One Money, Many Markets*

Monetary Transmission and Housing Financing in the Euro Area

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Abstract

We study the transmission of monetary shocks across euro-area countries using a dynamic factor model and high-frequency identification. We develop a methodology to assess the degree of heterogeneity, which we find to be low in financial variables and output, but significant in consumption, consumer prices, and variables related to local housing and labor markets. Building a small open economy model featuring a housing sector and calibrating it to Spain, we show that varying the share of adjustable-rate mortgages and loan-to-value ratios explains up to one-third of the cross-country heterogeneity in the response of output and private consumption.

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1 Introduction

Monetary policy in the euro area (EA) has long been challenged by financial, economic, and institutional heterogeneity among member countries. Although there has been some convergence over time 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. Because of these slow developments, policy and academic researchers have long been faced with two questions. First, to which extent is the transmission of the European Central Bank's (ECB) monetary policy heterogeneous across borders? Second, how do differences in institutional characteristics of specific markets weigh on the observed heterogeneity?[1]

In this paper, we provide novel empirical and quantitative answers to these questions, developing a methodology suitable to analyze and test the degree of cross-country heterogeneity in the transmission of monetary policy. On empirical grounds, we set up a dynamic factor model (DFM) and assemble a large dataset including economic and financial time series for the EA as a block and 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. We identify monetary policy shocks by constructing an external instrument using high-frequency changes in asset prices around ECB policy announcements, following Gurkaynak et al. (2005) and Gertler and Karadi (2015). To bring theory to bear on our findings, we build a small open economy with housing operating in a monetary union and assess quantitatively how much of the variation in individual EA countries' responses to a monetary policy shock can be explained by differences in housing financing. Our focus is on the share of mortgages with adjustable rates and average loan-to-value ratios.

Our main results are as follows. First, at the aggregate EA level, we find that results from the factor model 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 among responses to policy is instead low in financial variables and output. Third, we find that differences in mortgage market characteristics across the EA can explain up to one-third of the cross-country heterogeneity of responses in output and private consumption.

On methodological grounds, our main contributions are, first, how to measure and statistically test heterogeneity in the responses of economic variables to a common shock in both theoretical and empirical applications. While confidence intervals around impulse response functions and

[1] See Angeloni et al. (2003) for a discussion of the early debate on these issues. Naturally, the ECB would benefit from knowing how monetary policy affects the individual member countries differently. At the same time, policymakers would gain from understanding the implications of their policies and reforms for the transmission of monetary policy.

Wald tests on the differences of these functions test whether responses are statistically different, they do not provide a measure of the degree of heterogeneity. To bridge this gap, we propose the following: 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 (CoV) 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 statistical measure of the dispersion of impulse responses allows for an intuitive and meaningful comparison of variables. As a first application using the CoV, we measure the degree of heterogeneity in the DFMs estimated monetary transmission to key macro variables across EA member countries, and carry out hypothesis testing based on a bootstrapping procedure, which yields error bands for the coefficient of variation of each variable as well as pairwise differences across variables. As a second application, we use the CoV to measure the heterogeneity in the simulated theoretical responses from varying model parameters, which can then be directly compared to its empirical counterpart.

Our second contribution consists of a quantitative assessment of the effects of cross-country differences in mortgage markets on monetary policy transmission in a monetary union. We calibrate our baseline economy to Spain, and, using this benchmark calibration, vary the loan-to-value ratios and shares of adjustable-rate mortgage contracts to mimic observed data for different countries. This procedure allows us to compare the dispersion of the simulated impulse response functions with the dispersion we estimated in the empirical section of the paper. As we do not recalibrate the model for each country in our sample, our quantitative responses may not account for several economic factors other than housing financing that may potentially help to match the evidence. However, holding all parameters other than the share of adjustment-rate mortgages and loan-to-value ratio constant allows us to isolate more clearly the specific role played by housing financing in monetary transmission.

Literature In specifying our empirical model, we build on the factor modeling literature developed in the 1970s[2] and recently popularised in the context of monetary policy analysis. In their seminal contribution, Bernanke et al. (2005) model macroeconomic interaction with a factor-augmented VAR (FAVAR) that combines factors and perfectly observable series, typically interest rates, in one dynamic system. The dynamic factor model that we employ in our analysis is a special case of FAVARs, in that it only contains unobservable factors. From an applied perspective, the prime advantage of a factor approach 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 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

[2] Stock and Watson (2016) provides a comprehensive exposition of factor models, including their early history. See also Giannone et al. (2005) and Forni and Gambetti (2010).

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.[3]

While closely following the methodology of Stock and Watson (2012) in constructing our DFM, we identify monetary policy shocks with an external high-frequency instrument. 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. As in Gurkaynak et al. (2005) and Gertler and Karadi (2015), we pursue a high-frequency approach, stipulating that asset price movements occurring within a narrow time window around policy announcements are most likely associated with monetary policy shocks.[4]

We construct our external instrument series based 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. This instrument has been proven to be economically meaningful, in that 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 (see e.g. (Altavilla et al. (2019)). Our instrument series is a broad measure of monetary policy surprises that incorporates all of the communication channels above.

Relative to the literature, our contribution is to show how to overcome 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.[5] We test for the relevance of the series in a small VAR, confirming its validity as an external instrument. Based on historical tick data, Jarocinski and Karadi (2018) 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. The effects of the monetary shocks we identify in this paper are close to the effects of the policy shocks (as opposed to information shocks) these authors document in their work.

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

[4]The two leading contributions using external instruments to identify monetary policy shocks in the US are Romer and Romer (2002), pursuing the narrative approach, and Gurkaynak et al. (2005), pursuing the high-frequency approach. 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). Building on these contributions, Gertler and Karadi (2015) identify monetary policy shocks in a VAR using high frequency changes in Fed funds futures. Further applications of high-frequency identification in the context of monetary policy can be found in Hanson and Stein (2015), Nakamura and Steinsson (2018), Bagliano and Favero (1999), Cochrane and Piazzesi (2002), Faust et al. (2004) and Barakchian and Crowe (2013), among others.

[5]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 is not significantly different for the sub-sample. See Section 2.3.1 for details. In addition, our instrument series strongly correlates (0.9) with the monetary event window surprises in the euro-area monetary policy event-study database (Altavilla et al. (2019)). The latter has the advantage of being updated regularly.

The analysis of the housing channel conducted in our paper is closely related to Calza et al. (2013), who also study how heterogeneity in the structure of housing financing across the euro area can affect the transmission of monetary policy to housing prices, consumption and output. Relative to this work, our paper differs in the empirical methodology and identification, and, most importantly, in that it provides a quantitative assessment using a fully calibrated model. More generally, our work is related to the vast 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. Recently, Slacalek et al. (2020) develop a back-of-the-envelope calculation, applying a HANK model to the EA to study the effects of monetary policy on household consumption. They conclude that the housing wealth effect is a relevant determinant of the aggregate consumption response to monetary policy and helps explain the cross-country heterogeneity in these responses in the EA.

The rest of the paper is organized as follows. 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 introduces our analytical model to uncover how institutional differences in housing markets affect monetary transmission across the euro area. Section 5 concludes.

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 member countries.[6] Recovering both the effects on the block and member countries imposes some empirical challenges and trade-offs. On the one hand, fully recovering the effects of monetary policy on each individual 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

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

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 the 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 euro wide variables—often weighted averages of individual member 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 euro wide 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 issue 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 the 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 the cost of higher parameterisation relative to the dynamic factor model. Given that we are not explicitly interested in these interactions 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[7].

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

[7] See Stock and Watson (2016) for further details on the estimation of DFMs.

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, Olea and Watson (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"[8]

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. 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.

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.

[8]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.

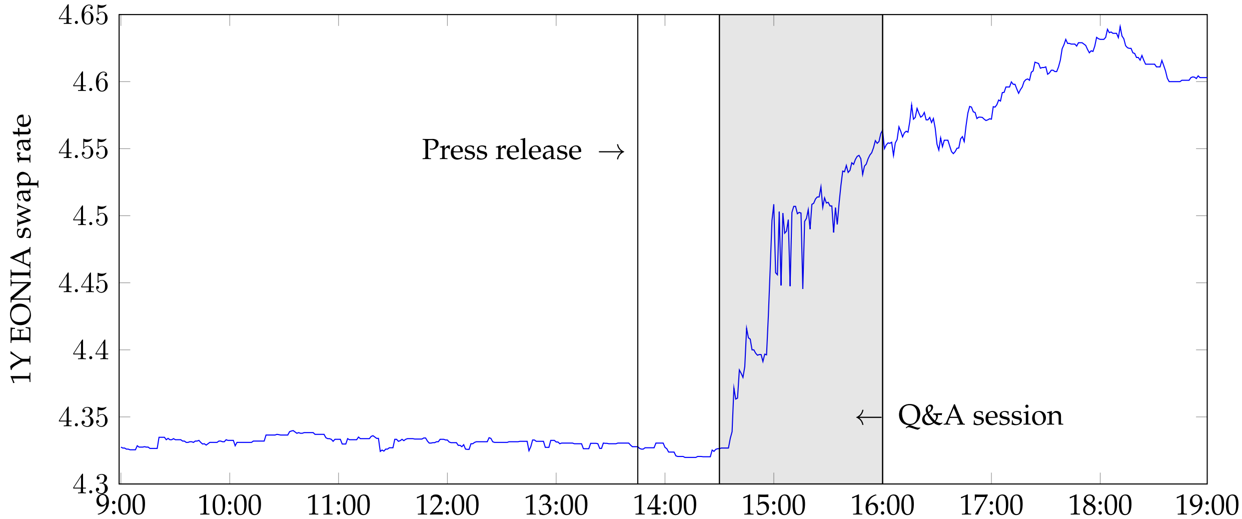

Figure 1: 1-year EONIA swap rate on 5 June 2008. Horizontal axis shows Central European Time (CET). Source: Bloomberg, authors' calculations.

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, as also recently pointed out by contemporaneous work by Jarocinski and Karadi (2018) and Altavilla et al. (2019). 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.[9]

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 if one wants to study the effect of all monetary actions. On 5 June 2008, the Governing Council

[9]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.

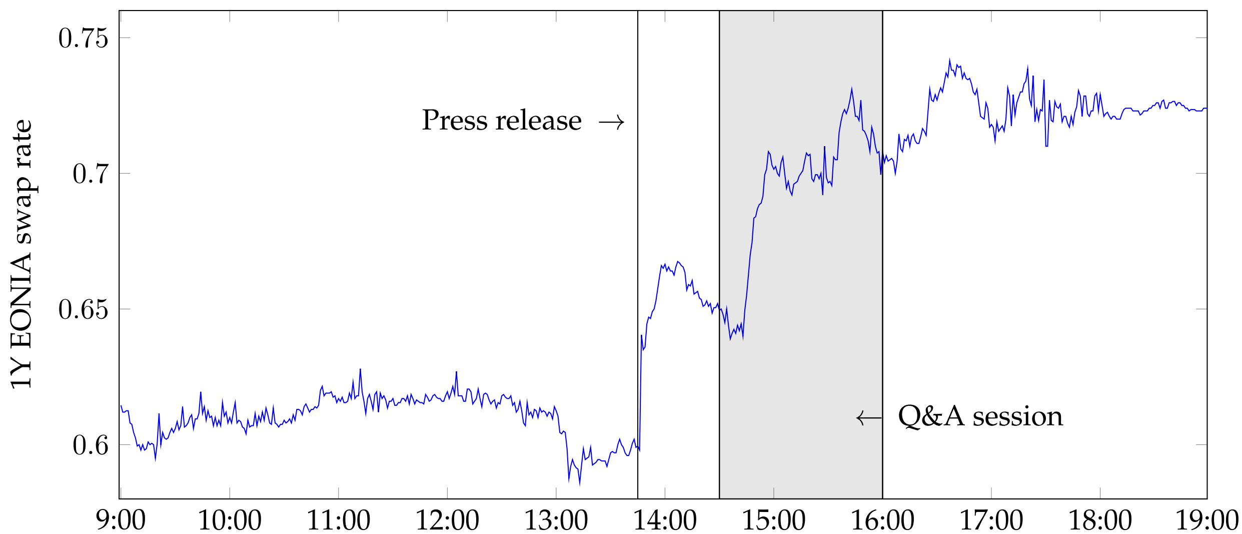

Figure 2: 1-year EONIA swap rate on 6 October 2011. Horizontal axis shows Central European Time (CET). Source: Bloomberg, authors' calculations.

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, 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. On one hand, Jarocinski and Karadi (2018) have suggested a separation of monetary policy *instrument* shocks from monetary policy *communication* shocks, sometimes also termed *target* and *path* shocks. On the other hand, Altavilla et al. (2019) have separately constructed monetary surprises for the press release and Q&A event window. For the purpose of our paper, we want to use a broad measure of monetary policy shocks that encompasses all forms of surprises related to monetary actions.

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.[10]

To get a better understanding of our instrument, we plot its time series 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.[11] 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 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

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

[11] 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.

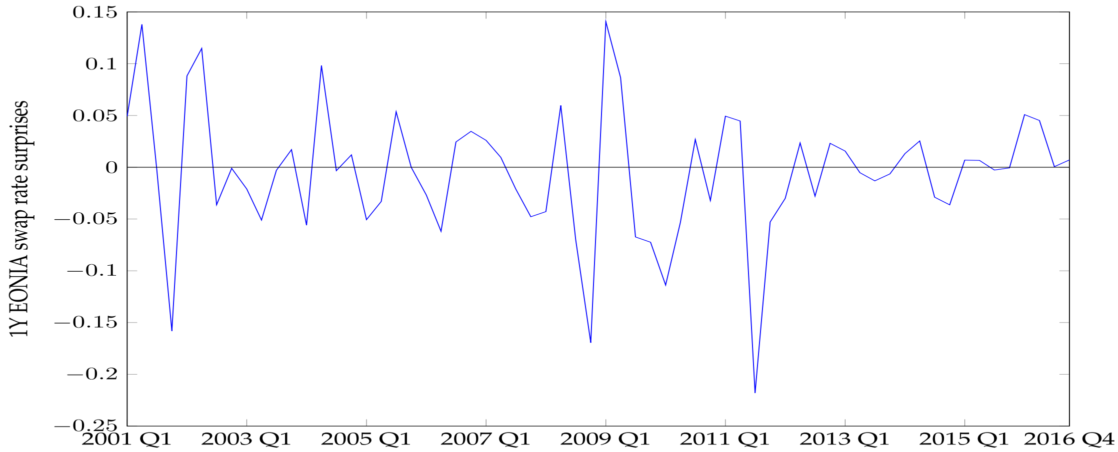

Figure 3: Instrument - Quarterly 1-year EONIA swap rate surprises from 2001Q1 to 2016Q4

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[12] 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

[12] See e.g. Stock and Watson (2012).

series for factor extraction.

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

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 et al. (2016)[13] suggesting $r = 8$. We choose as our baseline specification $r = 5$, that is, the average of these results. Figure 14 in Appendix A shows the variance of the data explained by each additional factor. Five factors account for 80% of the total data variance.[14]

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

[13] see Figure 13 in Appendix A.

[14] As can be seen in Figure 14, the bulk of the variance in the data is explained by the first two factors. 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
Housing 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	-	-	-

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 18 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.

3 Empirical Results

This section gives an overview of our empirical findings, starting at the aggregate level for the euro area 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).[15] 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 moves in the opposite direction of the monetary 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

[15] 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

of mortgages are characterised by fixed rates that do not adapt to changes in policy. In the 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, housing 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. Dias and Duarte (2019)) suggests that a worsening of conditions in the mortgage market leads agents to substitute house purchase with renting, thus exerting pressure on rental prices. The euro exchange rate appreciate, although only with a delay.

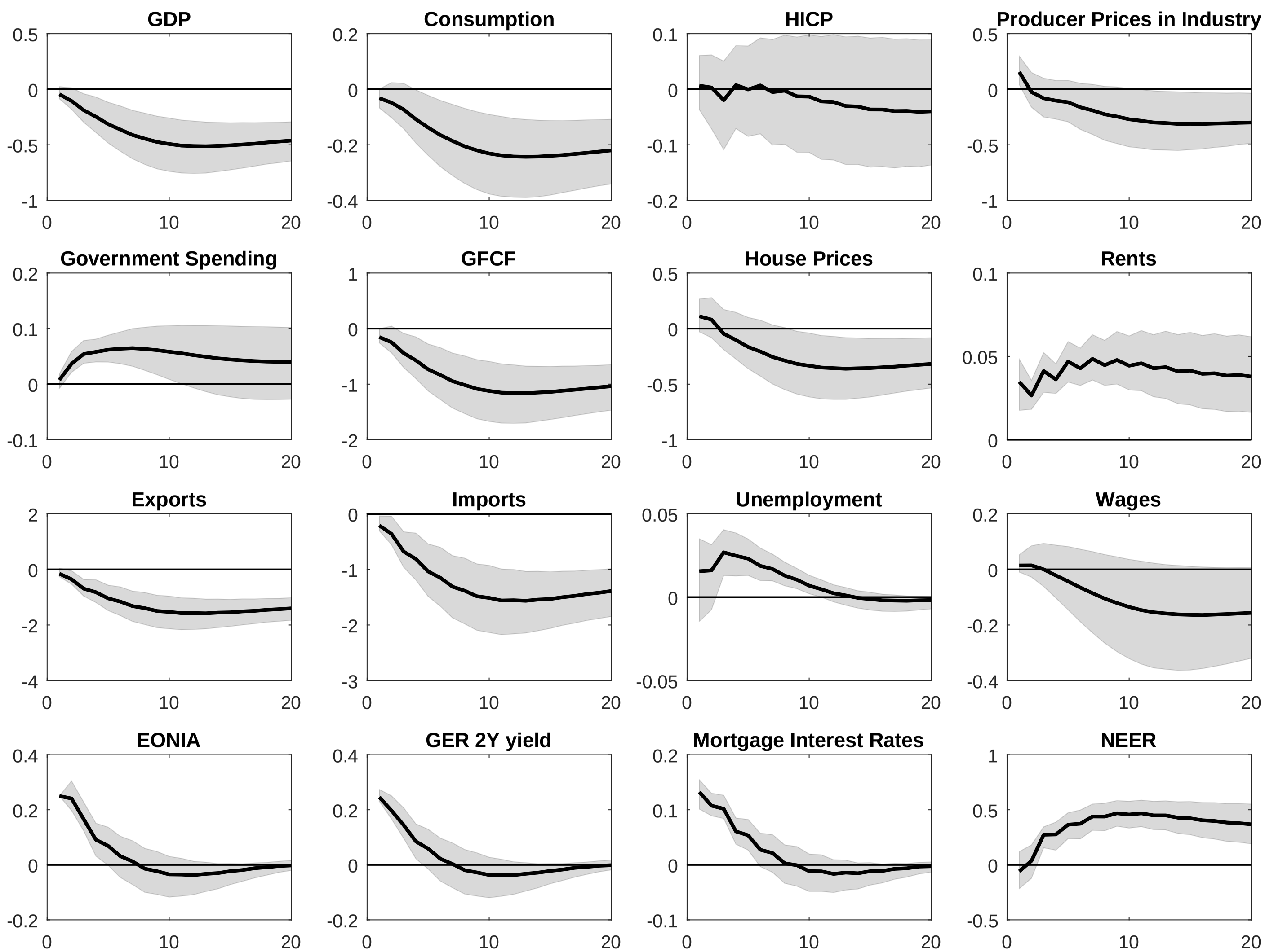

Figure 4: Percentage responses of selected euro-wide variables to a 25bp contractionary policy shock. Note: Confidence intervals are obtained from a wild bootstrap procedure with a simple (Rademacher) distribution.

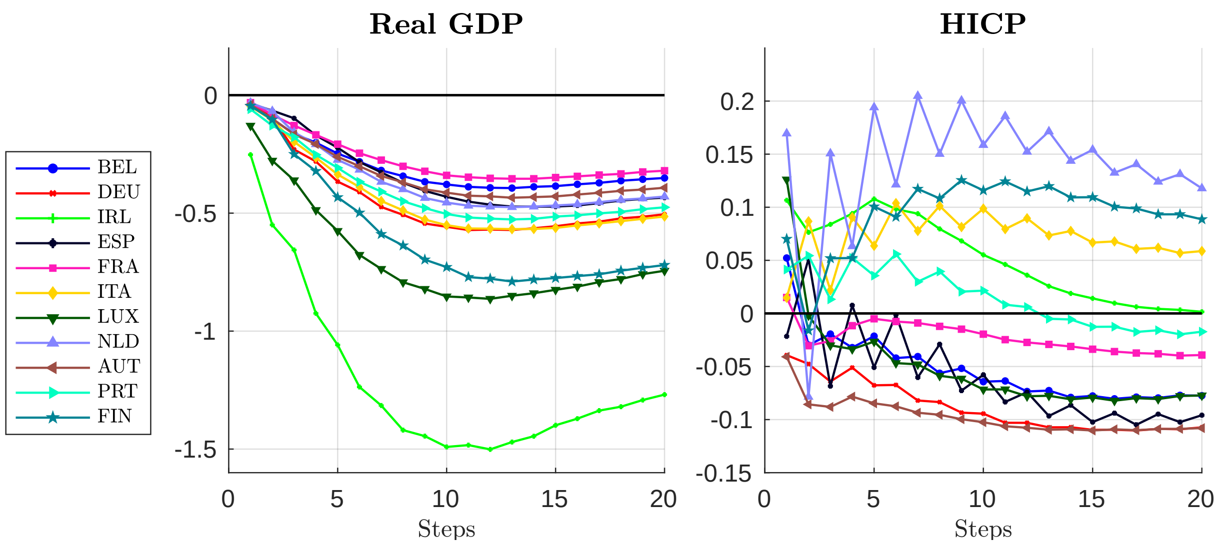

Figure 5: Percentage responses of real GDP and HICP to a 25bp contractionary policy shock across euro-area member countries.

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 unemployment. We point out, however, that the model produces impulse response functions for all series in our sample.[16]

Figure 5 shows the responses of 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 real GDP and HICP across countries appear to be quite heterogeneous.[17] In terms of HICP, the responses are positive for half of the countries while they are negative for the other half. In addition, the mean HICP response is negative and very low, which makes the relative distance of responses quite large when compared to that of real GDP. Turning to real GDP, 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.

[16] Given that the time period used for the estimation of the DFM includes both the global financial crisis and the European debt crisis, a natural concern is whether the heterogeneity in monetary transmission was largely driven by these events. In section G of the online appendix, we provide a sub-sample robustness check where we split the sample into before and after the financial crisis and estimate the DFM separately for both sub-samples. We find that the main conclusions remain the same. The heterogeneity in monetary transmission remains large for variables related to private consumption, housing and labor in the period preceding the great recession

[17] Later on in the text, we propose a methodology to assess heterogeneity based on coefficients of variation.

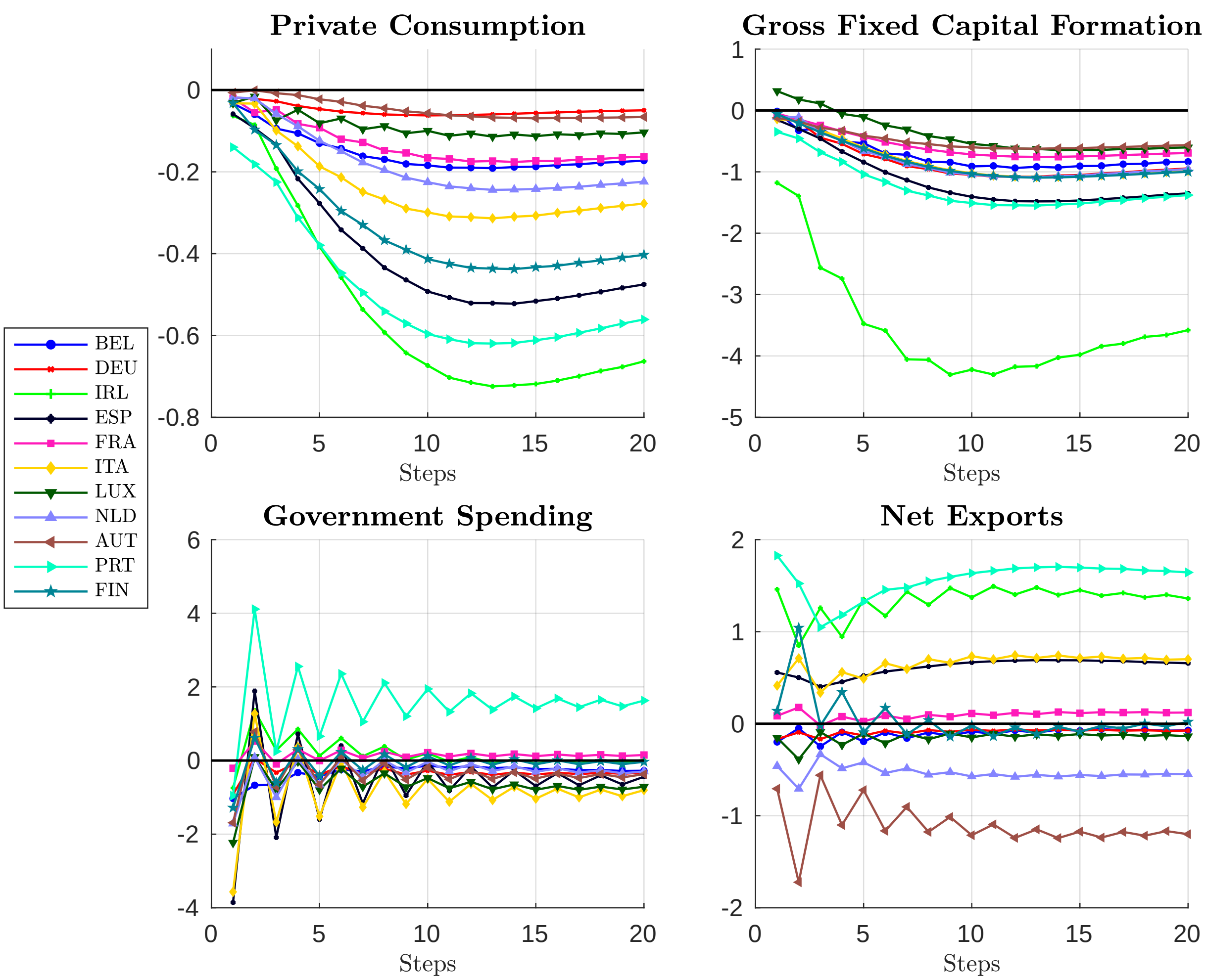

Figure 6: Percentage responses of GDP components to a 25bp contractionary policy shock across euro-area member countries.

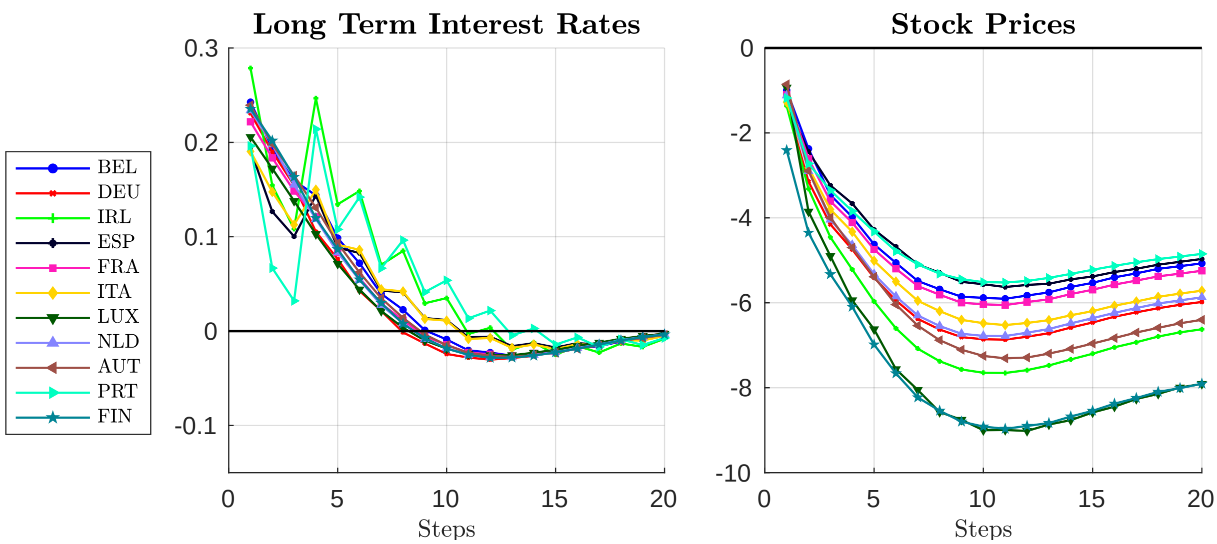

Figure 7: Percentage responses of long-term interest rates and local equity indices to a 25bp contractionary policy shock across euro-area member countries. Long-term interest rates are defined in accordance with OECD methodology, conforming to government bonds of (in most cases) 10 year maturity.

For a first pass at this question, Figure 6 contains the reactions of the components of GDP. The IRFs highlights two main observations. Firstly, the responses of national private consumption and gross fixed capital formation, have the same sign and follow similar patterns. In contrast, the responses of national government spending and net exports do not have the same sign. 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, depending on the degrees of pro- and counter-cyclicality of fiscal policy that tend to vary both across countries and over time.

Secondly, whether or not the responses move in the same direction, there is a visible degree of heterogeneity. In particular, consider the disparity in the reaction of private consumption. While the drop in private consumption reaches a maximum at about 0.02 percentage points in Germany, the drop in Ireland is more than 20 times as large, at 0.4 percentage points. Aside from Ireland, which could be considered an outlier, the drop in consumption in Italy, Finland, Spain and Portugal is roughly 10 times the size of the drop in Germany.

In some notable cases, we find that the degree of heterogeneity in the impulse responses may reflect (inversely) the state of convergence in particular markets across the euro area. In particular, financial markets have experience a relatively stronger convergence than other markets.[18] This can be seen in the reaction of interest rates and stock prices across countries. Figure 7 shows that, while the response of long-term interest rates to a policy shock is not uniform across countries on impact, it converges and become almost identical over time. By the same token, while the responses of

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

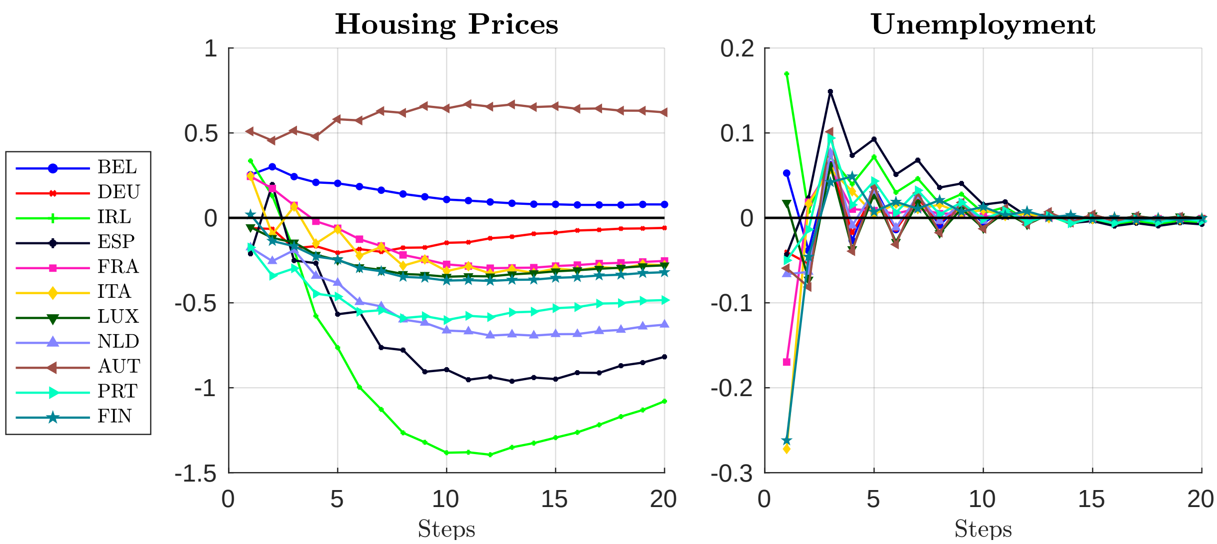

Figure 8: Percentage responses of housing prices and unemployment rate to a 25bp contractionary monetary policy shock across euro-area member countries.

national equity indices, displayed in the same figure, does not converge across equity markets, the confidence intervals around the IRF are mostly overlapping.

Among the markets with records of little or no convergence in institutional characteristics are the labour and housing markets. In Figure 8, we show that, after one year (4 steps) the shocks, housing prices fall and unemployment rises at quite different rates across border. [19]

To gain a firmer insight on the degree of heterogeneity in the impulse responses across countries, in what follows we propose and implement a more rigorous approach to testing. 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 variable. To make this measure comparable across different series, we normalise it by the size of the EA response. By doing so, we create a numerical measure for the dispersion of impulse responses that allows for intuitive and meaningful comparison between series. Table 11 reports the coefficients of variation for a selection of variables, evaluated on impact, as well as at the 8th and the 20th step. The table also reports a lower and a upper bound for the coefficients of variation, which we obtain from our bootstrapping procedure. The table shows that long-term interest rates and stock prices have a much smaller coefficient of variation than the other variables, in line with our discussion above suggesting a lower degree of heterogeneity for financial than for real variables. Remarkably, however, the table also shows that at the 20th step, GDP is also less heterogeneous than other real variables, namely private consumption and unemployment.

[19] Appendix F proposes an alternative representation of our result, to highlight the statistical significance of differences across IRFs. Figures 19 and 22 plot the highest and the lowest national response, together with the IRFs for the whole EA, showing confidence intervals. Figure 19 plots IRFs for real variables: GDP, private consumption and unemployment. Figure 22 plots IRFs for price-related series: interest rates, HICP and stock prices. The confidence intervals for the highest and the lowest IRS do not overlap for the real variables. In contrast, they are overlapping for most parts of the price-related series, with the exception of stock prices, which are diverging around the 10th step.

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
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 8th Step			
GDP	0.74	0.56	1.10
Private Consumption	1.01	0.99	1.12
Unemployment Rates	1.57	1.08	3.00
Housing Prices	1.20	0.84	3.57
HICP	1.69	0.80	6.00
Long-term Interest Rates	0.96	0.28	3.36
Stock Prices	0.20	0.18	0.22
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
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

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), and real housing prices (RHPI).

Summing up. Our empirical evidence suggests that, in line with our conjecture, heterogeneity in the responses to monetary shocks is lower in financial variables, such as interest rates and stock prices, reflecting a relatively high degree of integration, relative to variables related to much less integrated markets, such as the labour and housing markets. We also show that the heterogeneity in the response larger in consumption and consumer prices, than is in the response of output output. Our evidence, showing that in some cases the response can even have a different sign, has straightforward implications for policy. Further institutional convergence can be expected to enhanced cohesion in the euro area, by reducing unintended responses to common monetary stimulus or contraction across countries. That said, a much deeper understanding of the mechanisms at play is necessary to motivate and structure consistent convergence policies.

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
On Impact							
GDP	0	-0.99	1.20*	1.06*	0.16	-5.42*	-0.84
HICP	1.10	0	3.02*	2.85*	1.69	-3.81	0.66
LTINT	-1.19*	-3.02*	0	-0.13	-0.90*	-6.66*	-1.79*
SP	-1.04*	-2.85*	0.13	0	-0.84*	-6.84*	-1.60*
PCON	-0.16	-1.69	0.90*	0.84*	0	-5.20*	-0.75
U	5.32*	3.81	6.66*	6.84*	5.20*	0	5.02
RHPI	0.87	-0.66	1.79*	1.60*	0.75	-5.02	0
At the 8th Step							
GDP	0	-0.86	-0.23	0.54*	-0.30	-0.73*	-0.44
HICP	0.86	0	3.02*	2.85*	1.69	-3.81	0.66
LTINT	0.23	-0.60	0	-0.13	-0.90*	-6.66*	-1.79*
SP	-0.54*	-1.45*	-0.74*	0	-0.84*	-6.84*	-1.60*
PCON	0.30	-0.59	0.10	0.80*	0	-5.20*	-0.75
U	0.73*	-0.08	0.65	1.38*	0.51*	0	5.02
RHPI	0.44	-0.16	0.49	1.03*	0.18	-0.19	0
At the 20th Step							
GDP	0	-0.55	0.21	0.45*	-0.39*	-0.59*	-0.43*
HICP	0.55	0	0.64	1.02*	0.19	-0.18	-0.16
LTINT	-0.21	-0.64	0	0.24	-0.60	-0.99*	-0.62
SP	-0.45*	-1.02*	-0.24	0	-0.80*	-1.04*	-0.85*
PCON	0.39*	-0.19	0.60	0.80*	0	-0.20	0.00
U	0.59*	0.18	0.99	1.04*	0.20	0	0.20
RHPI	0.43*	0.16	0.62	0.85*	0.00	-0.20	0

4 Quantifying How Mortgage Markets Shape Monetary Transmission

A growing body of literature has recently reconsidered a "housing channel" in the transmission of monetary policy (Iacoviello (2005), Calza et al. (2013), Greenwald (2018), Wong (2019), Beraja et al. (2019), Cloyne et al. (2019) and Slacalek et al. (2020)). The importance of this channel is commonly motivated by noting that, for most households, their home is the single most important item on the asset side of their balance sheet, and their mortgage is the household's largest liability. In this section, we build an small open economy model featuring a housing sector, and use it to investigate the housing channel of monetary policy in a currency union in some detail. Specifically, we will make use of the European institutional setting to explore variation in the housing channel across EA countries, reflecting different characteristics of housing financing across member countries.

Many institutional characteristics of national housing markets differ substantially across EA members. Mortgage markets display marked variation in the relative share of fixed versus flexible rate contracts and typical loan-to-value ratios; rental markets are subject to different regimes and controls; 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. The importance of these differences for monetary policy transmission in Europe has not gone unnoticed, and previous literature, most notably Calza et al. (2013), has produced empirical and qualitative assessments. However, to our knowledge, there is no quantitative assessment using a fully calibrated model.

In what follows, we study quantitatively how much of the variation in individual EA country responses to a monetary policy shock can be explained by differences in mortgage market characteristics. First, we describe the model, focusing on a set of institutional parameters that affect housing financing, namely the loan-to-value ratio and the share of adjustable-rate mortgage contracts. Our analysis merges the main elements of Calza et al. (2013) into a small open economy modeled after De Paoli (2009). Doing so allows us to quantitatively assess the importance of differences in institutional characteristics of mortgage markets in the transmission of monetary policy. Second, we calibrate the model to the Spanish economy in order to get empirically plausible long-term moments and impulse response functions to monetary policy shocks. Finally, we feed the model with the loan-to-value ratios and shares of adjustable-rate mortgage contracts observed in the data for each country, and compare the dispersion from these simulated IRFs with the dispersion we estimated using the DFM in the previous section.

4.1 Model

The economy features three types of agents — savers, fixed-rate borrowers, and variable-rate borrowers, as proposed by Rubio (2011) — and a collateral constraint in line with Campbell and Hercowitz (2005), Iacoviello (2005), Iacoviello and Neri (2010), and Liu et al. (2010). Savers are standard Ricardian agents who own all firms in the consumption and housing sectors as well as financial intermediaries, while borrowers are credit constrained in equilibrium and behave as hand-to-mouth consumers. As customary in the literature, we assume that the domestic economy is so small relative to the rest of the EA that domestic economic dynamics are irrelevant for equilibrium outcomes in the rest of the EA (see e.g. De Paoli (2009)).

4.1.1 Patient Households

There is a continuum of measure 1 of patient agents. Their economic size is measured by their wage share, which is assumed to be constant reflecting a Cobb-Douglas production function with unit elasticity of substitution. A representative patient household maximizes:

$$E_0 \sum_{t=0}^{\infty} \beta^t \left(\log\left(c_t - \zeta c_{t-1}\right) + j \log h_t - \frac{\left(n_{c,t}^{1+\theta} + n_{h,t}^{1+\theta}\right)^{\frac{1+\psi}{1+\theta}}}{1+\psi} \right), \tag{14}$$

where β is the discount factor, c_t is consumption of goods other than housing, j is a housing preference over consumption parameter, ζ captures consumption habit formation, θ indicates the elasticity of substitution between working in the consumption or housing sectors, and ψ is the inverse Frisch elasticity of labor supply. $n_{c,t}$ and $n_{h,t}$ denote hours worked in the consumption and housing sectors, respectively, and h_t denotes the consumption of housing services. The consumption of goods c_t is a bundle of home and foreign goods with the following form:

$$c_t = \frac{c_{H,t}^{1-(1-n)\nu} c_{F,t}^{(1-n)\nu}}{(1-(1-n)\nu)^{(1-(1-n)\nu)}((1-n)\nu)^{(1-n)\nu}} \tag{15}$$

Here $\nu \in [0,1]$ measures the home bias in consumption[20]. Here, the bundles of Home- and Foreign-produced goods are defined as follows:

$$c_{H,t} = \left[\left(\frac{1}{n}\right)^{\frac{1}{\varepsilon}} \int_0^n c_{H,t}(j)^{\frac{\varepsilon-1}{\varepsilon}} dj \right]^{\frac{\varepsilon}{\varepsilon-1}}, \quad c_{F,t} = \left[\left(\frac{1}{1-n}\right)^{\frac{1}{\varepsilon}} \int_n^1 c_{F,t}(j)^{\frac{\varepsilon-1}{\varepsilon}} dj \right]^{\frac{\varepsilon}{\varepsilon-1}}, \tag{16}$$

where $c_{H,t}(j)$ and $c_{F,t}(j)$ denote differentiated intermediate goods produced in Home and Foreign, respectively, and $\varepsilon > 1$ measures the elasticity of substitution between intermediate goods produced within the same country.

Patient households own all firms in this economy, accumulate houses and make loans to impatient households. Patient households maximize their utility subject to:

$$c_t + q_t h_t + Q_{t,t+1} D_{t+1} - b_t = D_t + \frac{W_{c,t}}{P_t} n_{c,t} + \frac{W_{h,t}}{P_t} n_{h,t} - \frac{R_{t-1} b_{t-1}}{\pi_t} + q_t (1-\delta_h) h_{t-1} + T_t \tag{17}$$

where q_t is the house price, $W_{c,t}$ is the nominal wage in the consumption sector, $W_{h,t}$ is the nominal wage in the housing sector, R_t is the gross nominal interest rate, δ_h is the housing depreciation rate, π_t is the inflation rate, P_t is the domestic price level index, T_t is total firm profits and $Q_{t,t+1}$ is the stochastic discount factor for one-period ahead nominal pay-offs relevant to the domestic household. We assume that patient households have access to a complete set of contingent claims, traded internationally.

[20]This specification of home bias follows Sutherland (2005) and De Paoli (2009). With $\nu = 1$, there is no home bias. If the relative price of foreign and domestic goods is unity, Home‘s consumption basket contains a share n of Home-produced goods and a share $(1-n)$ of imported goods. A lower value of ν implies that the fraction of domestically produced goods in final goods exceeds the share of domestic production in the world economy. Hence, in the other extreme case, if $\nu = 0$, there is full home bias and no trade across countries.

4.1.2 Impatient Households

There is a measure 1 of impatient households, a share ω of which have mortgage contracts with variable interest rates, denoted by subscript v, while the remaining $1-\omega$ possess a fixed-rate mortgage contract, denoted by subscript f. Similarly to patient households, they maximize

$$E_0 \sum_{t=0}^{\infty} \beta'^t \left(\log\left(c'_{i,t} - \zeta' c'_{i,t-1}\right) + j \log h'_{i,t} - \frac{\left(n_{ci,t}^{1+\theta'} + n_{hi,t}^{1+\theta'}\right)^{\frac{1+\psi'}{1+\theta'}}}{1+\psi'} \right), \quad \text{for } i = \{v, f\}, \tag{18}$$

where $\beta' < \beta$, which makes these households impatient. Differently from patient households, they do not own firms nor can they trade contingent claims internationally, and are subject to the following budget and collateral constraints:

$$\begin{aligned} c'_{i,t} + q_t h'_{i,t} - b'_{i,t} = & \frac{W'_{c,t}}{P_t} n'_{ci,t} + \frac{W'_{hi,t}}{P_t} n'_{hi,t} - \frac{R_{i,t-1} b_{i,t-1}}{\pi_t} \\ & + q_t (1-\delta_h) h_{i,t-1}, \quad \text{for } i = \{v, f\}, \end{aligned} \tag{19}$$

$$b'_{i,t} \leq m E_t \left(q_{t+1} h_{i,t} \frac{\pi_{t+1}}{R_{i,t}} \right) \tag{20}$$

where m is the loan-to-value ratio. In the steady state without uncertainty this last constraint will bind since $\beta' < \beta$. Impatient households with fixed-rate mortgages face $R_{f,t} = \bar{R}_t$, while those with variable-rate mortgages face $R_{v,t} = R_t$.

The two key institutional characteristics relevant to housing financing are thus encapsulated in the two parameters ω and m. The first is the share of households that finance their housing purchase with adjustable-rate mortgages, the second is the loan-to-value ratio.

4.1.3 Relationship among inflation, terms of trade and exchange rate

When maximizing utility, households take prices as given. Let $P_t(j)$ denote the price that the producer of good j charges in the Home country, denoted in Home currency. Let $P_t(j)$ denote the price that the producer charges for the same good in the Foreign country, expressed in Foreign currency. The consumer price indices in Home and Foreign are given by

$$P_t = P_{H,t}^{(1-(1-n)\nu)} P_{F,t}^{(1-n)\nu} \tag{21}$$

$$P_t^* = P_{F,t}^{*(1-(1-n)\nu)} P_{H,t}^{*(1-n)\nu} \tag{22}$$

where $P_{H,t}$ ($P_{H,t}^*$) is the price sub-index for Home-produced goods expressed in domestic (foreign) currency and $P_{F,t}$ ($P_{F,t}^*$) is the price sub-index for Foreign-produced goods expressed in the domestic (foreign) currency.

$$P_{H,t} = \left[\left(\frac{1}{n}\right) \int_0^n P_t(j)^{1-\varepsilon} dj \right]^{\frac{1}{1-\varepsilon}}, \quad P_{F,t} = \left[\left(\frac{1}{1-n}\right) \int_n^1 P_t(j)^{1-\varepsilon} dj \right]^{\frac{1}{1-\varepsilon}} \tag{23}$$

$$P_{H,t}^{*}=\left[\left(\frac{1}{n}\right)\int_{0}^{n}P_{t}^{*}(j)^{1-\varepsilon}dj\right]^{\frac{1}{1-\varepsilon}}, \quad P_{F,t}^{*}=\left[\left(\frac{1}{1-n}\right)\int_{n}^{1}P_{t}^{*}(j)^{1-\varepsilon}dj\right]^{\frac{1}{1-\varepsilon}} \tag{24}$$

Moreover, we assume that the law of one price holds for intermediate goods, so that

$$P_t(j)=\xi_t P_t^{*}(j) \tag{25}$$

ξ_t is the nominal exchange rate measured as the price of Foreign currency in terms of Home currency. A rise in ξ_t, thus, marks a nominal depreciation from Home‘s perspective.

Therefore, equations (21), (22) together with condition (25), imply that $P_{H,t}=\xi_t P_{H,t}^{*}$ and $P_{F,t}=\xi_t P_{F,t}^{*}$. However, as equations (23) and (24) illustrate, the home bias specification leads to deviations from purchasing power parity, that is, $P_t \neq \xi_t P_t^{*}$. For this reason, we denote the real exchange rate by $RS_t=\frac{\xi_t P_t^{*}}{P_t}$.

Assuming that $n \to 0$, and using the preferences of consumers, we can derive total demand for a generic good j, produced in country H:

$$Y_t^{d}(j)=\left(\frac{P_t(j)}{P_{H,t}}\right)^{-\varepsilon}\left(\frac{P_{H,t}}{P_t}\right)^{-1}\left[(1-\nu)C_t+\nu RS_t C_t^{*}\right] \tag{26}$$

4.1.4 Firms

Consumption Sector. Producers of intermediate consumption goods operate under monopolistic competition and face the demand function (26). The production function is given by:

$$Y_t(j)=n_{c,t}(j)^{\alpha}\, n_{c,t}(j)'^{1-\alpha}, \tag{27}$$

where $n_{c,y}(j)$ and $n_{c,y}(j)'$ denote labor services from patient and impatient households, respectively, employed by firm $j \in [0,n]$ in period t. We assume that prices are set in the currency of the producer and that price setting is constrained exogenously a la Calvo, such that in each period only a fraction of intermediate good producers $(1-\phi)$ may adjust their price. When firm j has the opportunity, it sets $\tilde{P}_t(j)$ to maximize the expected discounted value of net profits:

$$\max_{\bar{P}_{H,t}(j)} E_t\left\{\sum_{s=0}^{\infty}(\phi\beta)^{s}\Lambda_{t,t+s}\left(Y_{t+s}(j)(\bar{P}_{H,t}(j)-MC_{t+s}^{n})\right)\right\} \tag{28}$$

subject to the sequence of demand constraints

$$Y_{t+s}(j) \leq Y_{t+s}^{d}, \tag{29}$$

where $\Lambda_{t,t+s}$ is the stochastic discount factor and MC_{t+s}^{n} denotes the nominal marginal cost.

Housing Sector. We rule out nominal rigidities in the housing market. On the one hand, housing is relatively expensive on a per-unit basis, implying large incentives to negotiate on the price. On the other hand, most homes are priced for the first time only when they are sold.

In the housing sector there is a representative firm that produces residential investment according to the following technology:

$$IH_t={n_{h,t}}^{\alpha}\,{n'_{h,t}}^{1-\alpha}. \tag{30}$$

Hence, assuming perfect competition, this firm takes the price of housing as fixed and optimally chooses labor input in order to maximize profits.

$$\max_{n_{h,t},n'_{h,t}} q_t IH_t - W_{h,t}n_{h,t} - W'_{h,t}n'_{h,t}. \tag{31}$$

Financial Intermediaries. There is a financial intermediary that accepts deposits from savers and extends both fixed- and variable-rate loans to borrowers. We assume a competitive framework under which the intermediary takes variable interest rates as given. The profits of the financial intermediary are defined as

$$F_t = \omega R_{t-1}b'_{v,t-1} + (1-\omega)\bar{R}_{t-1}b'_{f,t-1}, \tag{32}$$

In equilibrium, aggregate borrowing and saving must be equal, that is:

$$\omega b'_{v,t} + (1-\omega)b'_{f,t} = b'_t. \tag{33}$$

Substituting (33) into (32), one obtains,

$$F_t = (1-\omega)b'_{f,t-1}(R_{t-1} - \bar{R}_{t-1}). \tag{34}$$

In order for the two types of mortgages to be offered in equilibrium, the fixed interest rate has to be such that the intermediary is indifferent between lending at a variable or fixed rate. Hence, the expected discounted profits from issuing new debt in a given period at a fixed interest rate must be equal to those from issuing at a variable rate. Also, since the financial intermediaries are owned by the savers, their stochastic discount factor is applied in computing the optimal equilibrium value of the fixed rate in period t, given by:

$$\bar{R}_t^{opt} = \frac{E_t \sum_{\tau=t+1}^{\infty} \beta^{\tau-(t+1)} \Lambda_{t+1,\tau} R_{\tau-1}}{E_t \sum_{\tau=t+1}^{\infty} \beta^{\tau-(t+1)} \Lambda_{t+1,\tau}} \tag{35}$$

Hence, new debt issued at date t is associated with a different fixed interest rate set by equation (35). However, this implies that the aggregate return on the whole stock of debt is a function of new debt as well as rates set on past debt. Therefore the aggregate fixed interest rate that a financial intermediary charges at date t is an average of what was charged last period for the previous stock of mortgages and what is charged for new debt:

$$\bar{R}_t = \begin{cases} \frac{\bar{R}_{t-1}\, b'_{f,t-1} + \bar{R}_t^{opt}(b'_{f,t} - b'_{f,t-1})}{b'_{f,t}}, & \text{if } b'_{f,t} > b'_{f,t-1} \\ \bar{R}_{t-1}, \quad \text{if } b'_{f,t} \leq b'_{f,t-1}, \end{cases} \tag{36}$$

4.1.5 Monetary Policy

Since the Home economy belongs to a currency union, its monetary policy adjusts interest rates so as to make sure that the nominal exchange rate is unchaged for all periods:

$$\Delta \xi_t = 0. \tag{37}$$

In doing so, the Home country gives up monetary autonomy. Given a fixed nominal exchange rate and uncovered interest parity, Homes interest rate in equilibrium follows the Foreign rate one-to-one. Finally, the monetary authority for the currency union adjusts interest rates according to the following Taylor rule:

$$R_t^*/R_{ss}^* = \left(R_{t-1}^*/R_{ss}^*\right)^{\gamma_{R^*}} \ \pi_t^{*\gamma_\pi(1-\gamma_{R^*})} \left(Y_t^*/Y_{t-1}^*\right)^{\gamma_{Y^*}(1-\gamma_{R^*})} \exp(\epsilon_{R^*}). \tag{38}$$

4.1.6 Aggregation and Market Clearing

Total borrowers' consumption, labor supply in the consumption and housing sectors, and housing are given by:

$$c_t' = \omega\, c_{v,t}' + (1-\omega)\ c_{f,t}' \tag{39}$$
$$n_{c,t}' = \omega\, n_{cv,t}' + (1-\omega)\ n_{cf,t}' \tag{40}$$
$$n_{h,t}' = \omega\, n_{hv,t}' + (1-\omega)\ n_{hf,t}' \tag{41}$$
$$h_t' = \omega\, h_{v,t}' + (1-\omega)\ h_{f,t}' \tag{42}$$

The aggregate consumption is given by:

$$C_t = c_t + c_t'; \tag{43}$$

and housing and goods market clear:

$$H_t = h_t + h_t', \tag{44}$$

$$IH_t = H_t - (1-\delta_h)\ H_{t-1}. \tag{45}$$

Finally, we define the real GDP measure defined in terms of home consumption goods for our economy:

$$Y_t = \left(\frac{P_{h,t}}{P_t}\right)^{-1} \ [(1-\nu)\ C_t + \nu\, RS_t\, C_t^*] \tag{46}$$

$$GDP_t = Y_t \frac{P_{h,t}}{P_t} + q_t\, IH_t \tag{47}$$

4.1.7 Equilibrium

In our model, the EA block can be treated as exogenous to the Home economy. The EA block is a standard New Keynesian economy with price stickiness. We dispense with a full description as the definition of equilibrium in this economy is standard.[21] Since there is no growth in this model, all variables are stationary. The model is solved with a second order perturbation method around the deterministic steady state.

[21] The full set of equilibrium equations can be found in the online appendix, Section H.

4.2 Calibration

We calibrate the model to the Spanish economy. We pick parameters to reflect quarterly data and to match well both the relevant long-term moments of the Spanish economy as well as short-term dynamics of the transmission of monetary policy shocks to the Spanish and EA economies. We have 24 parameters in our model, out of which 18 are calibrated and the remaining 6 are estimated. Table 5 summarises our calibration. We set $\beta^* = \beta = 0.9925$, implying a steady-state annual real interest rate of 3% both for Spain and the EA. The elasticity of substitution in intermediate goods consumption in both regions, ε^* and ε, is set at 7.66 in order to get a steady-state markup of 15%, as in Iacoviello and Neri (2010). The EA Taylor rule parameters regarding inflation and the output gap, γ_π and γ_y, are set according to Christoffel et al. (2008). For the lagged nominal interest rate parameter γ_r we choose a slightly lower value — 0.6 instead of 0.8 — because we want to match the EA HICP and GDP reactions to monetary policy shocks with the ones estimated in the DFM.

Table 5: Calibrated parameters.

Parameter	Value	Target
Euro Area		
β^*	0.9925	EA Steady-state annual real interest rate of 3%
ψ^*	0.5	Smets and Wouters (2003)
ε^*	7.66	Steady-state markup of 15%
γ_π	1.7	Christoffel et al. (2008)
γ_y	0.125	Christoffel et al. (2008)
γ_r	0.6	Christoffel et al. (2008)
Spain		
β	0.9925	EA Steady-state annual real interest rate of 3%
β'	0.97	Iacoviello and Neri (2010)
θ'	0.97	Iacoviello and Neri (2010)
ψ	0.5	Burriel et al. (2010)
ψ'	0.5	Burriel et al. (2010)
j	0.2	Housing wealth to GDP ratio in the steady-state of 3.5
δ_h	0.005	7% steady-state residential investment share of GDP
m	0.7	Average loan-to-value ratio in Spain, Calza et al. (2013)
ω	0.9	Share of adjustable-rate mortgages, Albertazzi et al. (2018)
ε	7.66	Steady-state mark-up of 15%
ϕ	0.78	Spain average price duration of 4.6 quarters, Alvarez et al. (2006)
α	0.68	Steady-state housing stock value share owned by wealthy hand-to-mouth household of 18%, Slacalek et al. (2020)

Following Iacoviello (2005) we fix the discount of the impatient households β' at 0.97 to ensure that a steady-state with binding borrowing constraint is accurate. We fix $\psi^* = \psi = \psi'$ to match a Frisch labor supply elasticity of 2 for the EA as in Smets and Wouters (2003), as well as for both savers and borrowers in Spain, in line with Burriel et al. (2010). Next, we pick the housing preference parameter j, which essentially governs the steady-state housing wealth-to-GDP ratio, to be at 0.2. This value twice the size of the parameter used in Iacoviello (2005) and Iacoviello and Neri (2010), as the ratio of housing wealth to GDP is much higher in Spain than in the US. According to Martínez-Toledano (2017), the housing wealth-to-GDP ratio for the time period we study was at approximately 3.5 in Spain. The quarterly housing depreciation rate δ_h is set at 0.005 which is consistent with an empirically reasonable 2% annual depreciation rate and with a steady-state residential investment share of GDP in Spain of approximately 7%. The institutional parameters on housing financing are taken from previous studies. The typical loan-to-value ratio in Spain reported in Calza et al. (2013) is 70%, while the average share of adjustable-rate mortgages is around 90% according to bank-level data reported in Albertazzi et al. (2018). The share of firms that do not reset prices each period ϕ is set at 0.78 in order to match the average price duration of 4.6 quarters in Spain as reported in Alvarez et al. (2006). Finally, the share of borrowing constrained agents α is set at 0.68 in order to match the share of housing stock in the hands of agents that face liquidity constraints to a level of 18% as reported in Slacalek et al. (2020).

Since we only include one shock in the economy, the remaining 6 parameters are estimated using a limited information approach. First, we pick the model variables that are of interest in relation with the observed heterogeneity found in the empirical section. Second, we select the following variables for the small open economy: GDP, aggregate consumption, inflation and housing prices. For the EA we pick GDP, nominal interest rates and inflation. Third, we estimate these parameters by minimizing a measure of the distance between the DFM's empirical impulse responses and the model responses. Let $\mathbf{\Gamma} \equiv (\xi^*, \phi^*, \xi, \xi', \delta, \nu)$ be a vector with the remaining 6 parameters, and let $\mathbf{\Psi}(\mathbf{\Gamma})$ denote the mapping from the deep parameters $\mathbf{\Gamma}$ to the model impulse response functions. Further, let $\hat{\mathbf{\Psi}}$ denote the corresponding empirical DFM estimates. We include the first 20 elements of each response function. Our estimator of $\mathbf{\Gamma}$ is the solution to

$$J = \min_{\mathbf{\Gamma}} \left[\hat{\mathbf{\Psi}} - \mathbf{\Psi}(\mathbf{\Gamma})\right]' \boldsymbol{V}^{-1} \left[\hat{\mathbf{\Psi}} - \mathbf{\Psi}(\mathbf{\Gamma})\right], \tag{48}$$

where $\boldsymbol{V}$ is a weighting matrix. We choose $\boldsymbol{V}$ to be the inverse of the matrix with the sample variances of the DFM's impulse responses on the main diagonal. Table 6 summarizes our point estimates and standard errors of the parameters in vector $\mathbf{\Gamma}$. The point estimates we get are in line with the previous literature and are precisely estimated.[22] The point estimate for the habit formation parameter in the EA ξ^* is 0.78 which is reasonably close to the 0.69 estimated in Adolfson et al. (2007). The point estimate for the Calvo price parameter in the EA ϕ^* is 0.88, in line with both Smets and Wouters (2003) and Adolfson et al. (2007). The point estimates for the parameter on habit formation in consumption for savers and borrowers, ξ and ξ', are 0.84 and 0.8, respectively.

[22]Standard errors were computed using the asymptotic delta function method applied to the first-order condition associated with the minimization problem.

These are consistent with the value of 0.847 reported in Burriel et al. (2010). The point estimate for the parameter on labor mobility between sectors of savers δ is 0.66, which surprisingly is identical to the estimate reported in Iacoviello and Neri (2010). Finally, we get a slightly lower home bias estimate $1-\nu$ of 0.73 than the 0.81 reported in Burriel et al. (2010). In Figure 25 we show that the theoretical impulse response functions based on estimated parameters are reasonably close to their empirical counterparts.

Table 6: Estimated parameters and their standard errors.

Parameter	Value	S.E.
Euro Area		
ζ^*	0.78	0.006
ϕ^*	0.88	0.005
Spain		
ζ	0.84	0.019
ζ'	0.8	0.006
θ	0.66	0.168
ν	0.27	0.015

4.3 Quantitative Exercise: one money, many housing markets

In this section, we delve into an assessment of the extent to which differences in institutional characteristics of mortgage markets alone can account for the heterogeneity in monetary policy transmission in the EA. To this end, we take the model calibrated to the Spanish economy, and feed it with the loan-to-value (LTV) ratios and shares of adjustable-rate mortgages (ARM) for Spain as well as the other EA countries. We then compare the dispersion of the simulated impulse response functions using the model, with the dispersion estimated using our DFM. In other words, we look at how different the transmission of monetary policy in Spain would be if this country had the LTV ratios and ARM shares of other EA member countries. A comment is in order concerning our methodology. One the one hand, the model's impulse response functions are not directly comparable to those obtained from the DFM because, by construction, we do not calibrate the model to each individual country. On the other hand, keeping all other parameters constant allows us to isolate the effect of changing the housing financing parameters on monetary policy transmission, consistent with the goal of our exercise.

In Table (7) we report loan-to-value ratios and the shares of Adjustable-rate mortgage in our EA sample countries. The discrepancy in these institutional characteristics is apparent. Notably, there are countries, such as Belgium and France, that combine a high LTV ratio with a low shares of ARM. For these reasons, we find it important to use both in the model, so to assess the impact of potentially counteracting forces.

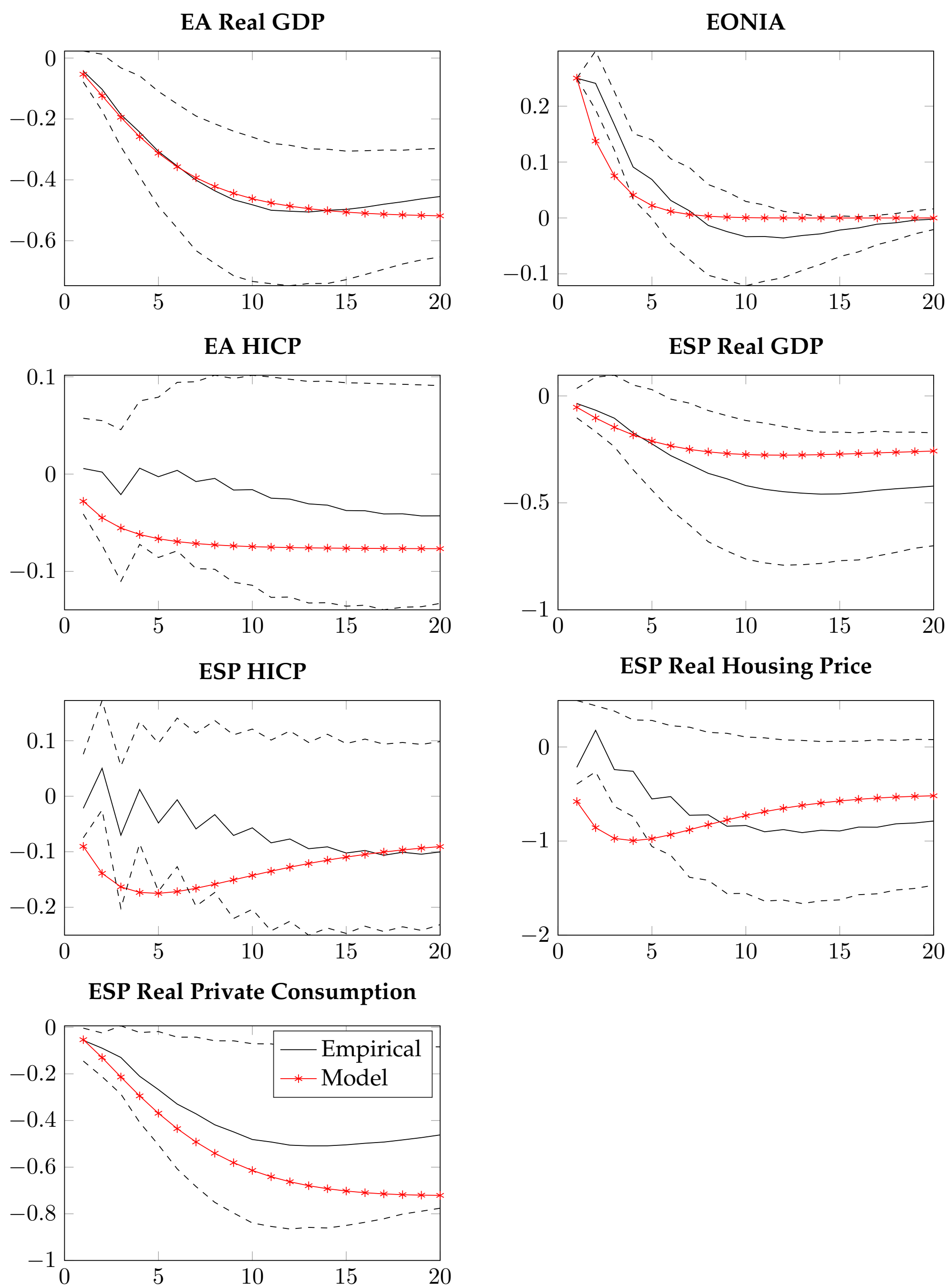

Figure 9: Model vs. empirical impulse response functions.

In Table 8 and Figures 10 - 12 we present the main results of the quantitative exercise.[23]

[23]Here we include only results from changing the mortgage market parameters. In the online appendix, Section I.2, we show how differences in Calvo pricing parameters generate differences in monetary policy transmission. We find that differences in price stickiness generate more dispersion in GDP responses to monetary policy shocks than in housing prices and private consumption responses, which is at odds with our empirical findings. More importantly, the responses implied by the model with different Calvo parameters are not in line with the individual country responses estimated in the DFM.

Table 7: Institutional parameters of EA countries' mortgage systems.

Country	LTV ratio	ARM share
BEL	0.83	0.20
DEU	0.7	0.15
IRL	0.74	1.00
ESP	0.7	0.90
FRA	0.75	0.15
ITA	0.5	0.70
LUX	0.8	0.60
NLD	0.9	0.10
AUT	0.6	0.50
PRT	0.85	0.98
FIN	0.75	0.98

Source: Calza et al. (2013) and Albertazzi et al. (2018).

Our main results are fourfold. First, differences in LTV ratios generate more dispersion in the responses of consumption, output, and housing prices to monetary shocks than differences in the shares of ARM. This result follows from comparing the different columns of Table 8, which show how much of the dispersion in the DFM responses at different horizons (steps) is explained by the model, when we feed the LTV ratios and shares of ARM of the countries in our sample. Both on impact and at the 8th and 20th step, the variation in LTV ratios generates a substantially higher level of dispersion in GDP, housing prices, CPI, and private consumption. This result stands in contrast to the numerical illustration by Calza et al. (2013), suggesting that LTV ratios and the share of ARM are roughly equivalent in explaining the impulse responses. In our calibrated model, differences in the observed shares of ARM generate relatively smaller differences in the macro and price responses to monetary shocks. Furthermore, under the reasonable assumption that the share of ARM correlates with the households' net interest rate exposure, our results are also in line with the result shown in Figure 7 of Slacalek et al. (2020). These authors show that large differences in net interest rate exposure across Germany, France, Spain, and Italy, have a minimal effect on the response of consumption to monetary policy shocks in these countries.

Second, in Figure 10 through (12), we plot the responses from the DFM against the responses from the model obtained from changing either LTV ratios, or the share of ARM, or both. A key result from comparing the figures is that the correlation is weak for LTV ratios, strong for the share of ARM. In other words, while feeding the model with different LTV ratios generates a high level of dispersion in the IRFs, the majority of the simulated responses do not align with the DFM responses. By way of example, in Figure 10 bottom right corner, the model predicts that, at the 20th step, the most negative response of private consumption (PCON) is obtained by using the Netherlands LTV ratio, which is the highest in our countries sample. At the same time, however, in the estimated DFM, the PCON response in the Netherlands is average relative to other countries.

This is in contrast with the results from feeding different shares of ARM: the model's IRFs have a high correlation with those estimated in the DFM. In Figure 11, this high correlation is apparent for output and consumption. The R-square from a linear regression for output is 0.48 for the impact response and 0.5 at the 8th step.[24] For consumption, the R-square is 0.63 at impact and 0.79 at the 8th step. So, an important conclusion from our exercise is that, while varying the relative share of ARM does not generate sizeable heterogeneity in monetary policy transmission, it does help the model to generate IRFs that are more in line with the evidence from DFM's.

Third, when we use both LTV ratios and the shares of ARM from the data, the model can account for approximately one-third of the estimated dispersion of the IRFs to a monetary policy shock for GDP and private consumption. The simulated responses are remarkably in line with the DFM's. In Figure (12), for GDP and consumption, the R-squared at the 8th step is 0.21 and 0.41, respectively. Using our institutional parameters jointly produces heterogeneity in monetary policy transmission that is both sizeable and in line with the evidence. Nonetheless, the correlation is much weaker for the other two variables[25], which brings us to our final result.

Fourth, we find that differences in LTV ratios, alone or when combined with differences in the shares of ARM, generate substantial variation in housing prices at the 8th and 20th step. Yet, the simulated variation is not in line with what we observe in the data. One possible reason for this puzzling[26] result is that the response of housing prices to monetary shocks are not precisely estimated by our DFM, while output and consumption are. Housing prices clearly deserve further investigation.

Overall, in addition to providing novel and disaggregated empirical and quantitative evidence on the role of different institutional features of housing financing, our analysis lends support to the empirical findings of Calza et al. (2013), obtained using a different methodology. Also, they are in line with the back-of-the-envelope calculation using a HANK model in Slacalek et al. (2020), which shows how the monetary policy transmission in the EA is affected by differences in households' balance sheets across countries. The link between our results and those in Slacalek et al. (2020) is best understood in light of the fact that, in equilibrium, different institutional parameters for mortgage markets imply differences in the compositions of households' balance sheets.

Our analysis has notable implications for macroprudential policy. While previous studies, such as Arena et al. (2020), have focused on uncovering the effect of macroprudential policies on housing prices, our work highlights the potential for such measures to shape the monetary transmission mechanism. Our results suggest that national macroprudential policies, reflected in the share of

[24]The R-square is computed here from a linear regression where the slope coefficient is constrained to be 1. We impose this restriction to grasp how much of the DFM responses gap relative to the mean can be explained by the model responses relative to their mean—allowing for differences on these means (hence, we do not restrict the intercept). When fitting a linear regression with a constrained slope, it is possible to get negative R-squares when the correlation between the model and the DFM responses is negative.

[25]Varying the parameters related to housing financing does not generate sizable heterogeneity in HICP responses. The observed heterogeneity in HICP responses to monetary shocks may nonetheless be rooted in differences in other markets, such as the labor market (see Campolmi and Faia (2011)).

[26]The puzzle stems from the fact that previous literature (see e.g. Mian et al. (2013) and Berger et al. (2018)) has shown a relevant direct link between housing prices and consumption responses.

adjustable mortgage rates and the loan-to-value ratio, can either amplify or dampen the transmission of ECB policy to a particular country. They provide quantitative insight on how a high degree of harmonisation of macroprudential regulation across countries can result in a more homogeneous transmission of monetary policy across the block.

Table 8: Coefficient of variation of the cross-country responses to a 25bp monetary policy shock — estimated DFM vs. model.

Variable	Coefficient of Variation (CoV)				$\mathrm{CoV}_{\mathrm{Model}}/\mathrm{CoV}_{\mathrm{DFM}}$ (%)		
	DFM	LTV	ARM	LTV + ARM	LTV	ARM	LTV + ARM
On Impact							
GDP	0.95	0.53	0.17	1.18	55.97	17.36	123.43
Housing Prices	2.39	0.01	0.02	0.04	0.42	0.85	1.73
HICP	1.39	0.28	0.00	0.27	19.89	0.07	19.55
PCON	1.04	0.34	0.02	0.34	32.60	2.16	33.15
At the 8th Step							
GDP	0.56	0.18	0.02	0.20	32.26	4.26	35.47
Housing Prices	1.39	0.30	0.02	0.24	21.52	1.26	16.98
HICP	1.44	0.12	0.12	0.17	8.58	8.40	11.93
PCON	0.76	0.30	0.08	0.26	39.33	11.15	34.44
At the 20th Step							
GDP	0.51	0.19	0.02	0.17	36.72	4.66	33.37
Housing Prices	1.47	0.38	0.17	0.30	25.95	11.48	20.65
HICP	1.16	0.09	0.05	0.08	7.57	4.73	6.90
PCON	0.75	0.19	0.14	0.20	24.84	18.57	27.12

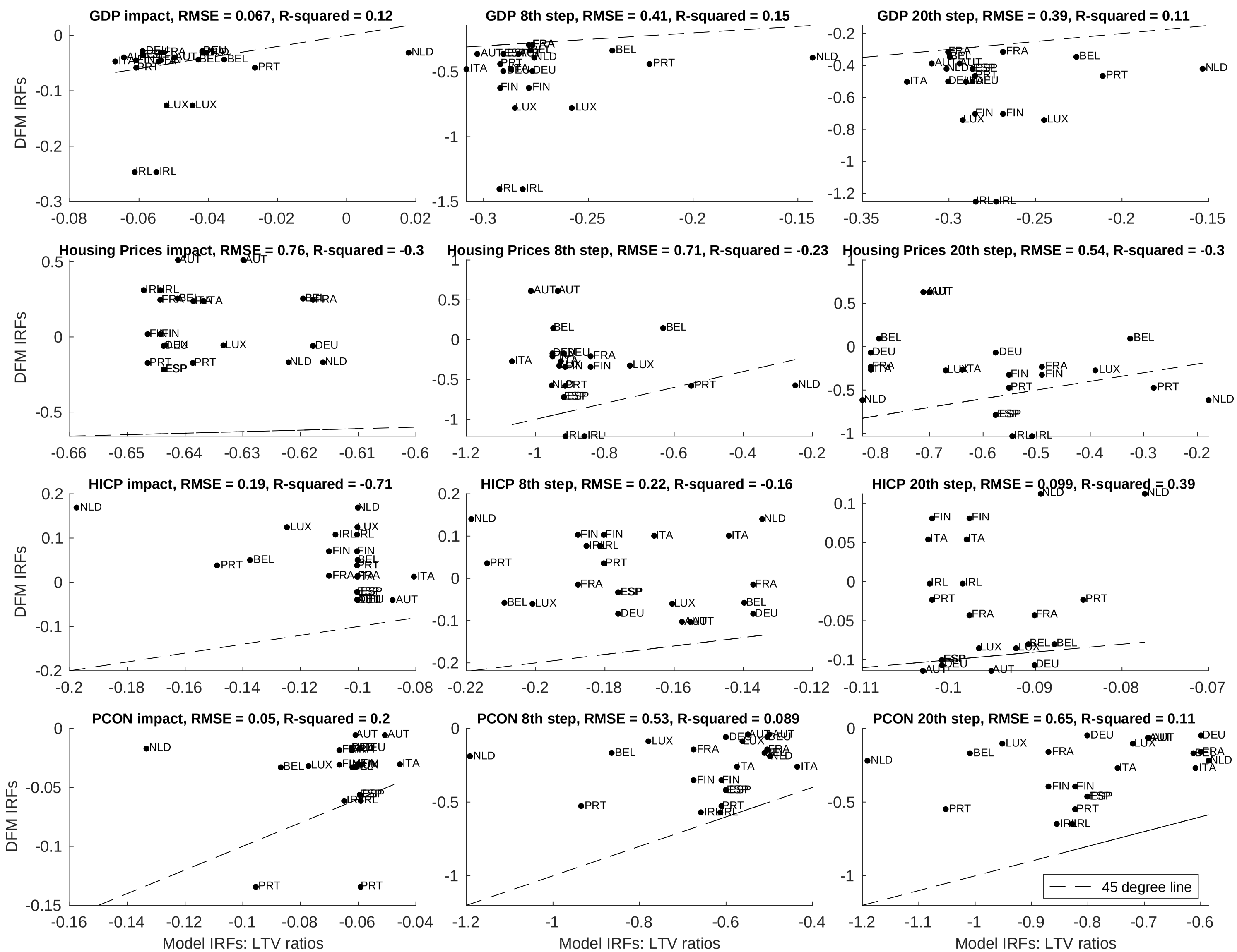

Figure 10: Impulse response functions of analytical model featuring different LTV ratios, compared to DFM. We plot the analytical model's responses on the x-axis and the estimated responses from the DFM on the y-axis, together with the 45 degree line, for our main variables of interest — GDP, housing prices, HICP, and private consumption (PCON). The rows of the figure depict scatter plots for different variables while the columns present them by the response steps — on impact, at the 8th step, and at the 20th step after the shock hits.

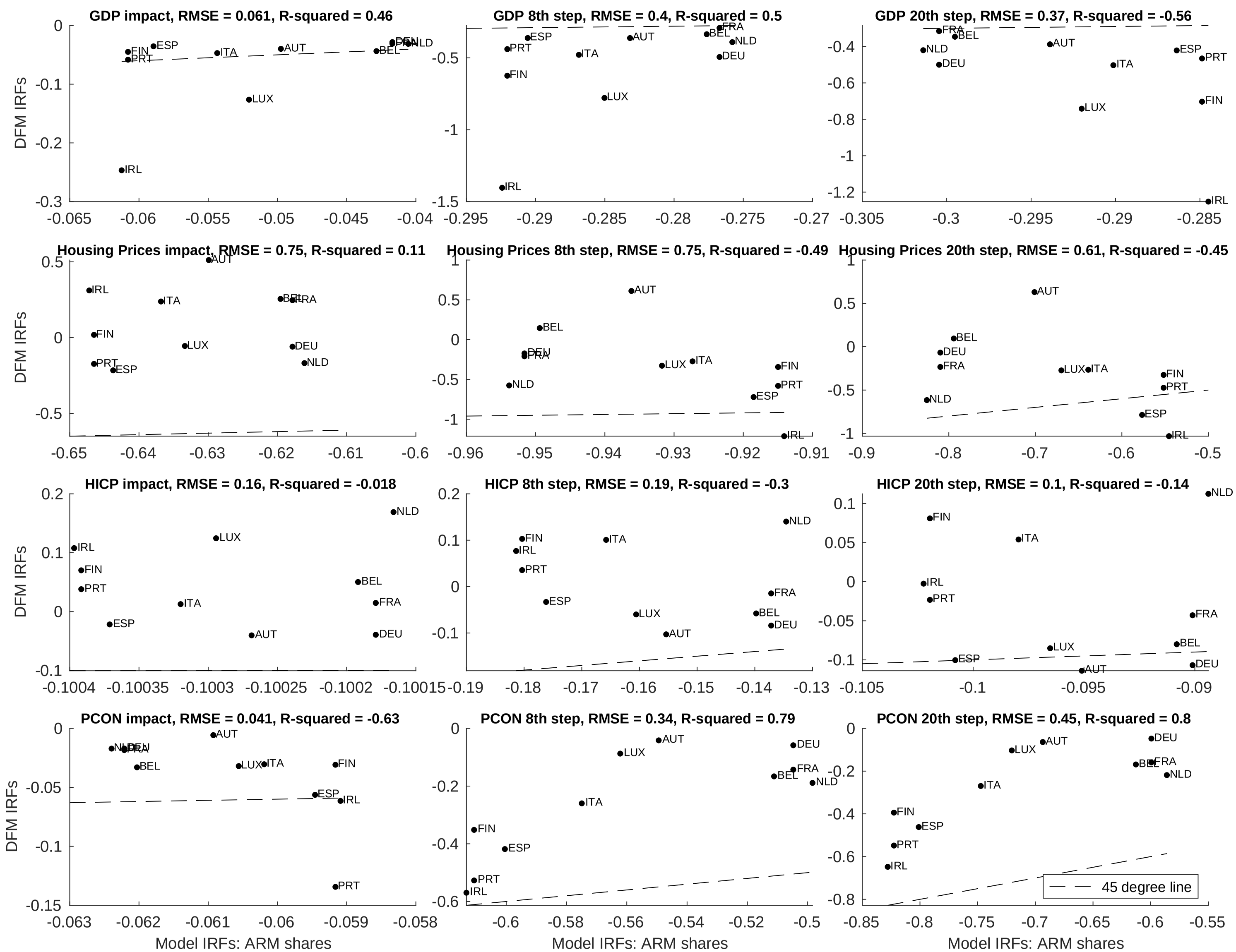

Figure 11: Impulse response functions of analytical model featuring different shares of ARM, compared to DFM. We plot the analytical model's responses on the x-axis and the estimated responses from the DFM on the y-axis, together with the 45 degree line, for our main variables of interest — GDP, housing prices, HICP, and private consumption (PCON). The rows of the figure depict scatter plots for different variables while the columns present them by the response steps — on impact, at the 8th step, and at the 20th step after the shock hits.

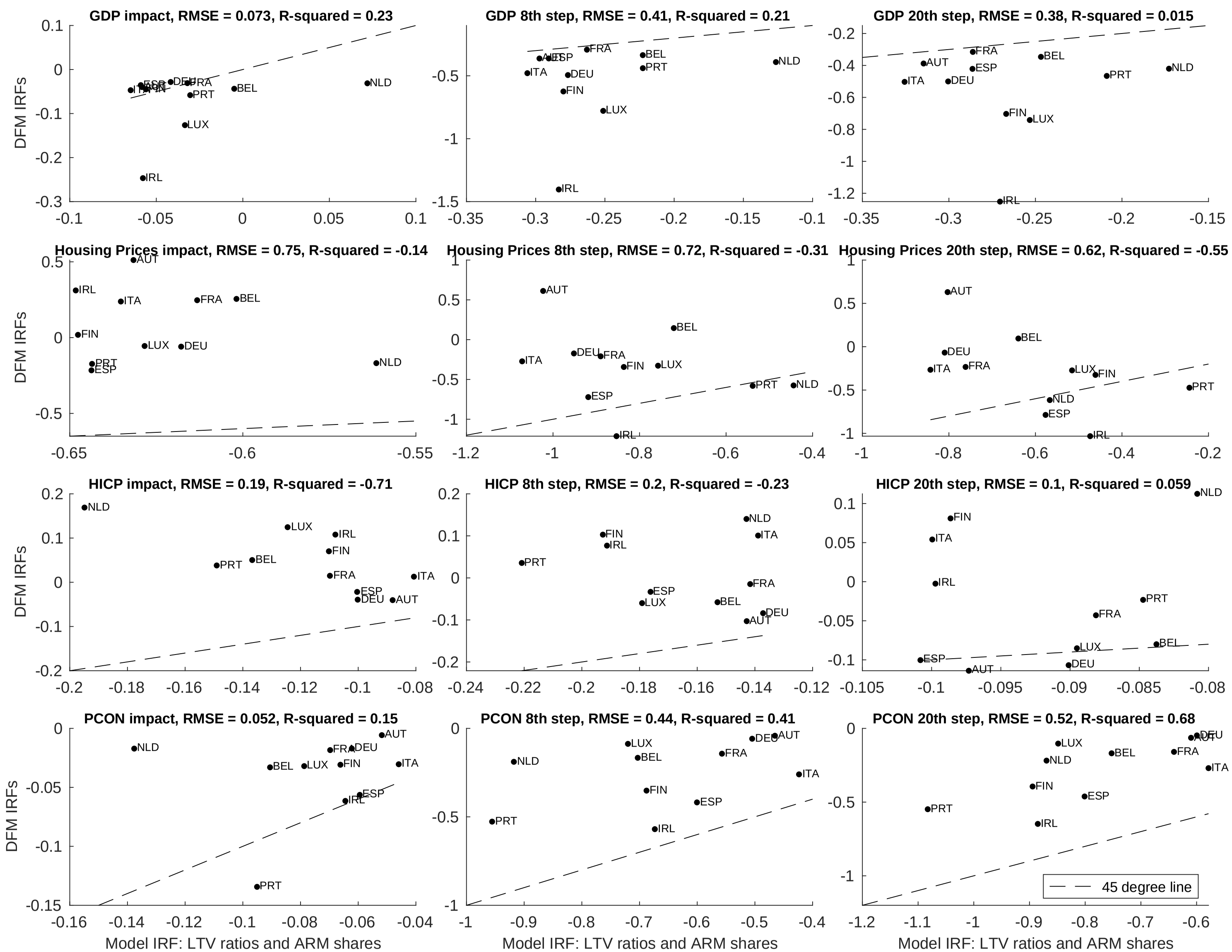

Figure 12: Impulse response functions of analytical model featuring different LTV ratios and shares of ARM, compared to DFM. We plot the analytical model's responses on the x-axis and the estimated responses from the DFM on the y-axis, together with the 45 degree line, for our main variables of interest — GDP, housing prices, HICP, and private consumption (PCON). The rows of the figure depict scatter plots for different variables while the columns present them by the response steps — on impact, at the 8th step, and at the 20th step after the shock hits.

5 Conclusion

Using a dynamic factor model with high-frequency identification, this paper investigates the heterogeneous effects of monetary policy across the euro area. We contribute to the literature a measure of the degree of heterogeneity in the effects of monetary policy. Focusing on housing financing as a case study, we provide quantitative evidence and insight into institutional determinants of country-specific transmission mechanisms.

In our findings, across all variables of interest, the average dispersion of country-specific responses to a monetary shock is twice the size of the mean response. There are, however, significant differences across variables. Country-level financial variables and output react fairly similarly across borders: the dispersion in their responses is low—20 to 50% of the average response at EA level. On the contrary, variables naturally related to markets that have experienced little convergence, such as housing and labour markets, react in significantly asymmetric ways. This is novel evidence lending empirical support to the idea that the degree of heterogeneity is inversely related to the degree of cross-border institutional convergence.

We elaborate on this point with a case study of European housing markets. We build a model of a small open economy featuring housing, operating in a monetary union. We use this model to quantitatively assess how much of the variation in individual country-level responses to a EA monetary policy shock can be explained by differences in housing financing. We find that differences in mortgage market characteristics across the EA explain one-third of the cross-country heterogeneity of responses in output and private consumption.

Other features of the housing market can be expected to weigh on the transmission of monetary policy. By way of example, prima facie evidence points to a specific role of the share of home ownership.[27] In addition, our methodology could be extended to the analysis of institutional divergences in other markets, such as national labor markets. These are promising and intriguing areas that we leave to future research.

[27] See the working paper version of this text, Corsetti et al. (2018)

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Online Appendix - Not for Publication

A Selecting the Number of Factors - Additional Figures

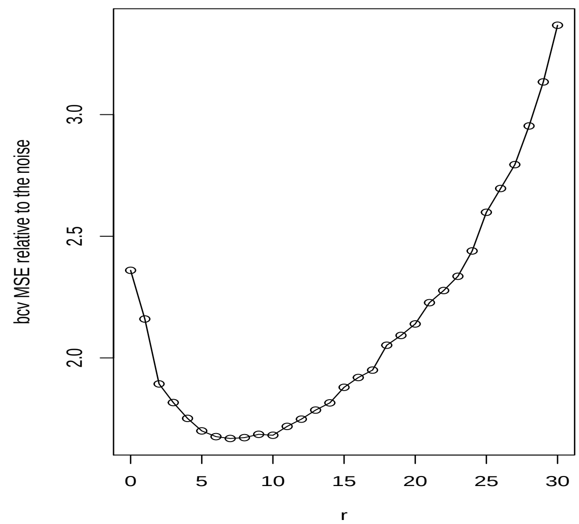

Figure 13: Bi-cross-validation method proposed by Owen et al. (2016)

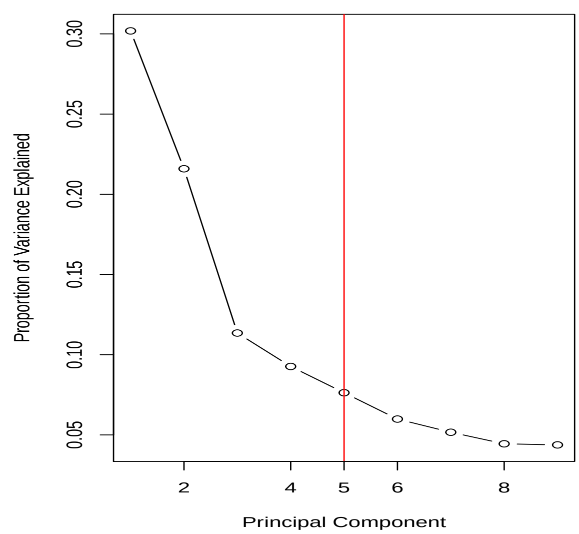

Figure 14: Variance explained by each additional factor

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.

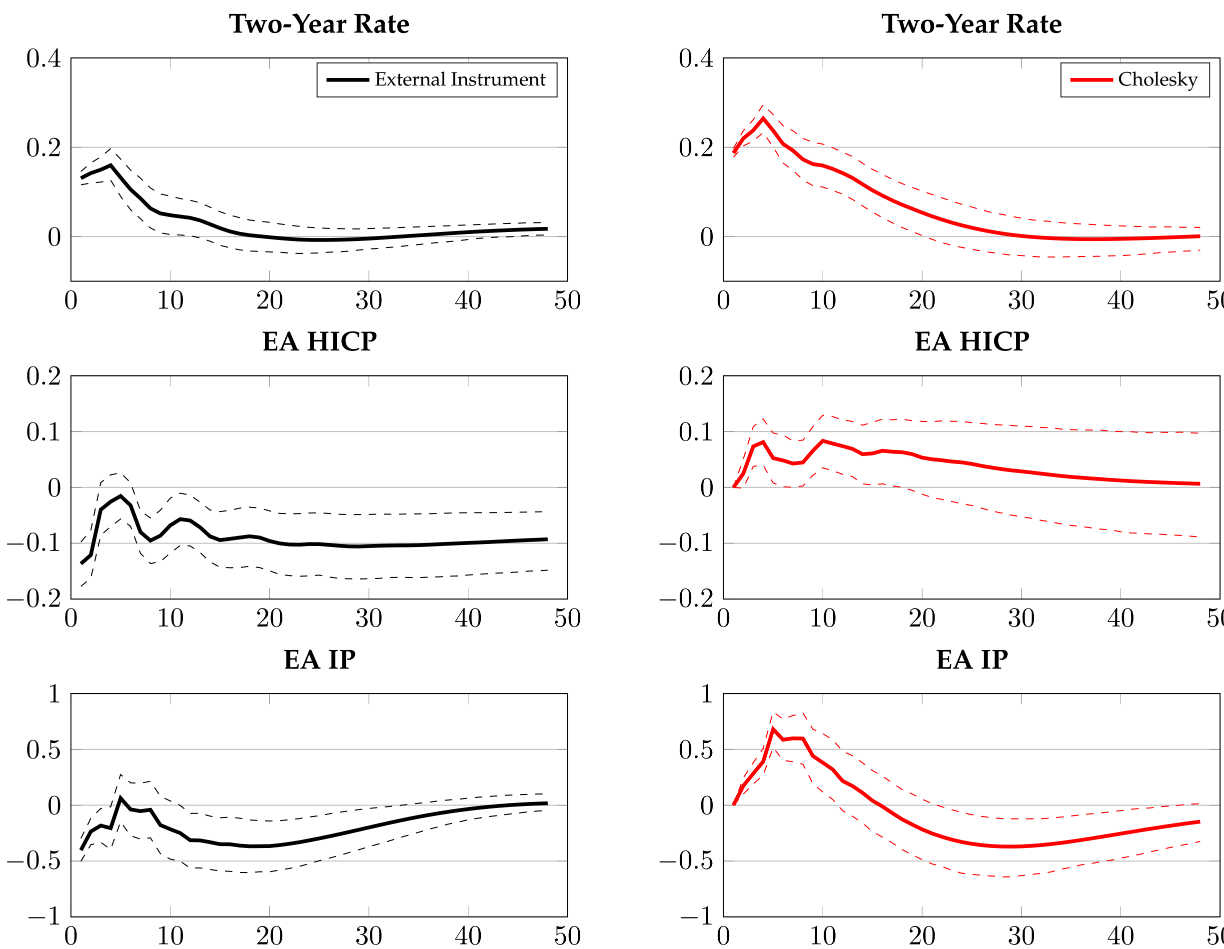

Figure 15: VAR using monthly data from 2000 to 2016. Here we show the responses to a one standard deviation shock in the policy indicator, comparing the high-frequency identification with a Cholesky identification strategy. The dashed lines report the bootstrapped 68% confidence intervals. The Cholesky 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%.

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 15. 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 16 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 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.

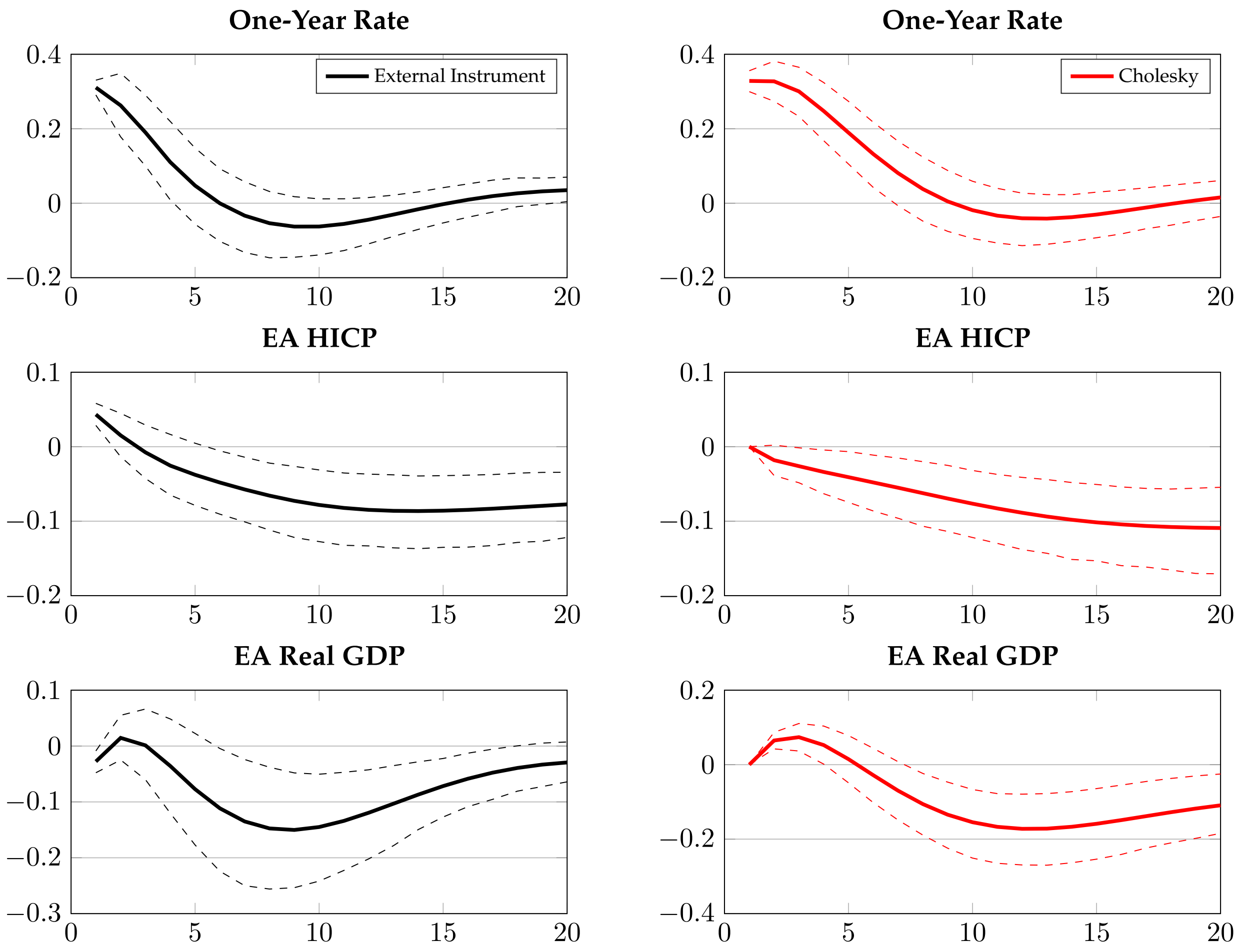

Figure 16: VAR using quarterly data from 2000 to 2016. Here we show the responses to a one standard deviation shock in the policy indicator using the high-frequency identification and the Cholesky identification. The dashed lines report the bootstrapped 68% confidence intervals. The Cholesky identification 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%.

Figure 17 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.

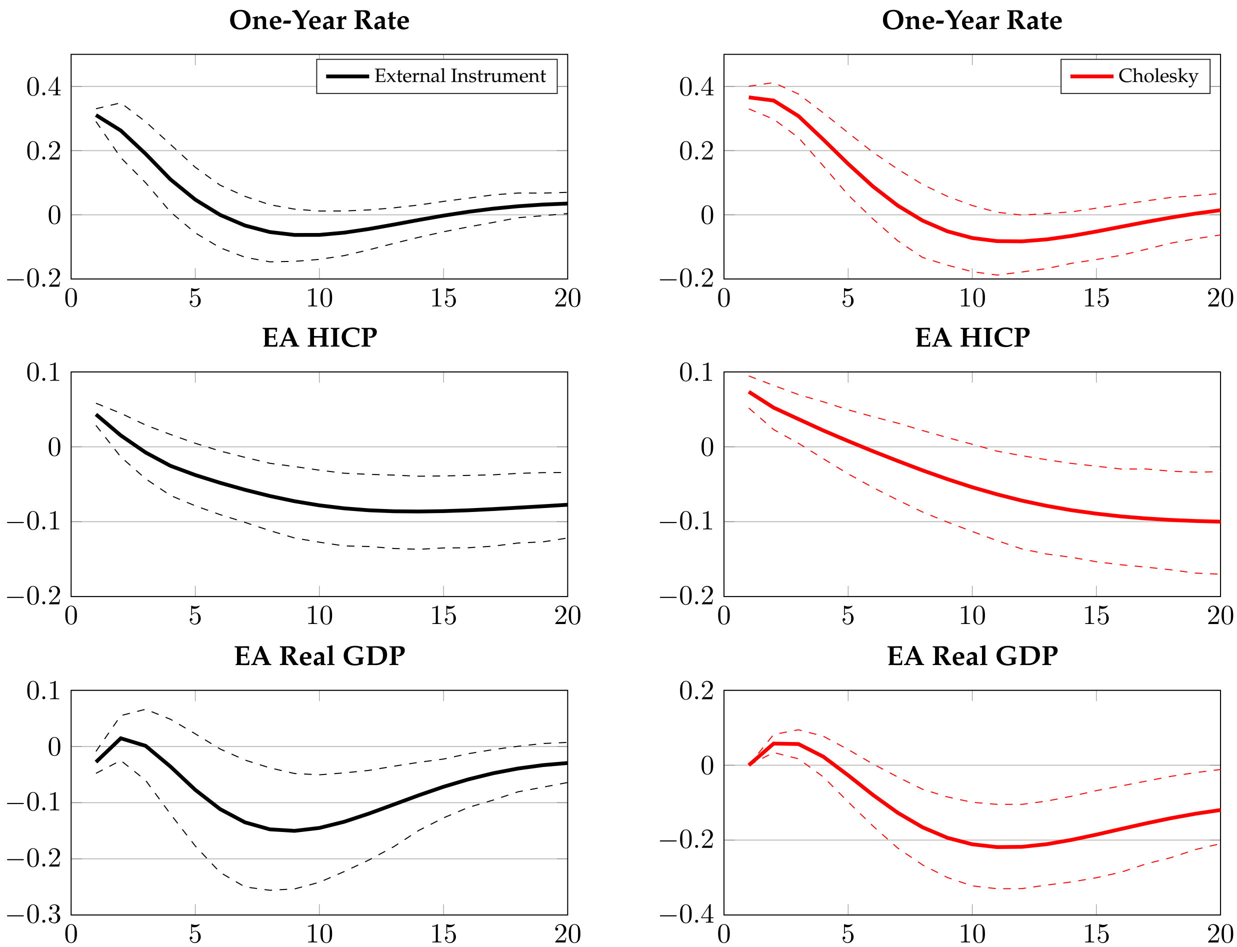

Figure 17: VAR using quarterly data from 2000 to 2016. Here we show the responses to a one standard deviation shock in the policy indicator using high-frequency and Cholesky identification. The dashed lines report the bootstrapped 68% confidence intervals. Here, the Cholesky identification orders the consumer prices last. The F-test for the first-stage regression on the external instrument is 19.45 and the R^2 is 22%.

C Data Set

Table 9 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 housing 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 housing 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 10, 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 10: 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
Factor 1	Producer Prices in Industry	0.67
	Harmonised Index of Consumer Prices	0.56
	Industrial Turnover Index, Manufacturing	0.53
	Compensation of Employees	0.49
	Gross Fixed Capital Formation Price Index	0.48
Factor 2	Cost of Borrowing for Households for House Purchase	0.49
	6-month Euribor	0.45
	1-year Euribor	0.45
	3-month Euribor	0.44
	Long-term Interest Rate Belgium	0.43
Factor 3	Government Spending Italy	0.61
	Unit Labour Cost Germany	0.61
	Government Spending Finland	0.61
	Unit Labour Cost Luxembourg	0.60
	Unit Labour Cost Italy	0.60
Factor 4	Unemployment Italy	0.63
	Unemployment Netherlands	0.49
	Real Housing Prices Ireland	0.44
	Unemployment Finland	0.43
	Real Housing Prices France	0.43
Factor 5	Real Housing Prices Netherlands	0.46
	GDP Spain	0.40
	Private Consumption Spain	0.33
	Housing Prices Netherlands	0.32
	Gross Fixed Capital Formation in Construction	0.32

E Explanatory Power of Factors

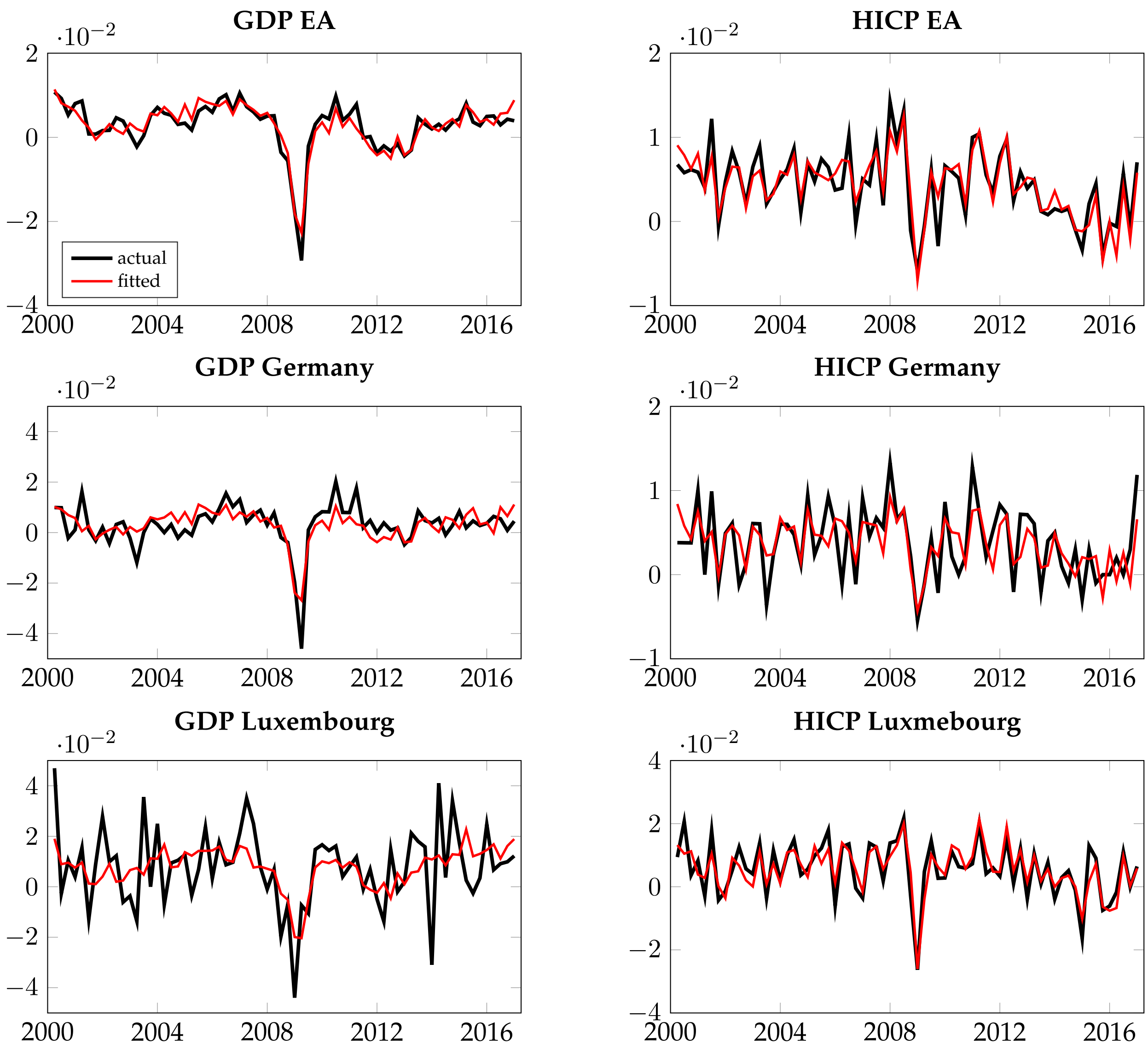

Figure 18: The figure compares actual (transformed) GDP and HICP data with corresponding fitted series on the basis of 5 extracted factors for the euro area (EA), Germany and Luxembourg from 2000 Q1 to 2016 Q4. Germany and Luxembourg represent the largest and smallest economies in our sample euro area, 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

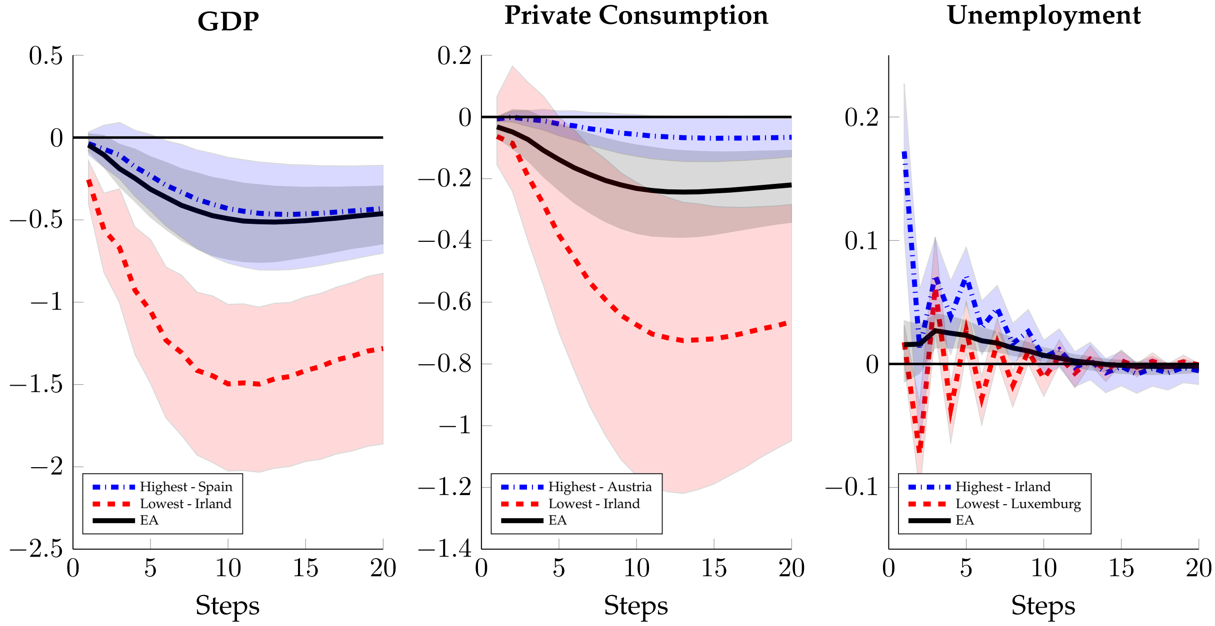

Figure 19: Highest/lowest percentage responses of selected real variables to a 25bp contractionary policy shock across euro area member countries.

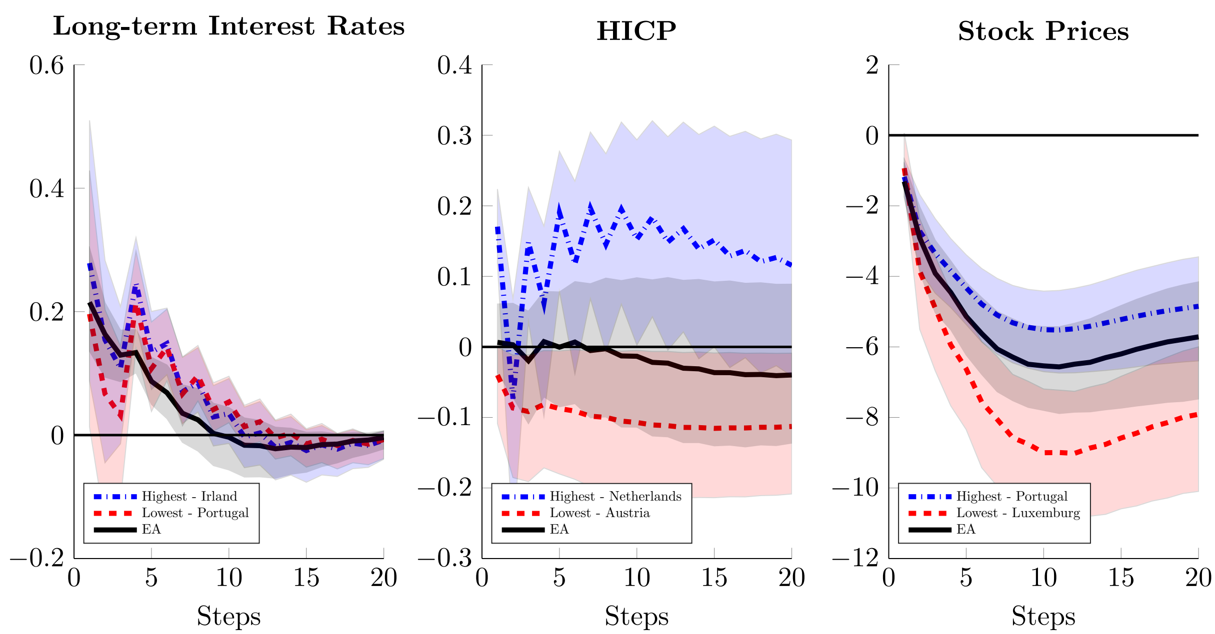

Figure 20: Highest/lowest percentage responses of selected prices to a 25bp contractionary policy shock across euro area member countries.

G Robustness

G.1 Sub-sample Analysis

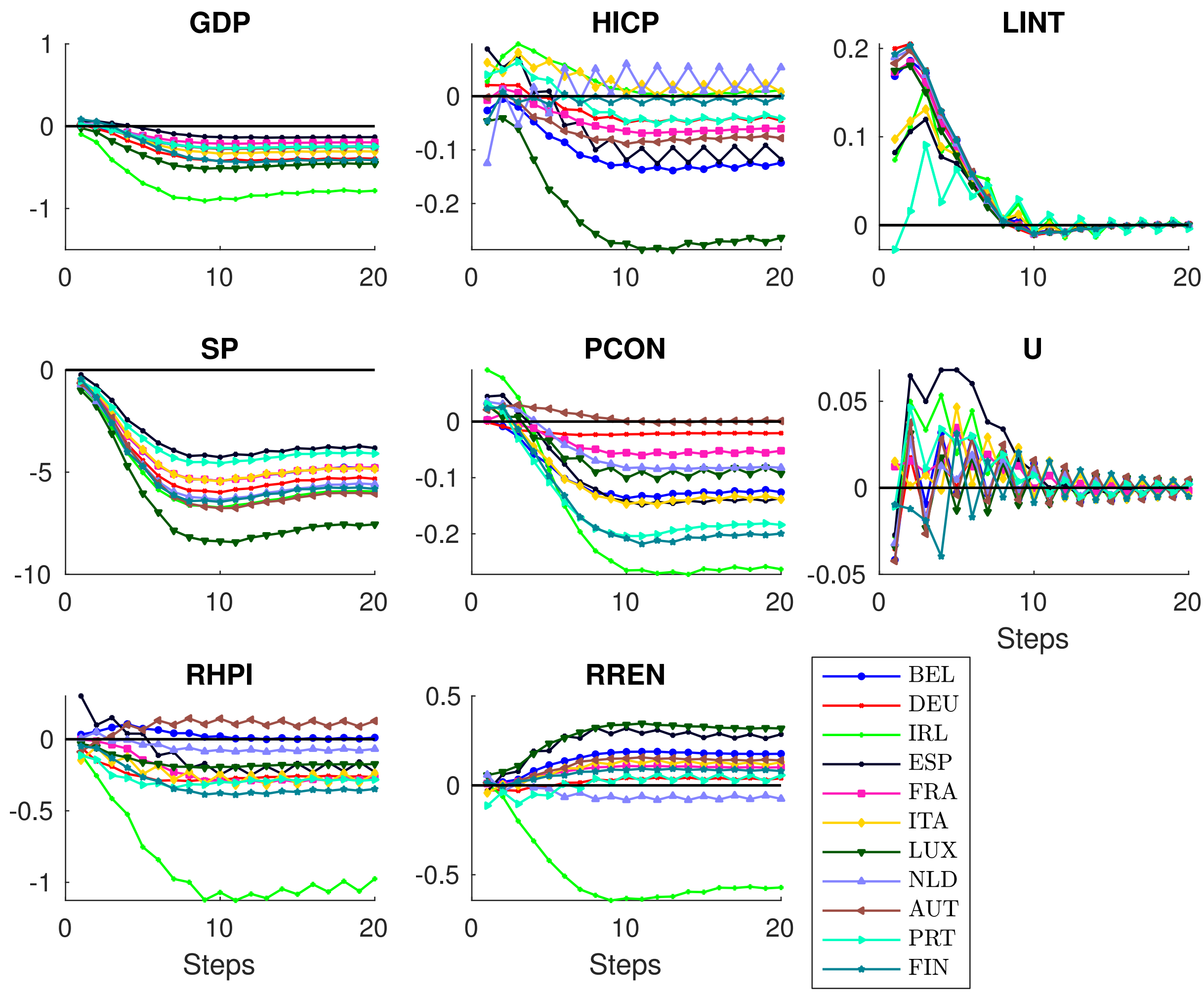

Figure 21: Cross-country impulse responses for selected variables when the model is estimated for the pre-crisis 2001Q1 to 2007Q4 period.

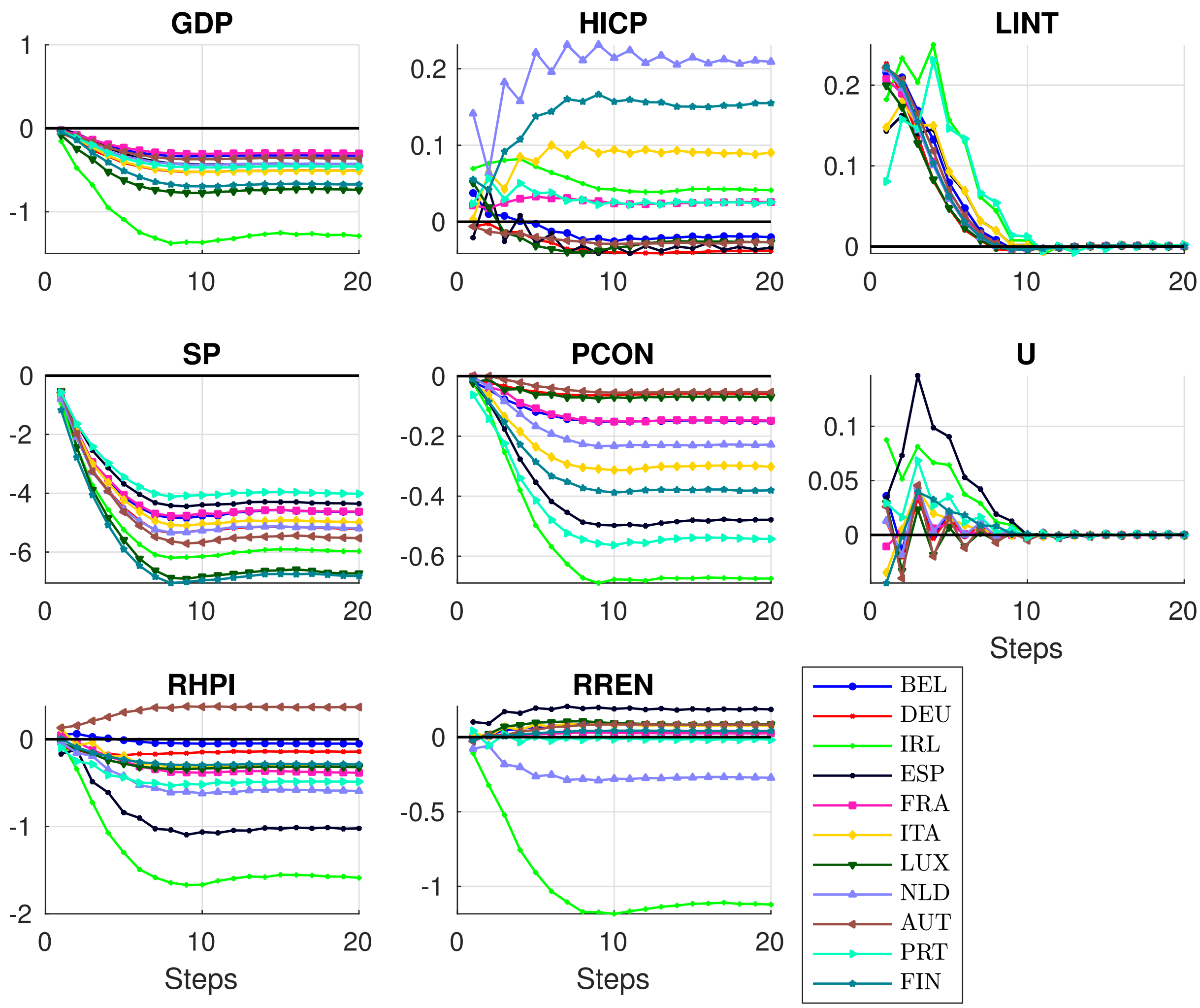

Figure 22: Cross-country impulse responses for selected variables when the model is estimated for the post-crisis 2008Q1 to 2016Q4 period.

H Model Equations

H.1 Home Economy Block

Patient households:

$$\left(n_{c,t}{}^{1+\theta} + n_{h,t}{}^{1+\theta}\right)^{\frac{\psi-\theta}{1+\theta}} \; n_{c,t}{}^{\theta} = u_{c,t} \, \frac{W_{c,t}}{P_t} \tag{A.1}$$

$$\left(n_{c,t}{}^{1+\theta} + n_{h,t}{}^{1+\theta}\right)^{\frac{\psi-\theta}{1+\theta}} \; n_{h,t}{}^{\theta} = u_{c,t} \, \frac{W_{h,t}}{P_t} \tag{A.2}$$

$$u_{c,t} \, q_t = \frac{j}{h_t} + \beta \, E_t \left(u_{c,t+1} \, q_{t+1} \; (1 - \delta_h)\right) \tag{A.3}$$

$$u_{c,t} = \beta \, E_t \left(u_{c,t+1} \, R_t / \pi_{t+1}\right) \tag{A.4}$$

$$u_{c,t} = (c_t - \zeta \, c_{t-1})^{-1} - \beta \, \zeta \; (c_{t+1} - \zeta \, c_t)^{-1}$$

$$u_{c,t+1} = (c_{t+1} - \zeta \, c_t)^{-1} - \beta \, \zeta \; (c_{t+2} - \zeta \, c_{t+1})^{-1}$$

Impatient households:

$$\left(n'_{ci,t}{}^{1+\theta'} + n'_{hi,t}{}^{1+\theta'}\right)^{\frac{\psi'-\theta'}{1+\theta'}} \; n'_{ci,t}{}^{\theta'} = u'_{ci,t} \, \frac{W'_{c,t}}{P_t}, \quad \text{for } i = \{c, f\} \tag{A.5}$$

$$\left(n'_{ci,t}{}^{1+\theta'} + n'_{hi,t}{}^{1+\theta'}\right)^{\frac{\psi'-\theta'}{1+\theta'}} \; n'_{hi,t}{}^{\theta'} = u'_{ci,t} \, \frac{W'_{h,t}}{P_t}, \quad \text{for } i = \{c, f\} \tag{A.6}$$

$$b'_{i,t} = m \, E_t \left(q_{t+1} \, h'_{i,t} \, \pi_{t+1} / R_{i,t}\right), \quad \text{for } i = \{c, f\} \tag{A.7}$$

$$\begin{aligned} c'_{i,t} + q_t \, h'_{it} = b'_{it} + n'_{ci,t} \, \frac{W'_{c,t}}{P_t} + n'_{hi,t} \, \frac{W'_{h,t}}{P_t} - \frac{R_{i,t-1}}{\pi_t} \, b'_{it-1} + \\ q_t \; (1 - \delta_h) \; h'_{it-1}, \quad \text{for } i = \{c, f\} \end{aligned} \tag{A.8}$$

$$\begin{aligned} u'_{ci,t} \, q_t = \frac{j}{h'_{it}} + E_t \left(u'_{ci,t+1} \, q_{t+1} \; (1 - \delta_h)\right) + \\ E_t \left(\lambda_{i,t} \, m \, q_{t+1} \, \pi_{t+1} / R_{i,t}\right), \quad \text{for } i = \{c, f\} \end{aligned} \tag{A.9}$$

$$u'_{ci,t} = \lambda_{i,t} + \beta' E_t \left(u'_{ci,t+1} \, R_{i,t} / \pi_{t+1}\right), \quad \text{for } i = \{c, f\} \tag{A.10}$$

$$u'_{ci,t} = \left(c'_{i,t} - \zeta' \, c'_{i,t-1}\right)^{-1} - \beta' \, \zeta' \; \left(c'_{i,t+1} - \zeta' \, c'_{i,t}\right)^{-1}, \quad \text{for } i = \{c, f\}$$

$$u'_{ci,t+1} = \left(c'_{i,t+1} - \zeta' \, c'_{i,t}\right)^{-1} - \beta' \, \zeta' \; \left(c'_{i,t+2} - \zeta' \, c'_{i,t+1}\right)^{-1}, \quad \text{for } i = \{c, f\}$$

$$R_{i,t} = \begin{cases} R_t, & \text{if } i = v \\ \bar{R}_t, & \text{if } i = f \end{cases}$$

Terms of trade and identities:

$$\frac{P_{h,t}}{P_t}^{\phi^*-1} = RS_t{}^{\phi^*} \tag{A.11}$$

$$\pi_t = \pi_{h,t}{}^{1-\nu} \, \pi_t^{*\nu} \tag{A.12}$$

$$u^*_{ct} = u_{c,t} \, RS_t \tag{A.13}$$

Consumption sector firms:

$$Y_t = {n_{c,t}}^{\alpha}\, {n'_{c,t}}^{1-\alpha} \tag{A.14}$$

$$n_{c,t}\, w_{c,t} = Y_t\, \alpha\, mc_t \tag{A.15}$$

$$n'_{c,t}\, w'_{c,t} = Y_t\, (1-\alpha)\, mc_t \tag{A.16}$$

$$\pi_{h,t} = \left(\phi + (1-\phi)\, \bar{\pi}_t^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}} \tag{A.17}$$

$$\bar{\pi}_t = \frac{\varepsilon}{\varepsilon - 1} \frac{a_t}{b_t} \tag{A.18}$$

$$a_t = \pi_{h,t} \left(Y_t\, \frac{P_{h,t}}{P_t}\, mc_t + \beta\, \phi\, \Lambda_{t,t+1}\, {\pi_{h,t+1}}^{-(1-\varepsilon)}\, a_{t+1} \right)$$

$$b_t = \frac{P_{h,t}}{P_t}\, Y_t + \beta\, \phi\, \Lambda_{t,t+1}\, {\pi_{h,t+1}}^{-(1-\varepsilon)}\, b_{t+1}$$

$$\Lambda_{t,t+1} = \frac{u_{c,t+1}}{u_{c,t}}$$

Residential investment sector firms:

$$IH_t = {n_{h,t}}^{\alpha}\, {n'_{h,t}}^{1-\alpha} \tag{A.19}$$

$$IH_t\, q_t\, \alpha = n_{h,t}\, w_{h,t} \tag{A.20}$$

$$IH_t\, q_t\, (1-\alpha) = w'_{h,t}\, n'_{h,t} \tag{A.21}$$

Financial intermediaries firms:

$$\bar{R}_t^{opt} = \frac{E_t \sum_{\tau=t+1}^{\infty} \beta^{\tau-(t+1)} \Lambda_{t+1,\tau} R_{\tau-1}}{E_t \sum_{\tau=t+1}^{\infty} \beta^{\tau-(t+1)} \Lambda_{t+1,\tau}} \tag{A.22}$$

$$\bar{R}_t = \begin{cases} \frac{\bar{R}_{t-1}\, b'_{f,t-1} + \bar{R}_t^{opt} (b'_{f,t} - b'_{f,t-1})}{b'_{f,t}}, & \text{if } b'_{f,t} > b'_{f,t-1} \\ \bar{R}_{t-1}, \quad \text{if } b'_{f,t} \leq b'_{f,t-1} \end{cases} \tag{A.23}$$

Aggregation and market clearing:

$$c'_t = c'_{v,t}\, \omega + c'_{f,t}\, (1-\omega) \tag{A.24}$$

$$n'_{c,t} = n'_{cv,t}\, \omega + n'_{cf,t}\, (1-\omega) \tag{A.25}$$

$$n'_{h,t} = n'_{hv,t}\, \omega + n'_{hf,t}\, (1-\omega) \tag{A.26}$$

$$h'_t = h'_{v,t}\, \omega + h'_{f,t}\, (1-\omega) \tag{A.27}$$

$$b'_t = b'_{v,t}\, \omega + b'_{f,t}\, (1-\omega) \tag{A.28}$$

$$C_t = c_t + c'_t \tag{A.29}$$

$$Y_t = \left(\frac{P_{h,t}}{P_t} \right)^{-1} \left[(1-\nu)\, C_t + \nu\, RS_t\, C_t^* \right] \tag{A.30}$$

$$IH_t = H_t - (1-\delta_h)\, H_{t-1} \tag{A.31}$$

$$H_t = h_t + h'_t \tag{A.32}$$

$$GDP_t = Y_t \frac{P_{h,t}}{P_t} + q_t\, IH_t \tag{A.33}$$

H.2 EA Economy Block

$$
\begin{aligned}
{n'_{h,t}}^{\psi^*} &= w_t^*\, u_{c,t}^* && \text{(A.34)}\\
\frac{\beta^*\, u_{c,t+1}^*}{u_{c,t}^*} &= \frac{\pi_{t+1}^*}{R_t^*} && \text{(A.35)}\\
u_{ct}^* &= \left(C_t^* - \zeta^*\, C_{t-1}^*\right)^{-1^*} - \beta^*\, \zeta^*\, \left(C_{t+1}^* - \zeta^*\, C_t^*\right)^{-1^*} &&\\
Y_t^* &= n^* && \text{(A.36)}\\
mc_t^* &= w_t^* && \text{(A.37)}\\
\pi_t^* &= \left(\phi^* + (1-\phi^*)\ {\bar{\pi}_t^*}{}^{1-\varepsilon^*}\right)^{\frac{1}{1-\varepsilon^*}} && \text{(A.38)}\\
\bar{\pi}_t^* &= \frac{\varepsilon^*}{\varepsilon^*-1}\,\frac{{a^*}_t}{{b^*}_t} && \text{(A.39)}\\
a_t^* &= \pi_t^*\ \left(Y_t^*\, mc_t^* + \beta^*\, \phi^*\, \Lambda_{t,t+1}^*\, {\pi_{t+1}^*}^{-(1-\varepsilon^*)}\, a_{t+1}^*\right) &&\\
b_t^* &= Y_t^* + \beta^*\, \phi^*\, \Lambda_{t,t+1}^*\, {\pi_{t+1}^*}^{-(1-\varepsilon^*)}\, b_{t+1}^* &&\\
\Lambda_{t,t+1}^* &= \frac{u_{c,t+1}^*}{u_{c,t}^*} &&\\
Y_t^* &= C_t^* && \text{(A.40)}
\end{aligned}
$$

Monetary Policy

$$
\begin{aligned}
\Delta\xi_t &= 0 && \text{(A.41)}\\
R_t^*/R_{ss}^* &= \left(R_{t-1}^*/R_{ss}^*\right)^{\gamma_{R^*}}\ {\pi_t^*}^{\gamma_\pi(1-\gamma_{R^*})}\left(Y_t^*/Y_{t-1}^*\right)^{\gamma_{Y^*}(1-\gamma_{R^*})}\exp(\epsilon_{R^*}) && \text{(A.42)}
\end{aligned}
$$

I Explaining heterogeneous transmission of monetary policy

I.1 With national institutional characteristics of mortgage systems

I.1.1 Figures

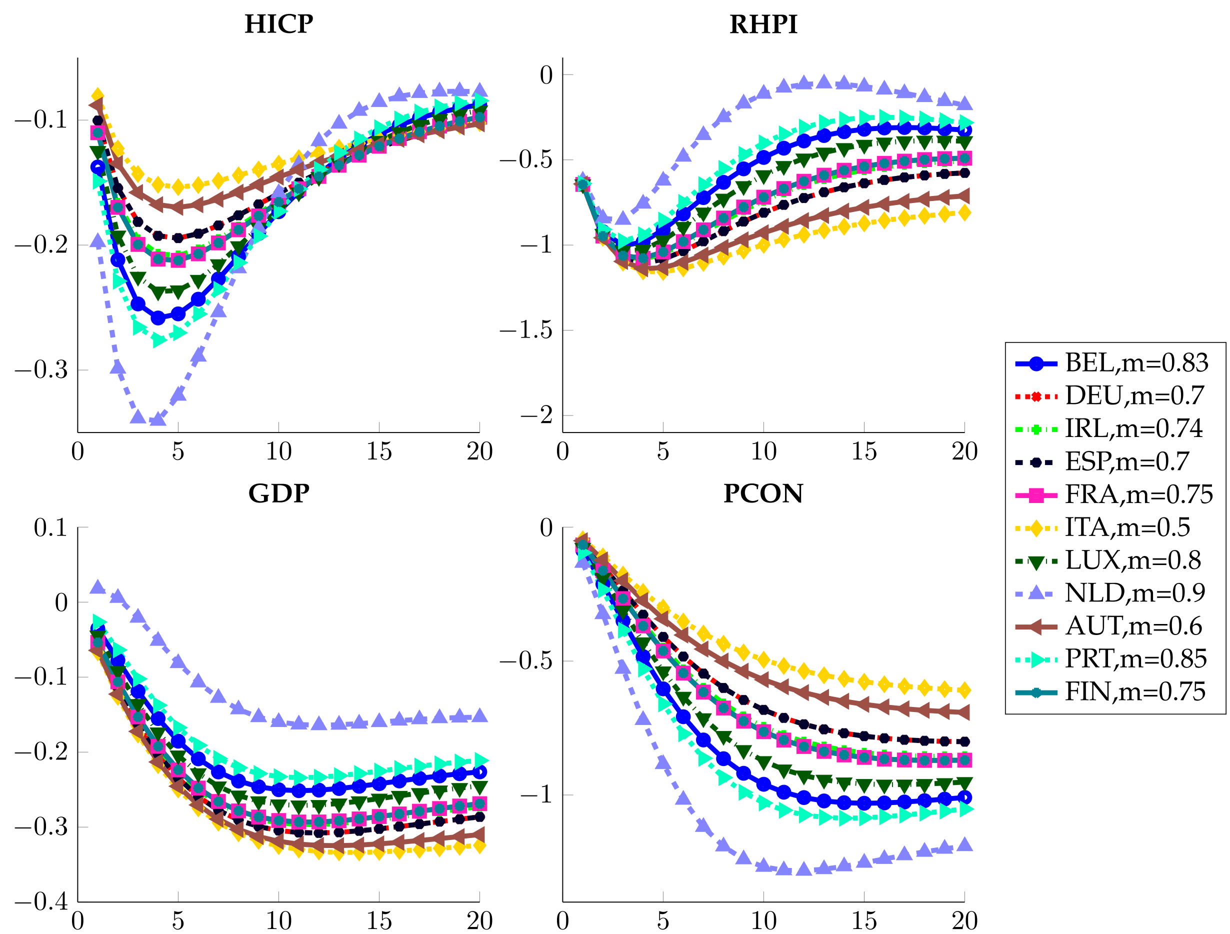

Figure 23: Model impulse response functions feeding in the LTV of each country.

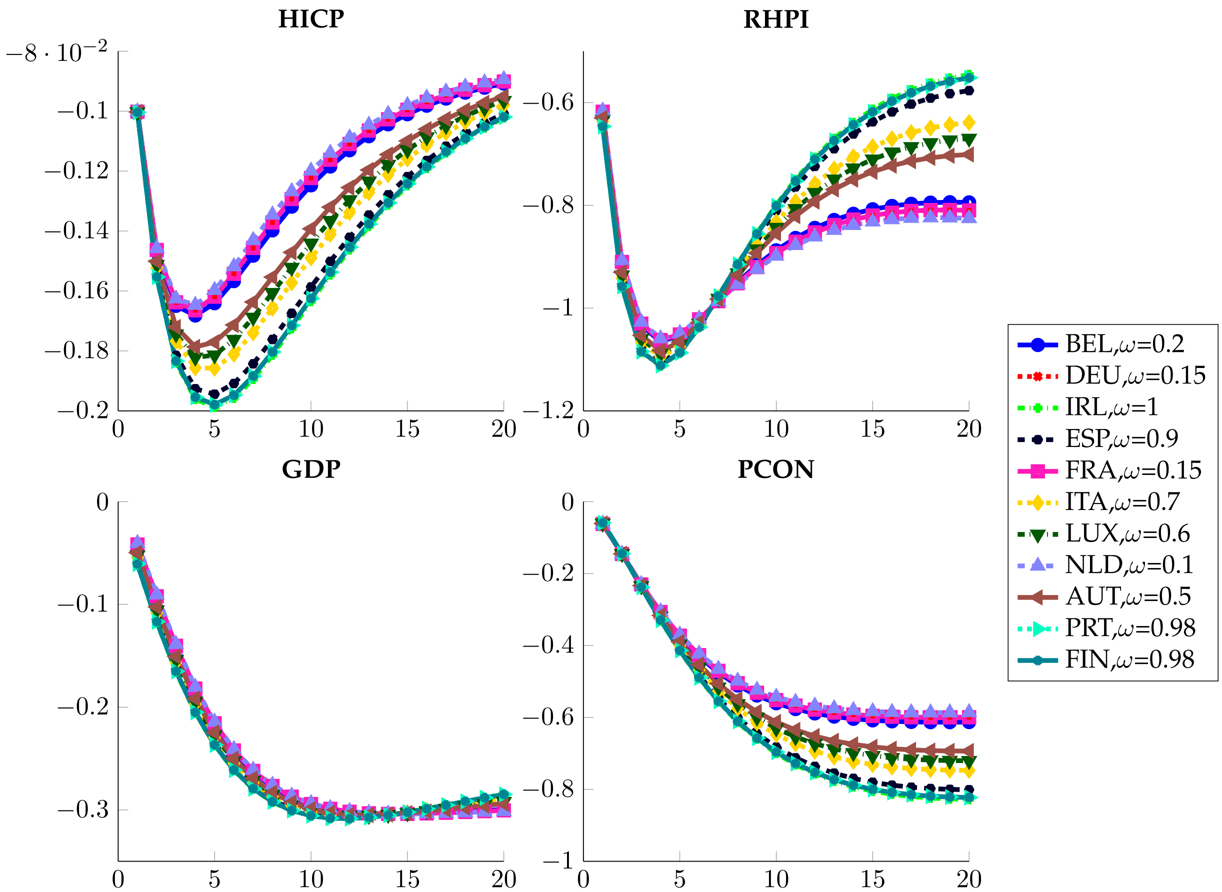

Figure 24: Model impulse response functions feeding in the ARM share of each country.

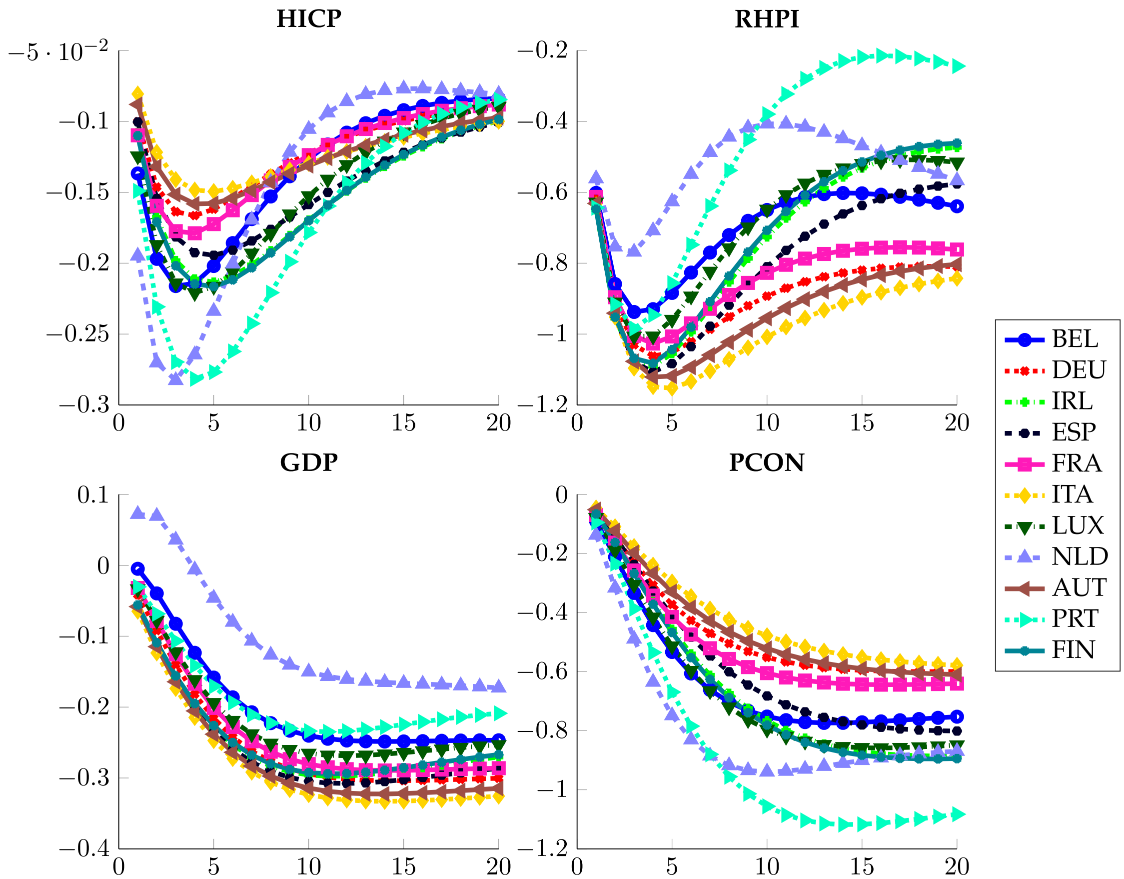

Figure 25: Model impulse response functions feeding in the LTV ratio and ARM share of each country.

I.2 With national price frequency adjustment

I.2.1 Table

Table 11: Coefficient of variation of the cross-country responses to a 25bp monetary policy shock - Theory vs. Data - Using Price stickness differences to explain observed responses dispersion.

Variable	Coefficient of Variation		Simulated/Data (%)
	Data	Simulated	
On Impact			
GDP	0.95	0.53	55.83
Housing Prices	2.39	0.12	4.94
HICP	1.39	0.46	32.92
PCON	1.04	0.18	17.22
At the 8th Step			
GDP	0.56	0.81	143.64
Housing Prices	1.39	0.40	28.81
HICP	1.44	0.03	2.43
PCON	0.76	0.26	34.46
At the 20th Step			
GDP	0.51	0.87	170.97
Housing Prices	1.47	0.54	36.87
HICP	1.16	0.04	3.50
PCON	0.75	0.26	35.28

I.2.2 Figure

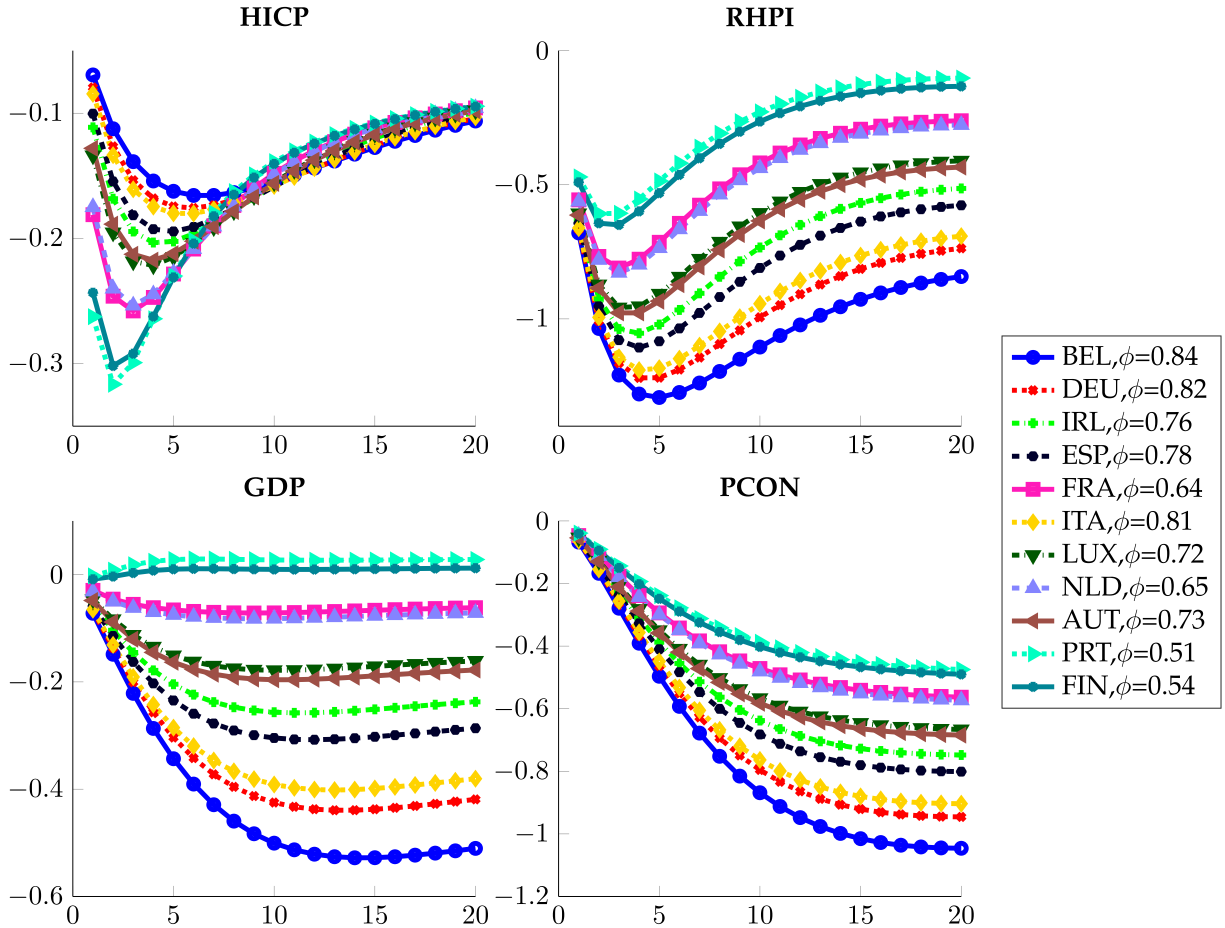

Figure 26: Model IRFs feeding in Average Price Duration of each country.

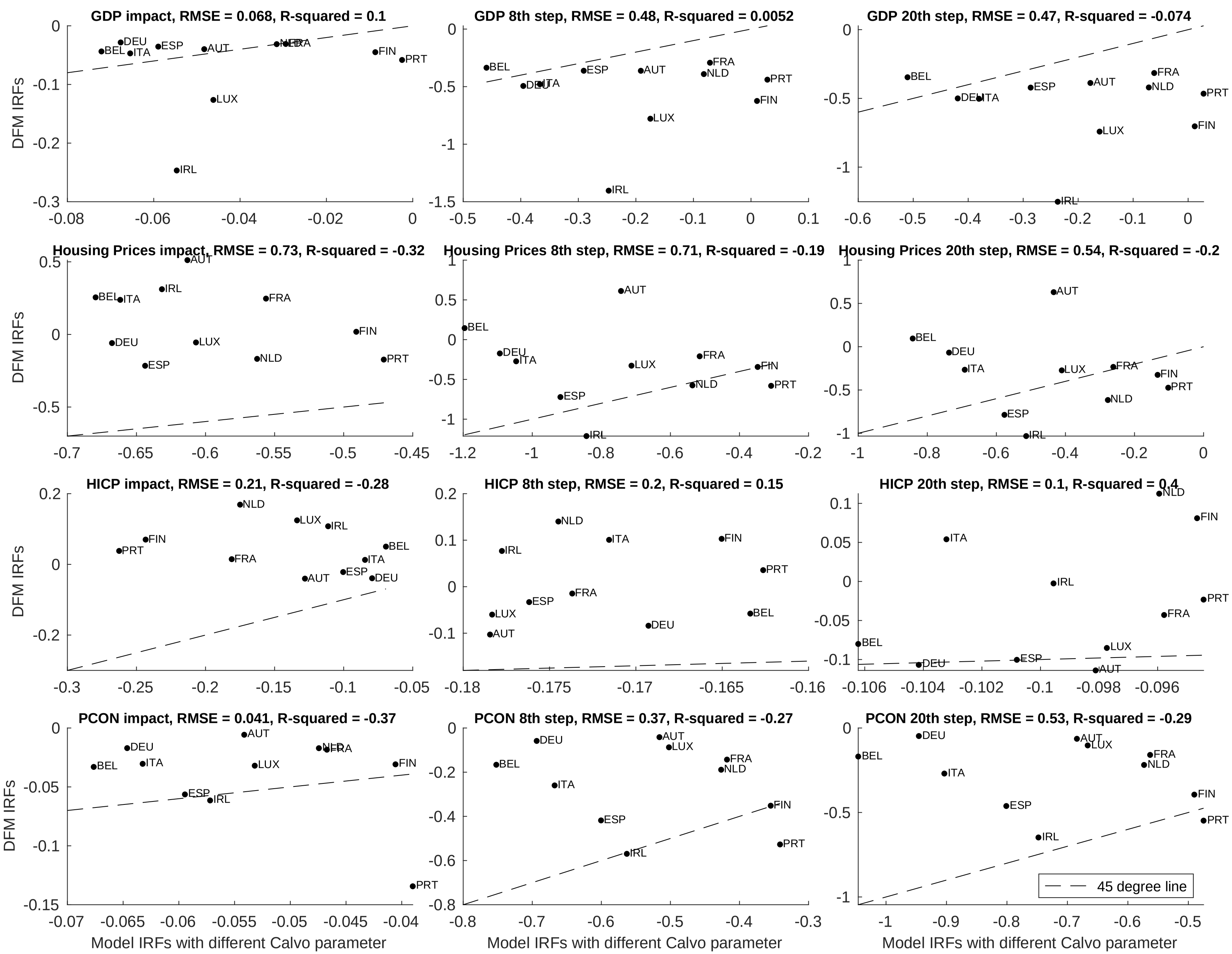

Figure 27: Impulse response functions of model when feeding different Calvo parameters compared to IRFs from DFM.