One Money, Many Markets*

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Abstract

We study heterogeneity in the transmission of monetary shocks across euro-area countries using a dynamic factor model and high-frequency identification. Deploying a novel methodology to assess the degree of heterogeneity, we find it to be low in financial variables and output but significant in consumption, consumer prices, and variables related to local housing and labour markets. We show that a large proportion of the variation in countries' responses to monetary shocks can be accounted for by differences in some characteristics of these markets across EA member countries: the share of adjustable mortgage contracts, homeownership rates, shares of hand-to-mouth and wealthy hand-to-mouth consumers, as well as wage rigidity.

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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 over time there has been some convergence in financial markets, the convergence process has slowed down markedly since the financial crisis (see ECB, 2017). Many markets have remained remarkably different across member countries. Most notably, the institutional background in labour and housing is still highly dissimilar across the currency block. In the light of a relatively slow integration process, policy and academic researchers have long been faced with two interrelated 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]

By having member countries with strikingly different institutional settings under the same monetary authority, the EA serves as a prime laboratory to study how institutional settings affect monetary transmission.[2] The institutional settings highlighted by earlier contributions as important factors in shaping monetary transmission include those resulting in different degrees of price and wage stickiness,[3] shares of hand-to-mouth consumers[4] and levels of employment protection.[5] More recently, new strands of the literature on monetary policy have highlighted the importance of housing,[6] and homeowners' liquid assets.[7] Finally, the transmission of monetary policy may differ across borders depending on the state of the national business cycle. In Bayoumi and Eichengreen (1992), diverging business cycle dynamics between core and periphery countries in the run-up to the formation of the EMU serve as motivation to debate whether monetary policy transmission can be expected to have the same effects in the two groups of countries.

In this paper, we provide novel empirical evidence on these issues, by developing a methodology suitable to analyzing and testing the degree of cross-country heterogeneity in the transmission of monetary policy. We set up a structural dynamic factor model (SDFM) 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 cross-border heterogeneity in the responses of a large set of macro variables to monetary policy shocks, including output, demand, asset prices, as

[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.

[2]While differences in institutional settings are smaller than in the EA, US states also present an interesting setting for studying how institutions affect the transmission of monetary policy shocks. Some examples of studies that explore transmission across US states include Beraja et al. (2019), which provides empirical evidence that regional variation in housing equity matters for the refinancing channel of monetary policy, and Furceri et al. (2019), which finds that monetary policy is transmitted mainly through the industry-mix and the housing market channels.

[3]Gordon (1990), Smets and Wouters (2003) and Christiano et al. (2005).

[4]Campbell and Mankiw (1989), Galí et al. (2007), Bilbiie (2008) and Broer et al. (2016).

[5]Smets and Wouters (2003).

[6]Iacoviello (2005), Rubio (2011), Calza et al. (2013), Ozkan et al. (2017) and Dias and Duarte (2019).

[7]Ravn and Sterk (2020), Kaplan et al. (2018) and Auclert (2019).

well as variables related to housing and labour markets. Moreover, we are able uncover patterns in the correlation between the observed heterogeneity and institutional and structural characteristics of countries. 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).

Our main empirical results are as follows. First, at the aggregate EA level, we find that results from the factor model are in line with theory. The responses of EA-wide macro variables have the expected sign and, notably, the transmission of monetary shocks does not suffer from the price puzzle, which has historically cast a shadow on identification in the VAR literature. Second, we find a remarkable dichotomy: the estimated country-level effects are significantly heterogeneous for 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 for financial variables (possibly reflecting the higher degree of integration in financial markets) as well as output (arguably reflecting offsetting movements of exports relative to other demand components). Third, we find that a large proportion of this variation in countries' responses to monetary shocks can be related to differences in housing market characteristics, such as the share of adjustable mortgage contracts and homeownership rates; differences in liquidity, as proxied by the shares of both "hand-to-mouth" consumers and "wealthy hand-to-mouth" consumers; as well as differences in labour market characteristics, as captured by wage rigidities. Conversely, we fail to detect heterogeneity in the response patterns associated with cross-border differences in loan-to-value ratios, price rigidities, employment protection, or total leverage.

While our analysis of the drivers of heterogeneity is exploratory, it adds value by uncovering aggregate stylised facts as a reference for policy and quantitative modelling, as well as further causal investigation. Specifically, our results suggest that the relatively homogeneous responses of overall economic activity may mask pronounced heterogeneity in demand composition—consumption, investment and net exports—which is consequential for the dynamics of growth and net foreign assets. Similarly, by relating response patterns to types of mortgages, homeownership rates, wealthy hand-to-mouth consumers and wage rigidities, our time series analysis can offer an aggregate test to discriminate between different mechanisms and guide model specification.

On methodological grounds, our main contribution consists of showing how to measure and statistically test heterogeneity in the responses of economic variables to a common shock, in a way that is amenable to both theoretical and empirical applications. Our point of departure is the observation that confidence intervals around impulse response functions, and Wald tests on the differences of these functions, can only test whether responses are statistically different from each other: they do not provide a measure of the *degree* of heterogeneity. To obtain such a measure, 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 (CV) 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. As a standardised statistical measure of the dispersion of impulse responses, the CV allows for an intuitive and meaningful comparison of variables. In this paper, we measure the degree of heterogeneity in the SDFM's 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.[8]

In specifying our empirical model, we build on the factor modeling literature developed in the 1970s[9] 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.

While closely following the methodology of Stock and Watson (2012) in constructing our SDFM, we identify monetary policy shocks with an external high-frequency instrument. This so-called external instrument approach overcomes the identification problem by employing information from outside the VAR, as opposed to the more common approach of imposing additional internal structure through timing or sign restrictions. 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.[10]

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 this literature, our contribution consists of showing 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.[11] We test for the relevance of the

[8]In related work, we use the CV to measure the heterogeneity in the simulated theoretical responses from varying model parameters, which can then be directly compared to its empirical counterpart.

[9]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).

[10]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.

[11]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.

series in a small VAR, confirming its validity as an external instrument. Based on historical tick data, Jarociński and Karadi (2020) 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.

The rest of the paper is organised 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 examines which institutional dimensions drive heterogeneity in the transmission of monetary policy. Section 5 concludes.

2 A Structural 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 dataset 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.[12] Recovering both the effects on the block and member countries raises a key trade-off. 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. A small data sample in the time dimension, as is the case 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

[12] 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.

to take account of the same information set. The SDFM achieves this. Finally, the dynamic factor model provides a format that is consistent with economic theory. We next address each of these points.

Since we use a dynamic factor model, we do not have to take a stand on specific observable measures corresponding to theoretical concepts, an argument convincingly put forward by Bernanke et al. (2005). Such an argument is particularly relevant in the EA context, as it is harder to construct observable Eurozone variables—taking 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 ECB 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.[13]

The state-space representation of the dynamic factor model also provides a clear link with economic theory, which in turn 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 SDFM approach pursued in this paper—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 on the grounds of efficiency gains. Ciccarelli et al. (2013) provide a further insightful discussion of the differences between these three approaches.

2.2 Empirical Framework

In using an SDFM to study the effects of monetary policy on EA countries, we follow the methodology proposed by Stock and Watson (2012). Written in its static form[14], the SDFM expresses an $n \times 1$ vector X_t of observed time series variables as a function of a small $r \times 1$ vector F_t of static factors and a mean-zero idiosyncratic component e_t, where both the latent factors and idiosyncratic

[13] In online appendix G.3 we show how the results change when we use aggregate data only to extract the factors. In terms of euro wide impulse response functions, we find that a price puzzle becomes present—consumer, producer prices and wages increase after a contractionary shock when the opposite is expected by standard monetary economics theories. As for cross-country impulse responses, we do not find them to be different with respect to the degree of heterogeneity in responses across variables.

[14] There is an alternative representation of the SDFM in its dynamic form. Let f_t be a $q \times 1$ vector of dynamic factors, $\Lambda = (\lambda_0, \lambda_1, \ldots, \lambda_p)$, p be the degree of the lag polynomial matrix $\lambda(L)$, where λ_h is the $n \times q$ matrix of coefficients on the hth lag in $\lambda(L)$, and $F_t = (f_t', f_{t-1}', \ldots, f_{t-p}')'$. Moreover, let $\Phi(L)$ be the matrix consisting of 1s,

terms are in general serially correlated:

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

$$F_t = \delta(L)F_{t-1} + \eta_t, \tag{2}$$

$$\eta_t = H\varepsilon_t, \tag{3}$$

where Λ is an $n \times r$ matrix of factor loadings, $\delta(L)$ is a $p \times r$ matrix of lag polynomials, η_t a vector of r innovations, H is a $r \times r$ matrix and ε_t is a vector of r uncorrelated structural shocks. We can interpret $\Lambda_i F_t$ as the common component of the ith variable, and e_{it} as its idiosyncratic component. Since the factors are unobserved, they are identified only up to arbitrary normalisations. We normalise it by imposing the restrictions that $n^{-1}\Lambda'\Lambda = I_r$ and $\Sigma_F = E(F_t F_t')$ is diagonal. Without loss of generality, we assume that the first structural shock is the monetary policy shock. Hence, we have from (3) that

$$\eta_t = \begin{bmatrix} H_1 & H_2 & \dots & H_r \end{bmatrix} \begin{bmatrix} \varepsilon_{mt} \\ \varepsilon_{2t} \\ \vdots \\ \varepsilon_{rt} \end{bmatrix}.$$

2.2.1 Structural Impulse Response Functions (SIRF)

With the SDFM at hand, we are interested in analyzing the effect of a monetary policy shock on all variables. This can be achieved by computing the SIRF. The SIRF traces out the dynamic causal effect on all n variables of a unit increase in ε_{mt}. To obtain it, first rewrite (2) as $\Phi(L)F_t = \eta_t$, where $\Phi(L) = I - \Phi_1 L - \cdots - \Phi_p L^p$. Second, substitute (3) into (2) to get $F_t = \Phi(L)^{-1}H_1\varepsilon_t$. Finally, substitute the result into (1) to get $X_t = \Lambda\Phi(L)^{-1}H_1\varepsilon_t + e_t$. The SIRF Ψ of a monetary policy shock is

$$\Psi = \Lambda\Phi(L)^{-1}H_1. \tag{4}$$

2.2.2 SIRF coefficient of variation (CV)

In order to have a quantitative measure of the degree of dispersion across a subset of variables $K_t \in X_t$ with size k, for the corresponding subset of SIRF we calculate the coefficient of variation statistic—the standard deviation of the subset of responses relative to the average of those responses. Relative to a simple standard deviation statistic, the CV has the advantage of allowing for a

0s, and the elements of $\Psi(L)$ and $\eta_t = G\nu_t$, where $G = [I_q \; 0_{q\times(r-q)}]'$, then the SDFM (1)-(3) can be rewritten as

$$X_t = \lambda(L)f_t + e_t$$
$$f_t = \Psi(L)f_{t-1} + \nu_t,$$
$$\nu_t = H\varepsilon_t.$$

meaningful comparison of dispersion between two different subsets $K_1, K_2 \in X_t$ with different means. For the subset of k variables, the sample CV is given by

$$CV(K) = \frac{\sigma(K)}{\mu(K)} = \frac{\sqrt{\frac{\sum_{i=1}^{k}(\Psi_i(K)-\bar{\Psi}(K))^2}{K-1}}}{\bar{\Psi}(K)}, \tag{5}$$

where $\Psi_i(K) = \Lambda_i(K)\Phi(L)^{-1}H_1$ and $\bar{\Psi}(K) = \frac{1}{k}\sum_{i=1}^{k}\Psi_i$. There is one important caveat in the use of the CV in the context of SIRF: When the mean value is close to zero, the coefficient of variation will approach infinity. Hence, for variables that have close to symmetrical responses with different signs, the CV will not be a useful statistic for measuring the degree of heterogeneity.

While Λ and $\Phi(L)^{-1}$ can be identified given data, H_1 cannot. Since the structural shocks are not observed, they cannot be identified without imposing further restrictions or external information into the SDFM. Given η_t, its variance-covariance matrix has $\frac{r^2+r}{2}$ parameters which are not enough to recover r^2 parameters. In the specific case of the monetary policy shock, we need to identify H_1 in order to be able to compute the statistics of interest: SIRF and CV. We deal with this identification issue in the next subsection.

2.3 Identification

This section turns to the identification of the monetary policy shocks in the SDFM. 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[15]. More recently, Olea et al. (2012) as well as others[16] 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. To identify the shock of interest, ε_{mt}, using the instrumental variable Z_t, the necessary conditions are:

[15] For robustness, in online appendix G.4, we estimate a FAVAR model assuming EONIA is observable and timing restrictions following the fast-slow approach proposed in Bernanke et al. (2005). We find that the euro wide responses to monetary shocks are similar to our benchmark DFM with high-frequency identification, except for consumer prices and wages that display a price puzzle in the short-run—after a contractionary monetary shock, consumer prices increase in the first four quarters after the shock, while wages increase in the first 6 quarters. Finally, in terms of individual country responses, our conclusions remain unchanged.

[16] Mertens and Ravn (2013a), Gertler and Karadi (2015) and Jarocinski and Karadi (2018).

1. Relevance: $E(\varepsilon_{mt} Z_t) = \alpha \neq 0$
2. Exogeneity: $E(\varepsilon_{jt} Z_t) = 0$, $j = 2, \ldots, r$
3. Uncorrelated shocks: $\Sigma_{\varepsilon\varepsilon} = D = diag(\sigma^2_{\varepsilon_m}, \ldots, \sigma^2_{\varepsilon_r})$,

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 (3) we get

$$E(\eta_t Z_t) = E(H\varepsilon_t Z_t) = (H_1 \cdots H_r) \begin{pmatrix} E(\varepsilon_{mt} Z_t) \\ \vdots \\ E(\varepsilon_{rt} Z_t) \end{pmatrix} = H_1 \alpha, \tag{6}$$

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. We normalise H_1 by way of fixing the response of EONIA at 25 basis points on impact to a one unit monetary policy shock.

2.3.1 Instrument - "Scripta Volant, Verba Manent"[17]

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

[17]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.

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.

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 Jarociński and Karadi (2020) 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.[18]

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 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

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

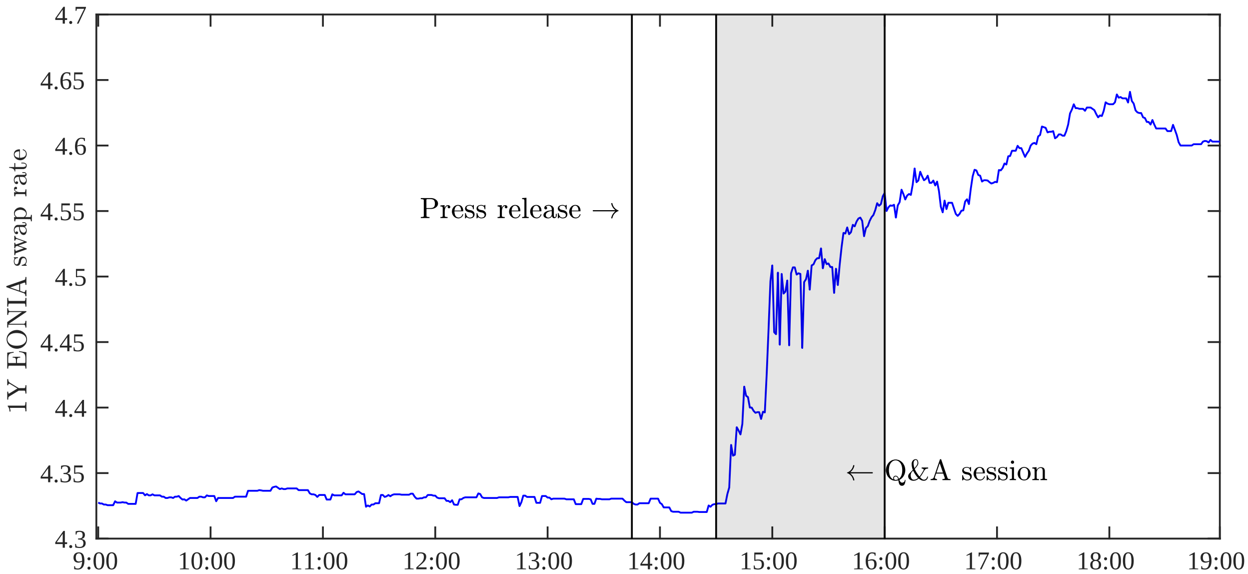


Figure 1: 1-year EONIA swap rate on 5 June 2008. Horizontal axis shows Central European Time (CET). Source: Bloomberg, authors' calculations.

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, Jarociński and Karadi (2020) 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

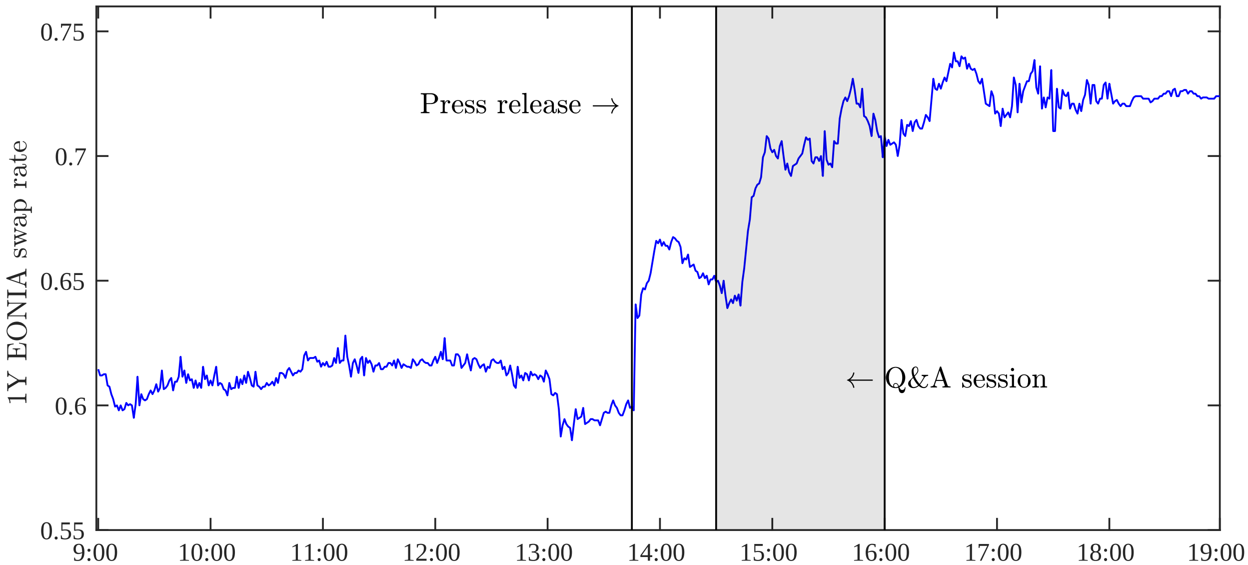


Figure 2: 1-year EONIA swap rate on 6 October 2011. Horizontal axis shows Central European Time (CET). Source: Bloomberg, authors' calculations.

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.[19]

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.[20] 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 contrac-

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

[20] 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 .

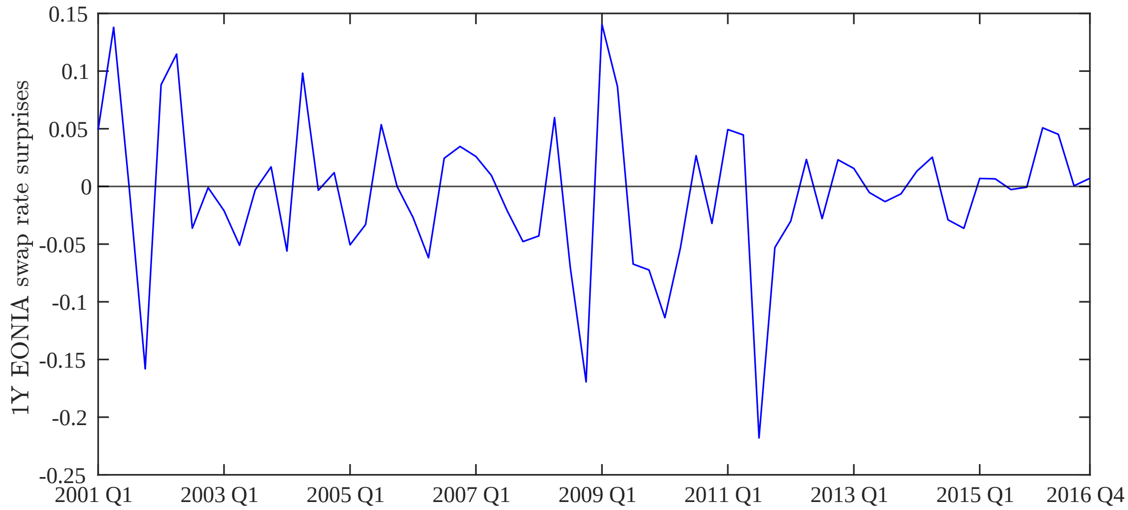


Figure 3: Instrument - Quarterly 1-year EONIA swap rate surprises from 2001Q1 to 2016Q4

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

Lastly, 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 online 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 Standard Errors for the Statistics of Interest

Treating the factors as data, we use the residual-based moving block bootstrap as proposed in Jentsch and Lunsford (2019) for inference on statistics such as the SIRF and the CV.[21] The algorithm is as follows. First we choose a block of length l and compute the number of blocks $N = T/l$, where T is the number of observations, rounding it up to the nearest integer so that we end up with $Nl \geq T$. Next, we collect the $r \times l$ blocks $\mathcal{U}_i = (\hat{u}_i, \ldots, \hat{u}_{i+l-1})$ for $i = 1, \ldots, T - l + 1$ and the l blocks $\mathcal{M}_i = (m_i, \ldots, m_{i+l-1})$ for $i = 1, \ldots, T - l + 1$. Then,

1. Independently draw N integers with replacement from the set $1, \ldots, T - l + 1$, putting equal probability on each element of the set. Denote these integers as $i_1, \ldots, i_N$.

2. Collect the blocks $(\mathcal{U}_{i_1}, \ldots, \mathcal{U}_{i_N})$ and $(\mathcal{M}_{i_1}, \ldots, \mathcal{M}_{i_N})$ and drop the last $Nl - T$ elements to produce the bootstrap quantities $(\tilde{u}_i^*, \ldots, \tilde{u}_T^*)$ and $(\tilde{m}_i^*, \ldots, \tilde{m}_T^*)$.

3. Center $(\tilde{u}_i^*, \ldots, \tilde{u}_T^*)$ and $(\tilde{m}_i^*, \ldots, \tilde{m}_T^*)$ according to

$$u_{jl+s}^* = \tilde{u}_{jl+s}^* - \frac{1}{T - l + 1} \sum_{\tau=1}^{T-l} \hat{u}_{s+\tau-1}$$

$$m_{jl+s}^* = \tilde{m}_{jl+s}^* - \frac{1}{T - l + 1} \sum_{\tau=1}^{T-l} m_{s+\tau-1}$$

   for $s = 1, \ldots, l$ and $j = 1, \ldots, N - 1$ in order to produce $(u_i^*, \ldots, u_T^*)$ and $(m_i^*, \ldots, m_T^*)$ and making sure they are centered conditionally on the data.

4. Set the initial condition $(F_{-p+1}^*, \ldots, F_0^*) = (F_{-p+1}, \ldots, F_0)$. Use the initial condition together with $\hat{\delta}(L)$ and u_t^* to recursively compute $(F_1^*, \ldots, F_T^*)$ with

$$F_t^* = \hat{\delta}(L) F_{t-1}^* + u_t^*.$$

5. Estimate $\delta(L)^*$ by least squares from the bootstrap sample $(F_1^*, \ldots, F_T^*)$ and set the new residuals $\hat{u}_t^* = F_t^* - \delta(L)^* F_{t-1}^*$.

6. Use $\hat{u}_t^*$ and m_t^* for $t = 1, \ldots, T$ to estimate $\widehat{\alpha H_1} = T^{-1} \sum_{t=1}^{T} m_t^* (\hat{u}_t^*)'$

7. Use $\hat{\delta}(L)^*$ and $\widehat{\alpha H_1}$ to produce the SIRF and the CV.

We repeat the algorithm two thousand times, collect the bootstrap statistics, and produce confidence intervals with a standard percentile interval.

[21] In online appendix G.2, we describe a residual-based moving block bootstrap that does not treat the factors as data. When implementing it, we show that while most of the responses of euro-wide variables turn insignificant, our main conclusions regarding the degree of heterogeneity of country-level responses remain mostly unchanged. The only difference being that output no longer statistically displays lower dispersion than private consumption and unemployment.

2.5 Data and Estimation

Our dataset 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. Online 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 online appendix C. As we lose one observation by differencing, our working dataset starts in 2000 Q1.

Principal component analysis is sensitive to double-counting[22] and we consequently only use a subset of our data for factor extraction. In practice, we avoid double-counting along two dimensions. Firstly, we do not include euro-area aggregates for indicators where we have included all individual country series. Secondly, we do not include category aggregates, such as GDP, when we have included its components, such as the components of GDP. Where possible, we avoid using high-level aggregate series altogether and instead include disaggregate series. In total, we use 179 series for factor extraction.

We estimate the SDFM with a three-step procedure. In the first step, we estimate the factor loadings Λ and the factors F_t directly from (1) with principal components estimation. In the second step, we treat the factors as data and estimate the reduced-form VAR (2). In the third and final step, we calculate the covariance between the factors' innovations and the instrument in order to estimate αH_1 and normalise α in order to match a 25 basis points response of EONIA on impact to a unit monetary policy shock[23].

Given our data sample and specific application, we prefer the nonparametric principal components estimation method to the alternative parametric state-space method for three reasons. First, state-space estimation entails specifying a full parametric model in the dynamic form of the SDFM, so that the likelihood can be computed, while the two-step procedure does not. Second, in using principal components one does not have to make assumptions about the distribution of errors. Third, if instability is limited across variables, the principal components estimator of the factors remains consistent (Bates et al. (2013)). These arguments are particularly relevant in the context of our data sample as it includes the great recession and public debt crisis periods.

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 $r \in 3, 4, 5$ (Table 1), the criterion by Bai and Ng (2002) suggesting $r = 5$, and the bi-cross-validation method proposed by Owen et al. (2016)[24] suggesting $r = 8$. We choose as our

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

[23] See Stock and Watson (2016) for further details on alternative ways of estimating of SDFMs.

[24] see Figure 11 in online appendix A.

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	0.778	0.145	0.046	0.058	0.069	0.08	0.09
1	0	0.081	0.033	0.046	0.058	0.069	0.08
2	0	0	0.019	0.033	0.046	0.058	0.069
3	0	0	0	0.995	0.229	0.306	0.373
4	0	0	0	0	0.127	0.229	0.306
5	0	0	0	0	0	0.56	0.799
6	0	0	0	0	0	0	0.482

baseline specification $r = 5$, that is, the average of these results. Figure 12 in online appendix A shows the variance of the data explained by each additional factor. Five factors account for 80% of the total data variance .[25]

On the basis of Akaike and Bayes Information Criteria we include one lag for the baseline of the SDFM. For the bootstrap, we pick the length of the block to be 14.[26]

To get a better understanding of how well the extracted factors characterise the data, Table 2 shows the variation in the data explained by the five factors. The second column shows the fraction of explained variation for a selection of aggregate area-wide series. The third column shows the corresponding average across series from individual member countries. In particular, two observations stand out. Firstly, the variation in most aggregate series is remarkably well explained by the five factors. With a few exceptions, notably the exchange rate, the R-squared ranges between 70% and 99%. Secondly, despite the granularity of the individual country series, the factors on average still explain more than half of all variation. In some cases, such as HICP inflation, government spending and, most notably, long-term interest rates, they explain considerably more. Columns 4 and 5 show the same information as column 3, but differentiate between the size of the countries. In particular, we separate the 5 countries in our sample with the largest economies (by nominal GDP) from the 6 countries with the smallest economies. As expected, the factors pick up information from the large economies to a much greater extent than for smaller economies. With the exception of exports, imports and rents, data from larger economies is consistently explained better by the factors. This difference is particularly strong for GDP (70% vs. 45%) and unemployment (68% vs. 36%). As concrete examples of the above, Figure 16 in online 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.

[25]As can be seen in Figure 12, 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 SDFM with three and four 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.

[26]We follow the rule used in Jentsch and Lunsford (2019), $l = 5.03T^{(1/4)}$

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

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

3 The transmission of EA monetary policy: aggregate and disaggregated evidence

This section presents our empirical findings about the effects of the ECB monetary shocks in the euro area, first at the aggregate, union-wide level, then at the disaggregate level. In the first step, we are specifically interested in verifying how good our model and monetary shock identification are. In the second step, we are interested in documenting cross-country differences in the response across a wide set of variables and dimensions of the economy.

3.1 Euro-wide Dynamic Effects

We start our analysis of the results with an overview of key 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 moving block bootstrapping procedure. 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 (2013b) and Gertler and Karadi (2015).

Notably, our results do not suffer from the "price puzzle"—i.e., a rising price level in reaction to a contractionary monetary policy shock—which is a long-standing issue in the VAR literature on monetary shocks. As apparent in Figure 4, while the harmonised index of consumer prices (HICP) does not have any significant reaction, 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 take these findings as an indication of the ability of the model to accurately characterise economic dynamics. In particular, we attribute the absence of the price puzzle in our results to the combination of correctly capturing information about prices in the economy (via the SDFM) and precisely identifying monetary policy shocks (via the high frequency instrument).[27] The remainder of the series in Figure 4 also behave as suggested by theory. GDP contracts overall, as do all its 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 contractionary shock, but displays imperfect pass-through—possibly reflecting the fact that a significant number of mortgages are characterised by fixed rates, hence do not adapt to changes in policy. In the labour market, unemployment rises, while wages fall. Interestingly,

[27] 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

the response of wages is not significant, hinting at a large degree of nominal wage stickiness. In the housing market, house prices fall significantly after a contraction, in line with economic theory suggesting 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)) entertains the hypothesis 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 with a delay.

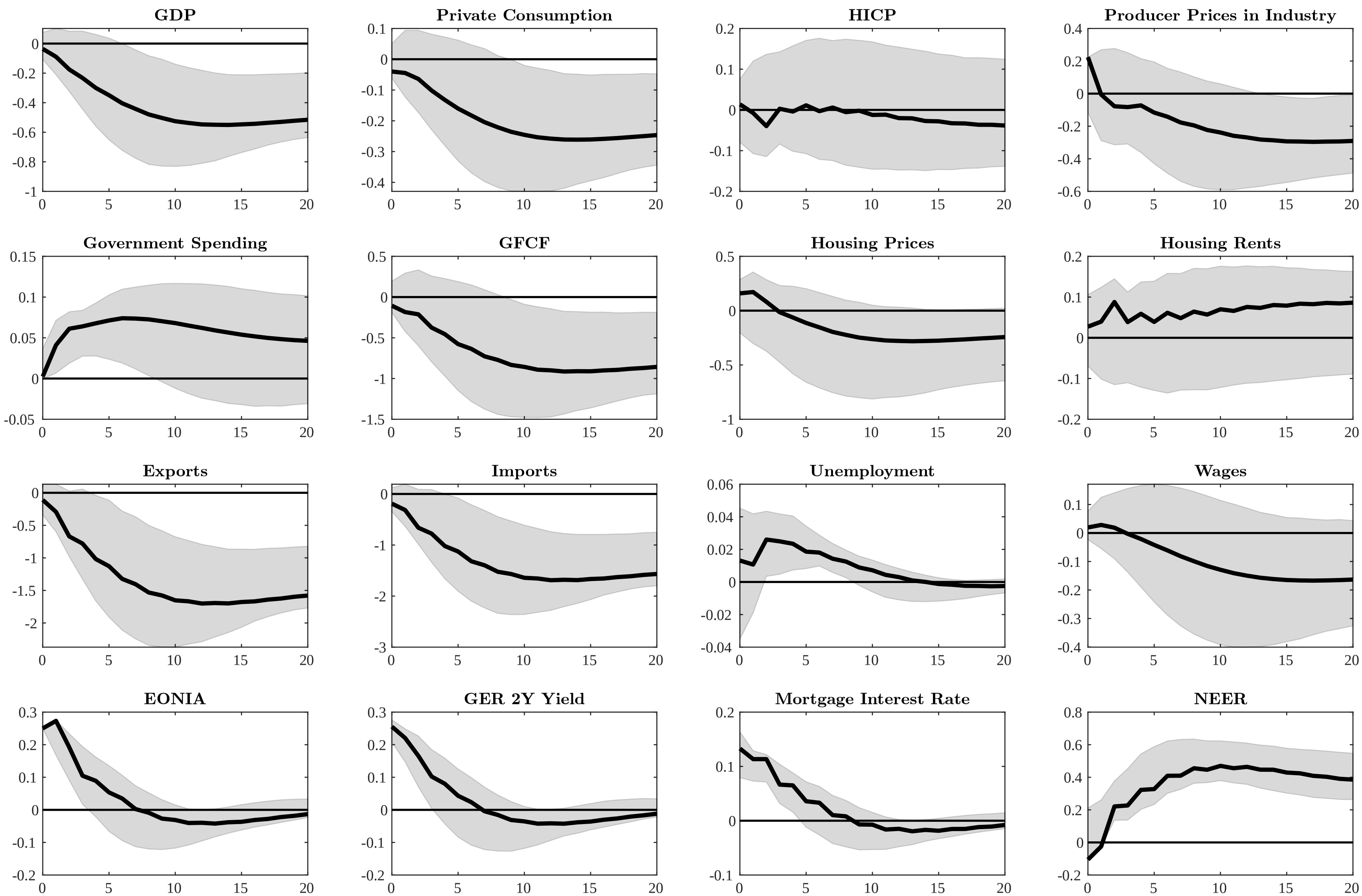


Figure 4: Percentage responses of selected euro-wide variables to a 25bp contractionary policy shock. Note: The shaded area represent 68% confidence bands obtained from a moving block bootstrap procedure.

3.2 Cross-Country Dynamic Effects

In this section, we bring our empirical model to bear on the responses of GDP, the components of GDP, interest rates, equities, house prices and unemployment at individual country level—shown in Figures 5-7. Moving on to analyze country-level responses uncovers the potential of the SDFM, when it comes to providing results for a large number of series. We stress that, besides the representative sub-sample reported in the figures, we can use our model to obtain impulse response functions for all 342 individual country series in our sample.[28] In the three figures in this subsection, we omit error bands for ease of presentation,[29] as we carry out a formal analysis of heterogeneity later on in the text.

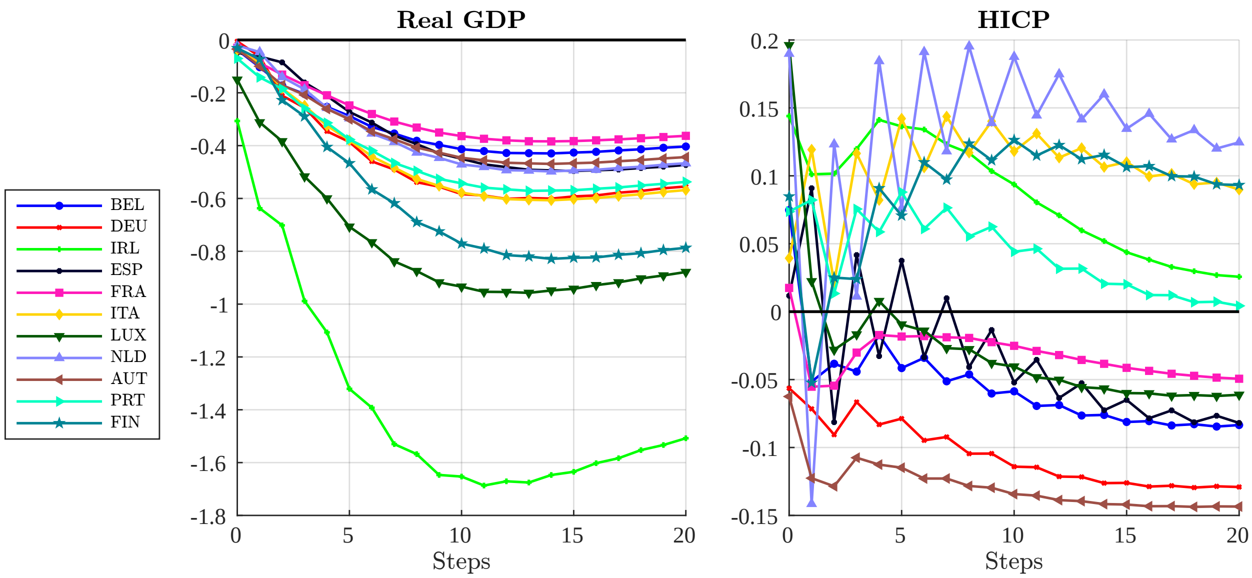


Figure 5: Percentage responses of real GDP and HICP to a 25bp contractionary policy shock across euro-area member countries.

Figure 5 shows the responses of real GDP and HICP across the 11 euro-area countries in our sample. Starting from the latter, the responses of HICP are positive for half of the countries while 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

[28]Given that the time period used for the estimation of the SDFM 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 online appendix G.1, we provide a sub-sample robustness check where we split the sample into before and after the financial crisis and estimate the SDFM 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 labour in the period preceding the great recession.

[29]To highlight the statistical significance of differences across SIRFs, in the online appendix F we offer an alternative representation of these results. In Figures 17 and 18 we plot the highest and the lowest national response, together with the SIRFs for the whole EA, showing confidence intervals. Figure 17 plots SIRFs for real variables: GDP, private consumption and unemployment. Figure 18 plots SIRFs for price-related series: interest rates, HICP and stock prices. The confidence intervals for the highest and the lowest SIRFs 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.

to real GDP, 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 quite different from France and Spain, having non-overlapping confidence intervals from the 10th step onward (not shown). This heterogeneity is in itself noteworthy, but also raises the question which components of GDP are particularly prone to asymmetric reactions.

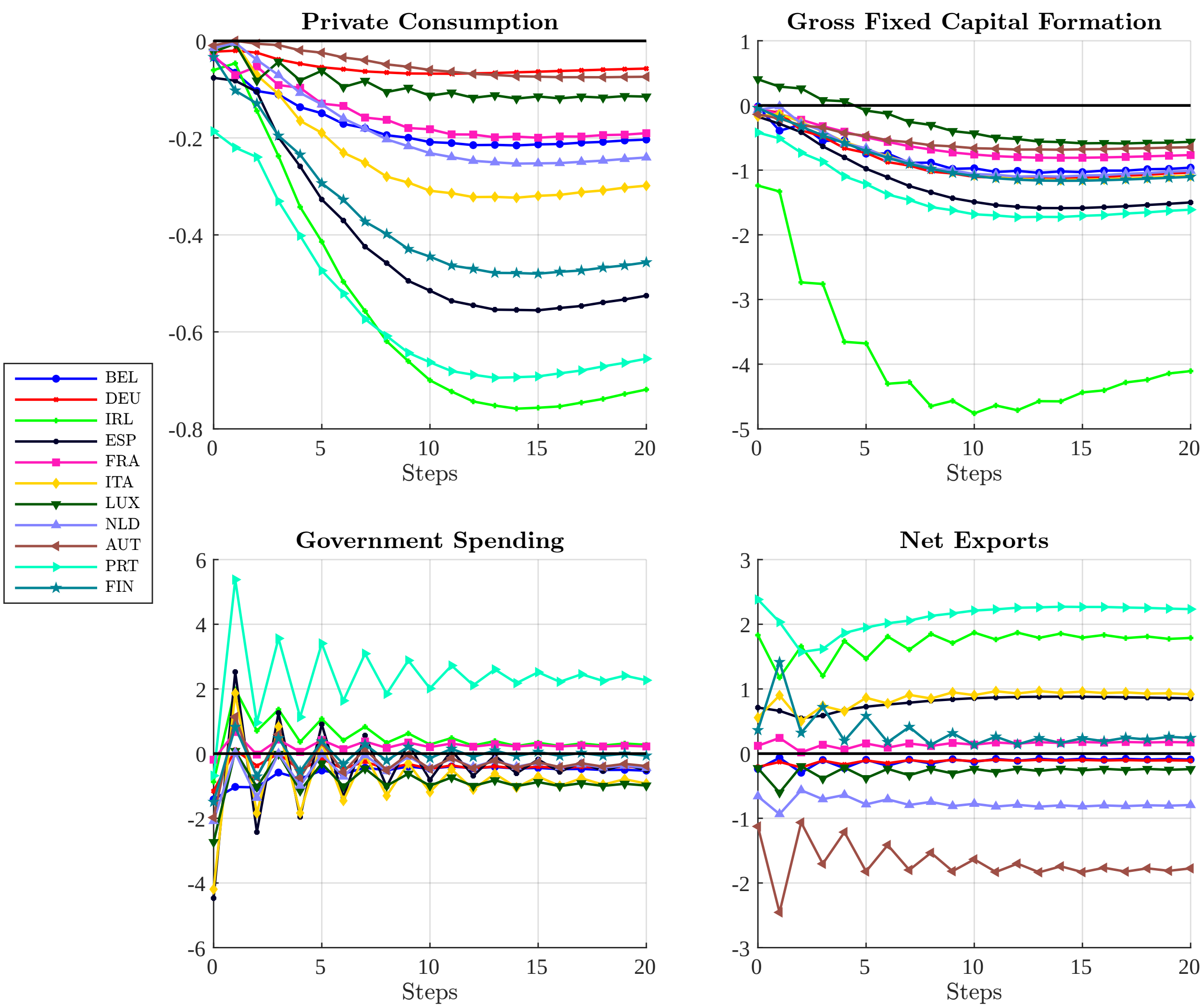


Figure 6: Percentage responses of GDP components to a 25bp contractionary policy shock across euro-area member countries.

Figure 6 shows the reactions of consumption, investment, net exports and government consumption. The SIRFs highlight two main results. 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. For government consumption, the difference is informative about how national stabilization policy is conducted, as reflected in the degrees of pro- and counter-cyclicality of fiscal policy. Public spending policies are clearly country-specific, and in principle may vary not only across borders but also over time as a function, e.g., of political cycles and the accumulation of public debt. The dispersion of net exports is instead informative about the equilibrium adjustment to shocks at aggregate level.

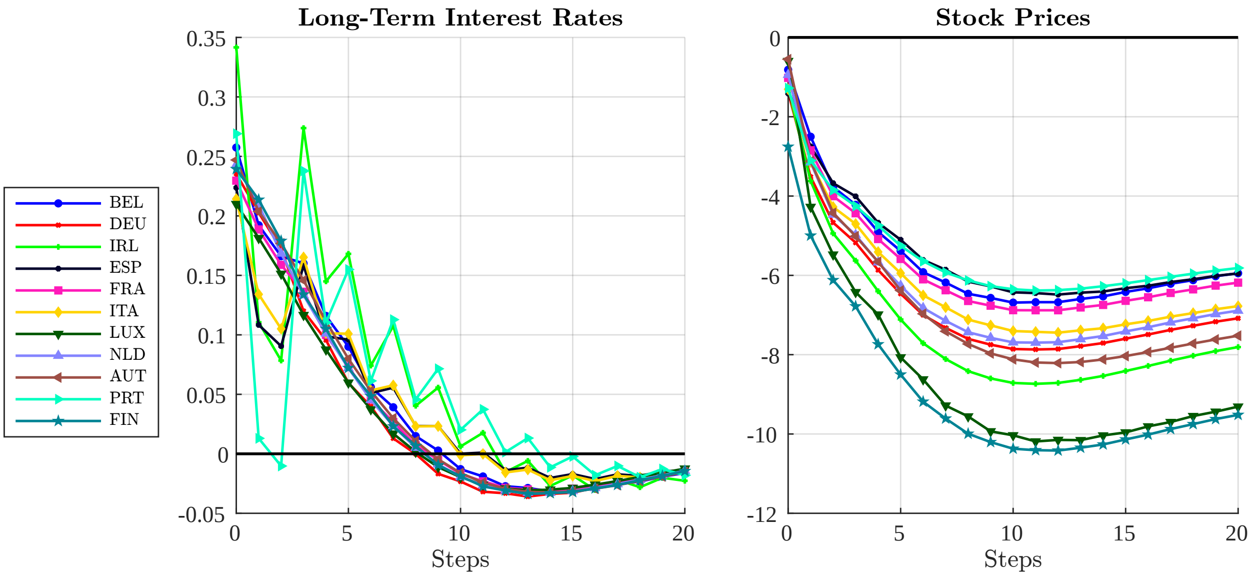


Figure 7: Percentage responses of long-term interest rates and local equity indices to a 25bp contractionary policy shock across euro-area member countries. Long-term interest rates are defined in accordance with OECD methodology, conforming to government bonds of (in most cases) 10 year maturity.

Secondly, whether or not the responses move in the same direction, there is a visible degree of heterogeneity. The disparity in the reaction of private consumption stands out. Against the drop in private consumption in Germany, which reaches a maximum at about 0.02 percentage points, the drop in consumption in Italy, Finland, Spain and Portugal is roughly 10 times the size of the drop in Germany. The drop in Ireland, by all means the outlier, is more than 20 times as large, at 0.4 percentage points.

The core hypothesis that guides our work is that the dispersion in country-specific responses to the common monetary shock reflect, inversely, the state of convergence in particular markets across the euro area. To a large extent, the impulse response analysis lends support to our hypothesis. On the one hand, financial markets have experienced a relatively stronger convergence than other markets in the euro area:[30] this corresponds to the relative tight reaction of interest rates and stock prices across countries in Figure 7. 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 national equity indices, displayed in the same figure, diverge to some extent, the confidence intervals around the SIRF are mostly overlapping.

On the other hand, among the markets with little or no convergence in institutional characteristics across the euro are the labour and housing markets. In Figure 8, we show that after one year

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

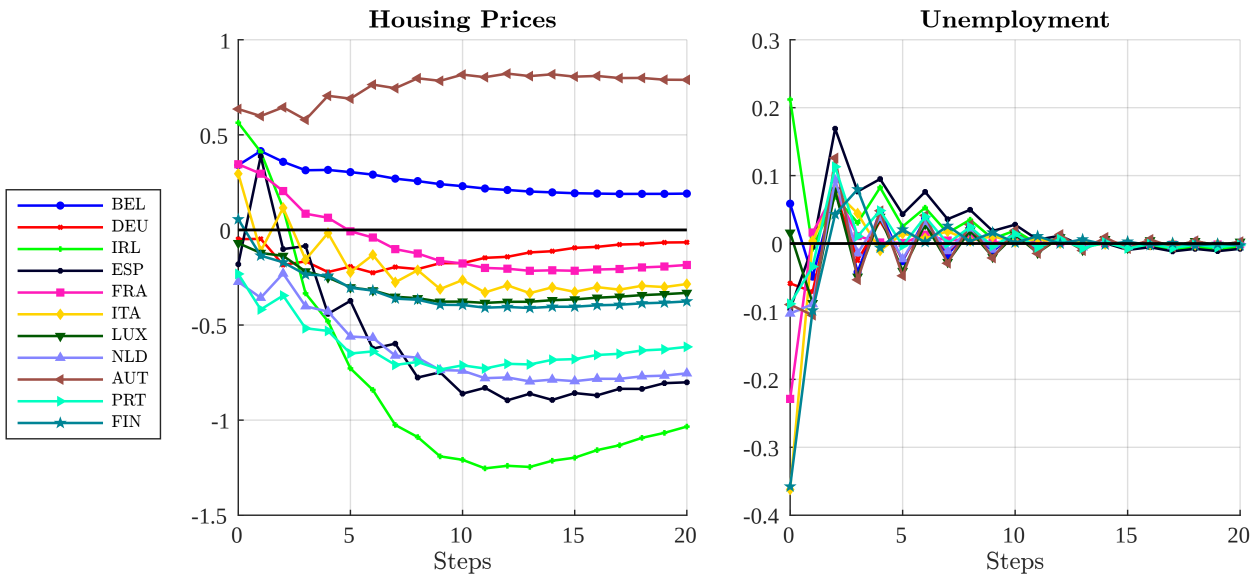


Figure 8: Percentage responses of house prices and unemployment rate to a 25bp contractionary monetary policy shock across euro-area member countries.

(4 steps), house prices fall and unemployment rises at quite different rates across border.

3.3 A measure of the degree of heterogeneity in impulse responses

To gain a firmer insight on the *degree* to which real and financial variables diverge across countries in response to monetary shocks, in what follows we propose and implement a more rigorous approach to testing heterogeneity in impulse responses. For each set of responses, we calculate the coefficient of variation, i.e. the standard deviation of responses among countries with respect to the EA response of the same 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 3 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 an 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 less heterogeneous than other real variables, namely private consumption and unemployment.

As most of the intervals around coefficients of variation are overlapping, we also bootstrap pairwise differences in the coefficient of variation. The results, presented in Table 4, mostly confirm earlier qualitative observations. Reactions of long-term interest rates (LTINT) and stock prices (SP) are significantly less dispersed than all other variables. However, new shaper quantitative observations emerge. Firstly, at the 20th step, GDP has a significantly lower coefficient of variation

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	0.63	0.51	1.57
Private Consumption	1.09	0.74	2.30
Unemployment	1.46	0.78	4.29
Housing Prices	1.58	1.19	4.23
HICP	1.31	0.59	3.48
Long-term Interest Rates	0.35	0.15	1.86
Stock Prices	0.26	0.15	0.70
At the 8th Step			
GDP	0.47	0.39	0.77
Private Consumption	0.76	0.70	0.94
Unemployment	0.99	0.71	1.90
Housing Prices	1.22	1.15	1.93
HICP	1.27	0.56	3.99
Long-term Interest Rates	0.61	0.24	1.95
Stock Prices	0.18	0.17	0.24
At the 20th Step			
GDP	0.43	0.37	0.71
Private Consumption	0.76	0.69	0.96
Unemployment	1.28	1.02	2.21
Housing Prices	1.27	1.16	1.97
HICP	1.09	0.54	3.34
Long-term Interest Rates	0.48	0.17	1.77
Stock Prices	0.19	0.18	0.24

Notes: The third column reports the median estimates. The fourth and fifth columns report the lower and upper bounds, respectively, using the 68% confidence level. The inference is drawn from a moving bootstrap procedure.

than private consumption (PCON), unemployment (U), and real house prices (RHPI). Secondly, unemployment, house prices and consumer prices responses to monetary shocks possess the highest degree of dispersion, followed in decreasing order by private consumption, GDP, long-term interest rates, and finally stock prices. Thirdly, there is quite a bit of uncertainty regarding the degree of dispersion of consumer prices as measured by HICP. Using one standard error, the range of the CV for HICP among all steps goes from 0.54 at its lowest to 3.99 at its highest. The uncovering of these more nuanced findings highlights the relevance of using the CV to measure heterogeneity in SIRF.

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 is larger for responses of consumption and consumer prices than for output. Our evidence, showing that in some cases responses can even have opposing signs, has straightforward implications for policy. Further institutional convergence can be expected to enhance cohesion in the euro area by reducing unintended responses to a 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.

4 Monetary Transmission Patterns in the Euro Area: exploratory analysis

In this section, we explore patterns in the responses to monetary policy shocks of key variables across countries—output, consumption, consumer prices, house prices, unemployment rates, long-term interest rates, stock prices, gross fixed capital formation, and net exports— and how they correlate with institutional characteristics of the national economies. To do so, we collect data on institutional characteristics related to housing, price and wage rigidity, employment protection, and leverage for the EA member countries in our sample. The characteristics, as well as their data sources, are reported in Table 5.

By having member countries with strikingly different institutional settings under the same monetary authority, the EA serves as a prime laboratory to empirically study how institutional settings affect monetary transmission. To identify which institutional settings may be expected to shape monetary transmission, we draw on a large set of leading contributions to the literature which, over time, have highlighted a number of factors. The list include the level of price and wage stickiness,[31] the share of hand-to-mouth consumers[32] and the level of employment protection.[33] More recently,

[31] Gordon (1990), Smets and Wouters (2003) and Christiano et al. (2005).

[32] Campbell and Mankiw (1989), Galí et al. (2007), Bilbiie (2008) and Broer et al. (2016).

[33] Smets and Wouters (2003).

Table 4: Bootstrapped pair-wise differences in the coefficient of variation of the cross-country responses to a 25bp monetary policy shock.

	HICP	LTINT	SP	PCON	U	RHPI
On Impact						
GDP	-0.50	0.32	0.42*	-0.31*	-0.45	-0.84
HICP		0.86	0.98*	-0.02	-0.24	-0.50
LTINT			0.04	-0.67	-0.80*	-1.21
SP				-0.63*	-1.01*	-1.21*
PCON					0.07	-0.42
U						-0.37
At the 8th Step						
GDP	-0.72	-0.17	0.27*	-0.29*	-0.45*	-0.76*
HICP		0.51	0.99*	0.45	0.12	-0.13
LTINT			0.41	-0.14	-0.32	-0.66
SP				-0.55*	-0.80*	-1.03*
PCON					-0.22*	-0.46*
U						-0.30
At the 20th Step						
GDP	-0.60	0.02	0.23*	-0.32*	-0.83*	-0.83*
HICP		0.46	0.87*	0.31	-0.27	-0.32
LTINT			0.25	-0.32	-0.88	-0.89
SP				-0.55*	-1.09*	-1.06*
PCON					-0.52*	-0.49*
U						-0.03

Notes: * marks differences in variation that are significant at the 68% confidence level. The inference is drawn from a moving bootstrap procedure.

Table 5: Selected institutional characteristics of EA member countries.

Country	Core country	LTV ratio (%)	AMR share (%)	Homeownership rate (%)	Wage rigidity (%)	Price rigidity (months)	Share of HtM (%)	Share of WHtM (%)	Employment protection (index)	Total Leverage (%)
BEL	Yes	83	20	72.2	40	18.9	19.1	10 .7	1.8	180
DEU	Yes	70	15	53.3	59	17.0	23.6	12 .1	2.5	100
IRL	No	74	100	78.2	84	12.2	35.4	19 .6	1.2	275
ESP	No	70	90	80.6	51	13.7	25.7	18 .0	2.2	150
FRA	Yes	75	15	61.8	27	8.3	19.5	9.5	2.5	145
ITA	No	50	70	73.2	72	15.8	23.1	13 .7	2.8	115
LUX	Yes	80	60	61.8	33	10.8	18.0	12 .2	2.1	325
NLD	Yes	90	10	63.9	41	8.4	17.9	9.2	3.3	225
AUT	Yes	60	50	59.2	15	11.0	12.7	4.2	2.3	125
PRT	No	85	98	80.6	72	6.1	26.6	17 .2	3.9	175
FIN	Yes	75	98	71.8	49	6.5	24.3	13.2	2.0	151

Notes: The third column reports the loan-to-value ratio for housing financing (Calza et al., 2013). The fourth column reports the share of adjustable mortgage contracts (Albertazzi et al., 2018). The sixth column reports the share of firms that adjusted wages less than once a year (ECB, 2016). The seventh column reports the average duration in months until prices are changed (Alvarez et al., 2006). The eighth and ninth columns report the share of households that are classified as hand-to-mouth and wealthy hand-to-mouth, respectively (authors' calculations following the classification procedure by Slacalek et al. (2020) and using data from the ECB's Household Finance and Consumption Network). The second to last column reports the employment protection index (OECD indicators of employment protection). The last column reports the ratio of total leverage to GDP (Eurostat).

the same literature has focused on housing,[34] and/or the importance of homeowners' liquid assets.[35] Finally, in the run-up to the formation of the EMU, Bayoumi and Eichengreen (1992) motivate a debate on whether monetary policy transmission would be different among countries experiencing divergent or non-coincident national cycles.

To identify and visualise patterns in SIRS, in the figures to follow we adopt the following conventions. When the criterion of country classification is discrete—say, a country either belongs to the "core" or the "periphery"—impulse responses differ by colour and line type. When the criterion is continuous—say, share of adjustable rate mortgages—we instead use a "heat map", distinguishing shades of colours and different colours—e.g., going from a dark blue for a low value, to a dark red for a high value.

We start our empirical analysis focusing on differences in the monetary transmission across "core" economies (dashed blue SIRS) and "periphery" economies (solid red SIRS) in Figure 9. Here we find a first clear pattern: consumption, gross fixed capital formation, unemployment, house prices and long-term interest rates in periphery economies respond to a shock more strongly than in core countries. In addition, we find that net exports react less negatively, and in some cases even positively, in periphery countries compared to core countries. Even when accounting for heterogeneity in government consumption, the response of net exports seem to contribute to explain the muted differences in output responses across the two groups. A muted divergence in the business cycle consequences of monetary impulses may explain why we also find no clear cross-group patterns in the response of consumer prices. Consistent with our prior, in light of the high degree of integration of financial markets, we find no difference in the response of stock prices.

In line with recent theoretical research, housing and liquidity are a primary candidate as factors impinging on the strength of monetary policy transmission. We turn to this dimension of the anal-

[34] Iacoviello (2005), Rubio (2011), Calza et al. (2013), Ozkan et al. (2017) and Dias and Duarte (2019).

[35] Ravn and Sterk (2020), Kaplan et al. (2018) and Auclert (2019)

ysis in the first three panels (a, b, c and d) of Figure 10. When looking at housing-related variables, a first important finding is that the share of adjustable mortgage contracts and the homeownership rate (but not LTV, not shown) correlate positively with the strength of monetary policy transmission. Countries with higher shares of ARM and homeownership rates display stronger output, consumption, gross capital formation, unemployment rate and house prices responses to monetary policy shocks—this is apparent from the different coloring and shades or the SIRS, that neatly order countries by increasing shares in both basic variables and the high reported correlation coefficients. In particular, the correlation between the shares of ARM and homeownership rates with private consumption is quite high—0.8 and 0.89, respectively. However, in either panel a and b of the figure, we find no particular pattern for the response of consumer prices and stock prices and only a weak pattern for net exports. It is worth stressing that, somewhat surprisingly, we find no visible pattern in the responses when mapped in different LTV ratios. A panel with the responses patterns for LTV and all other dimensions for which we do not find any patterns are shown in Section H of the online appendix.

This conclusion is further confirmed by the reported pair-wise coefficients of correlation between the peak responses and all institutional characteristics in Table 6.[36] While the coefficients of correlation are high and some even statistically significant in the case of ARM and homeownership, they are low and statistically insignificant, except unemployment, in LTV.

When it comes to liquidity, results paint a similar picture. We find a clear pattern for liquidity in general: both the share of hand-to-mouth and wealthy hand-to-mouth consumers do correlate significantly with the strength of monetary transmission. This conclusion is drawn from the combination of Panels c and d of Figure 10, and Table 6 results. Darker-red lines, which represent responses to monetary shocks in countries where both the shares of hand-to-mouth and wealthy hand-to-mouth consumers are high, are associated with the strongest responses. While darker-blue lines, which represent low shares, are instead associated with the weakest responses. In addition, as shown in Table 6, the correlation between both shares and the peak responses is high and statistically significant in the majority of key variables.

Hence, our findings lends support to both the TANK literature, which highlights the importance of hand-to-mouth consumers for monetary transmission, and the HANK literature, which further extending the TANK model showcases the importance of the share of wealthy hand-to-mouth consumers. As stressed by the HANK literature, housing typically being the largest asset owned by households, there is an important overlap between liquidity and housing in driving households' spending decision. Our results show that this is relevant also for monetary transmission—lending aggregate empirical support to this view. Further disentangling these effects at micro- and macro-level is clearly an important avenue for future research.

Last but not least, we find a pattern for the SIRF in terms of wage rigidity as shown in panel e of Figure 10. Remarkably, however, we detect no patterns for the SIRF along the dimensions of price stickiness, employment protection and total leverage.

[36] Scatter plots for all dimensions and peak responses can be found in Section I of the online appendix.

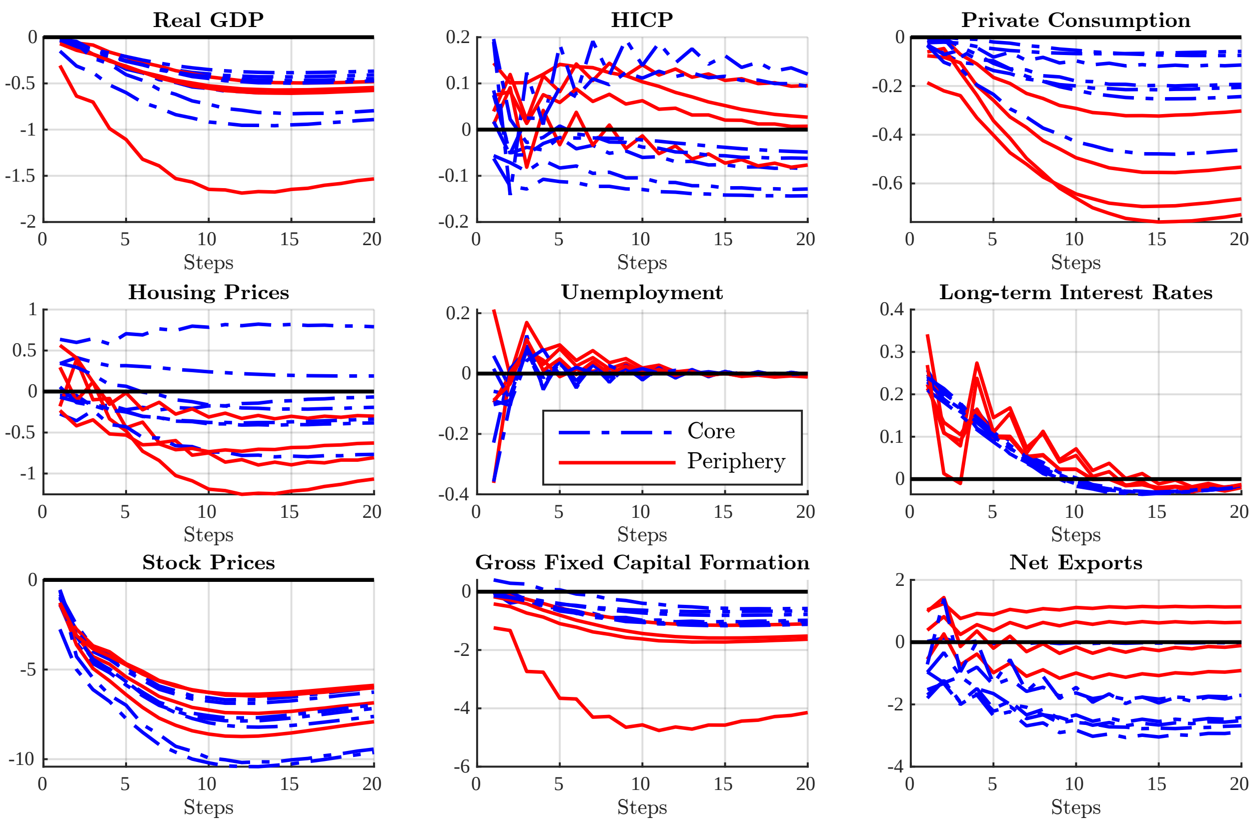
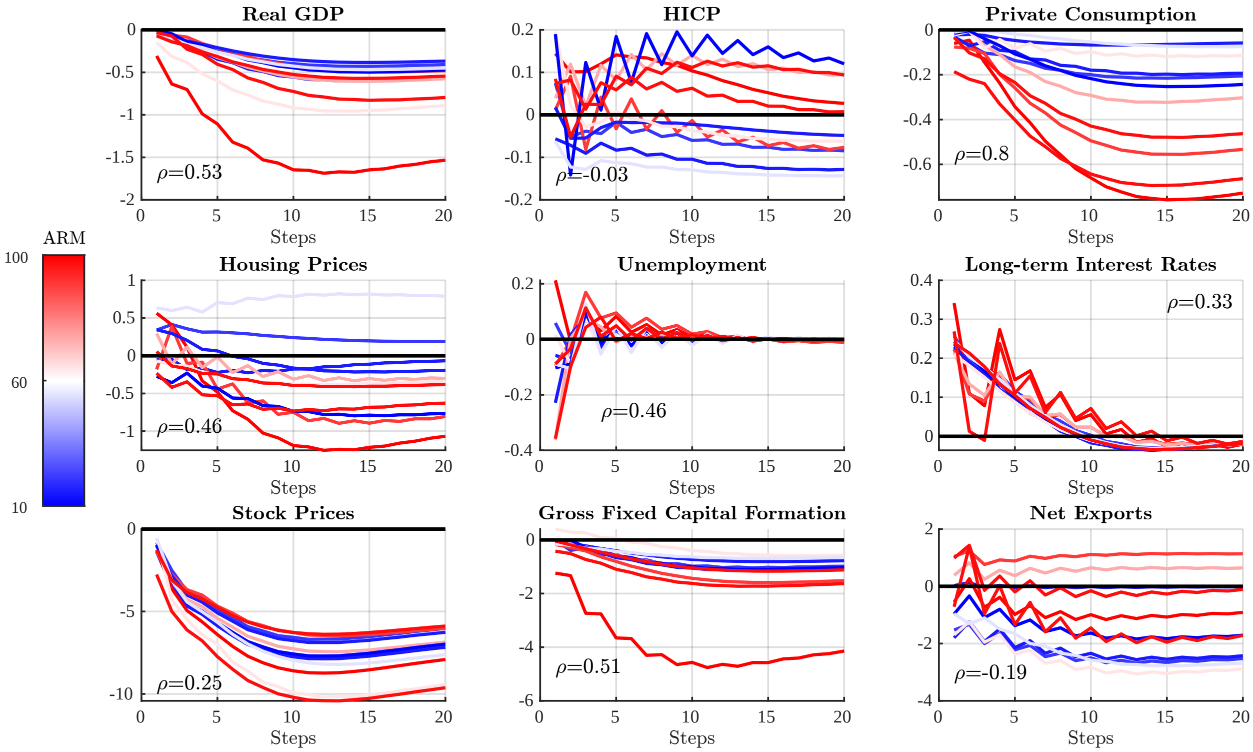


Figure 9: Percentage responses of selected variables to a 25bp contractionary policy shock across euro-area member countries grouped by core vs. periphery classification.

(a) Share of adjustable rate mortgage contracts



(b) Homeownership rate

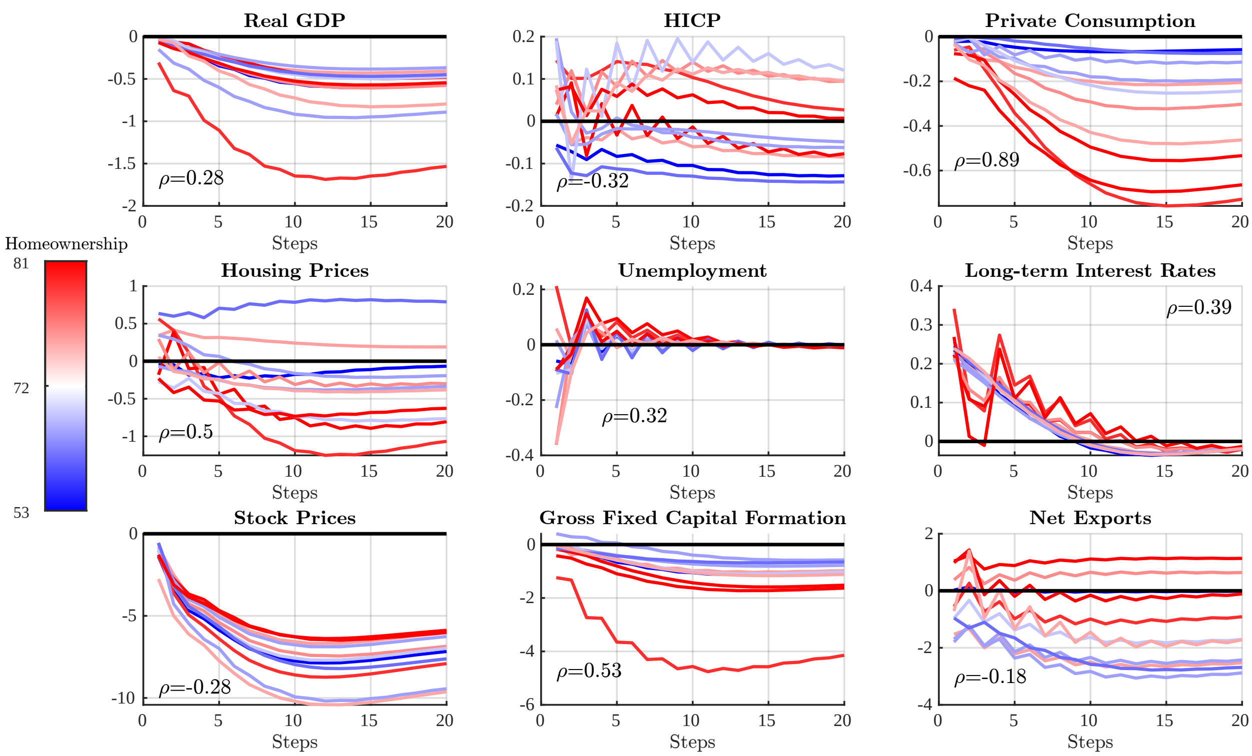
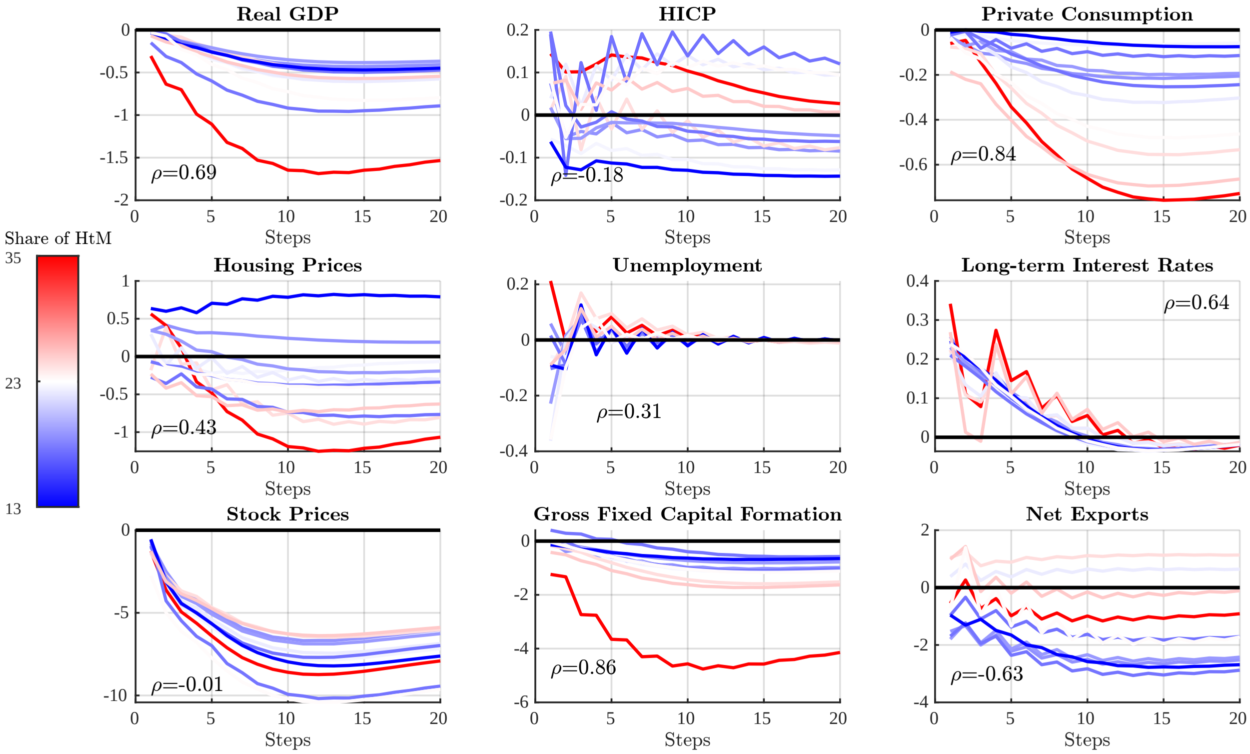


Figure 10: Percentage responses of selected variables to a 25bp contractionary policy shock across euro-area member countries with its colour intensity as a function of the level of an institutional characteristic— the first panel being the share of adjustable rate mortgage contracts, the second the homeownership rate, the third the share of hand-to-mouth consumers, the fourth the share of wealthy hand-to-mouth consumers, and the fifth the wage rigidity.

(c) Share of hand-to-mouth



(d) Share of Wealthy hand-to-mouth consumers

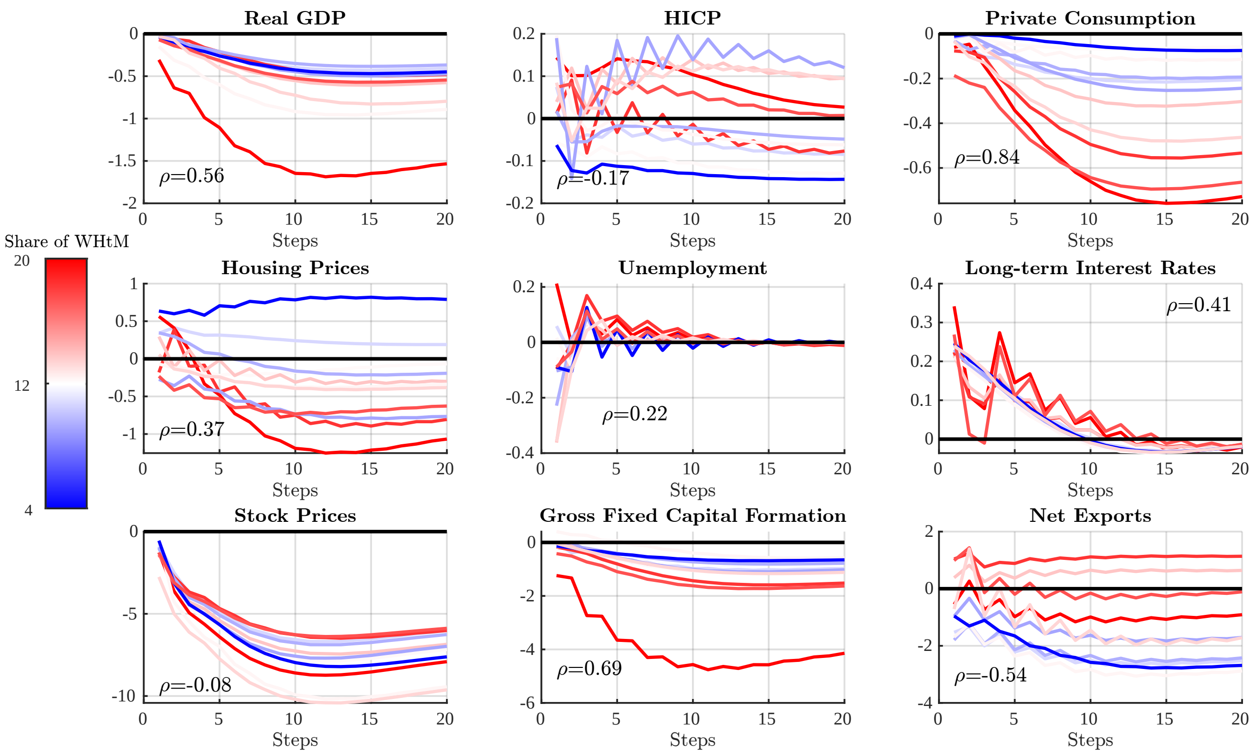


Figure 10: Percentage responses of selected variables to a 25bp contractionary policy shock across euro-area member countries with its colour intensity as a function of the level of an institutional characteristic— the first panel being the share of adjustable rate mortgage contracts, the second the homeownership rate, the third the share of hand-to-mouth consumers, the fourth the share of wealthy hand-to-mouth consumers, and the fifth the wage rigidity.

(e) Wage rigidity

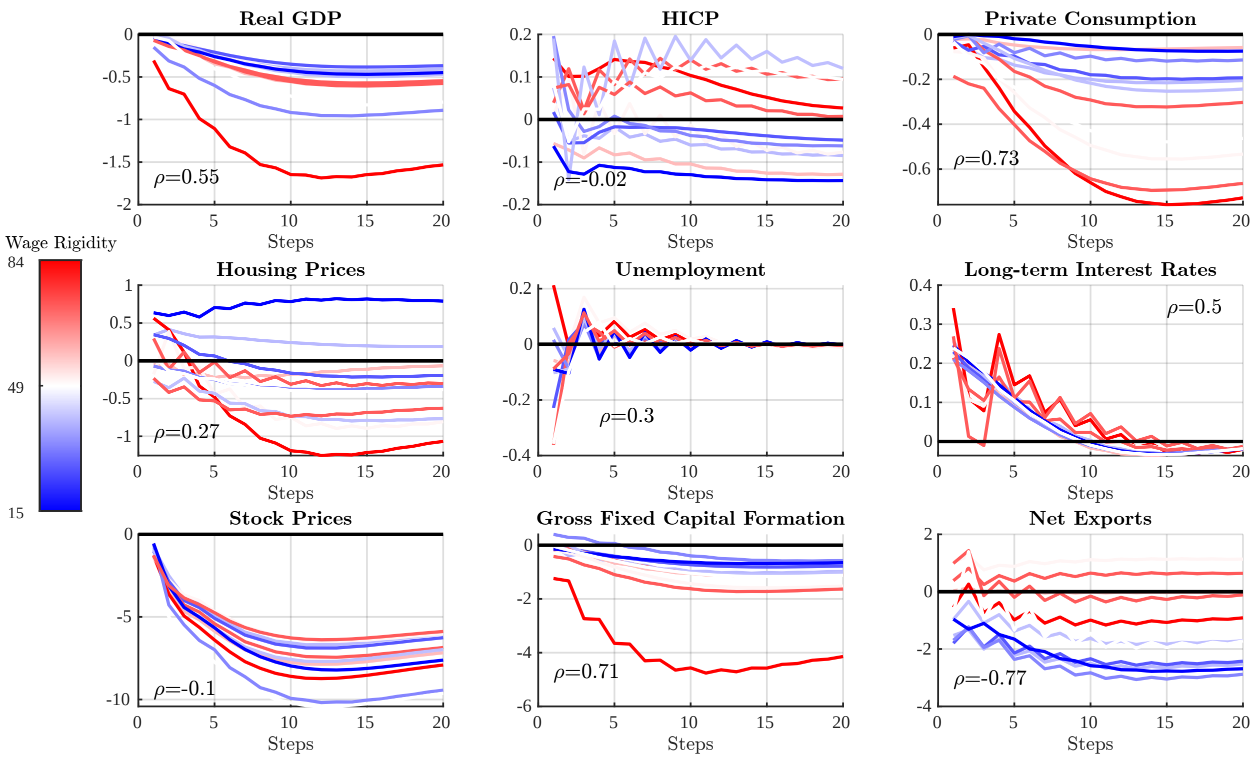


Figure 10: Percentage responses of selected variables to a 25bp contractionary policy shock across euro-area member countries with its colour intensity as a function of the level of an institutional characteristic— the first panel being the share of adjustable rate mortgage contracts, the second the homeownership rate, the third the share of hand-to-mouth consumers, the fourth the share of wealthy hand-to-mouth consumers, and the fifth the wage rigidity.

5 Conclusion

Using a dynamic factor model with high-frequency identification, this paper documents the degree of heterogeneity in monetary policy effects across the euro area, systematically analyzing the impulse response of a large number of macroeconomic and financial variables. We contribute to the literature a measure for the degree of heterogeneity in the effects of monetary policy. We use this measure in an exploratory analysis of "stylised facts", which shed light on potential institutional and structural 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 mean response size. There are, however, significant differences across variables. Country-level financial variables and output react similarly across countries: 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. These findings provide novel empirical support to the idea that the degree of heterogeneity is inversely related to the degree of cross-border institutional convergence.

Table 6: Coefficient of correlation between peak responses and institutional characteristics.

Inst. characteristics	GDP	HICP	PCON	RHPI	U	LTINT	SP	GFCF	NX
LTV	0.02	0.02	0.16	0.13	-0.53*	0.23	-0.02	0.05	0.30
	(0.33)	(0.33)	(0.33)	(0.33)	(0.28)	(0.32)	(0.33)	(0.33)	(0.32)
ARM	0.53*	-0.03	0.80***	0.46	0.46	0.33	0.25	0.51*	-0.19
	(0.28)	(0.33)	(0.20)	(0.30)	(0.30)	(0.31)	(0.32)	(0.29)	(0.33)
Homeownership	0.28	-0.32	0.89***	0.50*	0.32	0.39	-0.28	0.53*	-0.18
	(0.32)	(0.32)	(0.15)	(0.29)	(0.32)	(0.31)	(0.32)	(0.28)	(0.33)
Share of HtM	0.69***	-0.18	0.84***	0.43	0.31	0.64**	-0.01	0.86***	-0.63**
	(0.24)	(0.33)	(0.18)	(0.30)	(0.32)	(0.25)	(0.33)	(0.17)	(0.26)
Share of WHtM	0.56**	-0.17	0.84***	0.37	0.22	0.41	-0.08	0.69***	-0.54*
	(0.28)	(0.33)	(0.18)	(0.31)	(0.33)	(0.30)	(0.33)	(0.24)	(0.28)
Wage Rigidity	0.55**	-0.02	0.73***	0.27	0.30	0.50*	-0.10	0.71***	-0.77***
	(0.28)	(0.33)	(0.23)	(0.32)	(0.32)	(0.29)	(0.33)	(0.23)	(0.21)
Price Rigidity	-0.06	-0.06	-0.32	-0.22	-0.20	-0.06	-0.27	0.01	-0.29
	(0.33)	(0.33)	(0.32)	(0.33)	(0.33)	(0.33)	(0.32)	(0.33)	(0.32)
Employment Prot.	-0.57**	-0.02	-0.04	-0.21	-0.12	-0.35	-0.42	-0.42	-0.19
	(0.27)	(0.33)	(0.33)	(0.33)	(0.33)	(0.31)	(0.30)	(0.30)	(0.33)
Total Leverage	0.62**	0.52*	0.20	0.36	-0.28	0.31	0.44	0.35	0.39
	(0.26)	(0.28)	(0.33)	(0.31)	(0.32)	(0.32)	(0.30)	(0.31)	(0.31)

Notes: Standard errors are reported in parenthesis (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$). Caveat: The reported standard errors do not take into consideration the responses estimation uncertainty.

We elaborate on this point by exploring different institutional settings across EA member countries. We find that differences in housing—measured by the share of adjustable mortgage contracts and homeownership rates, liquidity—measured by the share of both hand-to-mouth and wealthy hand-to-mouth consumers, and wage rigidity explain a large proportion of the EA cross-country heterogeneity of responses in output, private consumption, gross capital formation, unemployment rate, house prices, long-term interest rates and net exports.

Other large countries, such as the US, may also display enough heterogeneity at local level to study which factors may affect transmission of (common) monetary policy shocks. In recent years, a number of leading studies have revived analysis on how monetary policy transmits across US states. Most notably, Beraja et al. (2019) provides empirical evidence that regional variation in housing equity matters for the extent to which households can refinance their mortgages, in turn determining heterogeneity in the elasticity of spending to policy rate movements. In addition to a specific role of the housing market Furceri et al. (2019) calls attention also to a specific role of the industry-mix, especially the share of manufacturing. Differences in institutional settings are arguably smaller, or in any case not directly comparable with the EA. Yet, the evidence points to housing-related variables as a key area of research.

Causal research on institutional settings and monetary transmission, and structural models that dig into how institutional characteristics shape monetary transmission qualitatively and quantitatively are promising and intriguing areas that we leave to future research.

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Online Appendix - Not for Publication

A Selecting the Number of Factors - Additional Figures

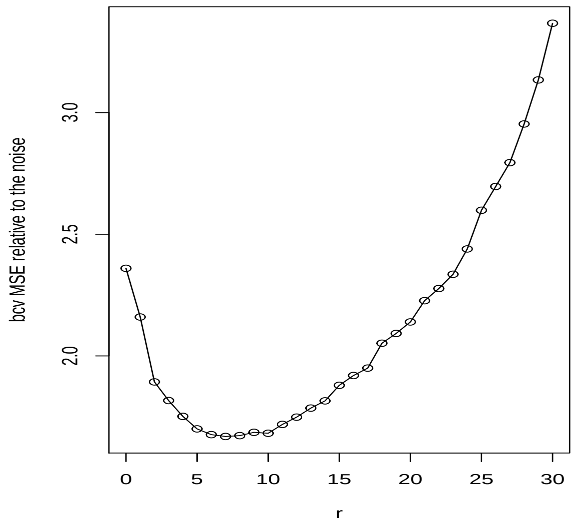


Figure 11: Bi-cross-validation method proposed by Owen et al. (2016)

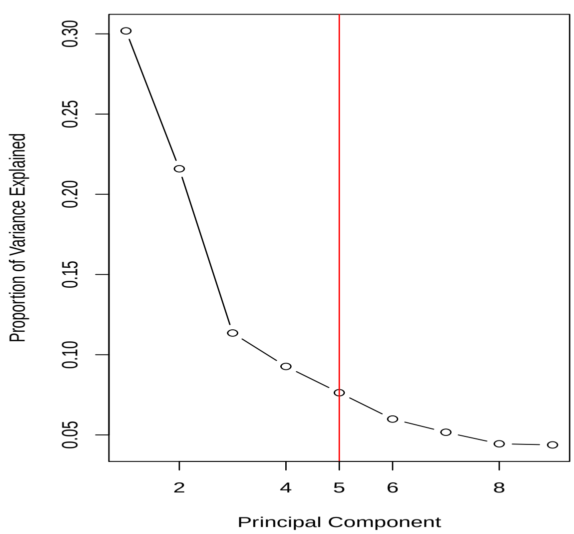


Figure 12: Variance explained by each additional factor

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.

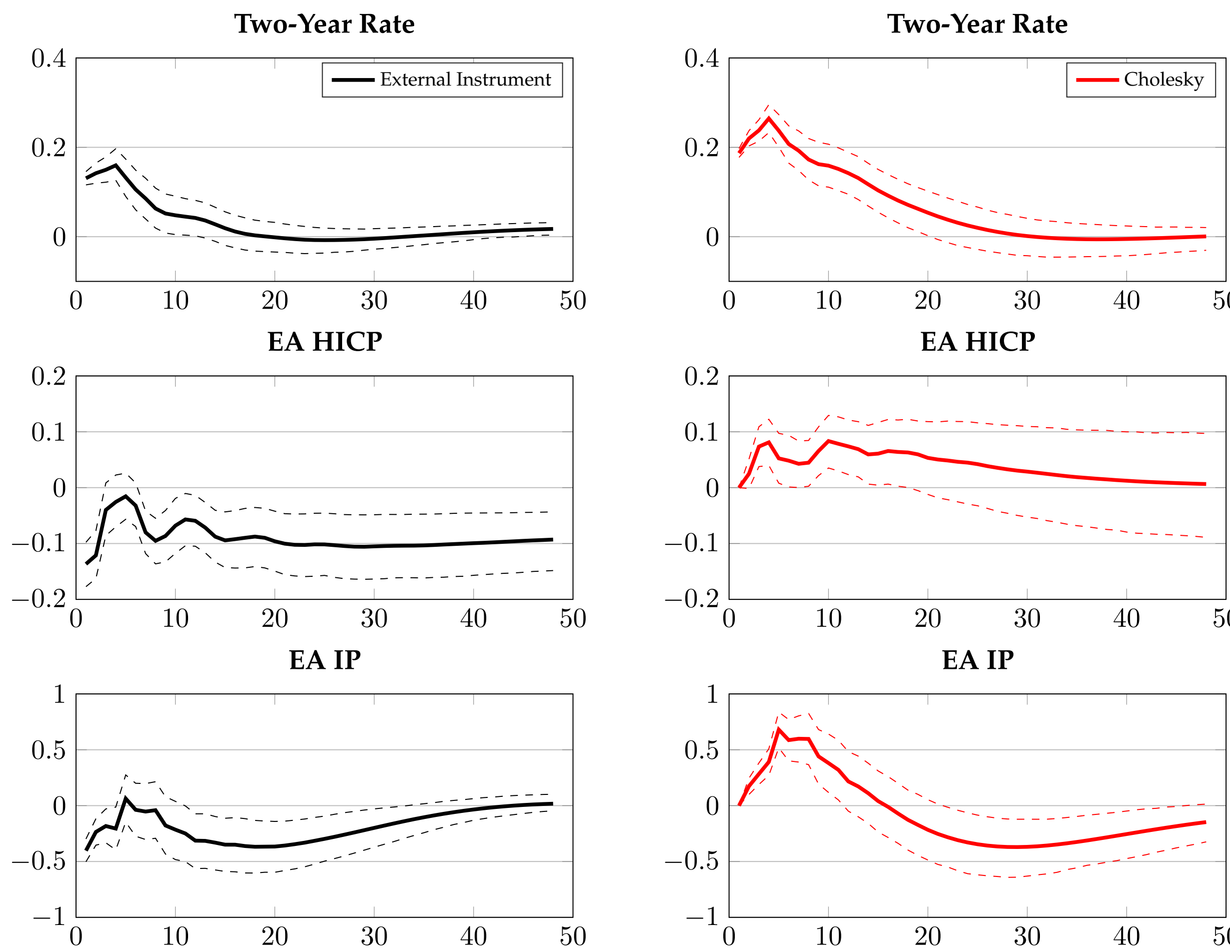


Figure 13: VAR using monthly data from 2000 to 2016. Here we show the responses to a one standard deviation shock in the policy indicator, comparing the high-frequency identification with a Cholesky identification strategy. The dashed lines report the bootstrapped 68% confidence intervals. The Cholesky 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 13. 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 14 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.

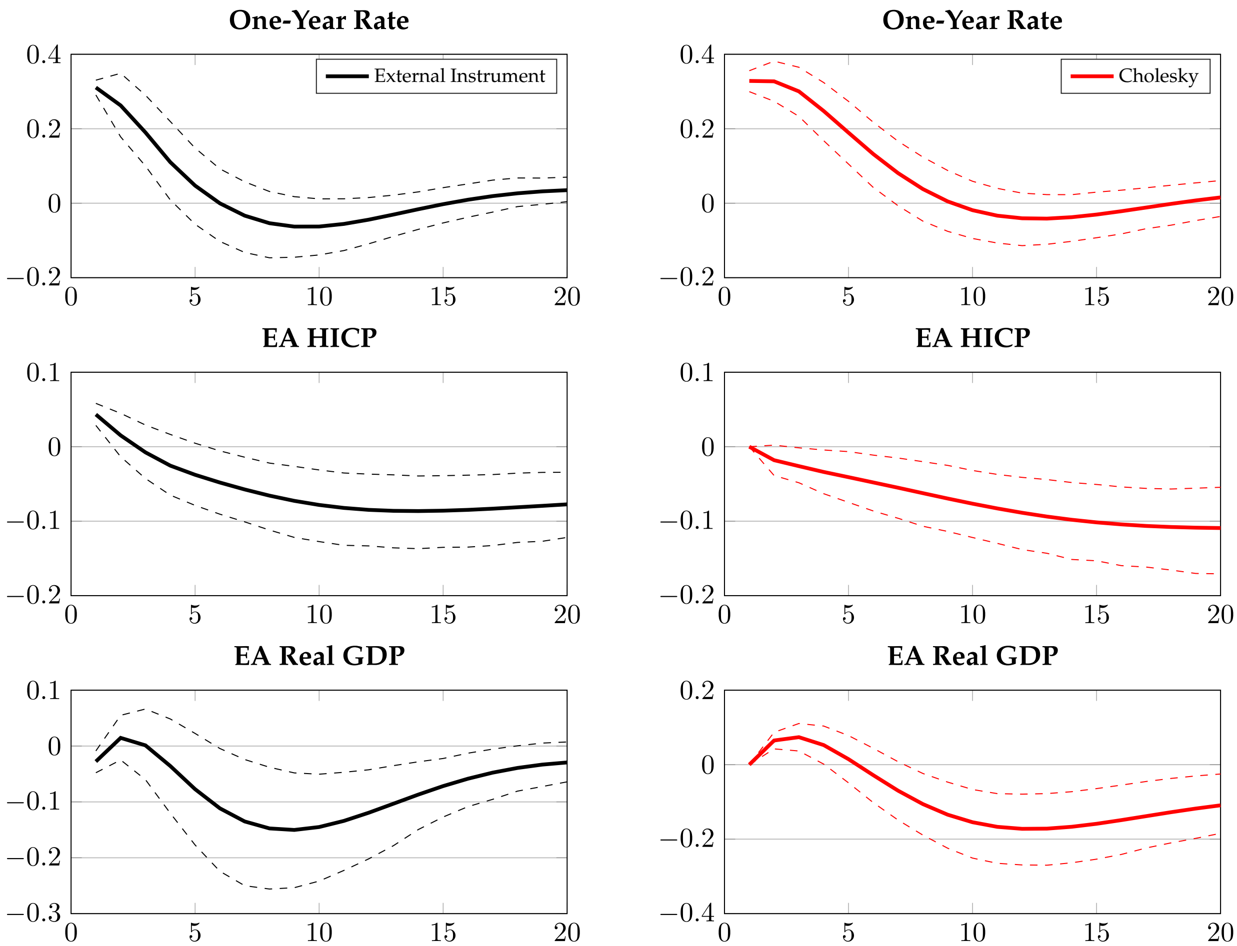


Figure 14: VAR using quarterly data from 2000 to 2016. Here we show the responses to a one standard deviation shock in the policy indicator using the high-frequency identification and the Cholesky identification. The dashed lines report the bootstrapped 68% confidence intervals. The Cholesky identification 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 15 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.

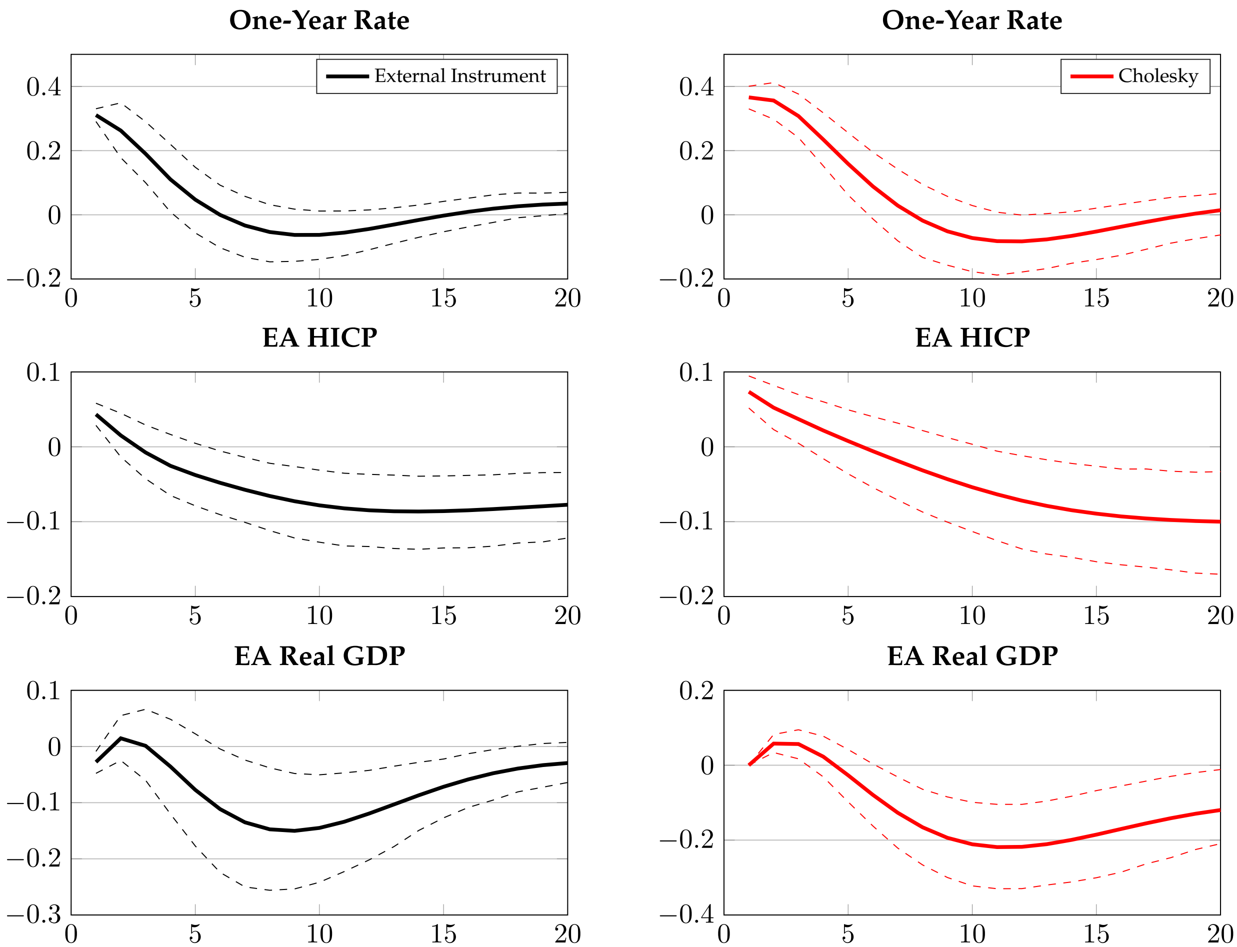


Figure 15: VAR using quarterly data from 2000 to 2016. Here we show the responses to a one standard deviation shock in the policy indicator using high-frequency and Cholesky identification. The dashed lines report the bootstrapped 68% confidence intervals. Here, the Cholesky identification orders the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

Table 7 contains a complete list of the series in our dataset 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 dataset 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	
IMDEF	Imports of goods and services, Price index (implicit deflator), 2010=100, euro, WDSA	5	Eurostat	EA12	2000 Q1	2016 Q4	
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	
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	
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	
House Prices							
RENTS	HICP Actual rentals for housing, Index, 2015=100	5	Eurostat	EACC	2000 Q1	2016 Q4	
HPI	House price index, 2010=100	5	Eurostat	EACC	2005 Q1	2016 Q4	
RHPI	Real house prices (=HPI/HICP00)	5	Eurostat	EACC	2005 Q1	2016 Q4	
RRENTS	Real rents (=RENTS/HICP00)	5	Eurostat	EACC	2000 Q1	2016 Q4	
BUILDCOSTI	Construction Cost Index, Residential Buildings (2010=100, WDSA)	5	Eurostat	EA19	2000 Q1	2016 Q4	
REN_i	HICP Actual rentals for housing, Index, 2015=100	5	Eurostat	EA11_i	2000 Q1	2016 Q4	
RREN_i	Real rents (=REN/HICP00)	5	Author's calculation	EA11_i	2000 Q1	2016 Q4	
HPI_i	House price index, 2010=100	5	Eurostat	EA11_i	2005 Q1	2016 Q4	
RHPI_i	Real house prices (=HPI/HICP00)	5	Author's calculation	EA11_i	2005 Q1	2016 Q4	
NDW_i	House price index, New dwellings, 2010=100	5	Eurostat	11 ex NLD	2005 Q1	2016 Q4	
EDW_i	House price index, Existing dwellings, 2010=100	5	Eurostat	EA11_i	2005 Q1	2016 Q4	
Exchange Rates							
NEER	Euro Nominal Effective Exchange Rate - 42 trading partners, Index, 2005=100	5	Eurostat	EA19	2000 Q1	2016 Q4	Y
EXRUK	Foreign Exchange Rate: United Kingdom (GBP per EUR - quarterly average)	5	Eurostat	EA	2000 Q1	2016 Q4	Y
EXRSW	Foreign Exchange Rate: Switzerland (CHF per EUR - quarterly average)	5	Eurostat	EA	2000 Q1	2016 Q4	Y
EXRJP	Foreign Exchange Rate: Japan (JPY per EUR - quarterly average)	5	Eurostat	EA	2000 Q1	2016 Q4	Y
EXRUS	Foreign Exchange Rate: United States of America (USD per EUR - quarterly average)	5	Eurostat	EA	2000 Q1	2016 Q4	Y
Expectations							
BSBCI	EA Business Climate Indicator (SA)	2	Eurostat	EA19	2000 Q1	2016 Q4	
BSCCI	Construction Confidence Indicator (SA)	2	Eurostat	EA19	2000 Q1	2016 Q4	
BSESI	Economic Sentiment Indicator (SA)	2	Eurostat	EA19	2000 Q1	2016 Q4	
BSICI	Industrial Confidence Indicator (SA)	2	Eurostat	EA19	2000 Q1	2016 Q4	
BSRCI	Retail Confidence Indicator (SA)	2	Eurostat	EA19	2000 Q1	2016 Q4	
BSCSMCI	Consumer Confidence Indicator (SA)	2	Eurostat	EA19	2000 Q1	2016 Q4	Y
BSSCI	Services Confidence Indicator (SA)	2	Eurostat	EA19	2000 Q1	2016 Q4	

D On Interpreting Factors

For Table 8, 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 8: 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 House Prices Ireland	0.44
	Unemployment Finland	0.43
	Real House Prices France	0.43
Factor 5	Real House Prices Netherlands	0.46
	GDP Spain	0.40
	Private Consumption Spain	0.33
	House Prices Netherlands	0.32
	Gross Fixed Capital Formation in Construction	0.32

E Explanatory Power of Factors

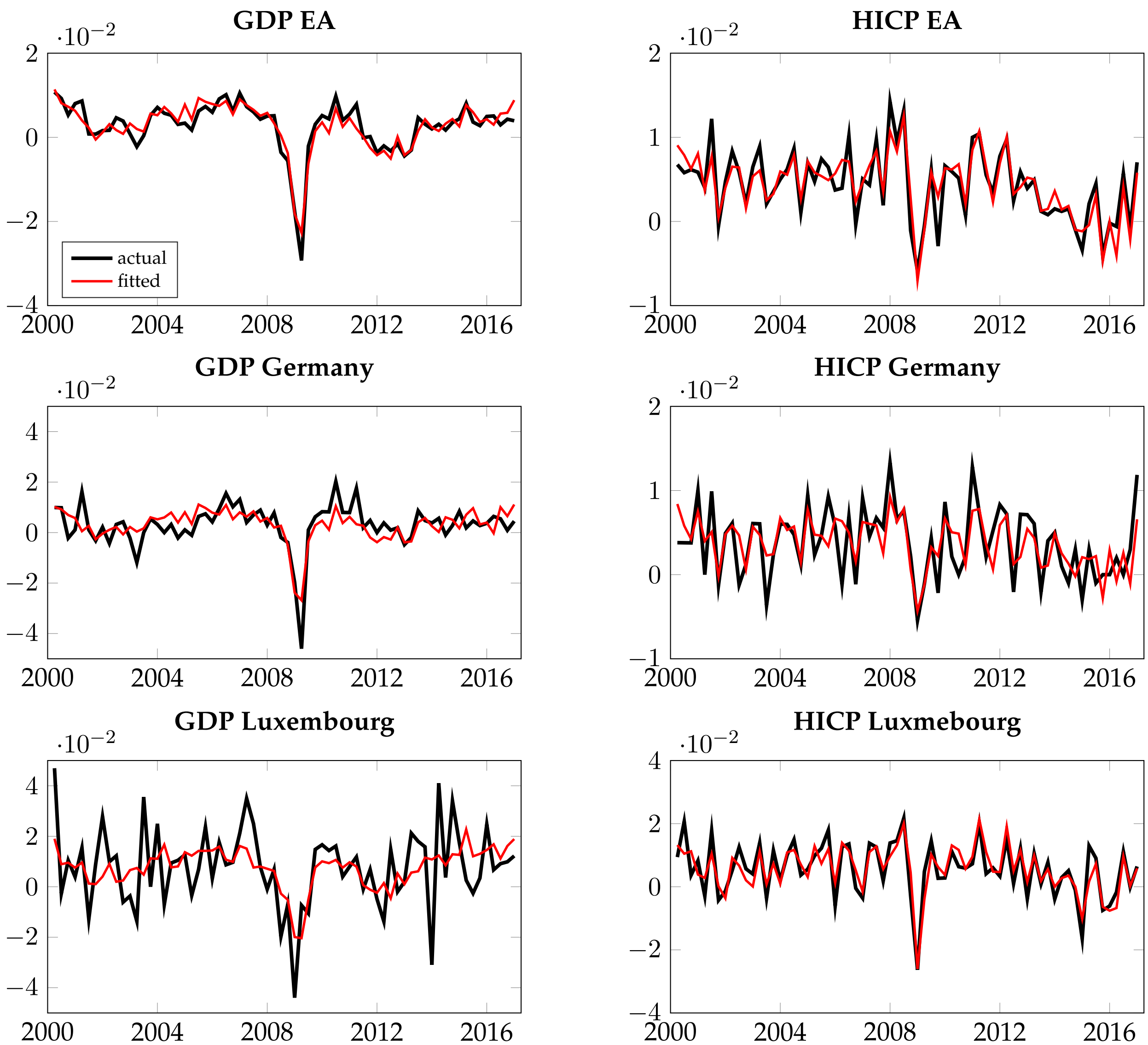


Figure 16: The figure compares actual (transformed) GDP and HICP data with corresponding fitted series on the basis of 5 extracted factors for the euro area (EA), Germany and Luxembourg from 2000 Q1 to 2016 Q4. Germany and Luxembourg represent the largest and smallest economies in our sample euro area, respectively. In SDFM 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

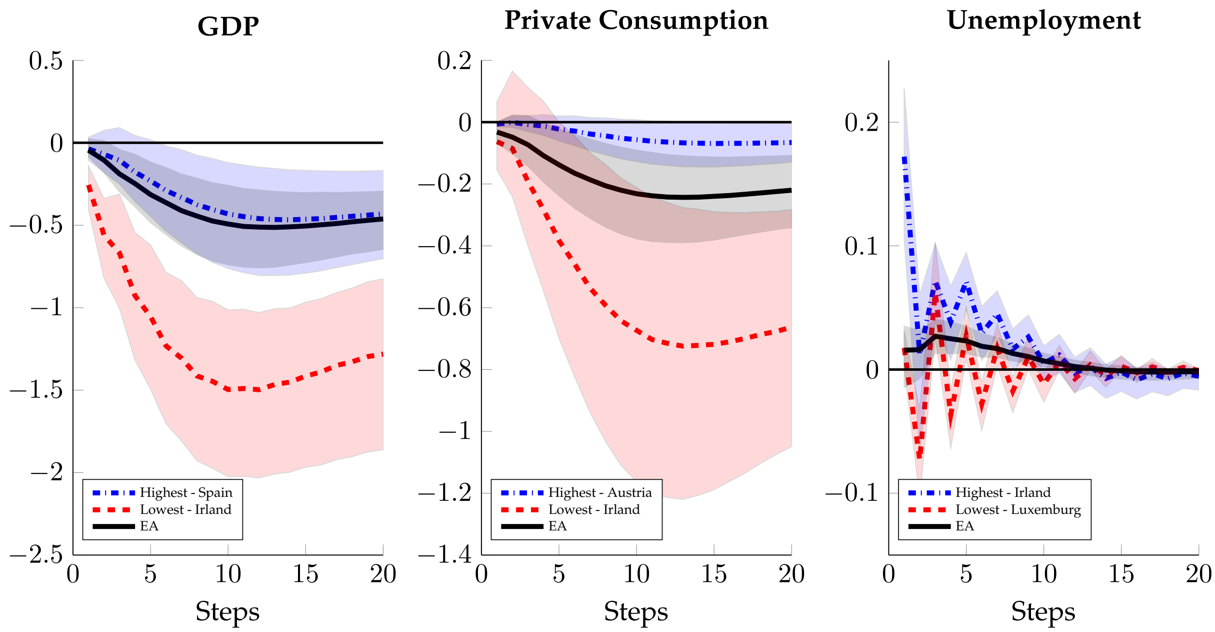


Figure 17: Highest/lowest percentage responses of selected real variables to a 25bp contractionary policy shock across euro area member countries.

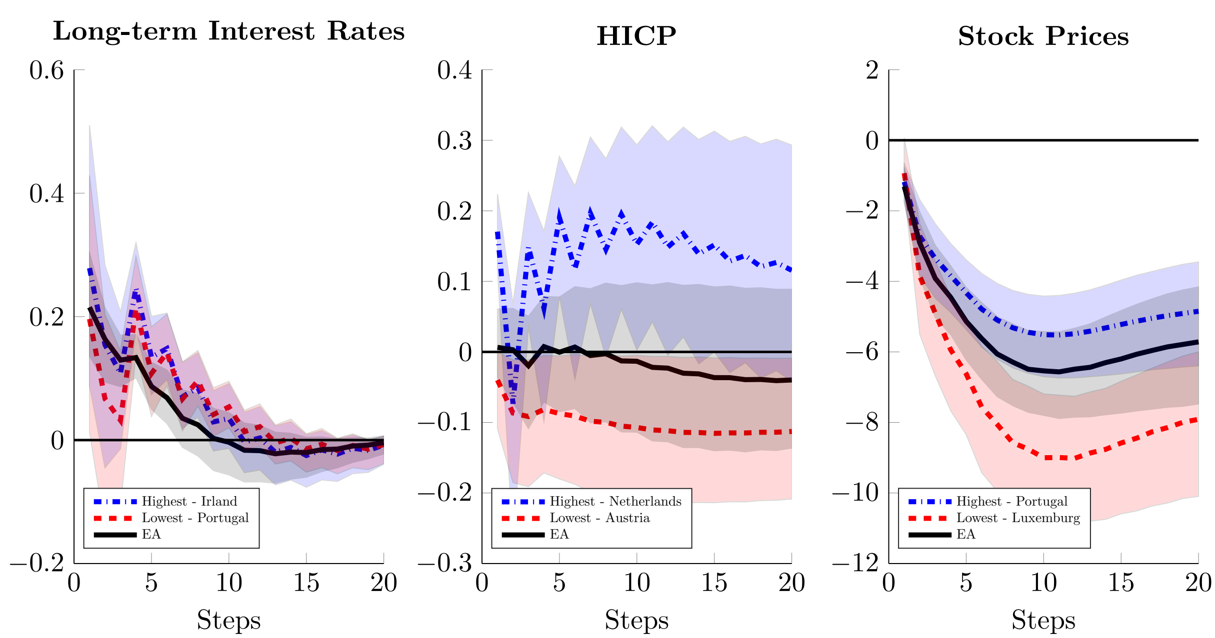


Figure 18: Highest/lowest percentage responses of selected prices to a 25bp contractionary policy shock across euro area member countries.

G Robustness

G.1 Sub-sample Analysis

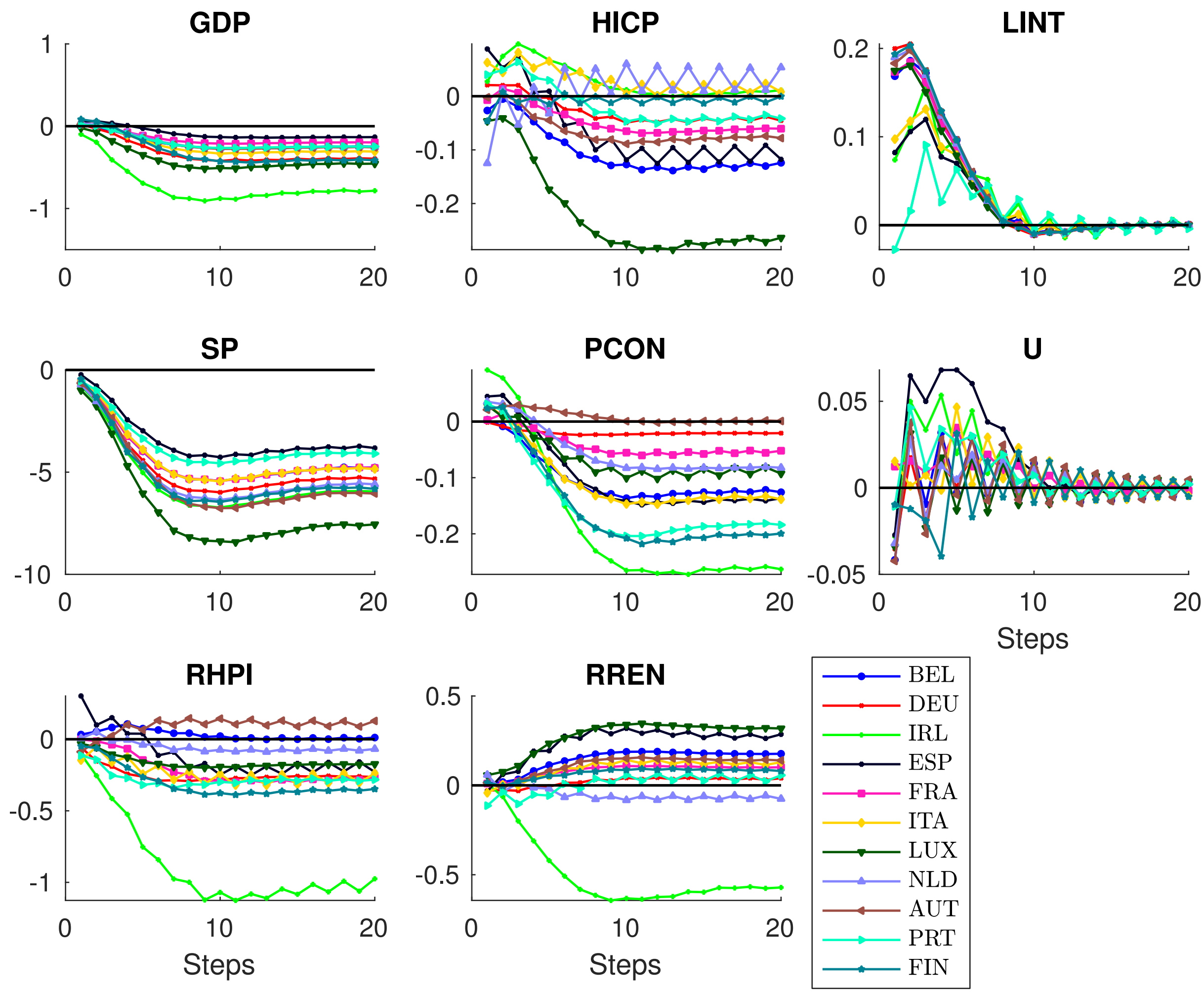


Figure 19: Cross-country impulse responses for selected variables when the model is estimated for the pre-crisis 2001Q1 to 2007Q4 period.

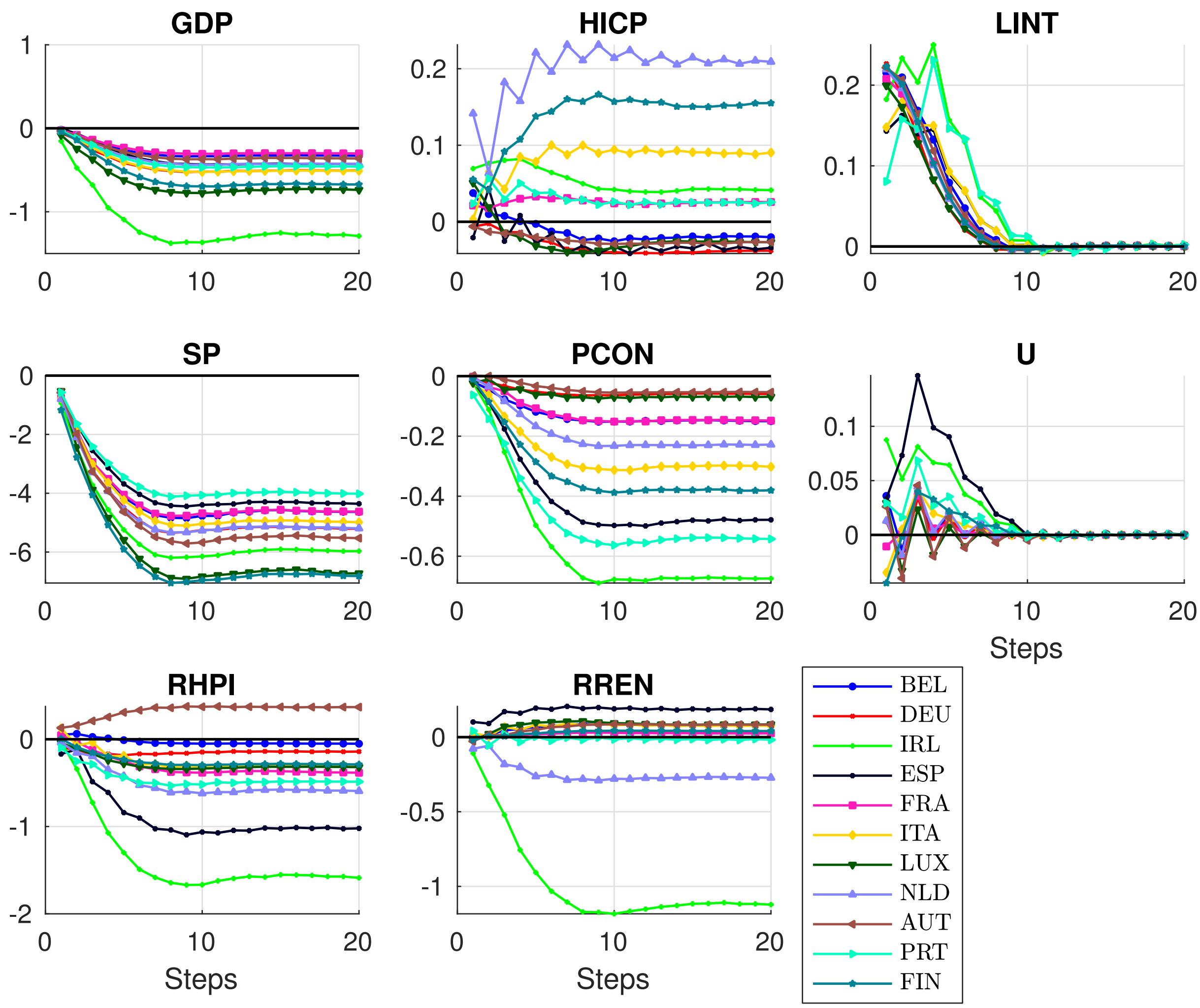


Figure 20: Cross-country impulse responses for selected variables when the model is estimated for the post-crisis 2008Q1 to 2016Q4 period.

G.2 Standard Errors for the Statistics of Interest Incorporating Factor Loadings Uncertainty

Here, we no longer take the factors as data. First we choose a block of length l and compute the number of blocks $N = T/l$, where T is the number of observations, rounding it up to the nearest integer so that we end up with $Nl \geq T$. Then,

1. Compute the idiosyncratic residual $\hat{e}_t = X_t - \hat{\Lambda}\hat{F}_t$.
2. Estimate one-lag univariate autoregressive processes for $\hat{e}_t$, $\hat{e}_{it} = \rho\hat{e}_{it-1} + \zeta_{it}$
3. Independently draw N integers with replacement from the set $1, \dots, T - l + 1$, putting equal probability on each element of the set. Denote these integers as $i_1, \dots, i_N$.
4. Collect the $n \times l$ blocks $\mathcal{Z}_i = (\hat{\zeta}_i, \dots, \hat{\zeta}_{i+l-1})$ for $i = 1, \dots, T - l + 1$, the $r \times l$ blocks

$\mathcal{U}_i = (\hat{u}_i, \ldots, \hat{u}_{i+l-1})$ for $i = 1, \ldots, T-l+1$ and the l blocks $\mathcal{M}_i = (m_i, \ldots, m_{i+l-1})$ for $i = 1, \ldots, T-l+1$.

5. Collect the blocks $(\mathcal{Z}_{i_1}, \ldots, \mathcal{Z}_{i_N})$, $(\mathcal{U}_{i_1}, \ldots, \mathcal{U}_{i_N})$ and $(\mathcal{M}_{i_1}, \ldots, \mathcal{M}_{i_N})$ and drop the last $Nl-T$ elements to produce the bootstrap quantities $(\tilde{\zeta}_i^*, \ldots, \tilde{\zeta}_T^*)$, $(\tilde{u}_i^*, \ldots, \tilde{u}_T^*)$ and $(\tilde{m}_i^*, \ldots, \tilde{m}_T^*)$.

6. Center $(\tilde{\zeta}_i^*, \ldots, \tilde{\zeta}_T^*)$, $(\tilde{u}_i^*, \ldots, \tilde{u}_T^*)$ and $(\tilde{m}_i^*, \ldots, \tilde{m}_T^*)$ according to

$$\zeta_{jl+s}^* = \tilde{\zeta}_{jl+s}^* - \frac{1}{T-l+1}\sum_{\tau=1}^{T-l} \hat{\zeta}_{s+\tau-1}$$
$$u_{jl+s}^* = \tilde{u}_{jl+s}^* - \frac{1}{T-l+1}\sum_{\tau=1}^{T-l} \hat{u}_{s+\tau-1}$$
$$m_{jl+s}^* = \tilde{m}_{jl+s}^* - \frac{1}{T-l+1}\sum_{\tau=1}^{T-l} m_{s+\tau-1}$$

   for $s = 1, \ldots, l$ and $j = 1, \ldots, N-1$ in order to produce $(\zeta_i^*, \ldots, \zeta_T^*)$, $(u_i^*, \ldots, u_T^*)$ and $(m_i^*, \ldots, m_T^*)$ and making sure they are centered conditionally on the data.

7. Set the initial condition $(\tilde{F}_{-p+1}, \ldots, \tilde{F}_0) = (F_{-p+1}, \ldots, F_0)$. Use the initial condition together with $\hat{\delta}(L)$ and u_t^* to recursively compute $(\tilde{F}_1, \ldots, \tilde{F}_T)$ with

$$\tilde{F}_t = \hat{\delta}(L)\tilde{F}_{t-1} + u_t^*.$$

8. Set the initial condition $e_{-1}^* = \hat{e}_{-1}$. Use the initial condition together with $\hat{\rho}$ and ζ_t^* to recursively compute $(e_1^*, \ldots, e_T^*)$ with

$$e_t^* = \hat{\rho} e_{t-1}^* + \zeta_t^*.$$

9. Generate bootstrap data as $X_t^* = \hat{\Lambda}\tilde{F}_t + e_t^*$

10. Estimate Λ^*, F_t^* using principal components on X_t^*. Get $\delta(L)^*$ by least squares from the bootstrap sample $(F_1^*, \ldots, F_T^*)$ and set the new residuals $\hat{u}_t^* = F_t^* - \delta(L)^* F_{t-1}^*$.

11. Use $\hat{u}_t^*$ and m_t^* for $t = 1, \ldots, T$ to estimate $\widehat{\alpha H_1} = T^{-1} \sum_{t=1}^{T} m_t^* (\hat{u}_t^*)'$

12. Use $\hat{\delta}(L)^*$ and $\widehat{\alpha H_1}$ to produce the SIRF and the CV.

We repeat the algorithm two thousand times, collect the bootstrap statistics, and produce confidence intervals with a standard percentile interval.

We re-do all of our analysis with this full moving block bootstrap method and report the results below. We find that while most of euro-wide variables turn insignificant, our main conclusions concerning the degree of heterogeneity in the responses of different variables to a monetary policy shock remain mostly unchanged. The only difference being that output no longer statistically displays lower dispersion than private consumption and unemployment.

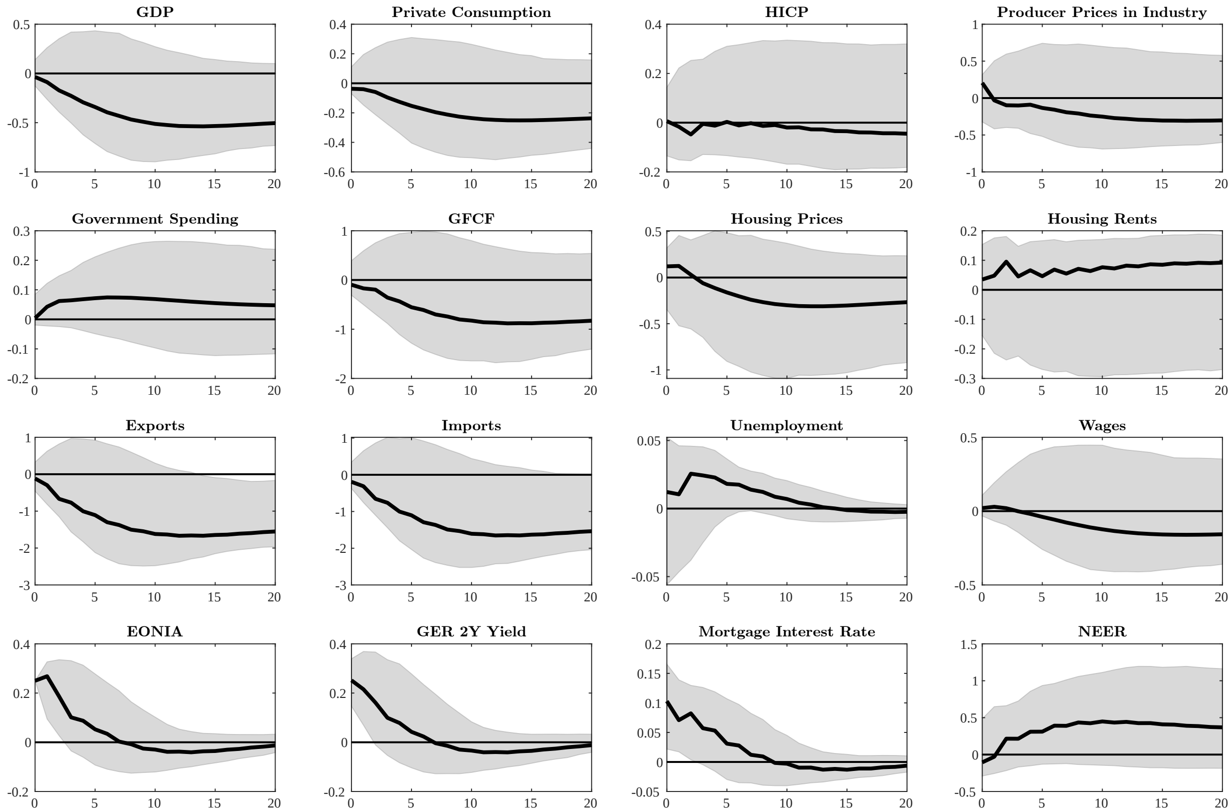


Figure 21: Percentage responses of selected euro-wide variables to a 25bp contractionary policy shock. Note: Confidence intervals are obtained from a moving block bootstrap procedure.

Table 9: 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	1.33	0.66	3.86
Private Consumption	1.47	0.92	4.31
Unemployment	1.47	0.98	4.08
Housing Prices	1.61	1.24	3.69
HICP	1.00	0.45	3.26
Long-term Interest Rates	0.80	0.23	3.43
Stock Prices	0.36	0.21	1.12
At the 8th Step			
GDP	0.60	0.39	1.69
Private Consumption	0.90	0.77	1.46
Unemployment	1.38	0.90	3.46
Housing Prices	1.29	1.10	2.15
HICP	0.95	0.41	3.09
Long-term Interest Rates	0.56	0.20	1.97
Stock Prices	0.25	0.17	0.71
At the 20th Step			
GDP	0.62	0.40	1.71
Private Consumption	0.92	0.78	1.55
Unemployment	1.40	0.97	2.84
Housing Prices	1.31	1.10	2.28
HICP	1.01	0.42	3.47
Long-term Interest Rates	0.54	0.19	1.90
Stock Prices	0.25	0.17	0.64

Notes: The third column reports the median estimates. The fourth and fifth columns report the lower and upper bounds, respectively, using the 68% confidence level. The inference is drawn from a moving bootstrap procedure that incorporates factor loadings uncertainty.

Table 10: Bootstrapped pair-wise differences in the coefficient of variation of the cross-country responses to a 25bp monetary policy shock.

	HICP	LTINT	SP	PCON	U	RHPI
On Impact						
GDP	0.32	0.63	0.84*	-0.21	-0.28	-0.31
HICP		0.18	0.47	-0.53	-0.63	-0.77
LTINT			0.22	-0.76	-0.78	-0.96
SP				-0.95*	-1.04*	-1.14*
PCON					-0.04	-0.18
U						-0.15
At the 8th Step						
GDP	-0.34	0.06	0.29*	-0.32	-0.62	-0.67*
HICP		0.33	0.62	0.00	-0.57	-0.39
LTINT			0.23	-0.38	-0.90	-0.73
SP				-0.62*	-1.04*	-0.98*
PCON					-0.42	-0.35*
U						-0.01
At the 20th Step						
GDP	-0.35	0.14	0.29*	-0.34	-0.71	-0.68*
HICP		0.35	0.64	0.01	-0.41	-0.37
LTINT			0.22	-0.43	-0.86	-0.80
SP				-0.63*	-1.05*	-0.99*
PCON					-0.39	-0.34*
U						0.04

Notes: * marks differences in variation that are significant at the 68% confidence level. The inference is drawn from a moving bootstrap procedure that incorporates factor loadings uncertainty.

G.3 Results using euro-wide aggregate data only

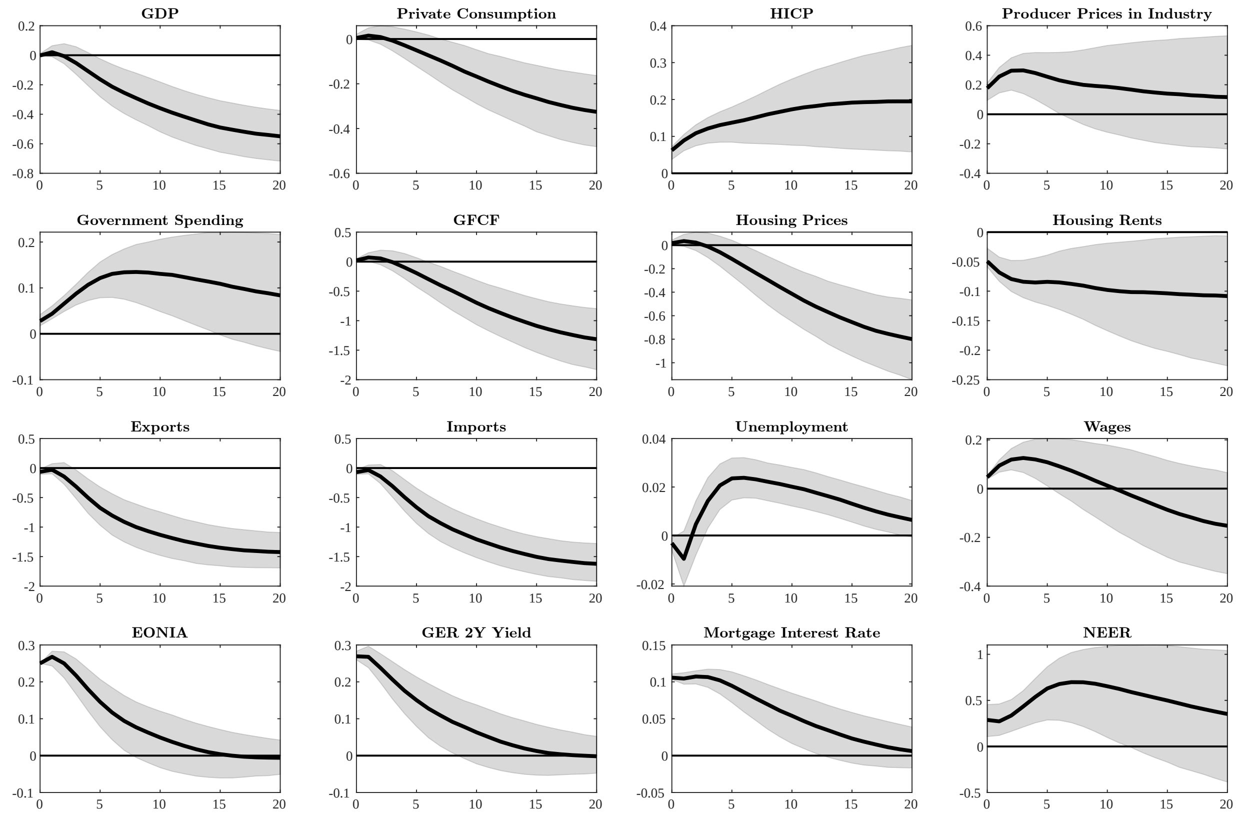


Figure 22: Percentage responses of selected euro-wide variables to a 25bp contractionary policy shock. Note: Confidence intervals are obtained from a moving block bootstrap procedure.

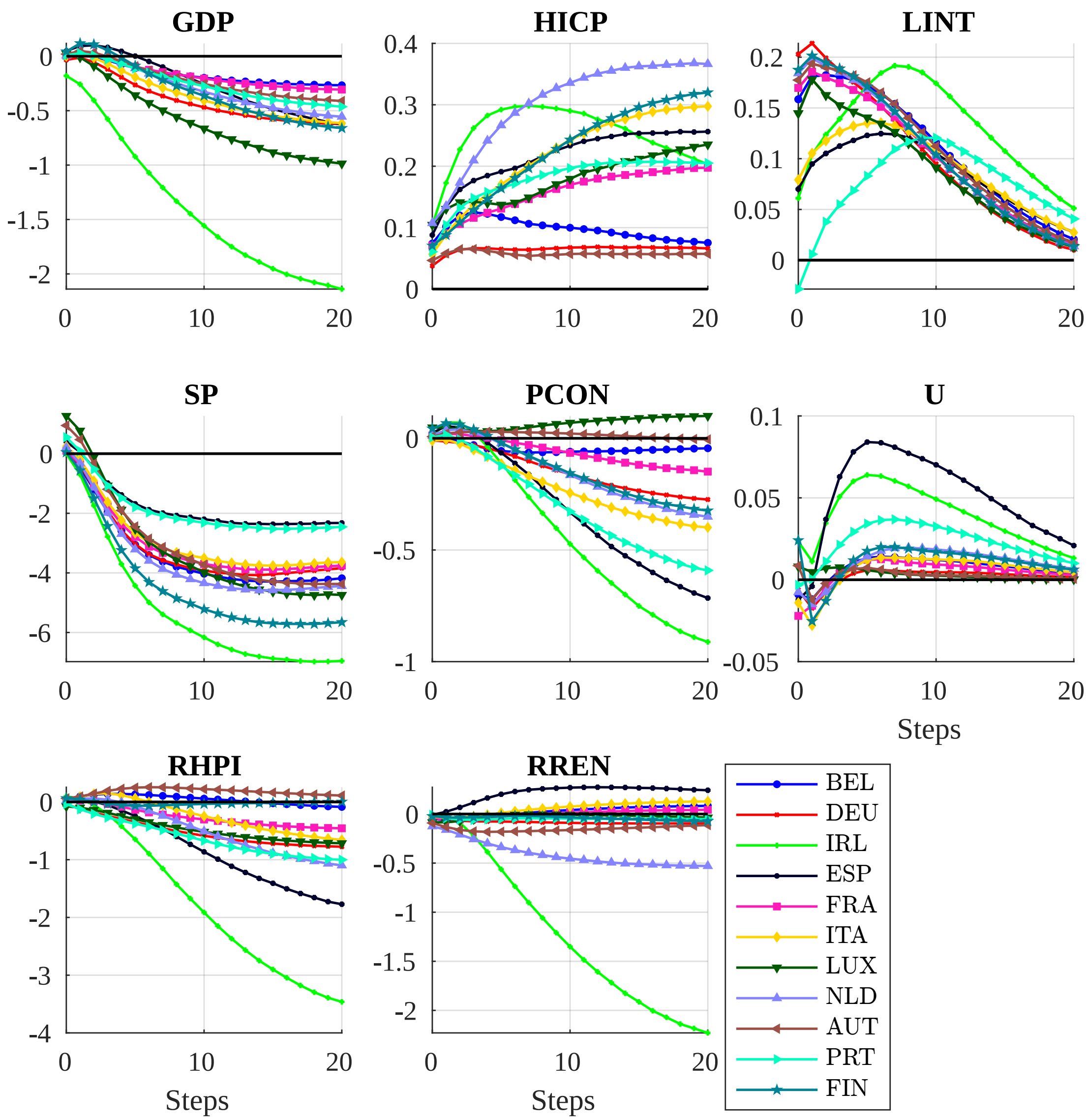


Figure 23: Percentage responses of selected variables when the model is estimated using aggregate data only.

G.4 Results using a FAVAR with a recursive identification

In this section, we show the SIRF of an estimated FAVAR, which assumes EONIA is observable and using the slow-fast variable recursive identification proposed in Bernanke et al. (2005).

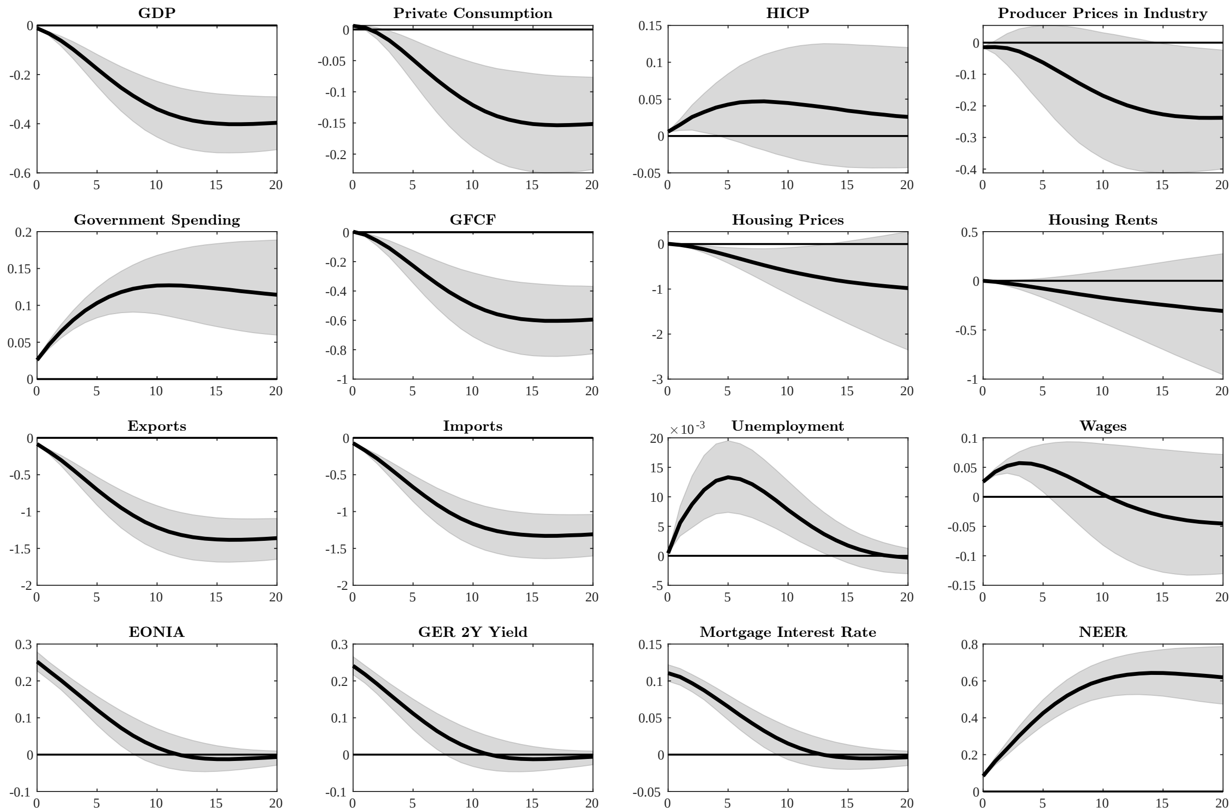


Figure 24: Percentage responses of selected euro-wide variables to a 25bp contractionary policy shock. Note: Confidence intervals are obtained from a moving block bootstrap procedure.

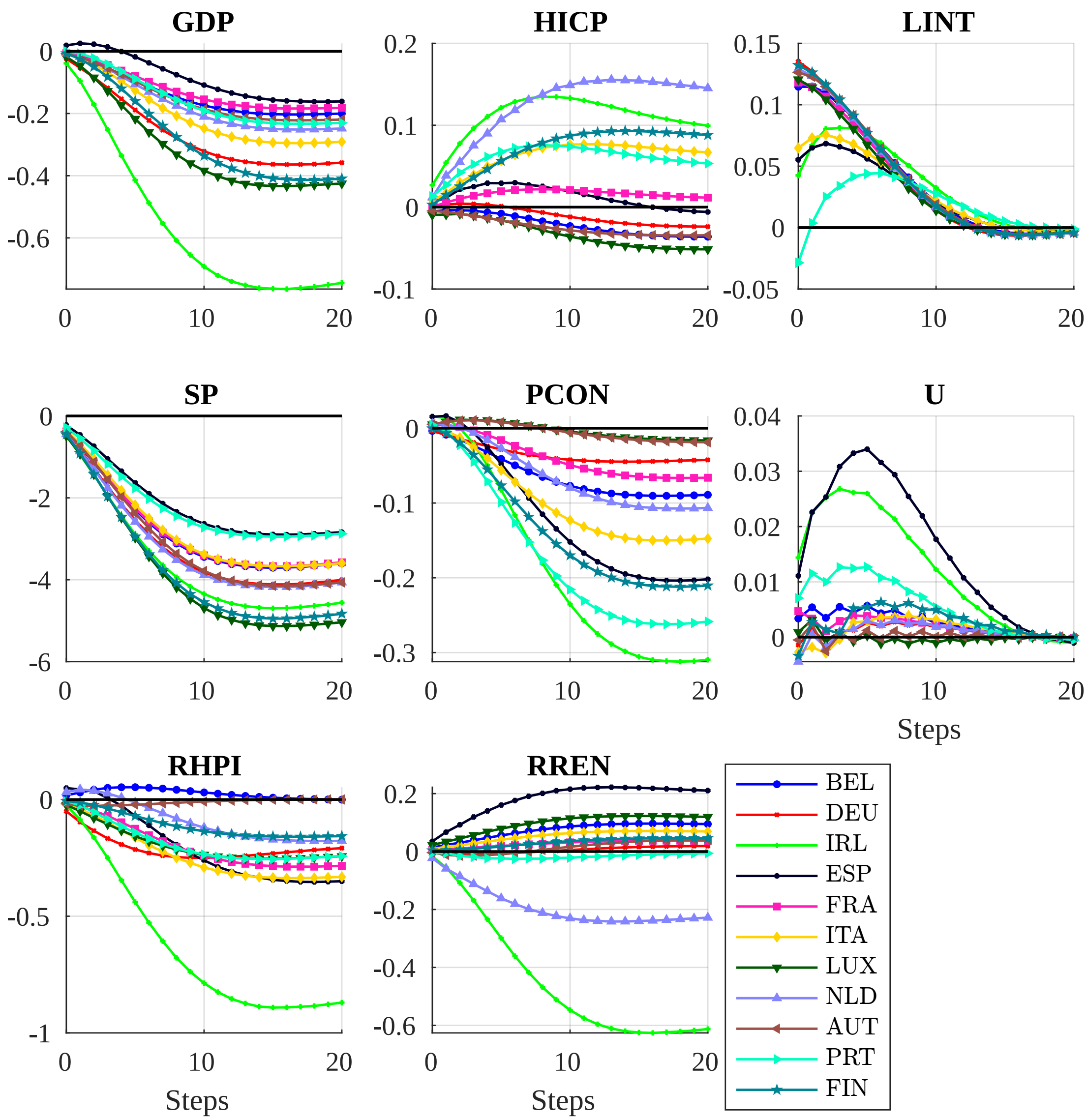
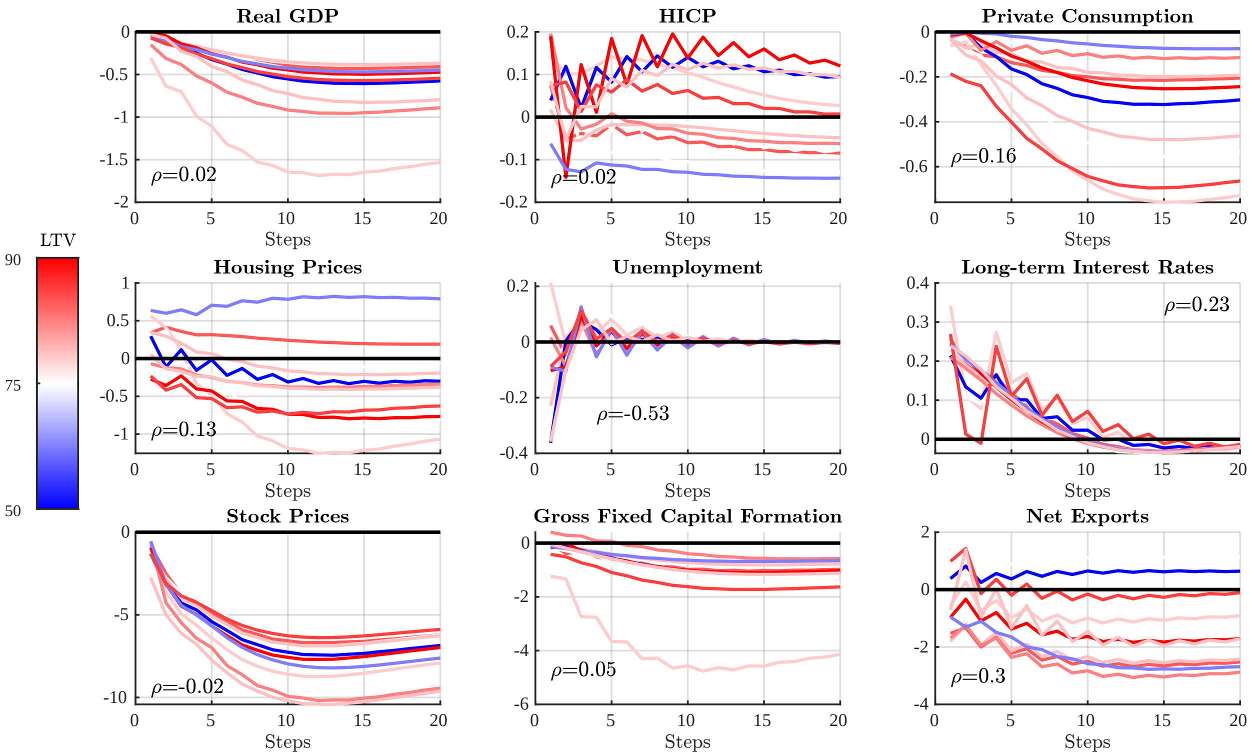


Figure 25: Percentage responses of selected variables when the model is estimated using aggregate data only.

H Institutional characteristics for which no pattern was found for monetary transmission

(a) Loan-to-value ratio



(b) Price rigidity

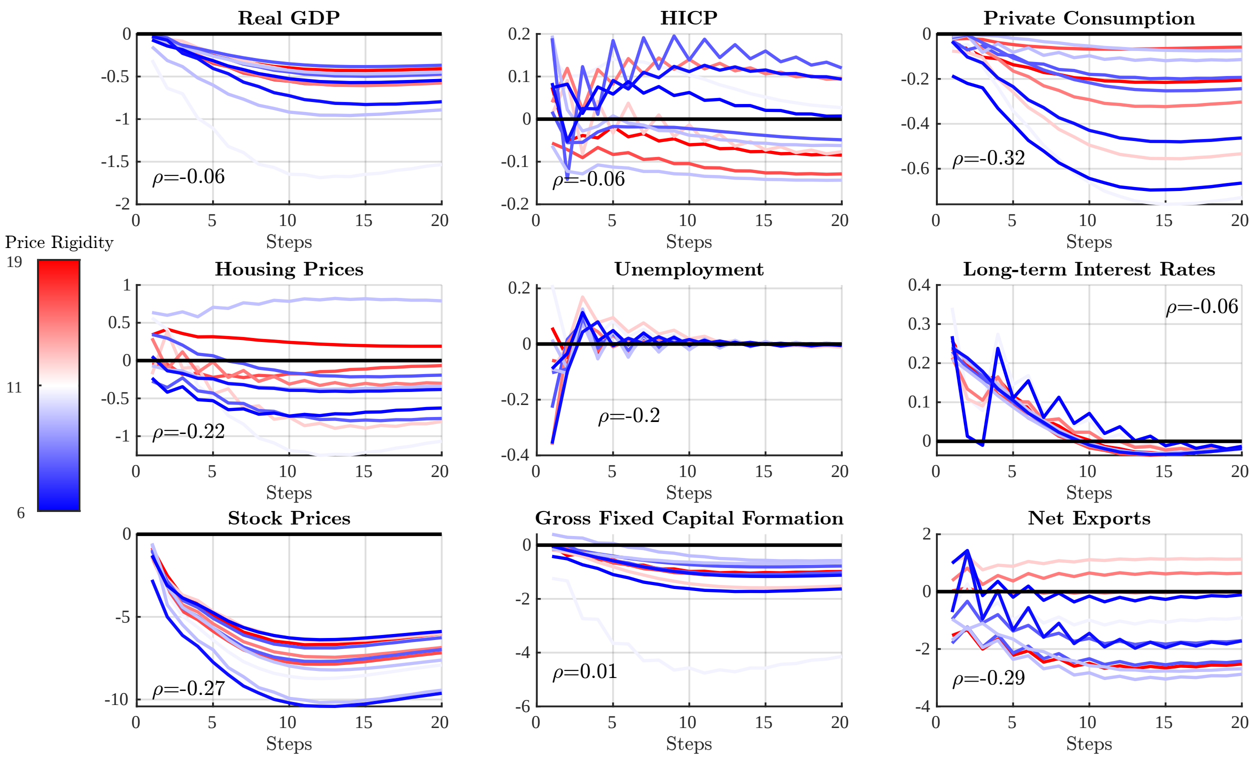
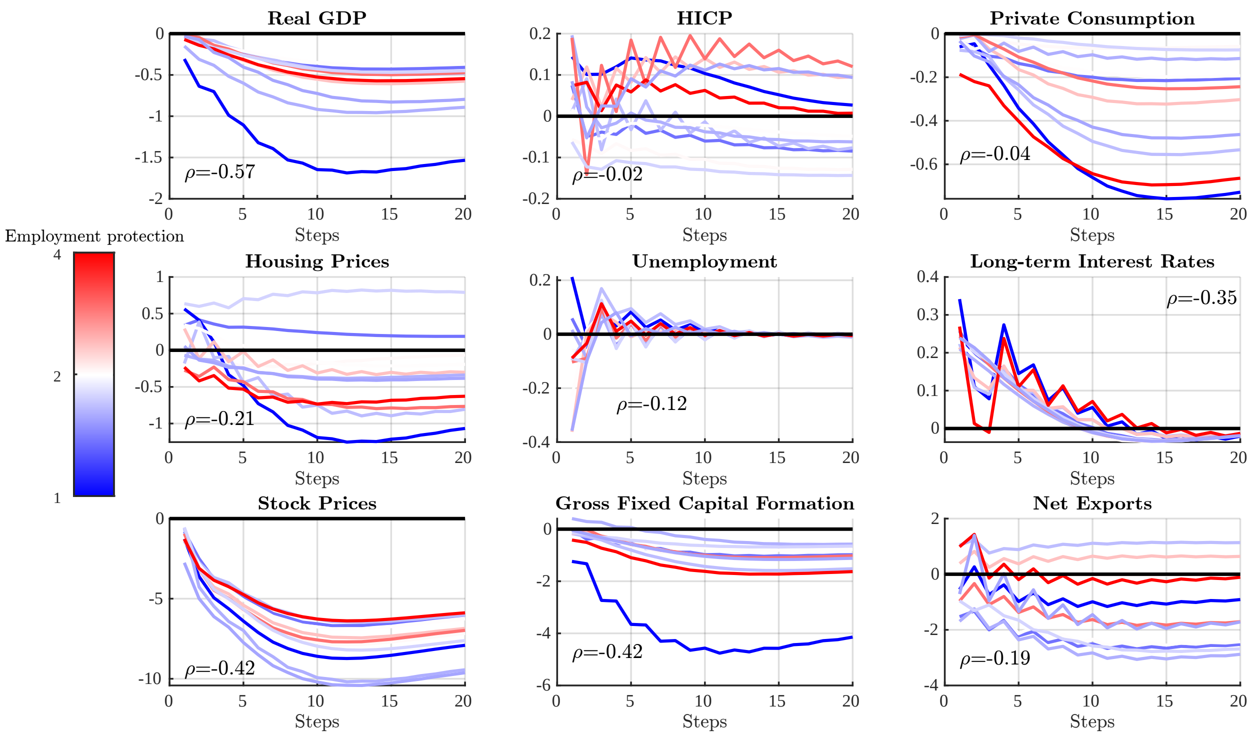


Figure 26: Percentage responses of selected variables to a 25bp contractionary policy shock across euro-area member countries with its colour intensity as a function of the level of an institutional characteristic— the first panel being the loan-to-value ratio, the second the price rigidity, the third the employment protection index, and the fourth the total leverage ratio.

(c) Employment protection



(d) Total leverage

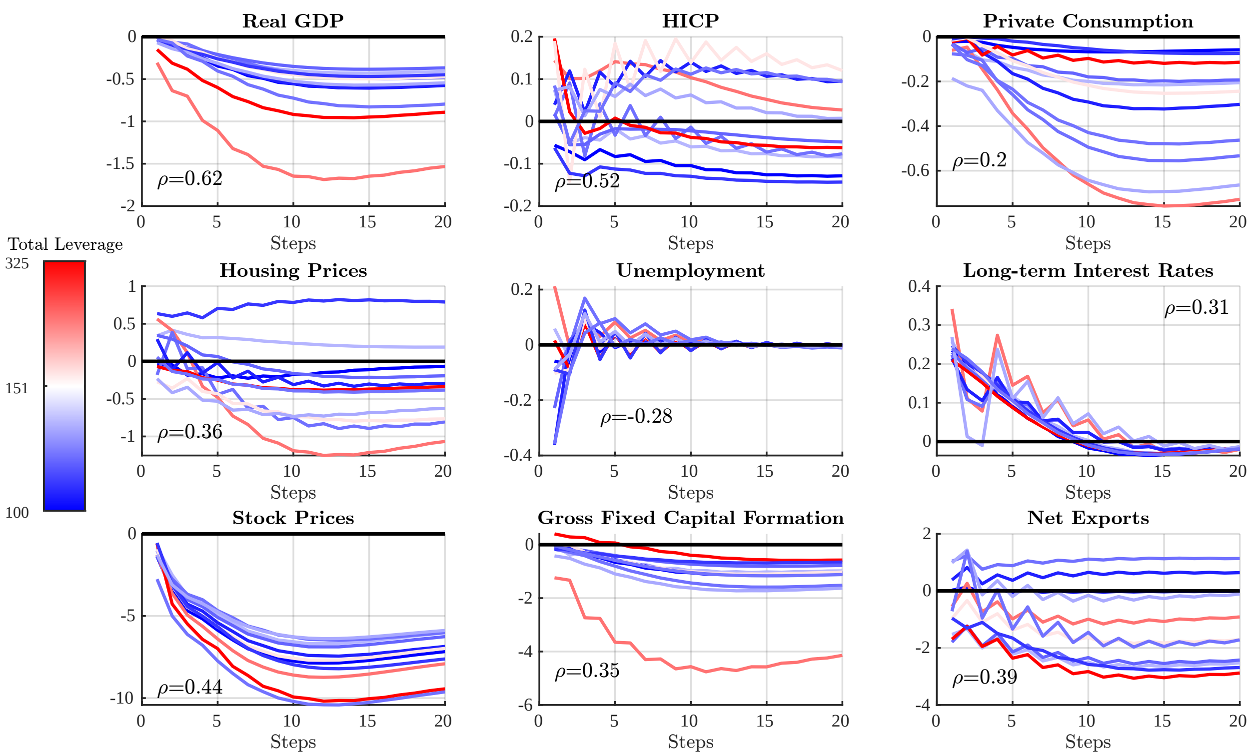
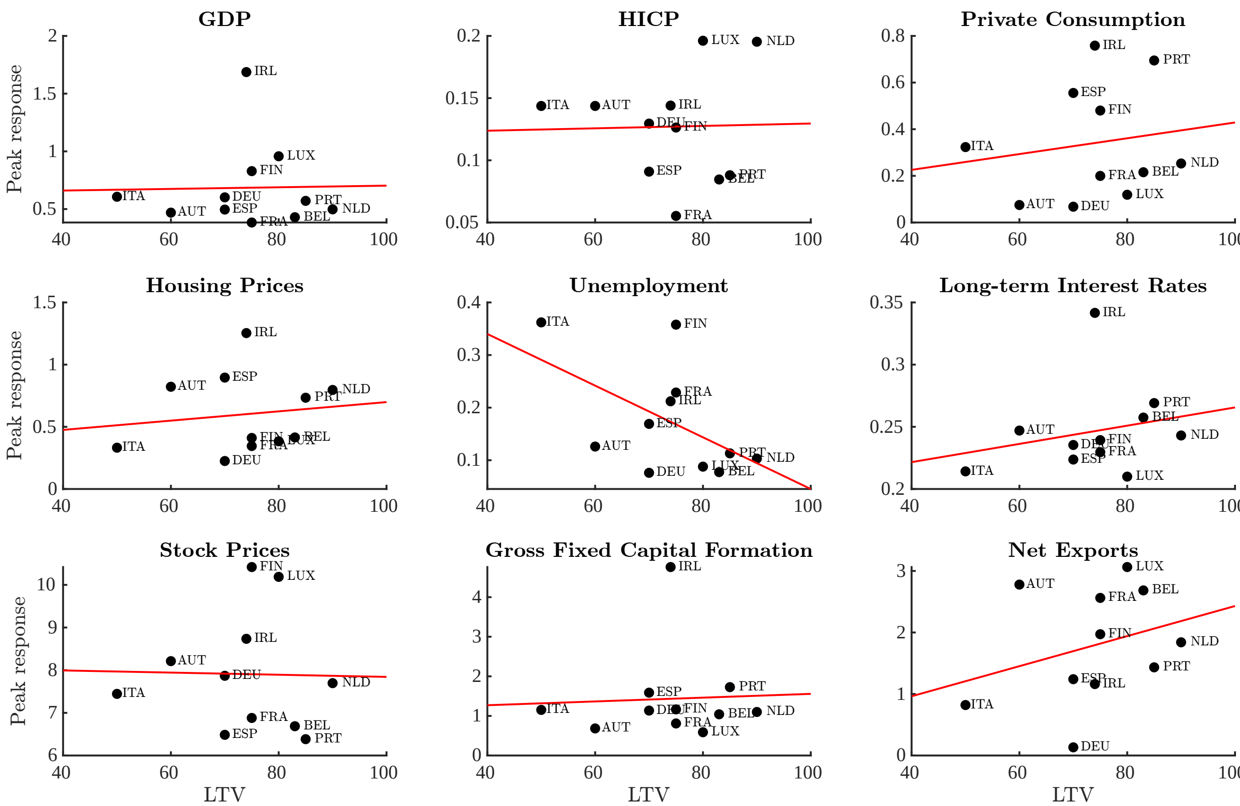


Figure 26: Percentage responses of selected variables to a 25bp contractionary policy shock across euro-area member countries with its colour intensity as a function of the level of an institutional characteristic— the first panel being the loan-to-value ratio, the second the price rigidity, the third the employment protection index, and the fourth the total leverage ratio.

I Scatter plots of institutional characteristics and peak responses

(a) LTV



(b) ARM

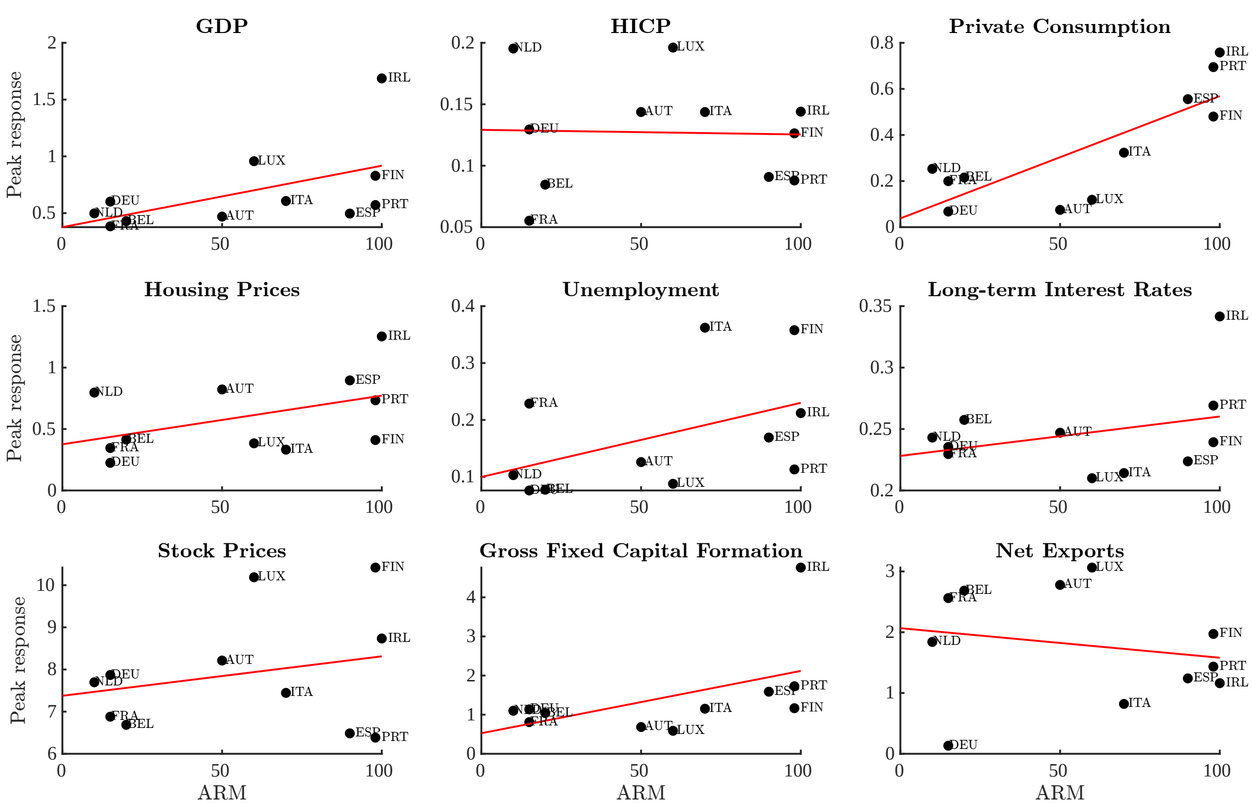
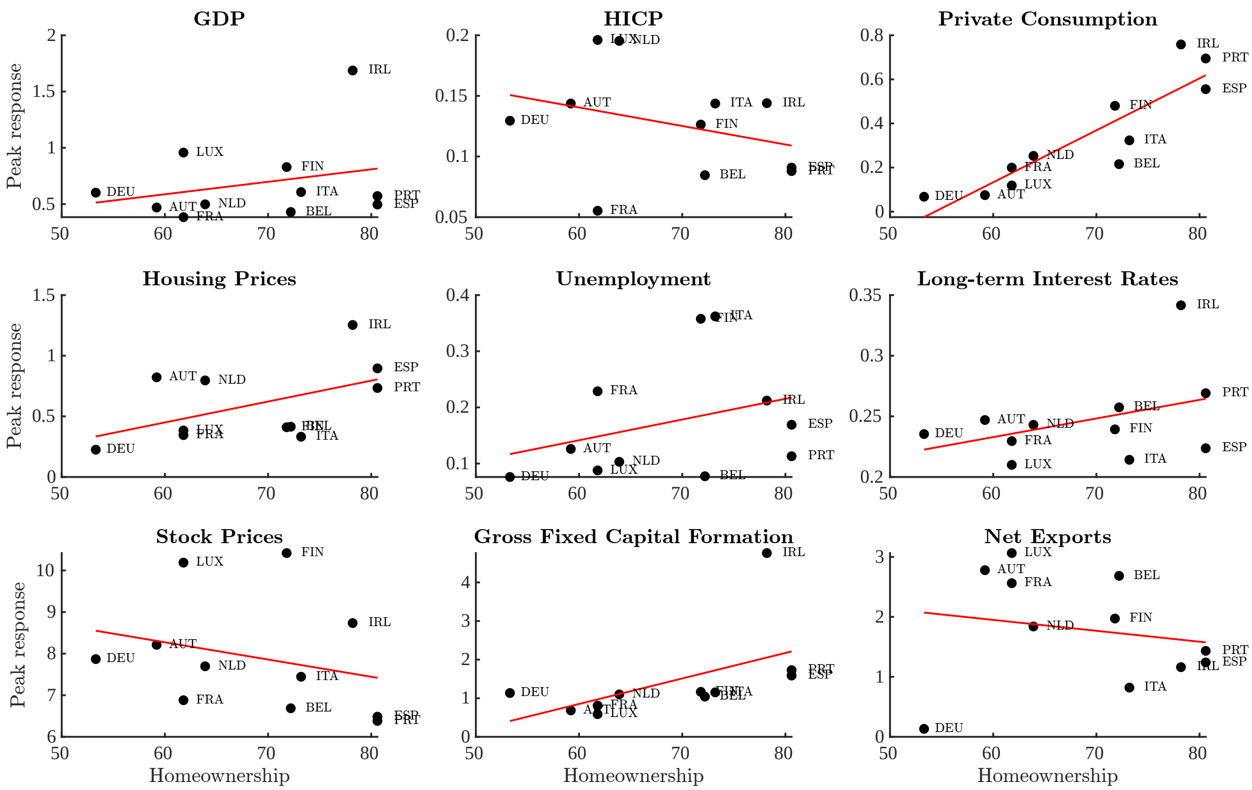


Figure 27: Scatter plot of responses of selected variables with: panel (a) the loan-to-value ratio, panel (b) adjustable-rate mortgage share, panel (c) homeownership rate, panel (d) share of HtM, panel (e) share of WtM, panel (f) wage rigidity, panel (g) price rigidity, panel (h) employment protection, and panel (i) total leverage to GDP ratio.

(c) Homeownership Rate



(d) Share of HtM

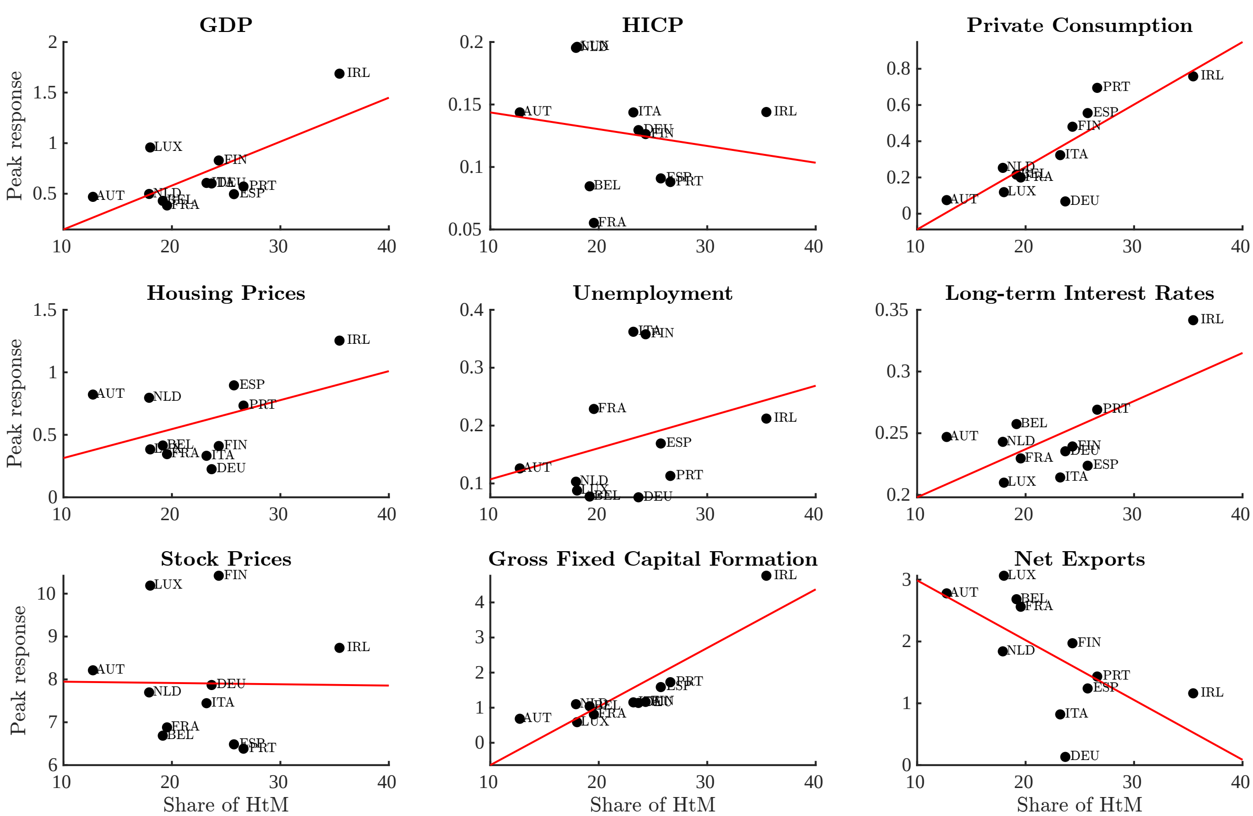
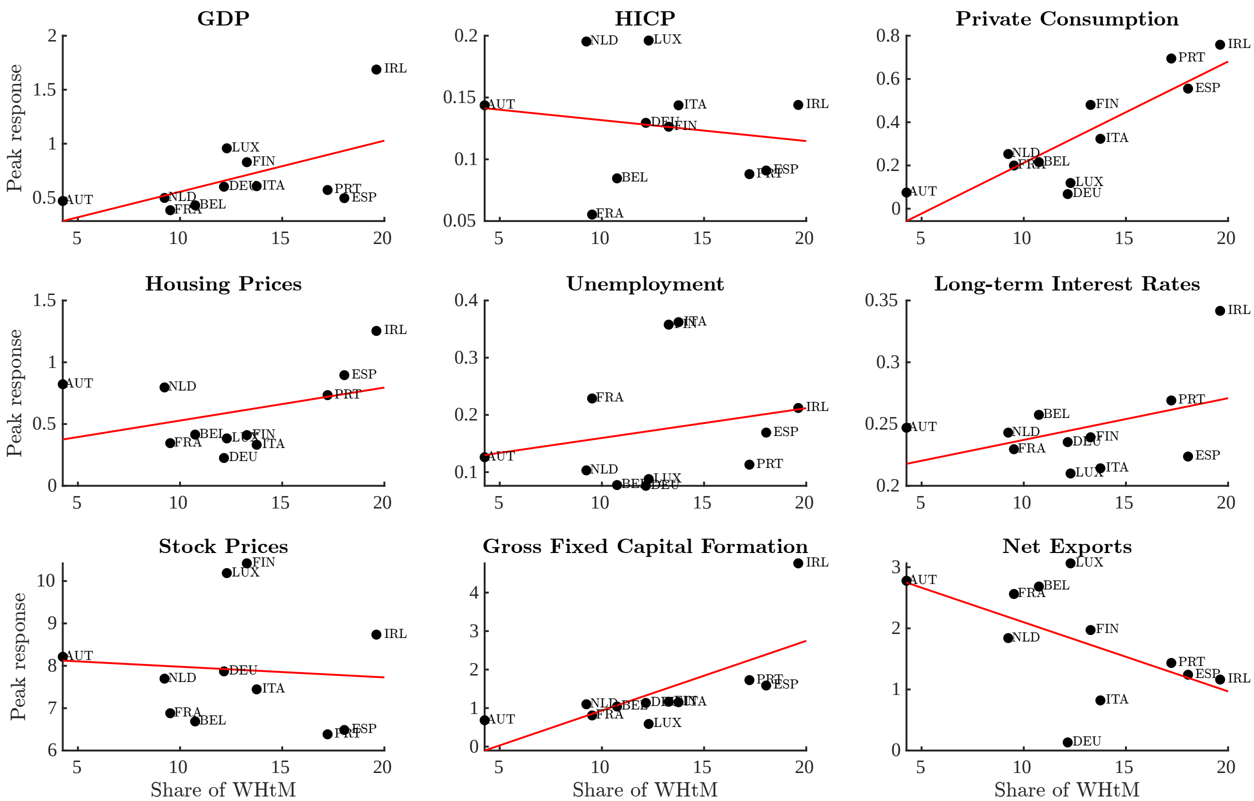


Figure 27: Scatter plot of responses of selected variables with: panel (a) the loan-to-value ratio, panel (b) adjustable-rate mortgage share, panel (c) homeownership rate, panel (d) share of HtM, panel (e) share of WtM, panel(f) wage rigidity, panel (g) price rigidity, panel (h) employment protection, and panel (i) total leverage to GDP ratio.

(e) Share of WHtM



(f) Wage Rigidity

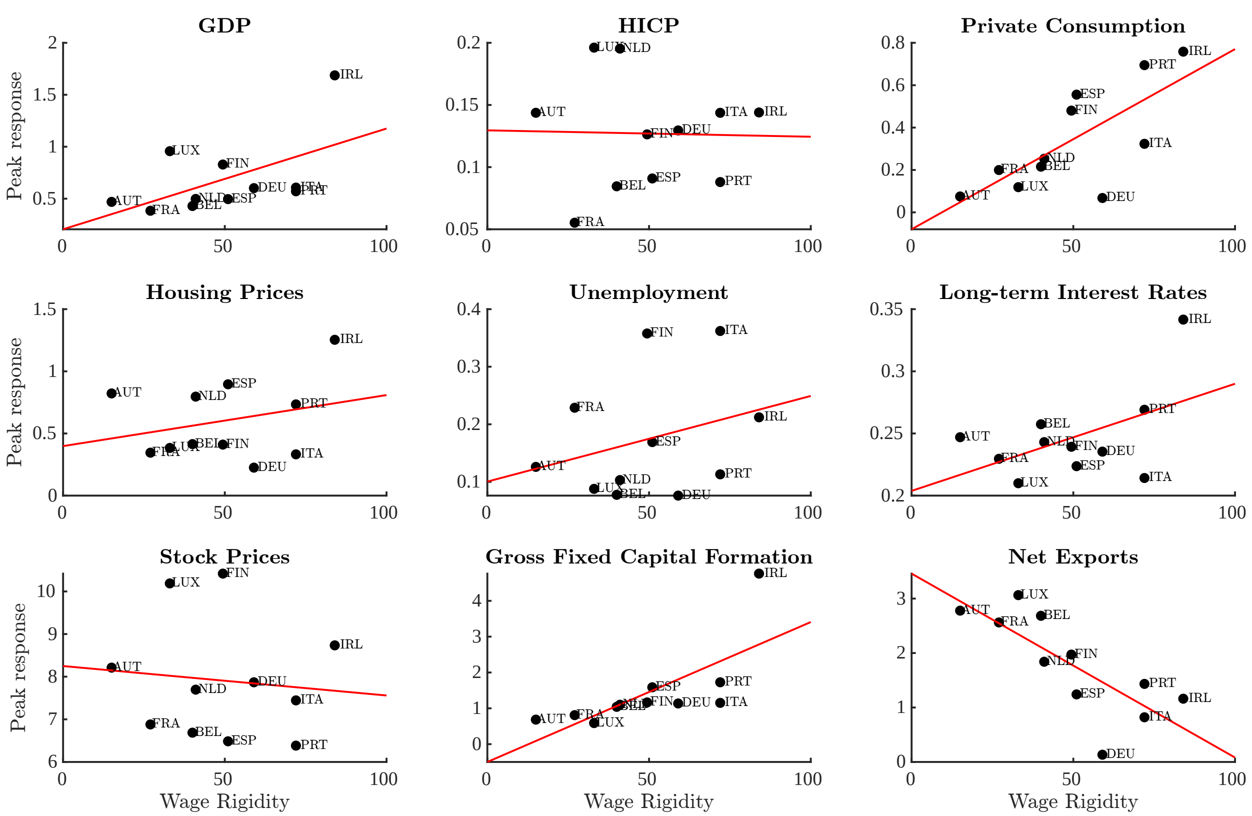
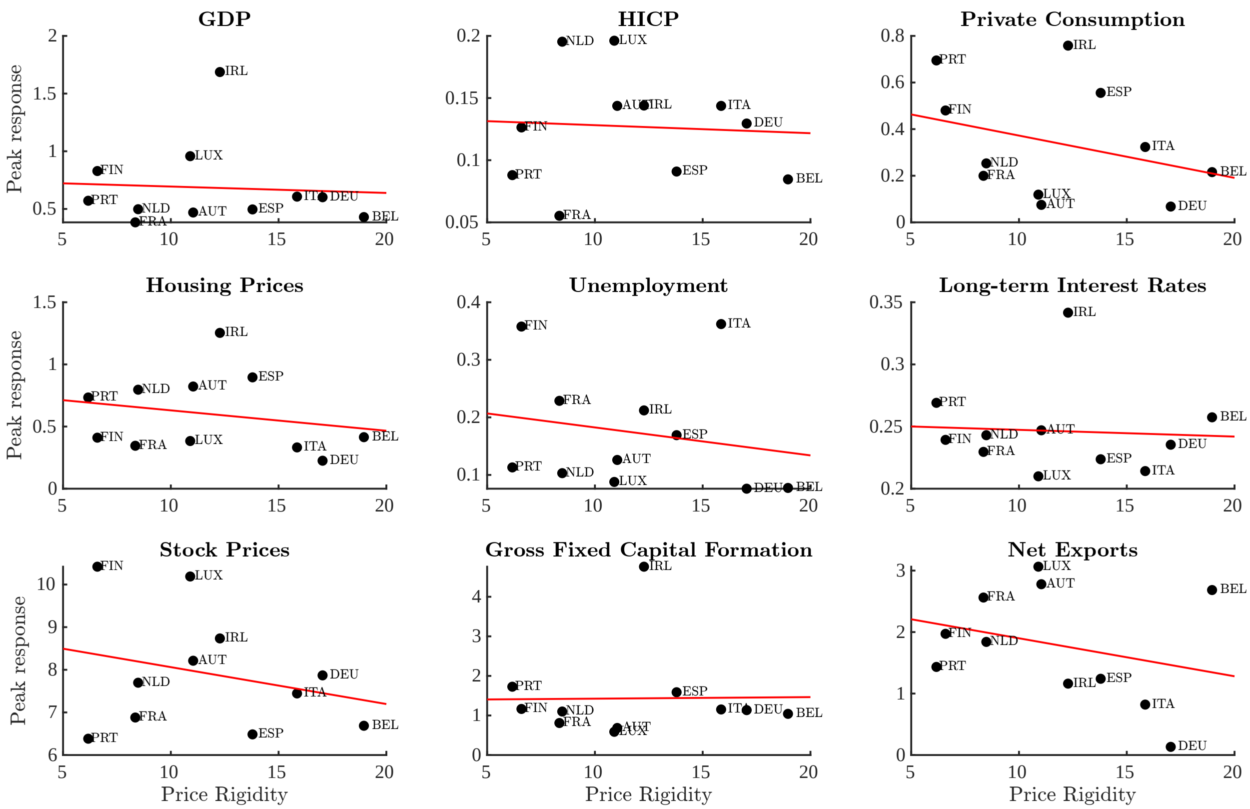


Figure 27: Scatter plot of responses of selected variables with: panel (a) the loan-to-value ratio, panel (b) adjustable-rate mortgage share, panel (c) homeownership rate, panel (d) share of HtM, panel (e) share of WtM, panel(f) wage rigidity, panel (g) price rigidity, panel (h) employment protection, and panel (i) total leverage to GDP ratio.

(g) Price Rigidity



(h) Employment Protection

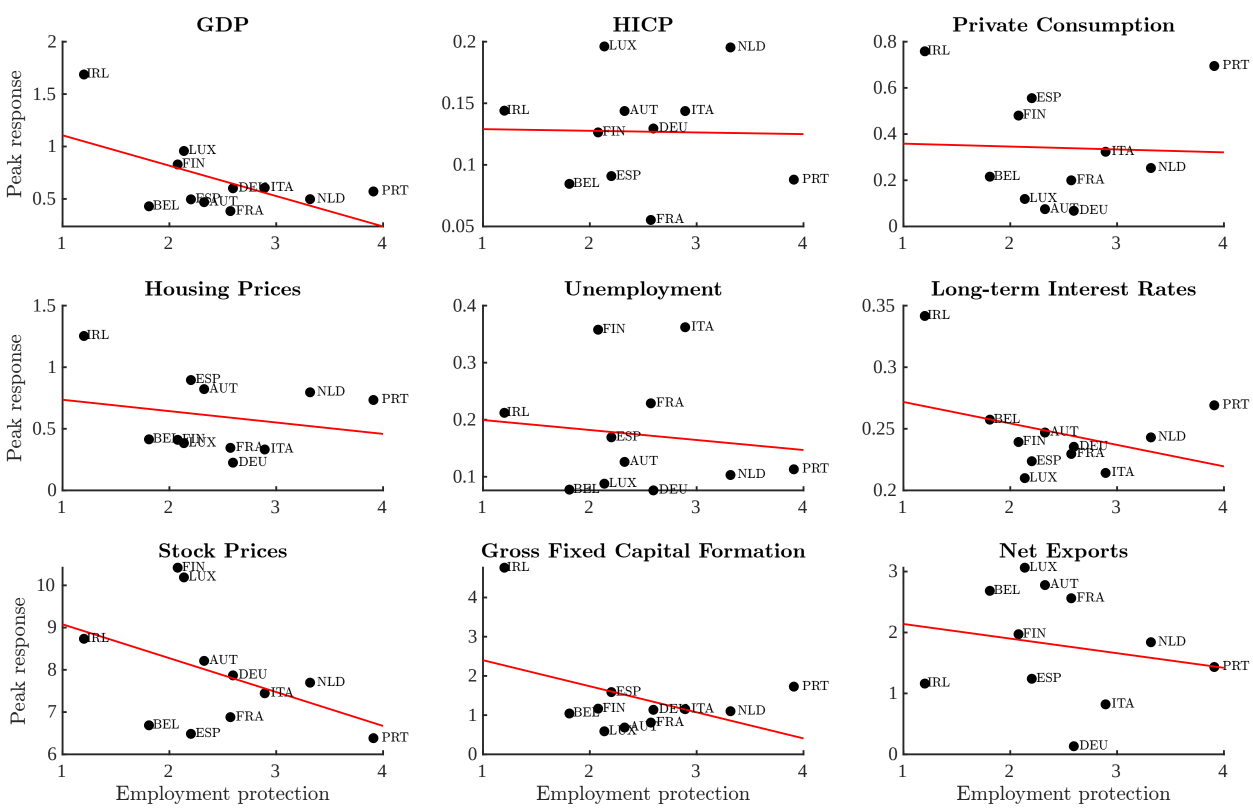


Figure 27: Scatter plot of responses of selected variables with: panel (a) the loan-to-value ratio, panel (b) adjustable-rate mortgage share, panel (c) homeownership rate, panel (d) share of HtM, panel (e) share of WtM, panel(f) wage rigidity, panel (g) price rigidity, panel (h) employment protection, and panel (i) total leverage to GDP ratio.

(i) Total Leverage

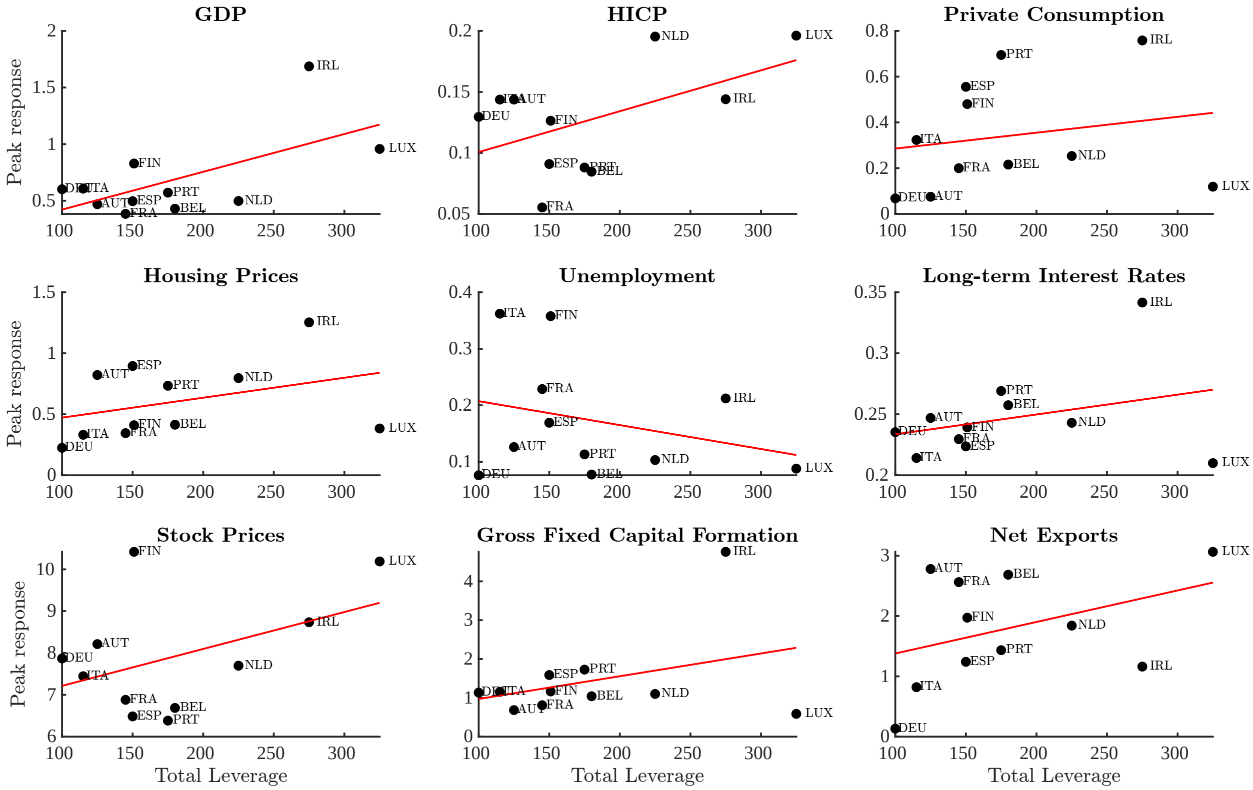


Figure 27: Scatter plot of responses of selected variables with: panel (a) the loan-to-value ratio, panel (b) adjustable-rate mortgage share, panel (c) homeownership rate, panel (d) share of HtM, panel (e) share of WtM, panel(f) wage rigidity, panel (g) price rigidity, panel (h) employment protection, and panel (i) total leverage to GDP ratio.