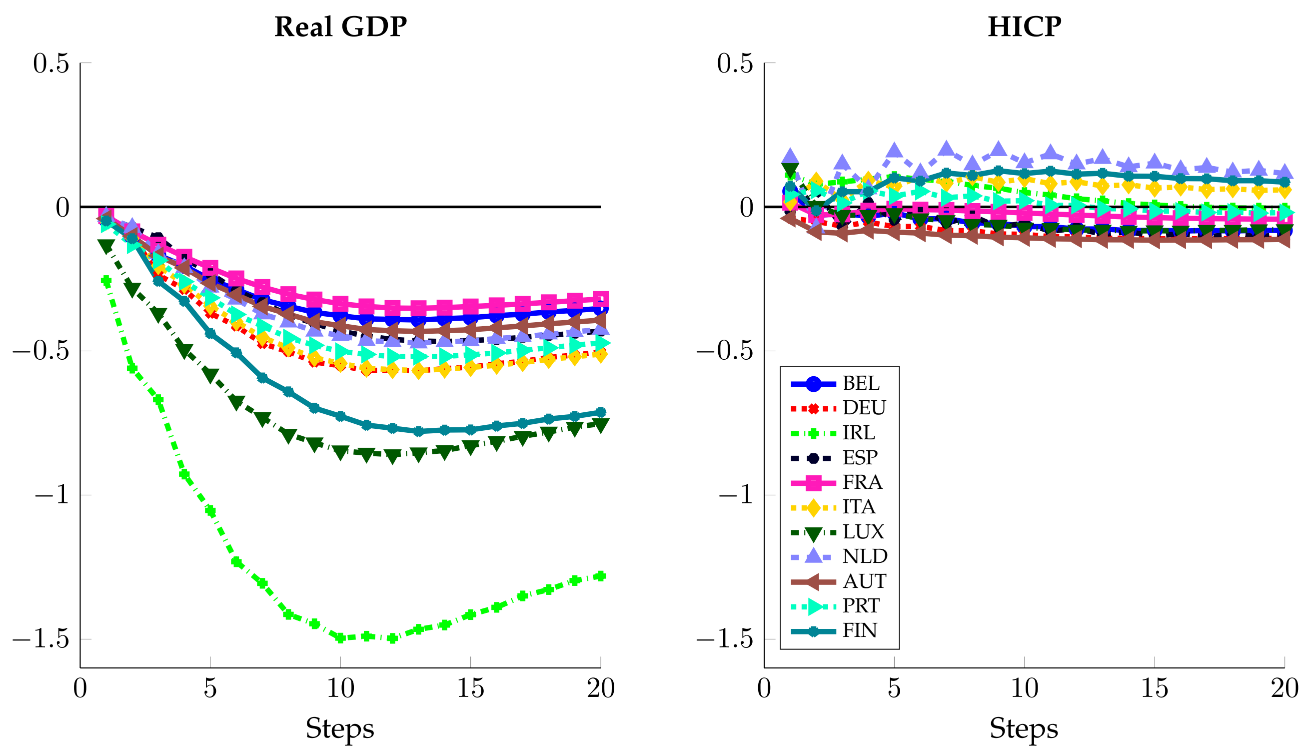

Figure 5: Percentage responses of real GDP to a 25bp contractionary policy shock across euro area member countries.

the same direction, large degrees of heterogeneity exist. In particular, we point out the disparity in reactions of private consumption. While German private consumption drops by a maximum of about 0.02 percentage points, the drop in Ireland is more than 20 times as large at 0.4 percentage points. Aside from Ireland, which could be classified an outlier, countries such as Italy, Finland, Spain and Portugal exhibit drops in consumption that are roughly 10 times the size of the reaction in Germany. One of the core questions we ask in Section 4 is what may be the cause of this degree of heterogeneity.

Taking a closer look at responses of other variables of interest, we find that the degree of heterogeneity in responses seems to be closely (and inversely) related to the state of convergence in a particular market across the euro area. In particular, financial markets have seen a large degree of convergence,[17] which is reflected in the reaction of interest rates and stock prices across countries. Figure 7 shows that while the immediate impact of a policy shock on long-term interest rates is not uniform across countries, their reaction over later periods is almost identical. Similarly, a look at the responses of local equity indices, displayed in the same figure, reveals a strong degree of homogeneity across equity markets.

[17] see e.g. ECB (2017).

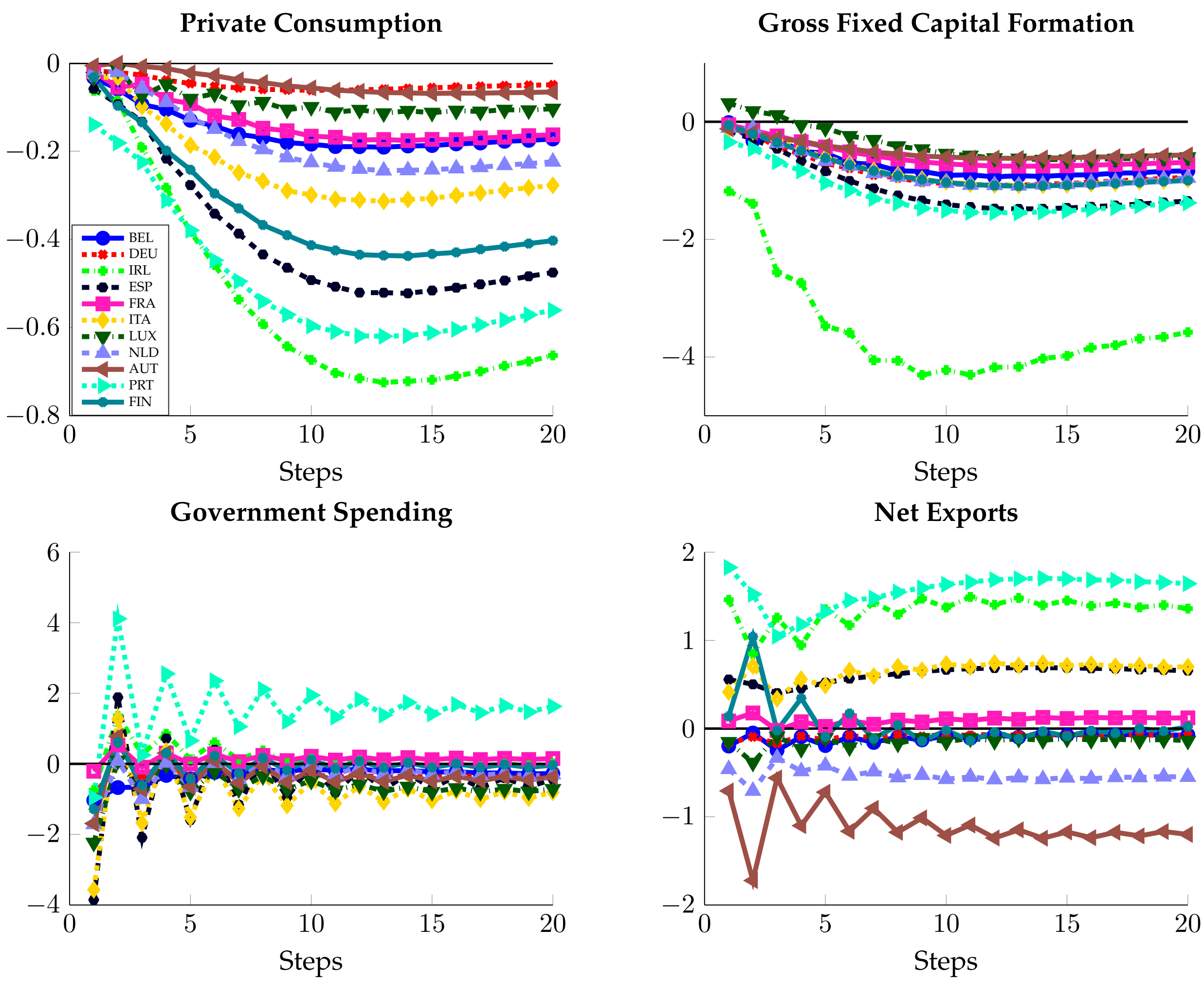

Figure 6: Percentage responses of GDP components to a 25bp contractionary policy shock across euro area member countries.

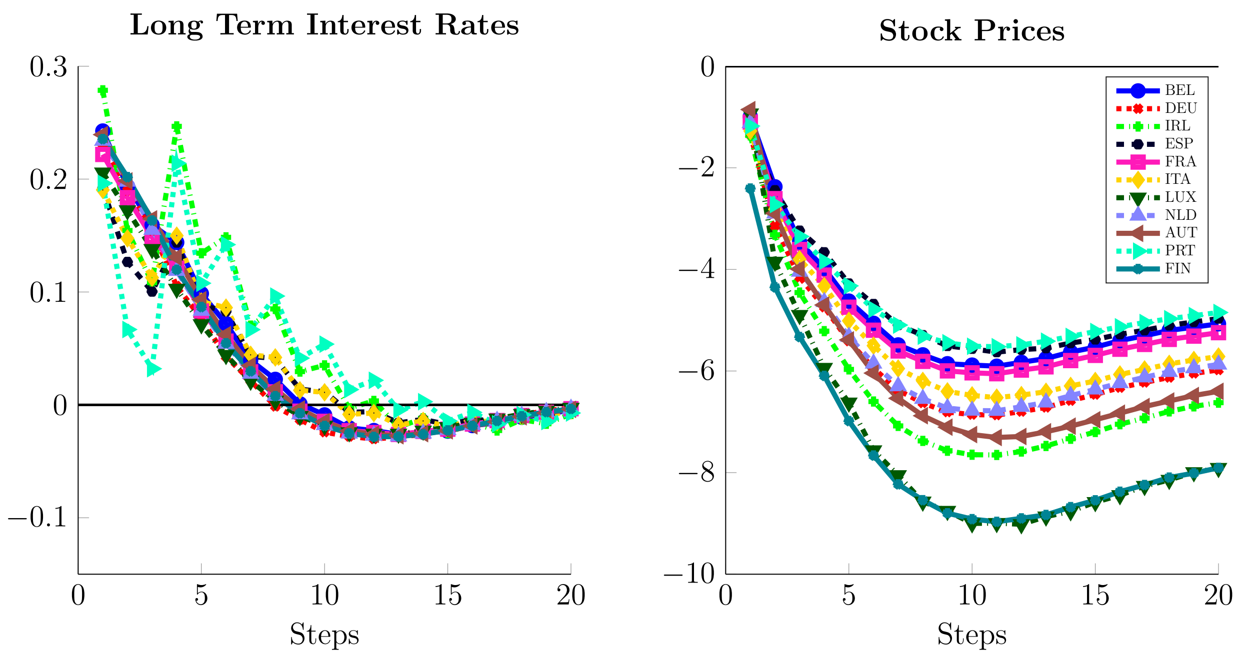

Figure 7: Percentage responses of long-term interest rates and local equity indices to a 25bp contractionary policy shock across euro area member countries. Long-term interest rates are defined in accordance with OECD methodology, conforming to government bonds of (in most cases) 10 year maturity.

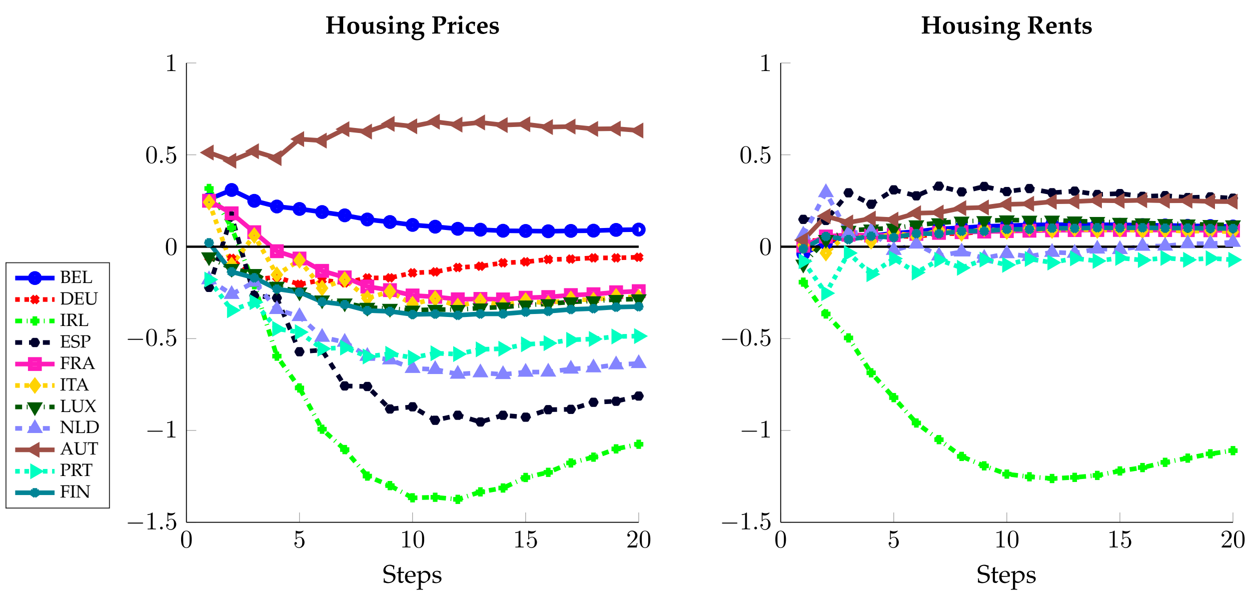

Figure 8: Percentage responses of house prices and rents to a 25bp contractionary monetary policy shock across euro area member countries.

While stock prices show more differentiated responses than long-term interest rates, the confidence intervals around stock price IRFs are mostly overlapping.

Among the markets that have seen only very little or no convergence in institutional characteristics are the labour and housing markets. It is the latter, seen in Figure 8, that we investigate in more detail in Section 4, thus attempting to clarify the role of institutional characteristics in shaping channels of the monetary transmission mechanism.[18]

Table 3: Coefficient of variation of the cross-country responses to a 25bp monetary policy shock.

Variable	Coefficient of Variation	Lower Bound	Upper Bound
On Impact			
GDP	1.45	0.70	4.00
Private Consumption	1.19	1.01	2.52
Unemployment Rates	7.16	2.83	25.02
Housing Prices	2.03	1.51	4.57
Housing Rents	3.81	3.15	6.96
HICP	3.24	0.99	13.25
Long-term Interest Rates	0.21	0.14	0.53
Stock Prices	0.37	0.21	0.65
At the 20th Step			
GDP	0.64	0.47	0.95
Private Consumption	1.02	0.99	1.11
Unemployment Rates	1.24	0.94	4.22
Housing Prices	1.08	0.84	2.02
Housing Rents	2.41	1.13	8.20
HICP	1.25	0.62	4.05
Long-term Interest Rates	0.46	0.17	1.87
Stock Prices	0.21	0.19	0.26

In the following step, we propose a more rigorous approach to test heterogeneity among responses. For each set of responses, we calculate the coefficient of variation, i.e. the standard deviation of responses (among countries) with respect to the EA response of the same

[18]In Appendix F, we present an alternative way of looking at IRFs across countries to better understand the statistical significance of our results. Figures 18 and 19 plot the highest and lowest responses, as well as EA IRFs for various series with their respective confidence intervals. Figure 18 contains these responses for real variables: GDP, private consumption and unemployment. Figure 19 shows responses for price-related series: interest rates, HICP and stock prices. Comparing the two groups, we notice that the highest and lowest responses for none of the real variables are overlapping. In contrast, IRFs are overlapping for most parts of the price-related series, with only stock prices diverging around the 10th step.

variable. To make this measure comparable across different types of series, we normalise it by the size of the EA response. In doing so, we create a numerical measure for the dispersion of impulse responses that allows for intuitive and meaningful comparison between series. Table 3 presents the coefficients of variation for a selection of variables, both on impact, as well as at the 20th step. Moreover, the table lists a lower and upper bound for the coefficients of variation, which we obtain from including the calculation in our bootstrapping procedure. As can be clearly seen, long-term interest rates and stock prices have a much smaller coefficient of variation than the other presented variables. At the 20th step, GDP is also markedly less heterogeneous than other variables such as private consumption.

As some of the intervals around coefficients of variation are overlapping, we also bootstrap pair-wise differences in the coefficient of variation. The results, presented in Table 4, mostly confirm earlier observations. Reactions of long-term interest rates (LTINT) and stock prices (SP) are significantly less dispersed than all other variables. Moreover, at the 20th step, GDP has a significantly lower coefficient of variation than private consumption (PCON), unemployment (U), real house prices (RHPI) and real rents (RREN). A few additional pairwise tests also show significance.

Overall, the findings confirm our earlier statement: The degree of heterogeneity in responses is lower in financial variables, such as interest rates and stock prices, as well as output, while it is larger in consumption, consumer prices and variables related to the labour and housing markets. Importantly, these results open up scope for potentially beneficial policy intervention. Further institutional convergence might increase the efficiency and precision of monetary policy, reducing unintended reactions in countries that would otherwise behave in an idiosyncratic manner. That said, a much deeper understanding of the mechanisms at play is necessary to justify policy intervention in the first place. By means of a case study, the following section takes the first step in the direction of improving our understanding for the example of the housing market.

4 Case-study of Heterogeneous Monetary Policy Transmission in the EA: One Money Market, Many Housing Markets

The recent literature has emphasized how the transmission of monetary policy operates through a "housing transmission channel".[19] A focus on this channel is commonly motivated

[19] Among the various contributions, Iacoviello (2005) and Kaplan et al. (2016) call attention to credit and liquidity constraints, while the role of rents is studied in Duarte and Dias (2016).

Table 4: Bootstrapped pair-wise differences in the coefficient of variation of the cross-country responses to a 25bp monetary policy shock. * marks differences in variation that are significant at the 68% confidence level. The inference is drawn from a bootstrap procedure.

	GDP	HICP	LTINT	SP	PCON	U	RHPI	RREN
On Impact								
GDP	0	-0.99	1.20*	1.06*	0.16	-5.42*	-0.84	-2.15
HICP	0.99	0	3.02*	2.85*	1.69	-3.81	0.66	-0.41
LTINT	-1.20*	-3.02*	0	-0.13	-0.90*	-6.66*	-1.79*	-3.43*
SP	-1.06*	-2.85*	0.13	0	-0.84*	-6.84*	-1.60*	-3.32*
PCON	-0.16	-1.69	0.90*	0.84*	0	-5.20*	-0.75	-2.48*
U	5.42*	3.81	6.66*	6.84*	5.20*	0	5.02	3.46
RHPI	0.84	-0.66	1.79*	1.60*	0.75	-5.02	0	-1.51
RREN	2.15	0.41	3.43*	3.32*	2.48*	-3.46	1.51	0
At the 20th Step								
GDP	0	-0.55	0.21	0.45*	-0.39*	-0.59*	-0.43*	-1.74*
HICP	0.55	0	0.64	1.02*	0.19	-0.18	-0.16	-0.93*
LTINT	-0.21	-0.64	0	0.24	-0.60	-0.99*	-0.62	-1.65*
SP	-0.45*	-1.02*	-0.24	0	-0.80*	-1.04*	-0.85*	-2.17*
PCON	0.39*	-0.19	0.60	0.80*	0	-0.20	0.00	-1.38*
U	0.59*	0.18	0.99	1.04*	0.20	0	0.20	-0.84
RHPI	0.43*	0.16	0.62	0.85*	0.00	-0.20	0	-0.66
RREN	1.74*	0.93*	1.65*	2.17*	1.38*	0.84	0.66	0

by noting that for most households, the single most important item on the asset side of their balance sheet is their home. In the form of the mortgage, it typically corresponds to a household's largest liability. In this section, we employ our dynamic factor model for the euro area to investigate the housing channel in more detail. Concretely, we will make use of the European setting to explore how various details of the housing channel shape the transmission of monetary shocks.

A remarkable feature of European housing markets are their substantial differences in institutional characteristics. Mortgage markets differ markedly in the relative share of fixed versus flexible rate contracts and maximum loan-to-value ratios, rental markets are subject to different regimes and controls, and property taxation is very heterogeneous, to name but a few aspects—see Osborne (2005), Andrews et al. (2011) and Westig and Bertalot (2016) for a comprehensive overview. Indeed, the effect of institutional characteristics on the transmission of monetary policy has previously been explored by Calza et al. (2013), who however focus mostly on housing finance.

Our point of departure is the idea that the transmission of monetary policy should be

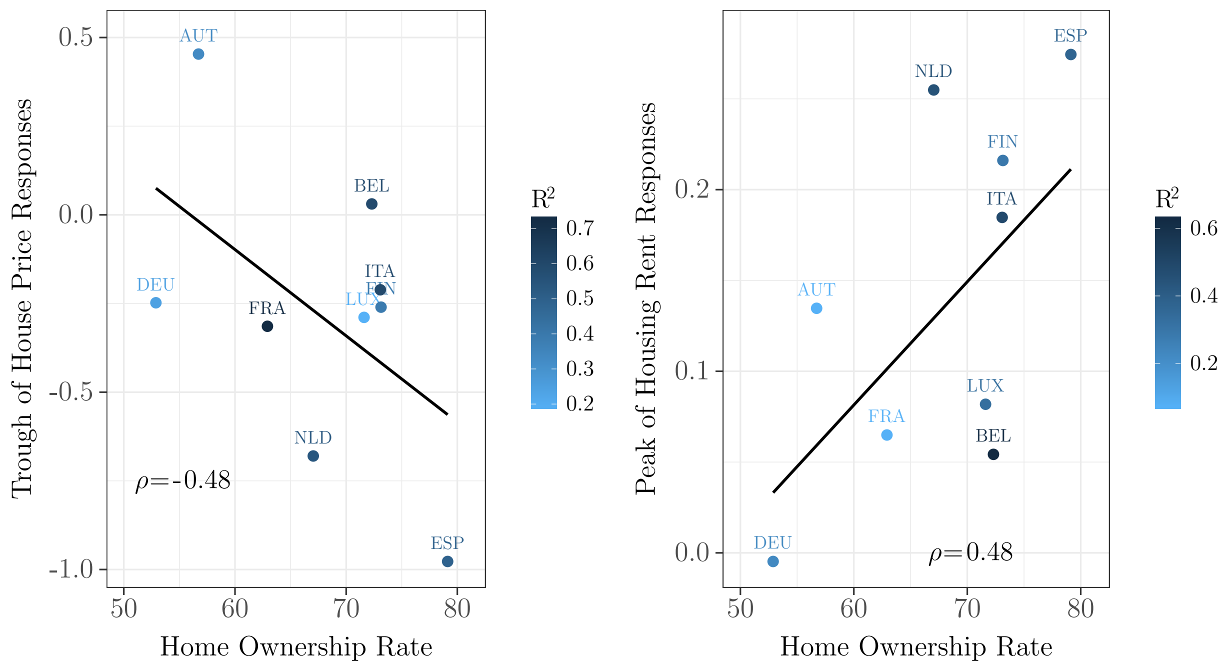

Figure 9: Correlation of house price response troughs and rent response peaks with home ownership rates. Figures exclude Ireland and Portugal.

stronger in an environment where rents and house prices move more in response to a shock. This—as we explain below—may occur where home ownership rates are high.

To bring this idea to the data, we use our dynamic factor model to trace out the transmission of a monetary policy shock through house prices and rents, as well as mortgage rates and cost of finance, with the goal of shedding light on each constituent component of the housing channel.

Figure 8 shows impulse response functions for house prices and rents across the euro area. As anticipated, house prices and rents feature a strong degree of heterogeneity, both in a qualitative as well as quantitative sense. In particular, we note that while the majority of house prices fall in response to a contractionary monetary policy shock, rents in fact *rise* in most countries. This is also reflected in the aggregate responses of euro area house prices and rents as seen in Figure 4. This dichotomy may seem counterintuitive when looking at rents and house prices from an asset pricing perspective: House prices should reflect the discounted sum of expected future rents, leading to parallel movements in both. While an asset pricing approach is helpful in explaining price developments when housing takes on the role of an investment good, it neglects particularities of housing as a consumption good. When an interest rate shock hits the housing market, mortgages become more expensive, which consequently leads to a fall in the demand for houses and hence their price. As

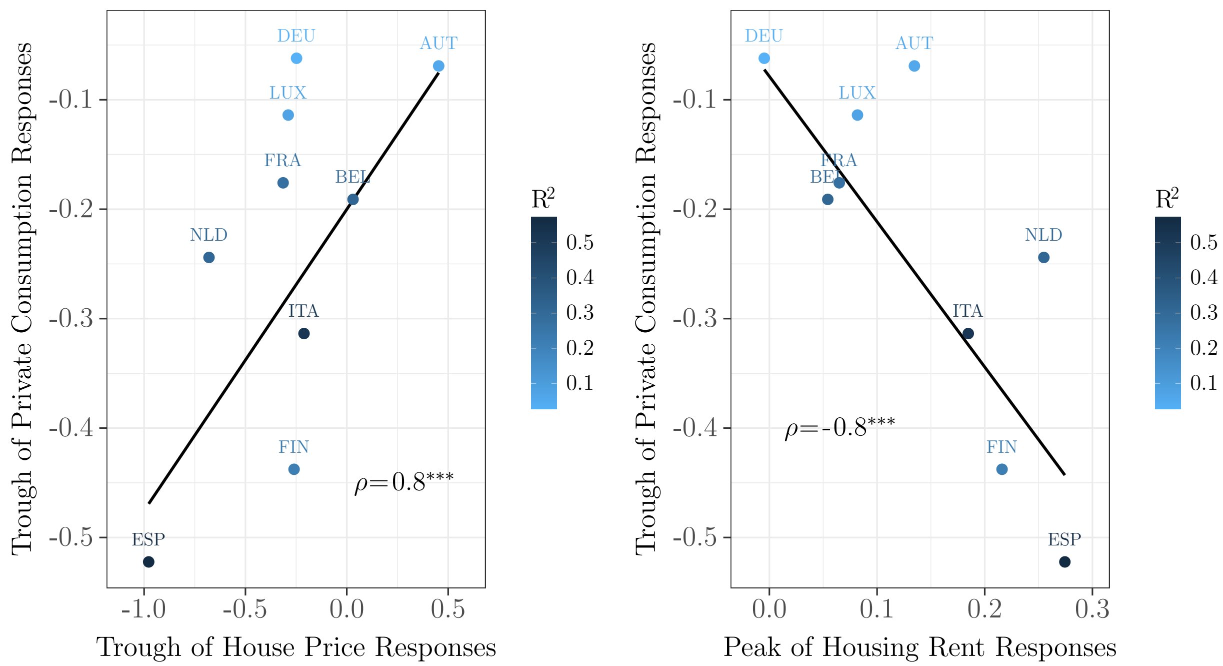

Figure 10: Correlation of house price response troughs and rent response peaks with private consumption response troughs. Figures exclude Ireland and Portugal.

highlighted in the recent literature,[20] when faced with more expensive mortgages, home buyers, at the margin, not only scale down the size of their mortgage (and house), but also substitute buying a house with renting. In doing so, demand for rental properties goes up, leading to an increase in rents. In line with our hypothesis above, the ability of a rental market to absorb the mass of agents that switch from buying to renting may be closely linked to the size of the rental market or, inversely, to the home ownership rate of a country. To get a better understanding of the importance of the home ownership rate in the transmission channel, in Figure 9 we plot the maximum response of each country's house price and rent IRF against the home ownership rate. Seeing that the responses of Ireland and Portugal are highly idiosyncratic, we treat them as outliers at this stage and do not include them in the scatter plots. Note that the correlation of consumption to rents is weakened by the inclusion of Ireland and Portugal, while all other correlations are strengthened by their inclusion.

Before analysing the scatter plots in detail, a note of caution regarding their interpretation is in order. With only 9 data points, our plots are meant to motivate and inform a structured approach to the monetary transmission channel—to be pursued in future research—rather than uncovering statistically significant relationships.

The right panel of Figure 9 plots the peak of rent responses against home ownership

[20] See Duarte and Dias (2016).

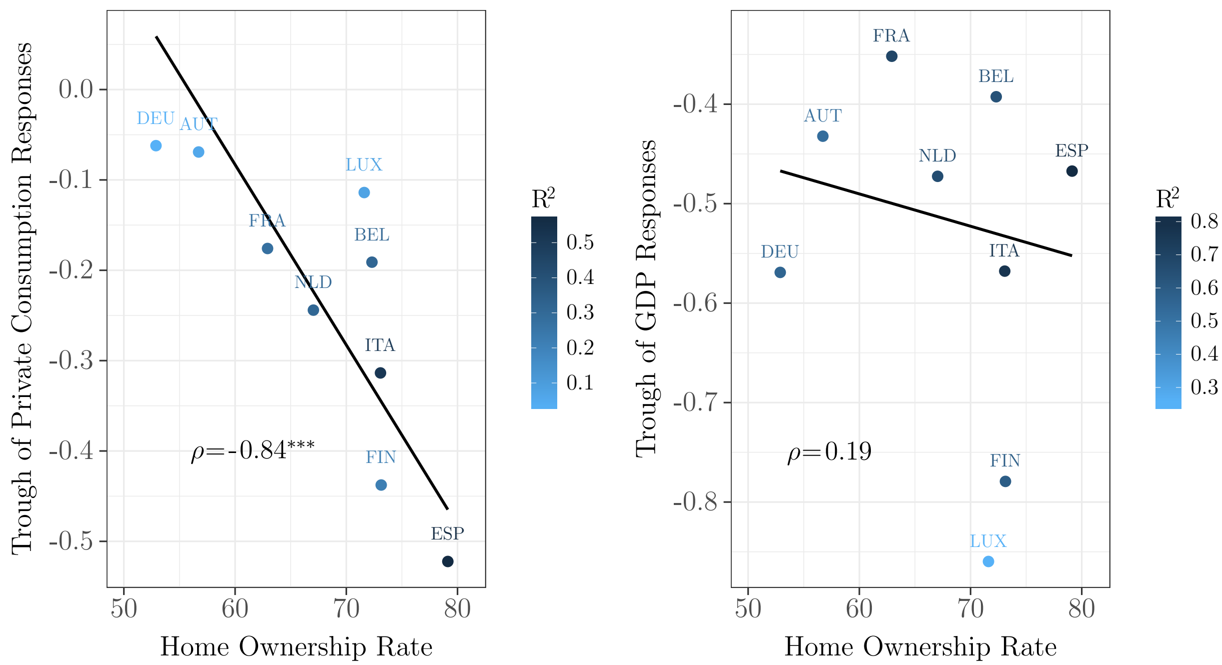

Figure 11: Correlation of private consumption and GDP response troughs with home ownership rates. Figures exclude Ireland and Portugal.

rates. The correlation is positive: The higher the home ownership rate, the larger the increase in rents. As indicated above, this finding is in line with the idea that housing is not only an asset, but also a consumption good. To gain insight on how this matters for monetary policy, observe that, if a shock reduces the demand for housing, so that households switch to renting, the vacancy rate in the housing stock for sale temporarily increases—since conversions between homes for sale and homes for renting are limited. Correspondingly, the pressure on the rental market builds up. Indeed, in countries where the rental market is insufficiently deep, as may be the case when the market is small (i.e., the ownership rate is high), everything else equal, new entrants will exert a greater upward pressure on prices. In the euro area, there are strong cross-border differences in this respect. In Germany, a deep rental market can easily absorb substantial movements at the extensive margin, with agents switching from buying to renting or vice-versa, without experiencing significant variations in rents. At the other extreme, Spain, Finland or Italy, where rental markets are relatively small, reflecting a number of institutional constraints, new entrants can lead to substantial changes in rents.

What remains to be shown is that the rental market actually forms a significant component of the housing channel. To address this issue, we plot the trough (minimum) of house price responses and peak (maximum) of rent responses against the response in private consumption. As can be seen on the two panels, consumption is strongly linked to both changes in house prices as well as changes in rents. The link between house prices and consumption points to a strong wealth effect of monetary policy, stressed by Mian et al. (2013) among others. The larger the drop in house prices, the stronger the direct impact on households' balance sheets, leading to a cut in consumption. Looking at rents, on the other hand, we see a strong negative relationship. Households who pay rent are, on average, less wealthy than households who receive rents, i.e. owners of rental properties. Given a marginal propensity to consume that is decreasing in wealth, this implies that, after an increase in rents, renters as a group cut consumption by a larger amount than landlords increase their consumption, leading to a negative demand shock overall. Moreover, it is plausible that, after a contractionary policy shock (associated with an increase in rents), more renters may become liquidity and credit constrained, causing them to reduce consumption more sharply than implied by any temporary drop in income. In summary, our results suggests that the housing channel should be investigated in its multiple components, including house prices and rents. The importance of these components in turn depends on institutional characteristics, such as the home ownership rate, which is plausibly related to housing finance.

Having traced the effect of the home-ownership rate to consumption through house prices and rents, as a last step we investigate whether we can make out a direct relationship between the home ownership rate and changes in consumption. Figure 10 plots the trough of private consumption responses against home ownership rates. The figure uncovers a surprisingly clear correlation. This result foreshadows large potential benefit from a systematic analysis of institutional characteristics in relation to the monetary transmission mechanism, in particular in a heterogeneous environment such as the EA. At the same time, it lends support to models stressing the housing channel.

5 Conclusion

Using a dynamic factor model with high frequency identification, this paper investigated the heterogeneous effects of monetary policy across the euro area. In doing so, we contribute to the literature by creating an external instrument for monetary policy identification and, by means of a case study on housing, presented a novel way of uncovering heterogeneity in the monetary transmission mechanism. The analysis has produced three main results.

Monetary policy transmission in the euro area appears to be persistently heterogenous across member countries. In this paper, we provided evidence consistent with the idea that the degree of heterogeneity is inversely related to the degree of cross-border institutional convergence. While country-level financial variables and output react fairly similarly to the same monetary policy shock, variables naturally related to markets that have seen little convergence, such as housing and labour markets, react in significantly asymmetric ways.

We elaborate on this point with a case study of European housing markets. We show that differences in the home ownership rate—an indicator reflecting many dimensions in which national housing markets differ from each other—is strongly correlated with the strength of monetary policy transmission across countries. Moreover, we show the importance of looking at the different components of the housing channel, including rents, in addition to house prices. Indeed, our analysis shows that, in most countries, house prices and rents respond to a contractionary policy shock in different directions, yet both contribute to a fall in consumption.

Our results point to a number of promising directions for future research. Firstly, once data availability improves, it would be highly interesting to break down our external instrument and uncover not only shocks to general monetary policy, but also to sub-components, such as monetary policy communications shocks or monetary policy instrument shocks. Secondly, our case study on the housing market is only of exploratory nature. In addition to the home ownership rate, many other institutional characteristics merit a closer look: loan-to-value ratios, aggregate mortgage debt to GDP and ease of credit, to name just a few. Finally, markets other than the housing market, such as the labour market, can and should be examined in a similar fashion.

References

Andrews, D., A. Caldera, and A. Johansson (2011). Housing markets and structural policies in OECD countries. OECD Economics Department Working Papers 836, OECD Publishing.

Angeloni, I., A. Kashyap, and B. Mojon (Eds.) (2003). *Monetary Policy Transmission in the Euro Area: A Study by the Eurosystem Monetary Transmission Network*. Cambridge University Press.

Bagliano, F. C. and C. A. Favero (1999). Information from financial markets and VAR measures of monetary policy. *European Economic Review 43*(4), 825 – 837.

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

Barakchian, S. M. and C. Crowe (2013). Monetary policy matters: Evidence from new shocks data. *Journal of Monetary Economics 60*(8), 950 – 966.

Barigozzi, M., A. M. Conti, and M. Luciani (2014). Do euro area countries respond asymmetrically to the common monetary policy? *Oxford Bulletin of Economics and Statistics 76*(5), 693–714.

Berben, R.-P., A. Locarno, J. Morgan, and J. Valls (2004). Cross-country differences in monetary policy transmission. Working Paper Series 400, European Central Bank.

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

Boivin, J. and M. Giannoni (2007). DSGE models in a data-rich environment. Working papers 162, Banque de France.

Calza, A., T. Monacelli, and L. Stracca (2013). Housing Finance And Monetary Policy. *Journal of the European Economic Association 11*, 101–122.

Campbell, J. R., C. L. Evans, J. D. Fisher, and A. Justiniano (2012). Macroeconomic effects of federal reserve forward guidance. *Brookings Papers on Economic Activity 2012*(1), 1–80.

Ciccarelli, M., A. Maddaloni, and J.-L. Peydró (2013). Heterogeneous transmission mechanism: monetary policy and financial fragility in the eurozone. *Economic Policy 28*(75), 459–512.

Cochrane, J. H. and M. Piazzesi (2002). The Fed and interest rates - a high-frequency identification. *American Economic Review 92*(2), 90–95.

Duarte, J. B. and D. A. Dias (2016). Housing and monetary policy in the business cycle: What do housing rents have to say? *mimeo 11*.

ECB (2017). Financial integration in Europe. Technical report.

Faust, J., E. T. Swanson, and J. H. Wright (2004). Identifying vars based on high frequency futures data. *Journal of Monetary Economics 51*(6), 1107 – 1131.

Forni, M. and L. Gambetti (2010). The dynamic effects of monetary policy: A structural factor model approach. *Journal of Monetary Economics 57*(2), 203 – 216.

Gertler, M. and P. Karadi (2015). Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics 7*(1), 44–76.

Giannone, D., L. Reichlin, and L. Sala (2005). Monetary policy in real time. In *NBER Macroeconomics Annual 2004*, Volume 19, pp. 161–224. MIT Press.

Gurkaynak, R. S., B. Sack, and E. T. Swanson (2005). Do actions speak louder than words? the response of asset prices to monetary policy actions and statements. *International Journal of Central Banking 1*(1), 55–93.

Hamilton, J. D. (2008). Daily monetary policy shocks and new home sales. *Journal of Monetary Economics 55*(7), 1171 – 1190.

Hanson, S. G. and J. C. Stein (2015). Monetary policy and long-term real rates. *Journal of Financial Economics 115*(3), 429 – 448.

Iacoviello, M. (2005). House Prices, Borrowing Constraints, and Monetary Policy in the Business Cycle. *American Economic Review 95*(3), 739–764.

Jarocinski, M. and P. Karadi (2018). Deconstructing monetary policy surprises: the role of information shocks. *ECB Working Paper Series* (2133).

Kaplan, G., B. Moll, and G. L. Violante (2016). Monetary policy according to HANK. *National Bureau of Economic Research*.

Kim, C. H. and L. Other (2017). The short-run effect of monetary policy shocks on credit risk - an analysis of the Euro Area.

Kuttner, K. N. (2001). Monetary policy surprises and interest rates: Evidence from the Fed funds futures market. *Journal of Monetary Economics 47*(3), 523 – 544.

Lloyd, S. (2017a). Estimating nominal interest rate expectations: Overnight indexed swaps and the term structure. Cambridge working papers in economics, University of Cambridge.

Lloyd, S. (2017b). Overnight indexed swap market-based measures of monetary policy expectations. Cambridge working papers in economics, University of Cambridge.

Mertens, K. and M. O. Ravn (2013). The dynamic effects of personal and corporate income tax changes in the United States. *American Economic Review 103*(4), 1212–47.

Mian, A., K. Rao, and A. Sufi (2013). Household balance sheets, consumption, and the economic slump. *Quarterly Journal of Economics 128*(4).

Montiel Olea, J. L., J. Stock, and M. W. Watson (2012). Inference in structural VARs with external instruments.

Nakamura, E. and J. Steinsson (2013). High frequency identification of monetary non-neutrality: The information effect. Working Paper 19260, National Bureau of Economic Research.

Onatski, A. (2009). Testing hypotheses about the number of factors in large factor models. *Econometrica 77*(5), 1447–1479.

Onatski, A. (2010). Determining the number of factors from empirical distribution of eigenvalues. *The Review of Economics and Statistics 92*(4), 1004–1016.

Osborne, J. (2005). Housing in the euro area - twelve markets one money. Quarterly Bulletin 4, Central Bank of Ireland.

Owen, A. B. and J. Wang (2015). Bi-cross-validation for factor analysis. *ArXiv e-prints*.

Romer, C. D. and D. H. Romer (2002). A rehabilitation of monetary policy in the 1950's. *American Economic Review 92*(2), 121–127.

Sargent, T. and C. Sims (1977). Business cycle modeling without pretending to have too much a priori economic theory. Working Papers 55, Federal Reserve Bank of Minneapolis.

Sargent, T. J. (1989). Two models of measurements and the investment accelerator. *Journal of Political Economy 97*(2), 251–287.

Stock, J. H. and M. W. Watson (2005). Implications of dynamic factor models for VAR analysis. Working Paper 11467, National Bureau of Economic Research.

Stock, J. H. and M. W. Watson (2012). Disentangling the channels of the 2007-2009 recession. NBER Working Papers 18094, National Bureau of Economic Research.

Stock, J. H. and M. W. Watson (2016). Dynamic factor models, factor-augmented vector autoregressions, and structural vector autoregressions in macroeconomics. Volume 2 of *Handbook of Macroeconomics*, pp. 415 – 525. Elsevier.

Westig, D. and L. Bertalot (2016). Hypostat 2016: A review of Europe's housing and mortgage markets. Technical report, European Mortgage Federation.

A Selecting the Number of Factors - Additional Figures

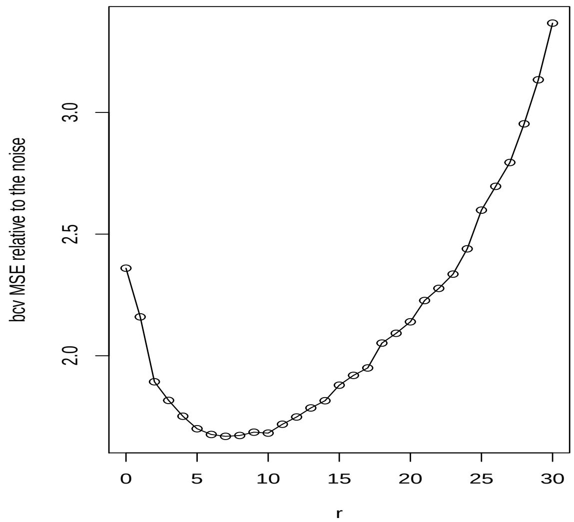

Figure 12: Bi-cross-validation method proposed by Owen and Wang (2015)

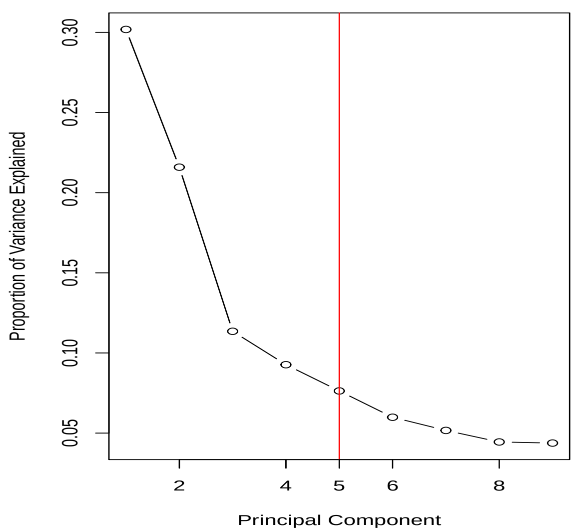

Figure 13: Variance explained by each additional factor

B Small VAR with High-Frequency Identification

In this section we use our instrument to identify monetary policy shocks in a simple VAR with three variables: output, consumer prices and a policy indicator. This simpler setting is useful to test the strength of the external instrument. Estimating a simple VAR for monthly and quarterly data, we test different instruments and policy indicators. The set of instruments to be tested comprises 3-month, 6-month and 12-month EONIA futures. The set of policy indicators is given by EONIA, one-year aggregate EA bond yields, one-year German government bond yields, as well as two-year German government bond yields. We use industrial production (IP) as a measure of output for monthly data, and real GDP for quarterly data. For consumer prices, we use HICP at both frequencies.

The combination of policy indicator and instrument that provides the best instrument strength is the one selected to report the dynamic effects of monetary policy shocks on output and consumer prices. For monthly data, the selected instrument is the 3-month EONIA future and the policy indicator is the two-year German government bond rate, while for the quarterly data the instrument that works best is the one-year EONIA future and the policy indicator is the one-year German government bond rate.

In order to compare our identification strategy for the EA with a more standard identification, we also estimate the impulse-response functions using the Cholesky decomposition with the following ordering: output, consumer prices and policy indicator. The results with monthly data are reported in Figure 14. The more traditional approach to identify monetary policy surprises exhibits both a price puzzle and an output puzzle. Interestingly, when using our external instrument approach, both puzzles disappear. The external instrument delivers responses that are more in line with standard economic theory where output falls temporarily and recovers in the medium-run (neutrality), and prices fall. In this specification, the instrument is weak as its F-test is below 10 which implies the possibility of biased estimates in a small sample such as ours. However, in the case of a just identified IV, it is possible to get approximately unbiased (or less biased) estimates even with weak instruments.

Using quarterly data, we get a significantly stronger instrument with a first-stage F-test of 19.45. Figure 15 shows the same set of variable responses, now using quarterly data. The Cholseky identification does not feature a price puzzle in this setup. There is, however, an output puzzle. With the high-frequency identification, on the other hand, we only get a price puzzle on the contemporaneous response, while there is no output puzzle. The limitations of an identification strategy based on timing restrictions are further highlighted at the quarterly frequency as it is hard to argue that consumer prices (collected on a monthly basis) do not react in the same quarter to monetary policy surprises. If we want to allow

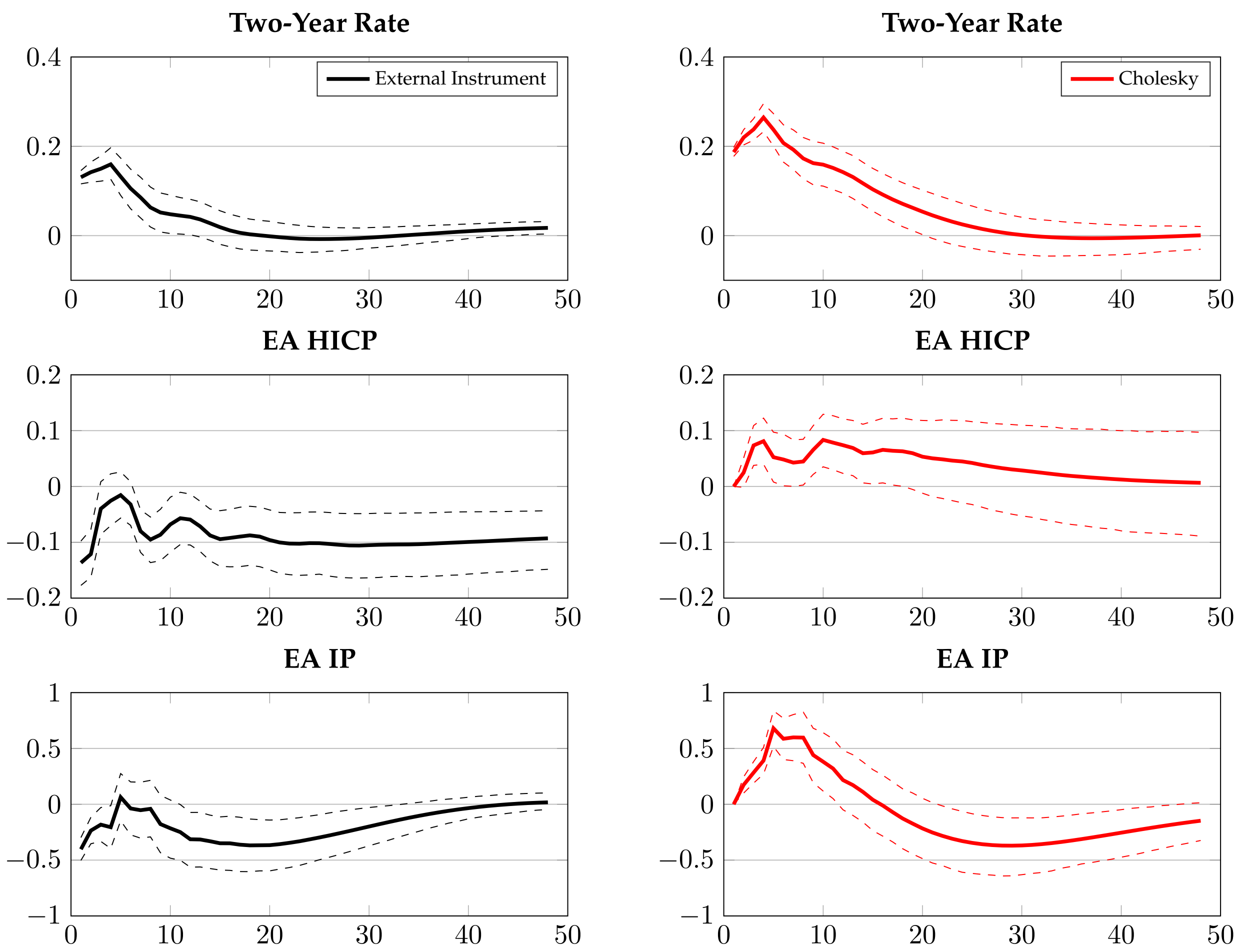

Figure 14: VAR using monthly data from 2000 to 2016. Here we show the responses to a one standard deviation shock in the policy indicator, comparing the high-frequency identification with a Cholesky identification strategy. The dashed lines report the bootstrapped 68% confidence intervals. The Cholesky identification orders the policy indicator last. The F-test for the first-stage regression on the external instrument is 4.85 and the R^2 is 2 percent.

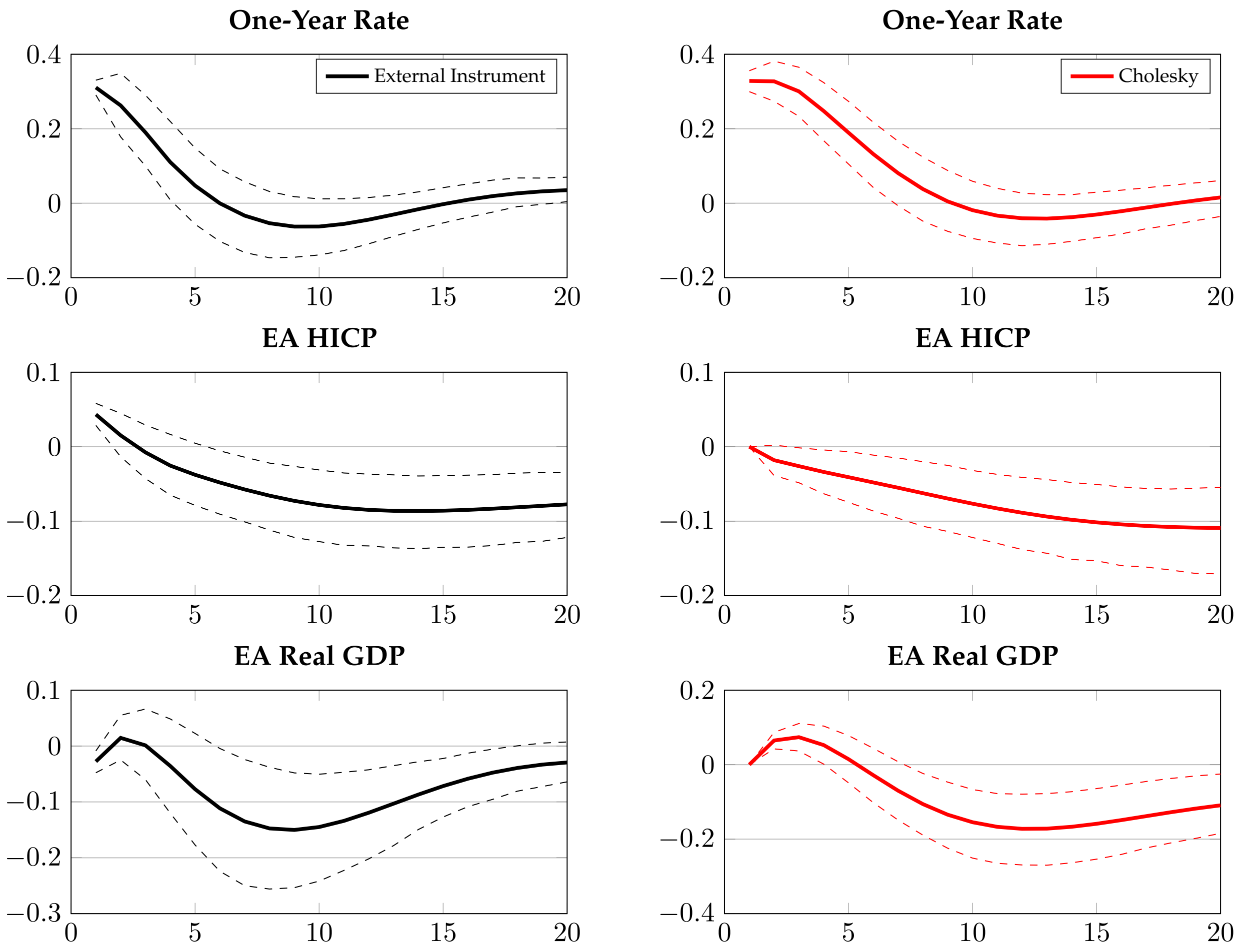

Figure 15: VAR using quarterly data from 2000 to 2016. Here we show the responses to a one standard deviation shock in the policy indicator using the high-frequency identification and the Cholesky identification. The dashed lines report the bootstrapped 68% confidence intervals. The Cholesky identification orders the policy indicator last. The F-test for the first-stage regression on the external instrument is 19.45 and the R^2 is 22 percent.

prices to respond contemporaneously, we can order consumer prices last (instead of the monetary policy indicator). However, in this case we also get the undesirable restriction of not letting monetary policy react to consumer prices contemporaneously. The external instrument is able circumvent this limitation.

Figure 16 shows the responses when we order the consumer prices last in the Cholesky decomposition. In this case, consumer prices are allowed to react contemporaneously to monetary policy shocks. When the consumer price response is not contemporaneously restricted to zero, we find that the price puzzle is present and, contrary to the high-frequency identification, it lasts for a few quarters after the shock hits the economy.

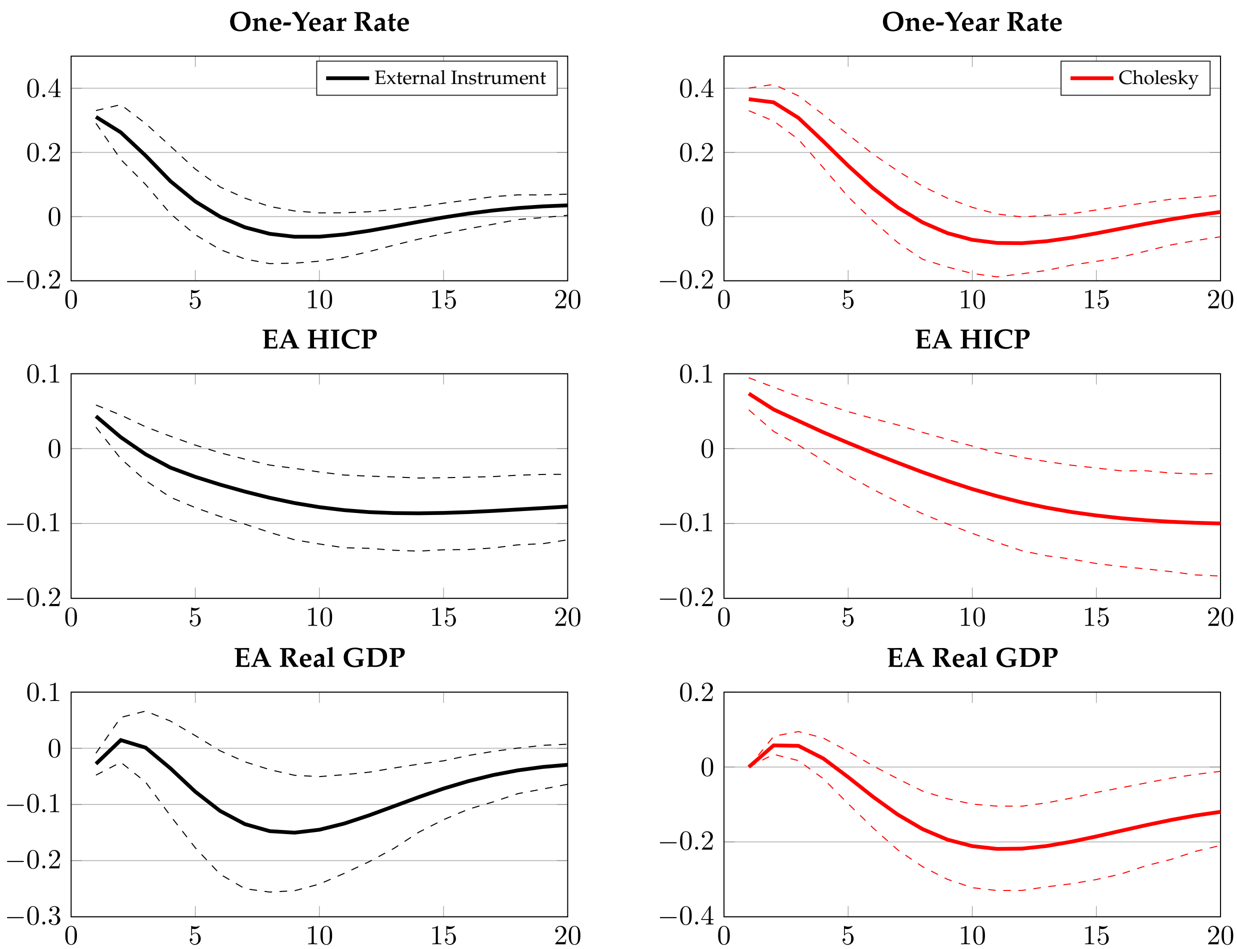

Figure 16: VAR using quarterly data from 2000 to 2016. Here we show the responses to a one standard deviation shock in the policy indicator using high-frequency and Cholesky identification. The dashed lines report the bootstrapped 68% confidence intervals. Here, the Cholesky identification orders the consumer prices last. The F-test for the first-stage regression on the external instrument is 19.45 and the R^2 is 22 percent.

C Data Set

Table 5 contains a complete list of the series in our data set as well as detailed descriptions and information regarding transformations, geographical coverage and sources. Abbreviations and codes are laid out in the following:

Transformation code (T)

1 - no transformation

2 - difference in levels

4 - logs

5 - difference in logs

Geography

EA - Euro area

EA12 - Euro area (12 countries)

EA19 - Euro area (19 countries)

EACC - Euro area (changing composition)

EA11_i - 11 individual series for sample countries

Factor analysis (F)

Y - included in data set for principal component analysis

Seasonal adjustment

WDSA - working day and seasonally adjusted

SA - seasonally adjusted

NA - neither working day nor seasonally adjusted

Note: National house price indices have different start dates across countries. They begin in 2005 Q4 for Spain, 2006 Q2 for France, 2007 Q1 for Luxembourg, 2008 Q1 for Portugal, 2010 Q1 for Italy and Austria, and 2005 Q1 for all other countries. Furthermore, unemployment data for France between 2000 Q1 and 2005 Q1, as well as Luxembourg between 2000 Q1 and 2003 Q1 is only available annually and has been linearly interpolated to create a quarterly data series. Thereafter all unemployment data is quarterly. Finally, import and export data for Germany, Spain and Italy is only available from 2012 Q1 onward.

	Description	T	Source	Geography	Start	End	F
GDP & Personal Income							
GDP	Gross Domestic Product at market prices, Chain linked volumes, 2010=100, WDSA	5	Eurostat	EA12	2000 Q1	2016 Q4	
PCON	Household and NPISH final consumption expenditure, Chain linked volumes, 2010=100, WDSA	5	Eurostat	EA12	2000 Q1	2016 Q4	
G	Final consumption expenditure of general government, Chain linked volumes, 2010=100, WDSA	5	Eurostat	EA12	2000 Q1	2016 Q4	
GFCF	Gross fixed capital formation, Chain linked volumes, 2010=100, WDSA	5	Eurostat	EA12	2000 Q1	2016 Q4	
EX	Exports of goods and services, Chain linked volumes, 2010=100, WDSA	5	Eurostat	EA12	2000 Q1	2016 Q4	
IM	Imports of goods and services, Chain linked volumes, 2010=100, WDSA	5	Eurostat	EA12	2000 Q1	2016 Q4	
GDP_i	Gross Domestic Product at market prices, Chain linked volumes, 2010=100, WDSA	5	Eurostat	EA11_i	2000 Q1	2016 Q4	
CON_i	Final consumption expenditure, Chain linked volumes, 2010=100, WDSA	5	Eurostat	EA11_i	2000 Q1	2016 Q4	
PCON_i	Household and NPISH final consumption expenditure, Chain linked volumes, 2010=100, WDSA	5	Eurostat	EA11_i	2000 Q1	2016 Q4	Y
G_i	Final consumption expenditure of general government, Chain linked volumes, 2010=100, WDSA	5	Eurostat	EA11_i	2000 Q1	2016 Q4	Y
GFCF_i	Gross fixed capital formation, Chain linked volumes (2010), million euro, WDSA	5	Eurostat	EA11_i	2000 Q1	2016 Q4	Y
EX_i	Exports of goods and services, Chain linked volumes, 2010=100, unadjusted data	5	Eurostat	EA11_i	2000 Q1	2016 Q4	Y
IM_i	Imports of goods and services, Chain linked volumes, 2010=100, unadjusted data	5	Eurostat	EA11_i	2000 Q1	2016 Q4	Y
Prices/Deflators							
GDPDEF	Gross domestic product at market prices, Price index (implicit deflator), 2010=100, euro, WDSA	5	Eurostat	EA12	2000 Q1	2016 Q4	
PCONDEF	Household and NPISH final consumption expenditure, Price index (implicit deflator), 2010=100, euro, WDSA	5	Eurostat	EA12	2000 Q1	2016 Q4	
GDEF	Final consumption expenditure of general government, Price index (implicit deflator), 2010=100, euro, WDSA	5	Eurostat	EA12	2000 Q1	2016 Q4	
GFCFDEF	Gross fixed capital formation, Price index (implicit deflator), 2010=100, euro, WDSA	5	Eurostat	EA12	2000 Q1	2016 Q4	
EXDEF	Exports of goods and services, Price index (implicit deflator), 2010=100, euro, WDSA	5	Eurostat	EA12	2000 Q1	2016 Q4	Y
IMDEF	Imports of goods and services, Price index (implicit deflator), 2010=100, euro, WDSA	5	Eurostat	EA12	2000 Q1	2016 Q4	Y
PPI	Producer prices in industry, domestic market, index 2010=100, unadjusted data	5	Eurostat	EA19	2000 Q1	2016 Q4	
HICP00	All-items HICP, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2016 Q4	
HICP01	HICP Food and non-alcoholic beverages, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2016 Q4	
HICP02	HICP Alcoholic beverages, tobacco and narcotics, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2016 Q4	
HICP03	HICP Clothing and footwear, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2016 Q4	
HICP05	HICP Furnishings, household equipment and routine household maintenance, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2016 Q4	
HICP06	HICP Health, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2016 Q4	
HICP07	HICP Transport, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2016 Q4	
HICP08	HICP Communications, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2016 Q4	
HICP09	HICP Recreation and culture, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2016 Q4	
HICP10	HICP Education, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2016 Q4	
HICP11	HICP Restaurants and hotels, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2016 Q4	
HICP12	HICP Miscellaneous goods and services, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2016 Q4	

HICPXFD	Overall HICP index excluding seasonal food, Index, 2015=100	5	Eurostat	EACC	2000 Q4	2016 Q4	
HICPXUTIL	Overall HICP index excluding housing, water, electricity, gas and other fuels, 2015=100	5	Eurostat	EACC	2000 Q1	2016 Q4	
HICPXHTH	Overall HICP index excluding education, health and social protection, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2016 Q4	
HICPUTIL	HICP Housing, water electricity, gas and other fuels, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2016 Q4	
PPIING	Producer Price Index, MIG - intermediate goods, unadjusted data, 2010=100	5	Eurostat	EA19	2000 Q1	2016 Q4	
PPICAG	Producer Price Index, MIG - capital goods, unadjusted data, 2010=100	5	Eurostat	EA19	2000 Q1	2016 Q4	
PPINDCOG	Producer Price Index, non-durable consumer goods, unadjusted data, 2010=100	5	Eurostat	EA19	2000 Q1	2016 Q4	
PPIM	Producer Price Index, Manufacturing, unadjusted data, 2010=100	5	Eurostat	EA19	2000 Q1	2016 Q4	
HICP_i	Individual country HICP	5	Eurostat	EA11_i	2000 Q1	2016 Q4	Y
UTIL_i	HICP Housing, water electricity, gas and other fuels, Index, 2015=100	5	Eurostat	EA11_i	2000 Q1	2016 Q4	
PPI_i	Producer prices in industry (except construction sewerage, waste management and remediation activities), Domestic output price index in national currency, 2010=100	5	Eurostat	EA11_i	2000 Q1	2016 Q4	Y
CDEF_i	Final consumption expenditure, Price index (implicit deflator), 2010=100, euro, WDSA	5	Eurostat	EA11_i	2000 Q1	2016 Q4	Y
PCONDEF_i	Household and NPISH final consumption expenditure, Price index (implicit deflator), 2010=100, euro, WDSA	5	Eurostat	EA11_i	2000 Q1	2016 Q4	
GFCFDEF_i	Gross fixed capital formation, Price index (implicit deflator), 2010=100, euro, WDSA	5	Eurostat	EA11_i	2000 Q1	2016 Q4	Y
CPIIMF	IMF World Commodity Price Index, USD denominated, weights based on 2002-2004 average world export earnings, non-fuel primary commodities and energy, 2005=100	5	IMF	World	2000 Q1	2016 Q4	
CPIECB	ECB Commodity Price Index, Euro denominated, use-weighted, Total non-energy commodity, unadjusted data, 2010=100	5	ECB SDW	EA19	2000 Q1	2016 Q4	Y
OIL	Brent crude oil 1-month forward, fob (free on board) per barrel, Euro	5	ECB SDW	EACC	2000 Q1	2016 Q4	Y
Industrial Production							
IPIT	Industrial Production Index, Total Industry, WDSA, 2005=100	5	ECB SDW	EA19	2000 Q1	2016 Q4	
IPIING	Industrial Production Index, MIG - intermediated goods, WDSA, 2010=100	5	Eurostat	EA19	2000 Q1	2016 Q4	
IPINRG	Industrial Production Index, MIG - energy, WDSA, 2010=100	5	Eurostat	EA19	2000 Q1	2016 Q4	Y
IPICAG	Industrial Production Index, MIG - capital goods, WDSA, 2010=100	5	Eurostat	EA19	2000 Q1	2016 Q4	Y
IPICOG	Industrial Production Index, MIG - consumer goods, WDSA, 2010=100	5	Eurostat	EA19	2000 Q1	2016 Q4	
IPIDCOG	Industrial Production Index, MIG - durable consumer goods, WDSA, 2010=100	5	Eurostat	EA19	2000 Q1	2016 Q4	Y
IPINDCOG	Industrial Production Index, MIG - non-durable consumer goods, WDSA, 2010=100	5	Eurostat	EA19	2000 Q1	2016 Q4	Y
IPIMQ	Industrial Production Index, Mining and quarrying, WDSA, 2010=100	5	Eurostat	EA19	2000 Q1	2016 Q4	
IPIM	Industrial Production Index, Manufacturing, WDSA, 2010=100	5	Eurostat	EA19	2000 Q1	2016 Q4	
ITIING	Industrial Turnover Index, MIG Intermediate Goods (2010=100, WDSA)	5	Eurostat	EA19	2000 Q1	2016 Q4	
ITINRG	Industrial Turnover Index, MIG Energy (2010=100, WDSA)	5	Eurostat	EA19	2000 Q1	2016 Q4	Y
ITICAG	Industrial Turnover Index, MIG Capital Goods (2010=100, WDSA)	5	Eurostat	EA19	2000 Q1	2016 Q4	Y
ITICOG	Industrial Turnover Index, MIG Consumer Goods (2010=100, WDSA)	5	Eurostat	EA19	2000 Q1	2016 Q4	
ITIDCOG	Industrial Turnover Index, MIG Durable Consumer Goods (2010=100, WDSA)	5	Eurostat	EA19	2000 Q1	2016 Q4	Y
ITINDCOG	Industrial Turnover Index, MIG Non-Durable Consumer Goods (2010=100, WDSA)	5	Eurostat	EA19	2000 Q1	2016 Q4	Y
CAPUTIL	Current level of capacity utilization, percent	1	Eurostat	EA19	2000 Q1	2016 Q4	Y
ITIM	Industrial Turnover Index, Manufacturing, 2010=100, SWDA	5	Eurostat	EA19	2000 Q1	2016 Q4	

Employment and Unemployment							
WIN	Compensation of employees, Current prices, million euro, WDSA	5	Eurostat	EA12	2000 Q1	2016 Q4	Y
U	Total Unemployment rate (quarterly average), WDSA	2	Eurostat	EACC	2000 Q1	2016 Q4	
EMP	Total employment	5	Eurostat	EA19	2000 Q1	2016 Q4	Y
U_i	Unemployment rate, total from age 15 to 74, percentage	2	Eurostat	EA11_i	2000 Q1	2016 Q4	Y
LABCON	Labour Input in Construction, Index of Hours Worked, 2010=100, WDSA	5	Eurostat	EA19	2000 Q1	2016 Q4	Y
Housing Starts							
BUILD	Building Permits, Residential Buildings, Index, 2010=100, WDSA	5	Eurostat	EA19	2000 Q1	2016 Q4	Y
GFCFC	Gross fixed capital formation: Total construction (gross), chain linked volumes, Index, 2010=100	5	Eurostat	EACC	2000 Q1	2016 Q4	
GFCFC_i	Gross fixed capital formation: Total construction (gross), chain linked volumes, Index, 2010=100	5	Eurostat	11 ex BEL	2000 Q1	2016 Q4	
GFCFD	Gross fixed capital formation: Dwellings (gross), chain linked volumes, Index, 2010=100	5	Eurostat	EACC	2000 Q1	2016 Q4	
GFCFD_i	Gross fixed capital formation: Dwellings (gross), chain linked volumes, Index, 2010=100	5	Eurostat	11 ex BEL	2000 Q1	2016 Q4	
PROCO	Production in Construction, Volume Index, 2010=100, WDSA	5	Eurostat	EA19	2000 Q1	2016 Q4	Y
Inventories, Orders and Sales							
ORDING	Industrial New Orders, MIG Intermediate Goods, 2010=100, SA	5	ECB SDW	EA19	2000 Q1	2016 Q4	
ORDCAG	Industrial New Orders, MIG Capital Goods, 2010=100, SA	5	ECB SDW	EA19	2000 Q1	2016 Q4	Y
ORDCOG	Industrial New Orders, MIG Consumer Goods, 2010=100, SA	5	ECB SDW	EA19	2000 Q1	2016 Q4	Y
ORDM	Industrial New Orders, Manufacturing, 2010=100, SA	5	ECB SDW	EA19	2000 Q1	2016 Q4	
Earnings and Productivity							
PRD_i	Real labour productivity per hour worked, 2010=100, unadjusted data	5	Eurostat	EA11_i	2000 Q1	2016 Q4	Y
ULC_i	Nominal unit labour cost based on hours worked, 2010=100, unadjusted data	5	Eurostat	11 ex BEL	2000 Q1	2016 Q4	
Money and Credit							
EUSWE1	1 year EONIA swap	1	Bloomberg	EA	2000 Q1	2016 Q4	
STINT	3-month money market interest rate	1	Eurostat	EACC	2000 Q1	2016 Q4	
LTINT	EMU convergence criterion long-term bond yields	1	Eurostat	EACC	2000 Q1	2016 Q4	
MIR	Bank interest rates - loans to households for house purchase (outstanding amount business coverage), average of observations through period, percent per annum	1	ECB SDW	EACC	2003 Q1	2016 Q4	
COB	Cost of borrowing for households for house purchase (new business coverage), average of observations through period, percent per annum	1	ECB SDW	EACC	2003 Q1	2016 Q4	
EURIBOR3MD	3-Month Euro Interbank Offered Rate (%, NSA)	1	ECB SDW	EA	2000 Q1	2016 Q4	
EURIBOR6MD	6-Month Euro Interbank Offered Rate (%, NSA)	1	ECB SDW	EA	2000 Q1	2016 Q4	
EURIBOR1YD	1-Year Euro Interbank Offered Rate (%, NSA)	1	ECB SDW	EA	2000 Q1	2016 Q4	
YLD_3Y	3-Year Euro Area Government Benchmark Bond Yield (%, NSA)	1	ECB SDW	EA	2004 Q4	2016 Q4	
YLD_5Y	5-Year Euro Area Government Benchmark Bond Yield (%, NSA)	1	ECB SDW	EA	2004 Q4	2016 Q4	
YLD_10Y	10-Year Euro Area Government Benchmark Bond Yield (%, NSA)	1	ECB SDW	EA	2004 Q4	2016 Q4	
EONIA	Euro Overnight Index Average (%, NSA)	1	ECB SDW	EA	2000 Q1	2016 Q4	Y
REFI	ECB Official Refinancing Operation Rate (effective, %, NSA)	1	ECB SDW	EA	2000 Q1	2016 Q4	
S3MDREFI	Spread EURIBOR3MD - REFI	1	ECB SDW	EA	2000 Q1	2016 Q4	
S10YYLDREFI	Spread YLD_10Y - REFI	1	ECB SDW	EA	2004 Q4	2016 Q4	

LTINT_i	Long-term interest rates, percent per annum	1	OECD	EA11_i	2000 Q1	2016 Q4	Y
STINT_i	Short-term interest rates, percent per annum	1	OECD	EA11_i	2000 Q1	2016 Q4	Y
MIR_i	Bank interest rates - loans to households for house purchase (outstanding amount business coverage), average of observations through period, percent per annum	1	ECB SDW	EA11_i	2003 Q1	2016 Q4	
COB_i	Cost of borrowing for households for house purchase (new business coverage), average of observations through period, percent per annum	1	ECB SDW	EA11_i	2003 Q1	2016 Q4	
Stock Prices, Wealth, Household Balance Sheets							
SP	Share prices, Index, 2010=100	5	OECD	EA19	2000 Q1	2016 Q4	
SP_i	Share prices, Index, 2010=100	5	OECD	EA11_i	2000 Q1	2016 Q4	Y
OWN_i	Distribution of population by tenure status: ownership, percentage	5	Eurostat	EA11_i	2003 Q1	2016 Q4	
Housing Prices							
RENTS	HICP Actual rentals for housing, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2016 Q4	
HPI	House price index, 2010=100	5	Eurostat	EACC	2005 Q1	2016 Q4	
RHPI	Real house prices (=HPI/HICP00)	5	Eurostat	EACC	2005 Q1	2016 Q4	
RRENTS	Real rents (=RENTS/HICP00)	5	Eurostat	EACC	2000 Q1	2016 Q4	
BUILDCOSTI	Construction Cost Index, Residential Buildings (2010=100, WDSA)	5	Eurostat	EA19	2000 Q1	2016 Q4	
REN_i	HICP Actual rentals for housing, Index, 2015=100	5	Eurostat	EA11_i	2000 Q1	2016 Q4	
RREN_i	Real rents (=REN/HICP00)	5	Author's calculation	EA11_i	2000 Q1	2016 Q4	
HPI_i	House price index, 2010=100	5	Eurostat	EA11_i	2005 Q1	2016 Q4	
RHPI_i	Real house prices (=HPI/HICP00)	5	Author's calculation	EA11_i	2005 Q1	2016 Q4	
NDW_i	House price index, New dwellings, 2010=100	5	Eurostat	11 ex NLD	2005 Q1	2016 Q4	
EDW_i	House price index, Existing dwellings, 2010=100	5	Eurostat	EA11_i	2005 Q1	2016 Q4	
Exchange Rates							
NEER	Euro Nominal Effective Exchange Rate - 42 trading partners, Index, 2005=100	5	Eurostat	EA19	2000 Q1	2016 Q4	Y
EXRUK	Foreign Exchange Rate: United Kingdom (GBP per EUR - quarterly average)	5	Eurostat	EA	2000 Q1	2016 Q4	Y
EXRSW	Foreign Exchange Rate: Switzerland (CHF per EUR - quarterly average)	5	Eurostat	EA	2000 Q1	2016 Q4	Y
EXRJP	Foreign Exchange Rate: Japan (JPY per EUR - quarterly average)	5	Eurostat	EA	2000 Q1	2016 Q4	Y
EXRUS	Foreign Exchange Rate: United States of America (USD per EUR - quarterly average)	5	Eurostat	EA	2000 Q1	2016 Q4	Y
Expectations							
BSBCI	EA Business Climate Indicator (SA)	2	Eurostat	EA19	2000 Q1	2016 Q4	
BSCCI	Construction Confidence Indicator (SA)	2	Eurostat	EA19	2000 Q1	2016 Q4	
BSESI	Economic Sentiment Indicator (SA)	2	Eurostat	EA19	2000 Q1	2016 Q4	
BSICI	Industrial Confidence Indicator (SA)	2	Eurostat	EA19	2000 Q1	2016 Q4	
BSRCI	Retail Confidence Indicator (SA)	2	Eurostat	EA19	2000 Q1	2016 Q4	
BSCSMCI	Consumer Confidence Indicator (SA)	2	Eurostat	EA19	2000 Q1	2016 Q4	Y
BSSCI	Services Confidence Indicator (SA)	2	Eurostat	EA19	2000 Q1	2016 Q4	

D On Interpreting Factors

For Table 6, we regress each transformed data series on one of the 5 factors at a time and subsequently report the series where these regression resulted in the highest R^2. While by nature principal component analysis does not identify factors economically, the table gives a rough indication of the information represented by them. On this basis, we suggest the following tentative interpretation:

Factor 1 is likely to represent prices in the economy. It shows a high correlation with a variety of price indices, from producer prices to HICP, and explains over half of the variance in these series. Factor 2 is very closely related to measures of interest rates. This includes money-market rates, as well as borrowing rates for house purchase. Factors 3 and 4 appear to contain a substantial amount of information about labour markets, with high correlations to unit labour cost and unemployment rates. That said, the factors are also closely related to other variables and an interpretation seem much more contentious than for factors 1 and 2. Factor 5 picks up information from various areas of macroeconomic activity and we do not believe that a straightforward interpretation of the factor is possible.

On the whole, we can emphasise that factors 1 and 2 seem to represent the economic concepts of *prices* and *interest rates*. More generally, the latter could also be interpreted as representing *financial conditions*.

Table 6: List of series that are best explained by a single extracted factor according to R-squared of a linear regression of the (transformed) series on the respective factor.

	Series	R-squared
	Producer Prices in Industry	0.67
	Harmonised Index of Consumer Prices	0.56
Factor 1	Industrial Turnover Index, Manufacturing	0.53
	Compensation of Employees	0.49
	Gross Fixed Capital Formation Price Index	0.48
	Cost of Borrowing for Households for House Purchase	0.49
	6-month Euribor	0.45
Factor 2	1-year Euribor	0.45
	3-month Euribor	0.44
	Long-term Interest Rate Belgium	0.43
	Government Spending Italy	0.61
	Unit Labour Cost Germany	0.61
Factor 3	Government Spending Finland	0.61
	Unit Labour Cost Luxembourg	0.60
	Unit Labour Cost Italy	0.60
	Unemployment Italy	0.63
	Unemployment Netherlands	0.49
Factor 4	Real House Prices Ireland	0.44
	Unemployment Finland	0.43
	Real House Prices France	0.43
	Real House Prices Netherlands	0.46
	GDP Spain	0.40
Factor 5	Private Consumption Spain	0.33
	House Prices Netherlands	0.32
	Gross Fixed Capital Formation in Construction	0.32

E Explanatory Power of Factors

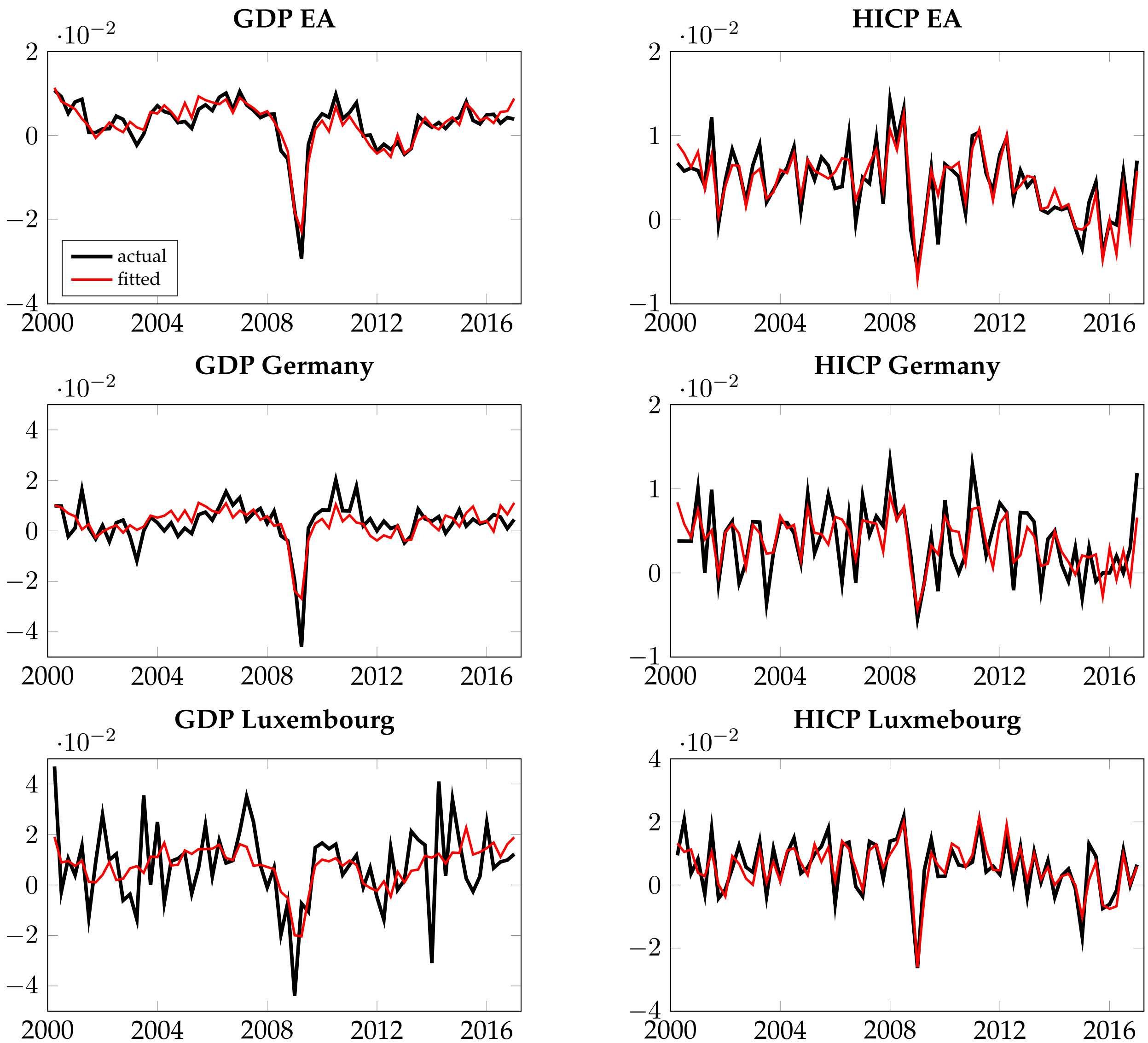

Figure 17: The figure compares actual (transformed) GDP and HICP data with corresponding fitted series on the basis of 5 extracted factors for the euro area (EA), Germany and Luxembourg from 2000 Q1 to 2016 Q4. Germany and Luxembourg represent the largest and smallest economies in our sample euro area, respectively. In DFM terminology, the fitted series represent the *systematic* component of the data series, while the actual series also contains an *idiosyncratic* component.

F Highest and lowest responses to monetary policy shock

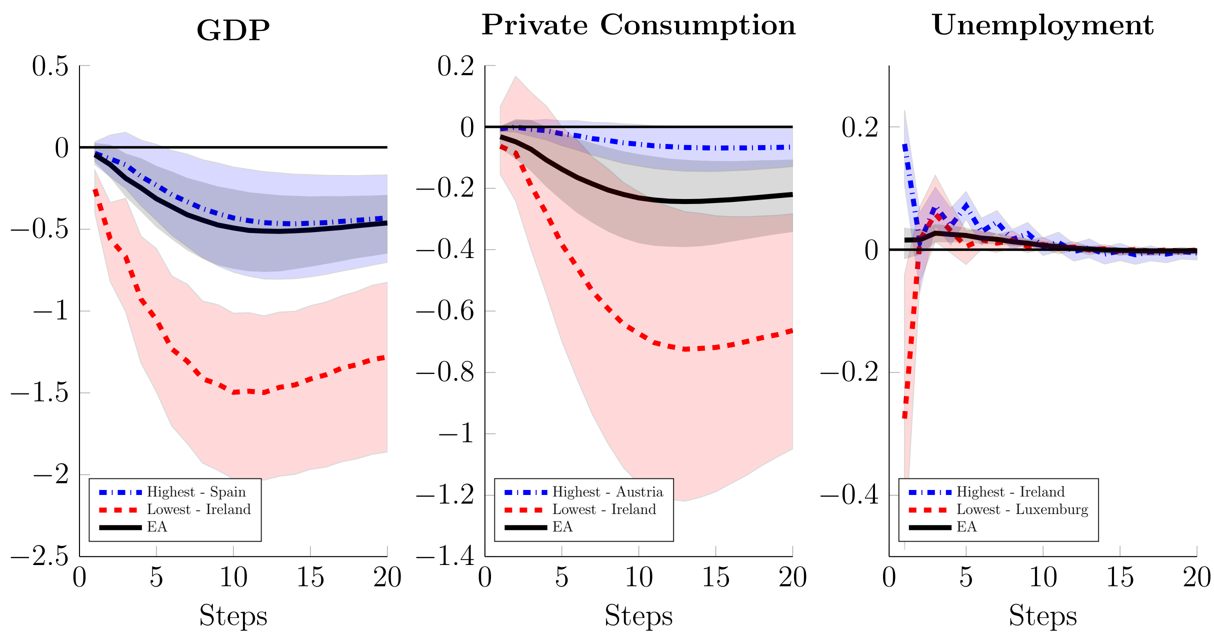

Figure 18: Highest/lowest percentage responses of selected real variables to a 25bp contractionary policy shock across euro area member countries.

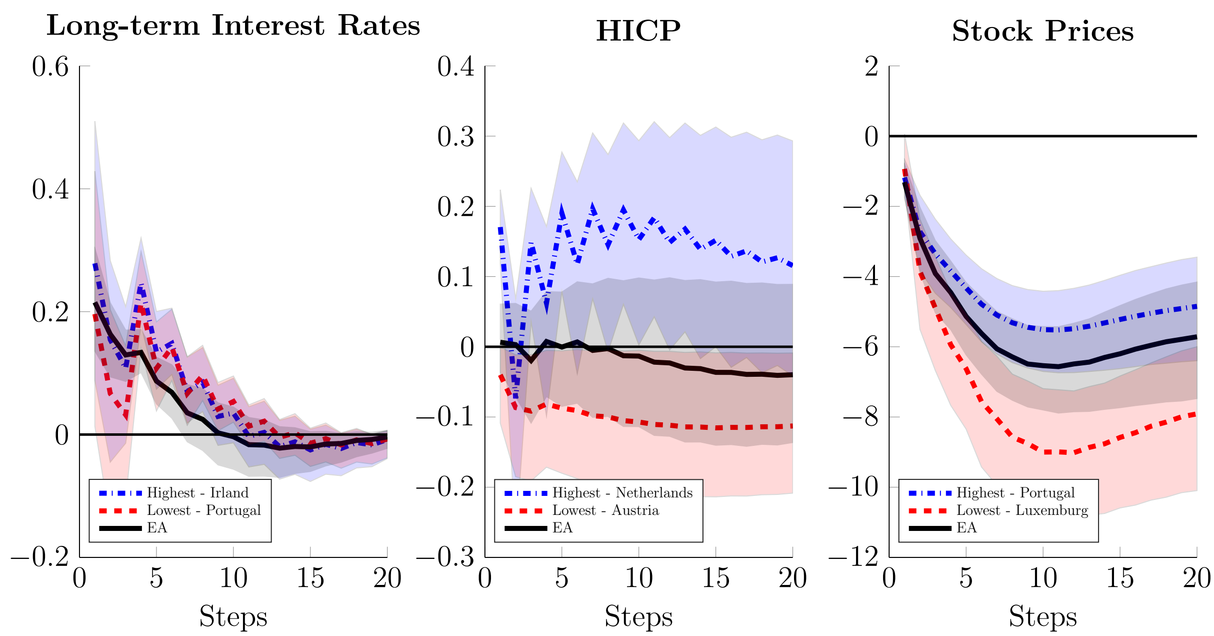

Figure 19: Highest/lowest percentage responses of selected prices to a 25bp contractionary policy shock across euro area member countries.