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Are There Asymmetric Price Responses in the Euro Area?

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Abstract:

A large body of empirical research has explored how monetary policy shocks affect consumer prices in the individual countries of the Euro area. The purpose of this study is to take into account major problems in existing literature. Our new empirical results show that the European Central Bank's monetary policy has a similar impact on prices in the individual countries.

Keywords: The ECB's monetary policy, asymmetry, Bayesian impulse response function

1. Introduction

The word ‘inflation’ appears to be the most commonly used economic term among the general public. It seems that people are interested in inflation because most of them think that inflation hurts their standard of living; see Shiller (1997). Consequently, the complicated challenge of modern central banks is to practice low inflation policy to keep the consumption path of the general public stable. This challenge may be even more complicated for the European Central Bank (ECB) because the diversity in the economic and institutional structures across the member countries is rationale for the expectation that a common monetary policy will have impacts of different magnitudes in the economies in the Euro area. Thus, due to known wage rigidities in the Euro area, possible asymmetric inflation responses may indeed cause undesired real income differences between European Monetary Union (EMU) countries, at least in the short-run.

Not surprisingly, there exists a large body of vector autoregressive (VAR) studies[1] in which the monetary policy shock in each of the individual countries of the EMU area is investigated and cross-country comparisons are made. The differences in the results, presented in this literature, are striking, since there is a host of theoretical, statistical, and data issues involved in empirical analyses. We pinpoint the following major problems of this literature highlighted by Peersman (2004):

- i) Typically, the same model is estimated for each individual country. This tends to be misleading since each country has a different economic structure and has its own monetary policy reaction function.
- ii) The size of the estimated monetary policy shock differs across countries. This tends to complicate the comparability of the effect of the shocks.
- iii) There is also an important difference between a domestic monetary policy shock and a common monetary policy shock due to large trade linkages between the member countries. These linkages may cause the effect of a common monetary policy shock to be more similar across countries than the effects of a domestic monetary policy shock.
- iv) It is not clear whether differences in monetary policy responses between countries are statistically significant, given the relative wide confidence bands around the responses.

Peersman (2004) puts forth an effort into taking these dilemmas into account and finds that there are statistically significant asymmetric price responses in the Euro area. His approach is based on synthetic Euro-area data for seven EMU countries and a large-scale near-VAR model; see also Sala (2001) and Clements et al. (2001). The major problem in the Peersman (2004) analysis (this problem relates most (all) of the existing literature) is that, while the autoregressive coefficients are estimated consistently, standard bootstrapped error bands for impulse responses may be inconsistent in a small sample size, especially in the presence of non-stationary data; see e.g. Kilian (1998).

1 For more detailed surveys, see for example Mojon and Peersman (2001) and Peersman (2004). See also Angeloni and Ehrmann (2004), who use quarterly EMU panel data over the period 01/1998-02/2003 to track down the sources of the inflation differences among the EMU member countries. They employ a similar but open economy version of the model as we use by letting the real exchange variable exist in both the Phillips and IS equations. They estimate a structural 12-country model consisting of all (original) EMU member countries with instrumental variable techniques and then simulate the model. They also perform a sensitivity analysis, changing the values of interesting parameter values inside their confidence intervals. They find that the magnitude of the inflation persistence is the driving force generating the inflation divergence, not the monetary policy transmission mechanism (via exchange rate), as has been suggested in the literature.

Additionally, the data-generating process of the synthetic Euro-area data is different than the data-generating process of real Euro-area data, and hence the estimation results of the models based on synthetic data may be unreliable.

Our paper adds to this literature as follows: firstly, this is to our knowledge the first VAR study that uses real EMU-area data. Empirical analysis based on the actual European Central Bank's monetary policy, rather than individual central banks' monetary policies, has some advantages. It enables us to use a common reaction function across the EMU countries. It also guarantees that the size of the monetary policy shock is the same across the economies. Furthermore, large trade linkages between the member countries may cause the effect of a common monetary policy shock to be more similar across countries than the effect of a domestic monetary policy shock.

Secondly, to fulfil our investigative purposes, we use a structural-form VAR model based on a 5-equation open economy dynamic stochastic general equilibrium (DSGE) model. The model describes the economic conditions of the *jth* individual country and the area-wide aggregate (excluding the *jth* individual country). Discussion on DSGE models can be found in e.g. Hetzel (2000), Clarida, Galí and Gertler (2000), Gerdesmaier and Roffia (2003), and Walsh (2003); see also the survey of Sungbae and Shorfheide (2005).

Thirdly, we employ a posterior distribution of structural VAR parameters to calculate the impulse responses of inflation in the individual country and the area-wide aggregate (excluding domestic inflation) to a shock to a common monetary policy instrument. Given the posterior distributions of inflation responses, we form the posterior distribution of the difference of the response of inflation in the individual country with the area-wide inflation response. This allows us to make an exact inference on the asymmetry of inflation responses. Note also that using posterior-based error bands rather than classical confidence bands allows us to report bands that characterise the true shape of the likelihood. This leads to a more precise statistical analysis, especially in the case of finite samples or nearly unit root series; see e.g. Sims and Zha (1999).

In contrast to Peersman (2004), we found that there is only very weak support for asymmetric price responses between the individual country and the area-wide aggregate. Specifically, actual Euro-area data is consistent with the difference of the response of inflation in the individual country with the area-wide inflation response being different from zero only in the cases of Belgium, France, and Finland. However, these responses vanish one month after the shock.

The paper is organised as follows: Chapter 2 presents the DSGE model and the density functions to be simulated. Chapter 3 presents the EMU data and gives comments on the drawn impulse response functions. Chapter 4 presents concluding remarks.

2.2 The Model

We briefly review the open economy macro model and then elaborate on how we can use it to generate impulse responses based on the actual ECB's monetary policy instrument. We point that the detailed derivations for the model equations can be found in Gali and Monacelli (1999)[2]. In the model, we assume that the Euro area's *jth* member country represents a small open economy. For simplicity, we presume that rest of the Euro area represents the rest of the world.

2 See also Gali and Monacelli (2005).

A representative household in a small open economy seeks to maximise the following periodic utility function

$$E_0\left[\sum_{t=0}^{\infty}\beta^t\left(\frac{C_t^{1-\sigma}}{1-\sigma}-\frac{N_t^{1-\phi}}{1-\phi}\right)\right], \tag{1}$$

where β is the discount factor and N_t denotes hours of labour. Parameter σ measures the elasticity of intertemporal substitution and ϕ is the substitution elasticity between labour and leisure. Variable C_t is a composite consumption index defined by

$$C_t = \left[(1-\alpha)^{1/\eta} C_{H,t}^{(\eta-1)/\eta} + \alpha^{1/\eta} C_{F,t}^{(\eta-1)/\eta}\right]^{\eta/(\eta-1)}, \tag{2}$$

where $C_{H,t} = \left(\int_0^1 C_{H,t}(i)^{(\varepsilon-1)/\varepsilon}\, di\right)^{\varepsilon/(\varepsilon-1)}$ and $C_{F,t} = \left(\int_0^1 C_{F,t}(i)^{(\varepsilon-1)/\varepsilon}\, di\right)^{\varepsilon/(\varepsilon-1)}$

are indices for the consumption of domestic and foreign goods in a small open economy. Parameters η (>0) and ε (>1) measure the elasticity of substitution between domestic and foreign goods and the elasticity of substitution among goods within each category, respectively.

Households maximise periodic utility (1) subject to the intertemporal budget constraint

$$\int_0^1 \left[P_{H,t}(i)C_{H,t}(i) + P_{F,t}(i)C_{F,t}(i)\right]di + E_t\{Q_{t,t+1}D_{t+1}\} \leq D_t + W_t N_t + T_t \quad ,(3)$$

where $Q_{t,t+1}$ is the stochastic discount factor, D_t is nominal payoff, W_t is nominal wage, and T_t contains periodic lump-sum taxes. The price of a riskless one-period bond is denominated as $R_t^{-1} = E_t\{Q_{t,t+1}\}$; hence, we can understand R_t as a gross return. Since we assume that markets for securities markets in the Euro area are complete, we can write that $R_t = R_t^*$, where, from now on, the star in the superscript refers to the rest of the Euro area.

The optimal allocation of any given expenditure within each category of goods yields downward sloping demand curves

$$C_{H,t}(i) = \left(\frac{P_{H,t}(i)}{P_{H,t}}\right)^{-\varepsilon} C_{H,t} \text{ and } C_{F,t}(i) = \left(\frac{P_{F,t}(i)}{P_{F,t}}\right)^{-\varepsilon} C_{F,t}, \tag{4}$$

for all $i \in [0,1]$,

where $P_{H,t} \equiv \left(\int_0^1 P_{H,t}(i)^{1-\varepsilon}\, di\right)^{1/(1-\varepsilon)}$ and $P_{F,t} \equiv \left(\int_0^1 P_{F,t}(i)^{1-\varepsilon}\, di\right)^{1/(1-\varepsilon)}$ are price indices for domestic and imported goods.

Throughout the presentation, we will assume that in the Euro area, the law of one price holds so that $P_{F,t}(i) = P_{F,t}^*(i)$, where $P_{F,t}^*(i)$ is the price of foreign good i in a foreign country. Doing the derivations, we finally end up with the equations that describe the optimal allocation of expenditures between domestic and foreign goods

$$C_{H,t} = (1-\alpha)\left(\frac{P_{H,t}}{P_t}\right)^{-\eta} C_t \quad \text{and} \quad C_{F,t} = (1-\alpha)\left(\frac{P_{F,t}}{P_t}\right)^{-\eta} C_t, \tag{5}$$

where the consumer price index (CPI) is defined as $P_t \equiv \left[(1-\alpha)P_{H,t}^{1-\eta} + \alpha P_{F,t}^{1-\eta}\right]^{\frac{1}{1-\eta}}$.

Production is assumed to be linear in labour, which can be hired by firms from households. Then firm i will produce a differentiated good i using a technology represented by the following production function

$$Y_t(i) = Z_t N_t(i), \tag{6}$$

where $Z_t \equiv \exp\{z_t\}$ and z_t follows an AR(1) process, i.e. $z_t = \rho z_{t-1} + u_t$. The error term u_t can be broadly interpreted as an i.i.d. technology shock that affects all firms in the same way. We assume that the government subsidises employment at a constant rate $1/\varepsilon$. Hence, the firm's nominal marginal cost is given by

$$MC_t = \left(1 - \frac{1}{\varepsilon}\right)\frac{W_t}{Z_t}. \tag{7}$$

As in Calvo (1983), we assume that in the beginning of any period t, producer i will be allowed to set a new product price with probability $1 - \theta$, and keep the price unchanged with the probability θ. It then follows that while setting a new price in period t, firm j seeks to maximise

$$\min_{P_t^{new}} \sum_{k=0}^{\infty} (\beta\theta)^k E_t\left\{Q_{t,t+k}\left[Y_{t+k}(j)\left(P_{H,t}^{new} - MC_{t+k}\right)\right]\right\} \tag{8}$$

subject to the sequence of demand constraints

$$Y_{t+k}(j) \leq \left(\frac{P_{H,t}^{new}}{P_{H,t+k}}\right)^{-\varepsilon}\left(C_{H,t+k} + C_{H,t+k}^{*}\right) \equiv Y_{t+k}^{d}\left(P_{H,t}^{new}\right). \tag{9}$$

The estimation form of the model is obtained using optimality conditions for the maximisation problems of agents. We assume that the economies in the small open economy and in the rest of the Euro area are identical and the weight of goods produced in a small economy is assumed to be negligible in the area-wide aggregate. The real exchange rate between the individual country and the rest of the Euro area is denoted as $REX_t = P_t^{*}/P_t$ and the terms of trade (TOT) as $S_t = P_{F,t}/P_{H,t}$. The consumption, output, and nominal wages are de-trended using the total factor productivity, Z_t. We define the percentage deviations of a variable $x_t = \log X_t$ from its trend $\tilde{X}_t$ as $\hat{x}_t = \log X_t - \log \tilde{X}_t$. The log-linearised system can be reduced, after some algebra, to five equations for large and small country outputs and inflations and terms of trade

$$\pi_t = \beta E_t\{\pi_{t+1}\} - \alpha\beta E_t\{\Delta\hat{s}_{t+1}\} + \alpha\Delta\hat{s}_t + \lambda\left(1 + \frac{\phi\omega}{\sigma}\right)\hat{s}_t + \lambda(\phi+\sigma)\hat{y}_t^* - \lambda(1+\phi)z_t, \tag{10}$$

$$\pi_t^* = \beta E_t\{\pi_{t+1}^*\} + \lambda(\phi+\sigma)\hat{y}_t^* - \lambda(1+\phi)z_t^*, \tag{11}$$

$$\hat{y}_t = \hat{y}_t^* + \frac{\omega}{\sigma}\hat{s}_t, \tag{12}$$

$$\hat{y}_t^* = E_t\{\hat{y}_{t+1}^*\} - \frac{1}{\sigma}\left(r_t^* - E_t\{\pi_{t+1}^*\}\right) \qquad \text{and} \tag{13}$$

$$\hat{s}_t = \frac{\beta}{\mu}E_t\{\hat{s}_{t+1}\} + \frac{1}{\mu}\hat{s}_{t-1} + \frac{\lambda(1+\phi)}{\mu}\left(z_t - z_t^*\right), \tag{14}$$

where consumer price inflation is conveniently defined as $\pi_t \equiv \log(P_t / P_{t-1})$. Additionally, we let $r_t^* \equiv \log(R_t^* / R^*)$, $\omega = 1 + \alpha(\sigma\eta - 1)(2-\alpha)$, $\mu = (1 + \beta + \lambda(1 + \phi\omega/\sigma))$, and $\lambda = (1-\theta)(1-\beta\theta)/\theta$.

Equations (10) and (11) are derived from the small economy's and the Euro area's firms' optimal price-setting problems and they govern inflation dynamics. Equation (12) determines the output as a function of foreign output, where an 'expenditure switching factor' is proportional to the terms of trade. The percentage deviations of the real marginal cost from its steady state values are determined as $m\hat{c}_t^* = (\phi+\sigma)\hat{y}_t^* - (\phi+1)z_t^*$ in the rest of the Euro area and $m\hat{c}_t = (\phi+\sigma)\hat{y}_t^* + (1+\phi\omega/\sigma)\hat{s}_t - (\phi+1)z_t$ in the small open economy. Equation (13) in turn is the Euler equation in the rest of the Euro area. This describes the demand side of the economy. Equation (14) is the stochastic difference equation for the terms of trade and it is derived assuming that the weight of the imports in the rest of the Euro-area's consumer price index can be considered negligible, and at time *t*, foreign $(\pi_{F,t}^*)$ and domestic $(\pi_{H,t})$ inflations are uncorrelated.

What it comes to choosing the statistical model, we could use e.g. a simple, empirical-based interest rate rule and approach developed by e.g. Christiano, Eichenbaum, and Evans (2005) to generate values for the impulse response function from the structural model presented above. However, we find that the impulse responses based on the Kalman filter estimates of the above model can only approximate impulse responses derived from the structural vector autoregressive (SVAR) model. There is also a possibility that simple structural model cannot approximate the data generating process of the true model satisfactorily. We therefore suggest the following strategy to generate impulse responses from a SVAR model that uses the information of the log-linearised model above; see discussion about the identification of SVAR models, e.g. Sims (1986), Gordon and Leeper (1994), and Cushman and Zha (1996).

We agree that the form of the theoretical model structure may be unknown for households and firms, but they may reasonably well assume that an endogenous variable depends linearly on the vector of exogenous observable shocks. Households and firms use this available information and form expectations like econometricians[3]. Since it seems that the prediction accuracy of the univariate models are at least as good as the accuracy of the multivariate models, it is assumed that households and firms in the Euro area use simple univariate autoregressive models in forming their inflation, output gap, and/or terms of trade expectations; see Stock and Watson (1999) and Marcellino, Stock and Watson (2003). Specifically these forecast functions are

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[3] These forecasts are intended to be a boundedly rational method in the spirit 'of rational expectations; see more discussion in e.g. Sargent (1993), Evans and Honkapohja (2001) and Branch (2004).

$$\pi_{t+1} = b_1(L)\cdot \pi_t + b_2(L)\cdot m\hat{c}_t, \tag{15}$$
$$\pi^*_{t+1} = b_3(L)\cdot \pi^*_t + b_4(L)\cdot m\hat{c}^*_t, \tag{16}$$
$$\hat{y}^*_{t+1} = b_5(L)\cdot \hat{y}^*_t + b_6(L)\cdot i^*_t \text{ and} \tag{17}$$
$$\hat{s}_{t+1} = b_7(L)\cdot \hat{s}_t, \tag{18}$$

where $i^*_t = r^*_t - E_t\{\pi^*_{t+1}\}$ is the Euro area's real interest rate and $b_i(L)$ is the polynomial of lag operator L with lag length p. Equations (15)-(16) are backward-looking Phillips curves, very standard in the econometric literature, while Equations (17)-(18) are formed in the spirit of equations of the log-linearised model above. The reader should note that we assume that learning processes are converged, providing that decisions made by agents are optimal[4]. In addition, this assumption allows us to use constant parameter values in the prediction functions above.

Given that the ECB uses an empirical-based Taylor rule with a smoothing term to conduct monetary policy, we then combine Equations (10)-(18) and the equations for real marginal costs to get the model into the form[5]

$$r^*_t = \beta_0 + (1-\rho)[\beta_1\pi^*_t + \beta_2 y^*_t] + \sum_{i=1}^{p}\rho_i \cdot r^*_{t-i} + \varepsilon_{r^*_t,t}, \tag{19}$$

$$(1-c_{0,1})\pi_t = c_1 + c_{0,2}\hat{y}^*_t + c_{0,3}s_t + \sum_{i=1}^{p}c_{i,1}\pi_{t-i} + \sum_{i=1}^{p}c_{i,2}\hat{y}^*_{t-i} + \sum_{i=1}^{p}c_{i,3}s_{t-i} - \sum_{i=0}^{p}c_{i,4}z_t, \tag{20}$$

$$(1-c_{0,5})\pi^*_t = c_{0,6}\hat{y}^*_t + \sum_{i=1}^{p}c_{i,5}\pi^*_{t-i} + \sum_{i=1}^{p}c_{i,6}\hat{y}^*_{t-i} - \sum_{i=0}^{p}c_{i,7}z^*_{t-i}, \tag{21}$$

$$(1-c_{0,8})\hat{y}^*_t = c_{0,9}r^*_t + c_{0,10}\pi^*_t + \sum_{i=1}^{p}c_{i,8}\hat{y}^*_{t-i} + \sum_{i=1}^{p}c_{i,9}r^*_{t-i} + \sum_{i=1}^{p}c_{i,10}\pi^*_{t-i} + \sum_{i=0}^{p}c_{i,11}z^*_{t-i} \text{ and} \tag{22}$$

$$(1-c_{0,12})s_t = c_2 + \sum_{i=1}^{p}c_{i,12}s_{t-i} + c_{13}(z_t - z^*_t). \tag{23}$$

An interested reader will find that the derivations of Equations (20)-(23) are given in the Appendix (Section A).

Our empirical analysis is based on the above system of equations. We estimate the system of the following form

$$A(L)y(t) + D = \eta(t), \tag{24}$$

[4]As Milani (2005) comments, introducing learning directly from the primitives of the DSGE model would lead to a different law of motions for inflation and output gap. Moreover, Preston (2005b) explains that decision rules that depend only on one-period-ahead expectations will generally not provide optimal decision rules under adaptive learning for the corresponding infinite horizon decision problems; see Sargent (1993), Evans and Honkapohja (2001), Preston (2005a,b), and Milani (2005).
[5] We drop Equation (10) out of the system since domestic output has no influence on the rest of the system.

where $y(t)$ is an $(m\times 1)$ vector of observations, $A(L)$ is an $(m\times m)$ matrix polynomial of lag operator L with lag length p and non-negative powers, D is a constant vector, $A = \Lambda^{-0.5}\Gamma$, and $\eta(t) = \Lambda^{-0.5}\varepsilon(t)$ so that

$$\eta(t)\big|y(s), s<t \sim N\left(0, \underset{m\times m}{I}\right);$$

see e.g. Sims and Zha (1998, 1999). In Equation (24) we let

$$y(t)=\begin{pmatrix}\pi_t^*\\ \hat{y}_t^*\\ r_t^*\\ \pi_t\\ s_t\end{pmatrix} \quad \text{and} \quad A(0)=\begin{pmatrix} a_{0,11} & a_{0,12} & 0 & 0 & 0\\ a_{0,21} & a_{0,22} & a_{0,23} & 0 & 0\\ a_{0,31} & a_{0,32} & a_{0,33} & 0 & 0\\ 0 & a_{0,42} & 0 & a_{0,44} & a_{0,45}\\ 0 & 0 & 0 & 0 & a_{0,55}\end{pmatrix},$$

suggesting that $A(0)$, where the zero restrictions are set using the system of equations (19)-(23), is a non-singular matrix, so that the model provides a complete description of the p.d.f. for the data conditional on the initial observations. This indicates that Equation (24) is of the same form as the system of equations (19)-(23), except that the unobservable error vector $\varepsilon(t)$ approximates the moving average of the productivity shocks u_t and u_t^* (except the third row of vector, that is $\varepsilon_{r_t^*,t}$), and there are zero restrictions only on the $A(0)$ matrix. Let us rewrite model (24) in the matrix form

$$YA_0 - XA_+ = E\,, \tag{25}$$

where the *tth* rows of $Y(T\times m)$, $X(T\times k)$, and $E(T\times m)$ are given by $y(t)$, $(1\ y'(t\text{-}1) \cdots y'(t\text{-}p))'$, and $\eta(t)$ respectively. Thus, $k = mp + 1$ is the number of coefficients corresponding to X, T is the number of observations, $A(0)' = A_0$, and A_+ is $(k\times m)$ matrix of parameters of lagged variables.

We assume a Gaussian likelihood function

$$L(Y|A) \propto |A_0|^T \exp\{-0.5tr(YA_0 - XA_+)'(YA_0 - XA_+)\}. \tag{26}$$

Let us denote $vec(A_0) = a_0$ and $vec(A_+) = a_+$. Then, defining $a = (a'_0\ a'_+)'$, we can write the joint prior p.d.f. of a in the form

$$p(a) = p_0(a_0)N(\tilde{a}_+; H), \tag{27}$$

where $p_0(a_0)$ is the marginal distribution of a_0 and $N(\tilde{a}_+, H)$ is the standard multivariate normal p.d.f. with $\tilde{a}_+$ mean and H covariance matrix. Thus, the posterior density of the parameters in vector a follows

$$\begin{aligned} q(a) \propto |A(0)|^T &\exp\{-0.5[a'_0(I\otimes Y'Y)a_0 - 2a'_+(I\otimes X'Y)a_0 + a'_+(I\otimes X'X)a_+]\}\\ &\times p_0(a_0)|H|^{-0.5}\exp\{-0.5(a_+ - \tilde{a}_+)'H^{-1}(a_+ - \tilde{a}_+)\}. \end{aligned} \tag{28}$$

Although the posterior density (28) is non-standard in general, the exponent in (28) is quadratic in a_+ for the given a_0, suggesting that the conditional distribution of a_+ given a_0 is Gaussian, making possible easy Monte Carlo sampling and analytic integration along the a_+ dimension; see Sims and Zha (1998).

We assume that the elements in vector a_+ are zero as a priori. To specify our prior variance for parameters (a_+) of lagged variables (we call the model of this prior specification *Model 1*), we let a_{+i} represent the regression parameters of lagged variables of the *ith* equation in linear multivariate model (24). Then

$$Var(a_{+i}) = \begin{cases} \lambda_1 p^{-1}, & \text{for non-zero parameters in the system of equations (19)-(23)} \\ \lambda_2 p^{-1}, & \text{for zero 'parameters' in the system of equations (19)-(23)} \\ \lambda_3 \ , & \text{for constant parameter} \end{cases}$$

As usual, p denotes the lag length, and the hyperparameters λ_i (i = 1, 2, 3) control the tightness of beliefs that we have. We set the hyperparameters $\lambda_1 = \lambda_3 = 10000$ and evaluate the posterior density of hyper parameter λ_2. In our prior variance, we do not use typical scale factors, as e.g. Kadiyala and Karlsson (1997) and Sims and Zha (1998), since we have no prior knowledge of these. One can of course follow Litterman (1986) and choose these as the sample standard deviations of residuals from univariate autoregressive models. We feel uncomfortable doing this since, at least in principle, these should be chosen on the basis of a priori reasoning or knowledge.

The idea of our prior variance structure of *Model 1* is that with a smaller value of λ_2, our linear multivariate model (24) is closer to the form of the system of equations (19)-(23), while high values of λ_1 and λ_3 indicate the importance of lagged variables that the system of equations (19)-(23) predicts to have influence on left-hand side variables. However, it is reasonable to assume that the importance of the lagged variables decreases with the lag length; see e.g. Kadiyala and Karlsson (1997).

One can show that, for posterior (28) with an exponential prior for hyper parameter λ_2, the conditional distribution of a_+ and the joint marginal distribution of λ_2 and a_0 can be derived as

$$q(a_+|a_0,\lambda_2) = N\left(\bar{a}_0;\left(I \otimes X'X + H(\lambda_2)^{-1}\right)^{-1}\right), \tag{29}$$

$$\begin{aligned} q(a_0,\lambda_2) \propto\ & p_0(a_0)|A(0)|^T \left|(I \otimes X'X)H(\lambda_2)+I\right|^{-0.5} \exp\left(-\frac{\lambda_2}{\tau}\right) \\ & \times \exp\left\{-0.5\left[a_0'(I \otimes Y'Y)a_0 + \tilde{a}_+'H(\lambda_2)^{-1}\tilde{a}_+ - \bar{a}_0'\left(I \otimes X'X + H(\lambda_2)^{-1}\right)\bar{a}_0\right]\right\}, \end{aligned} \tag{30}$$

where H is chosen to match the prior variance defined above, τ is the prior mean of hyper parameter λ_2, and

$$\bar{a}_0(\lambda_2) = \left(I \otimes X'X + H(\lambda_2)^{-1}\right)^{-1}\left((I \otimes X'Y)a_0 + H(\lambda_2)^{-1}\tilde{a}_+\right).$$

In the estimation, we set $\tau = 100$ so that the prior variance of hyper parameter λ_2 is 10,000. We use a 'flat' prior on $A(0)$; see discussion for 'flat' priors in this context in Sims and Zha (1998). In order to satisfy the rank condition for identification, we decided to fix the Taylor rule parameters so that $\beta_1 = 1.5$, $\beta_2 = 0.5$, and $\rho = 0.9$; see motivation to use these parameter values of β_1, β_2, and ρ in Gerdesmaier and Roffia (2003). Specifically, we acquire posterior modes of parameter matrices

$\Gamma(0)$ and Λ in linear multivariate model (24) where diagonal elements of $\Gamma(0)$ are normalised to one and β_1, β_2 and ρ remain fixed[6]. Then we transform the estimated modes of $\Gamma(0)$ and Λ back to the A(0) parameter space using the following relation $A(0) = \Gamma(0)\Lambda^{-0.5}$. We use these transformed values to set the non-zero restrictions on the elements $a_{0,31}$ and $a_{0,32}$ in matrix $A(0)$.

Since the sign of a row of $A(0)$ can be reserved without changing the likelihood function, we follow Waggoner and Zha (1997) and Sims and Zha (1999) in choosing a normalisation for each draw that minimises the distance of $A(0)$ from the posterior mode estimate of $A(0)$. As Sims and Zha comments, this method will tend to hold down spurious sign-switching of impulse responses and thereby deliver sharper results than e.g. normalisation where diagonal elements of $\Gamma(0)$ are normalised to one.

We will also modify the specification of *Model 1* such that we assume that large-country variables are block-exogenous with respect to small-country variables (let us call this *Model 2*). For *Model 2*, we use posterior density (28) with zero prior mean for a_+ and prior variance set as

$$Var(a_{+i}) = \begin{cases} \lambda_1 p^{-1}, & \text{for parameter on endogenous variables} \\ \lambda_2 p^{-1}, & \text{for parameter on exogenous variables} \\ \lambda_3 \ , & \text{for constant parameter} \end{cases} ,$$

where $\lambda_1 = \lambda_3 = 10000$ and $\lambda_2 = 0.005$. Our exogenous prior restrictions for lagged variables are determined using the assumption that the terms of trade and the small open economy's inflation has zero effects on the Euro-area inflation, output, and interest rates series; see Cushman and Zha (1996). The prior for $A(0)$ is equal to the one above; thus, the conditional and marginal posterior densities are

$$q(a_+|a_0) = N\left(\bar{a}_0; (I \otimes X'X + H^{-1})^{-1}\right), \tag{31}$$

$$q(a_0) \propto |A(0)|^T |(I \otimes X'X)H + I|^{-0.5} \\ \times \exp\left\{-0.5\left[a_0'(I \otimes Y'Y)a_0 + \tilde{a}_+' H^{-1}\tilde{a}_+ - \bar{a}_0'(I \otimes X'X + H^{-1})\bar{a}_0\right]\right\}, \tag{32}$$

where H is chosen to match the (exogenous) prior variances defined above, and

$$\bar{a}_0 = (I \otimes X'X + H^{-1})^{-1}\left((I \otimes X'Y)a_0 + H^{-1}\tilde{a}_+\right).$$

The joint marginal p.d.f. of A_0 and λ_2 for *Model 1* in Equation (30) and marginal p.d.f. of A_0 for *Model 2* in Equation (32) are not in the form of a standard p.d.f. We therefore have used a version of the random walk Metropolis algorithm for Markov Chain Monte Carlo (MCMC) sampling to generate a Monte Carlo sample from them.

2.3 Empirical Analysis

2.3.1. The Data

6 We use a flat 'prior on A(0), which is transformed to the ($\Gamma(0)$, Λ) parameter space, including the appropriate Jacobian term $|\Lambda|^{-(m+1)/2}$; see Sims and Zha (1999) and Waffoner and Zha (1997).

The aggregate data series and the series for each EMU member country[7] are collected from two sources: seasonally adjusted and construction activities excluded industrial production monthly indices (IIP) from the beginning of 1980 to the end of the 80s is from the OECD main economic indicators. EuroStat provides the rest of the IIP series up to April 2006. The annual series for Gross domestic product (GDP), population, and monthly series for Harmonized index of consumer price (HICP) and Euro overnight index average (EONIA) interest rates are also downloaded from EuroStat. The monthly series of the Producer Price Index (PPI) (without construction) over the period of 1998 to April 2006 is seasonally unadjusted with base year 2000, and is as well provided by EuroStat. The base year for the IIP index series is similarly year 2000; GDP is measured in year 2005 prices, and exchange rates and the base year for the HICP indices is 2005. Annual population is a measure of total population at the end of the current year. GDP values are from years 1991[8] to 2005 and the population variable covers the period from 1980 to 2005. The monthly series for HICP[9] are from January 1999 to April 2006, as are series for the EONIA interest rate depicting the values of monetary policy instruments.

Letting the statistical analysis be in line with the model, we assign each EMU member country in turn to be the small country and let the rest of the member countries represent the large country. Variables for a large country are marked with a *-superscript. We construct all 11[10] different datasets in a way that the values of the given small member country are neglected while calculating the variable values for the large country. To do this, we assume that the annual GDP and the annual population both have 50% weight in constructing the weight of the given country. In empirics, the original monthly series for the HICP and PPI series are used for the small member country *j* and the values of the relevant variables for the large country are constructed so that we first multiply the variable values of the remaining member countries with the annual weight share and sum these together to get the GDP and population weighted-averaged variables. Proceeding this way ensures that the information content of the small-country variables is not included in the large-country variables.

Figure A plots the actual EMU-area IIP aggregate and EONIA interest rate series, and Table 1 below Figure A contains the simple correlation coefficients between the log-differenced values for the actual EMU-area IIP aggregate and log-differenced[11] values for the above described large-country IIP series. We see that the correlation coefficients are high.

Figures B-D draws the EMU-area annual HICP inflation series together with the annual HICP inflation series for each EMU-member country together with the EONIA interest rate. In Figure B, we see that in general, the annual HICP inflation series for the whole EMU area and Germany, France, and Italy do show convergent behavior, while this is not the case for the rest of the EMU member countries. Table 2 collects the correlation coefficients between the log-differenced values of the constructed large-country HICP and the actual EMU-area HICP. In the table, we can see that

7 EMU member countries are Belgium, Germany, Spain, Austria, France, Italy, Ireland, Luxembourg, The Netherlands, Portugal, Finland. Values for Greece are taken into account from the beginning of 2001.

8 GDP values of 1991 are used to replace the unavailable GDP values for the years 1980 to 1990.

9 However, values for 1998 are used in the calculation of annual and monthly changes.

10 The dataset for the case of Greece is not constructed since Greece has been an EMU member country only from the beginning of 2001, and hence we would not have an equal amount of observations.

11 To avoid the possibility of spurious regression (correlation), we use first differenced series of variables in calculating the correlation coefficients.

these coefficients are really high; the sample correlation coefficients indicate near to perfect correlation (excluding Germany).

Figure E shows how the producer price inflation in the EMU area and the EONIA interest rate both have evolved under the common monetary policy era. Interestingly, while the EMU-area producer prices have had an upward trend, the values of the monetary policy instrument have remained practically on a constant level. The correlation coefficient between the log-differenced values of the constructed large-country PPI and the actual EMU-area PPI are high, but not as high as the correlation coefficients for the log-differenced HICP series.

Finally, since expectations play an important role in our macro model, we decided to use a one-sided version of the Hodrick-Prescott (HP) filter to produce a trend estimate for the Euro area's IIP[12] series. The one-sided trend estimate is constructed as the Kalman filter estimate of the Euro area's total factor productivity Z_t^* in the model

$$\log Y_t^* = \log \hat{Z}_t^* + v_t$$

$$(1-L)^2 \log \hat{Z}_t^* = \xi_t,$$

where $\hat{Z}_t^*$ is the unobserved trend component that approximates Z_t^*, and $\{v_t\}$ and $\{\xi_t\}$are mutually uncorrelated white noise sequences with relative variance $\delta = \mathrm{var}(\xi_t)/\mathrm{var}(v_t)$; see Stock and Watson (1999). We follow Stock and Watson (1999) and set $\delta = 0.75\times10^{-6}$ that approximately matches the spectral gain for the HP-filter.

In the literature, Galí and Gertler (1999) for example, the labour's share of output is also used as a proxy for the marginal costs in spite of the output gap variable. Neiss and Nelson (2003), on the contrary, report using data for the United States, the United Kingdom, and Australia, where labour costs do not manage to explain inflation dynamics as well as the output gap.

2.3.2 Results

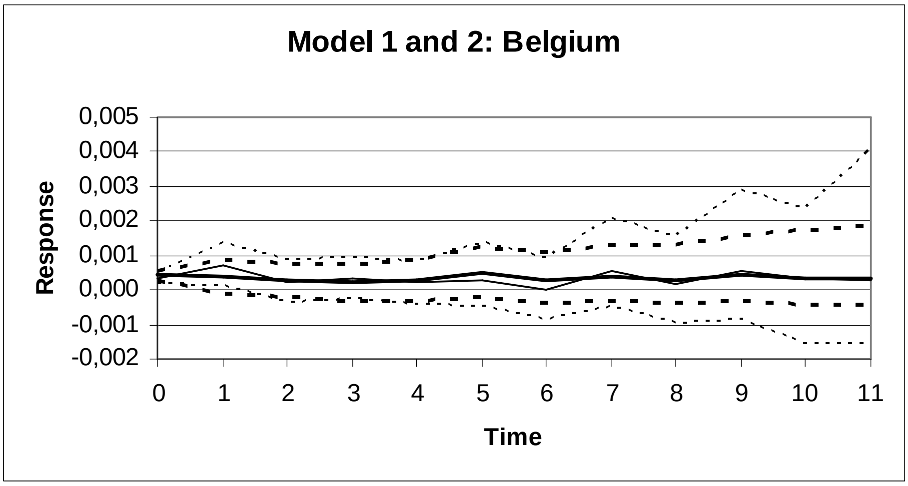
We start our analysis by estimating proper lag length for *Models 1* and *2* (we estimate in total 22 different SVAR models). Our lag length estimates are based on the fractional marginal likelihoods (FML) of the models; see Villani (2001).

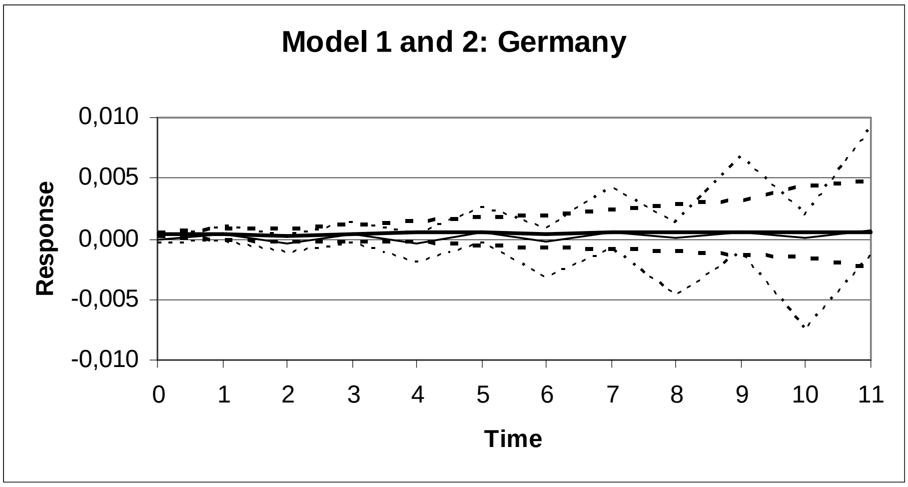
To generate a Monte Carlo sample from the joint posterior of the elements of $A(0)$ and λ_2 in Equation (30) and the posterior of the elements of $A(0)$ in Equation (32), we use a version of the random walk Metropolis algorithm for Markov Chain Monte Carlo (MMCMC). The algorithm uses a multivariate normal distribution for the jump distribution on changes in the elements of $A(0)$. In the case of *Model* 1 (Finland), our simulation procedure is as follows (others are close variants of this): We first simulate 20,000 draws using a diagonal covariance matrix with diagonal entries 0.00001 in the jump distribution. We then use the last 10,000 draws to estimate the posterior covariance matrix of λ_2 and the elements of $A(0)$ and scale it by the factor $(2.4)^2/2$ to obtain an optimal covariance matrix for the jump distribution; see e.g. Gelman et al (2004). If necessary, we continue the simulation and use these new draws to calculate a more accurate covariance matrix for

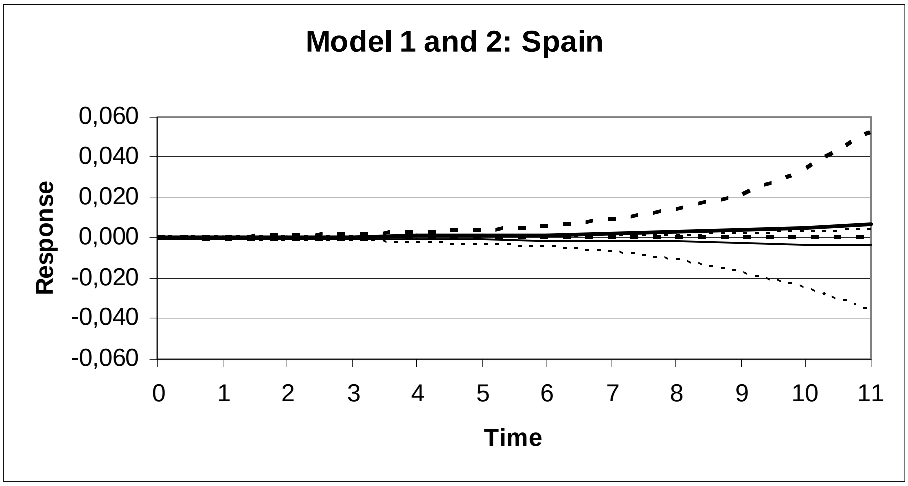
[12] Most of the methods that de-trend output variables use both future and past values of the series. This makes these methods unsuitable for forecasting purposes because households and firms cannot observe future observations when they form their expectations.

λ_2 and the elements of $A(0)$. Finally, we run 250,000 draws, and after eliminating the burn-in period, we pick up every 100th draw. In the other cases, the Markov Chains converged to stationary distributions after 50,000-250,000 draws. The convergence diagnostics, numbers of draws, the burn-in period, and the acceptance ratio are listed in Table 4 of the Appendix, Section C.

Figure 1 below shows the difference of the response of inflation in the individual country with the area-wide inflation (excluding domestic) response. The shown impulse responses are based on *Models* 1 and 2. The figures display a point estimate (median) of the impulse response and 68% posterior intervals. The monetary policy shock has the size of one standard deviation for each country.






Model 1 and 2: Spain
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0,020
0,000
-0,020
-0,040
-0,060
Response
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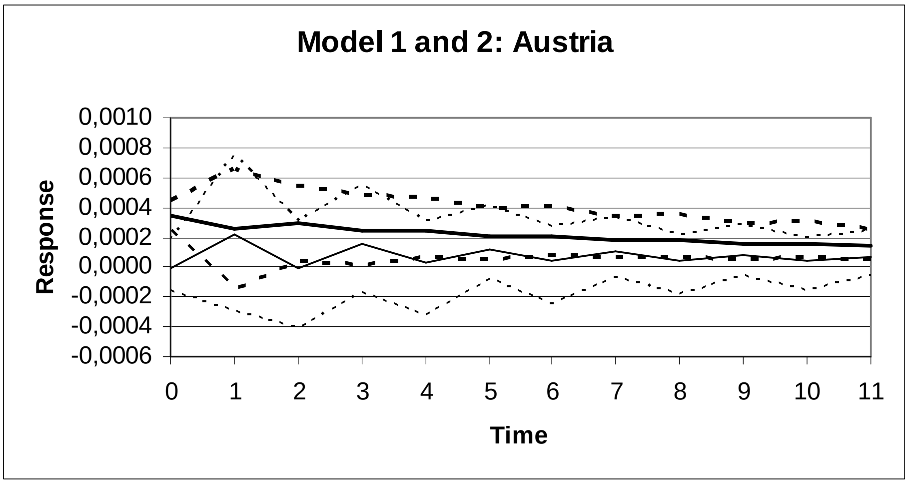
Time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0,0008
0,0006
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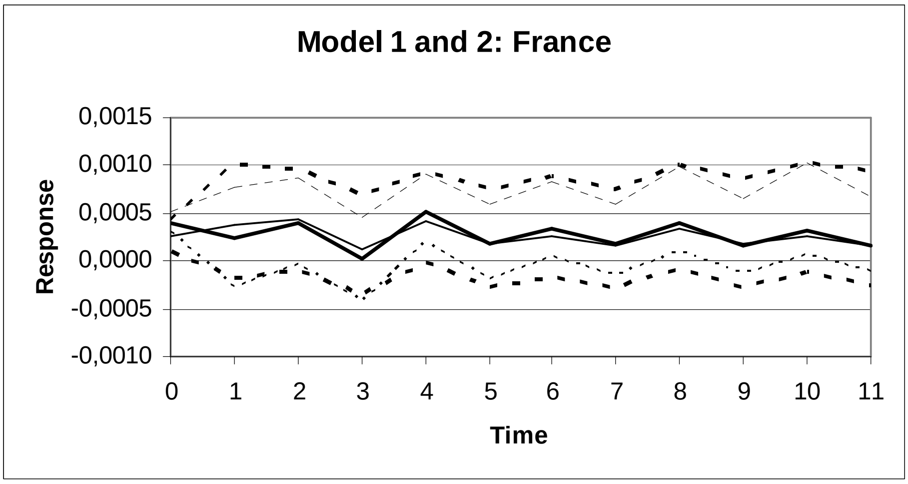
-0,0004
-0,0006
Response
0 1 2 3 4 5 6 7 8 9 10 11
Time


Model 1 and 2: France
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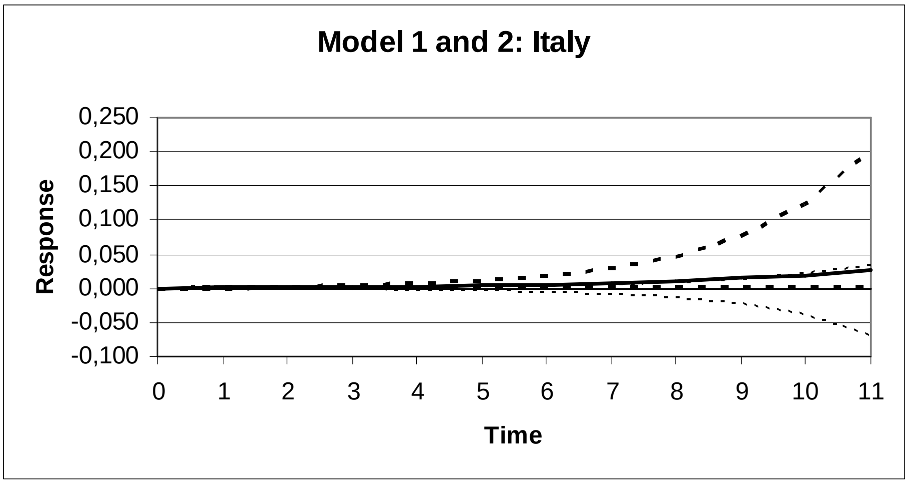
0,0010
0,0005
0,0000
-0,0005
-0,0010
Response
0 1 2 3 4 5 6 7 8 9 10 11
Time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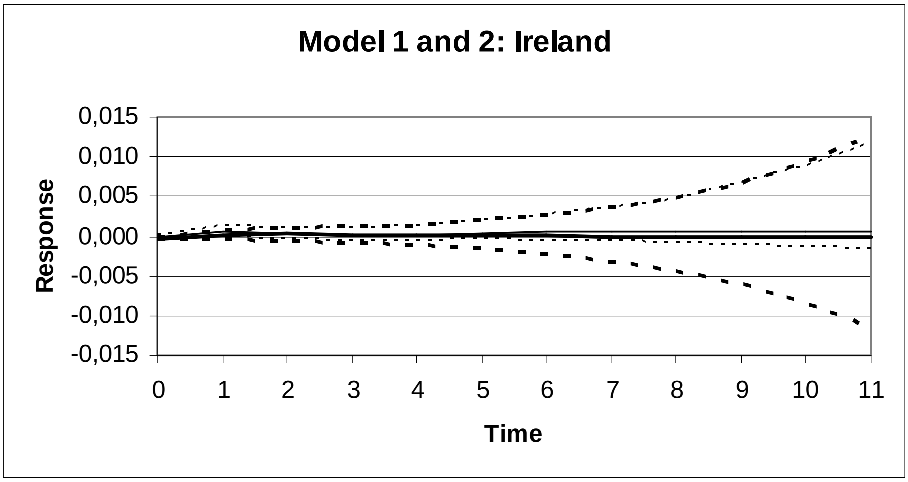
0,150
0,100
0,050
0,000
-0,050
-0,100
Response
0 1 2 3 4 5 6 7 8 9 10 11
Time


Model 1 and 2: Ireland
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0,000
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-0,010
-0,015
Response
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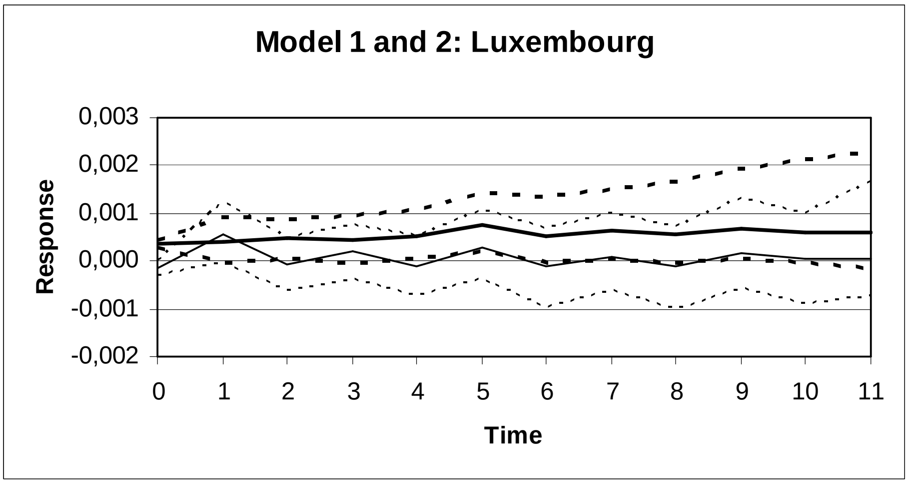
Time


Model 1 and 2: Luxembourg
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0,002
0,001
0,000
-0,001
-0,002
Response
0 1 2 3 4 5 6 7 8 9 10 11
Time

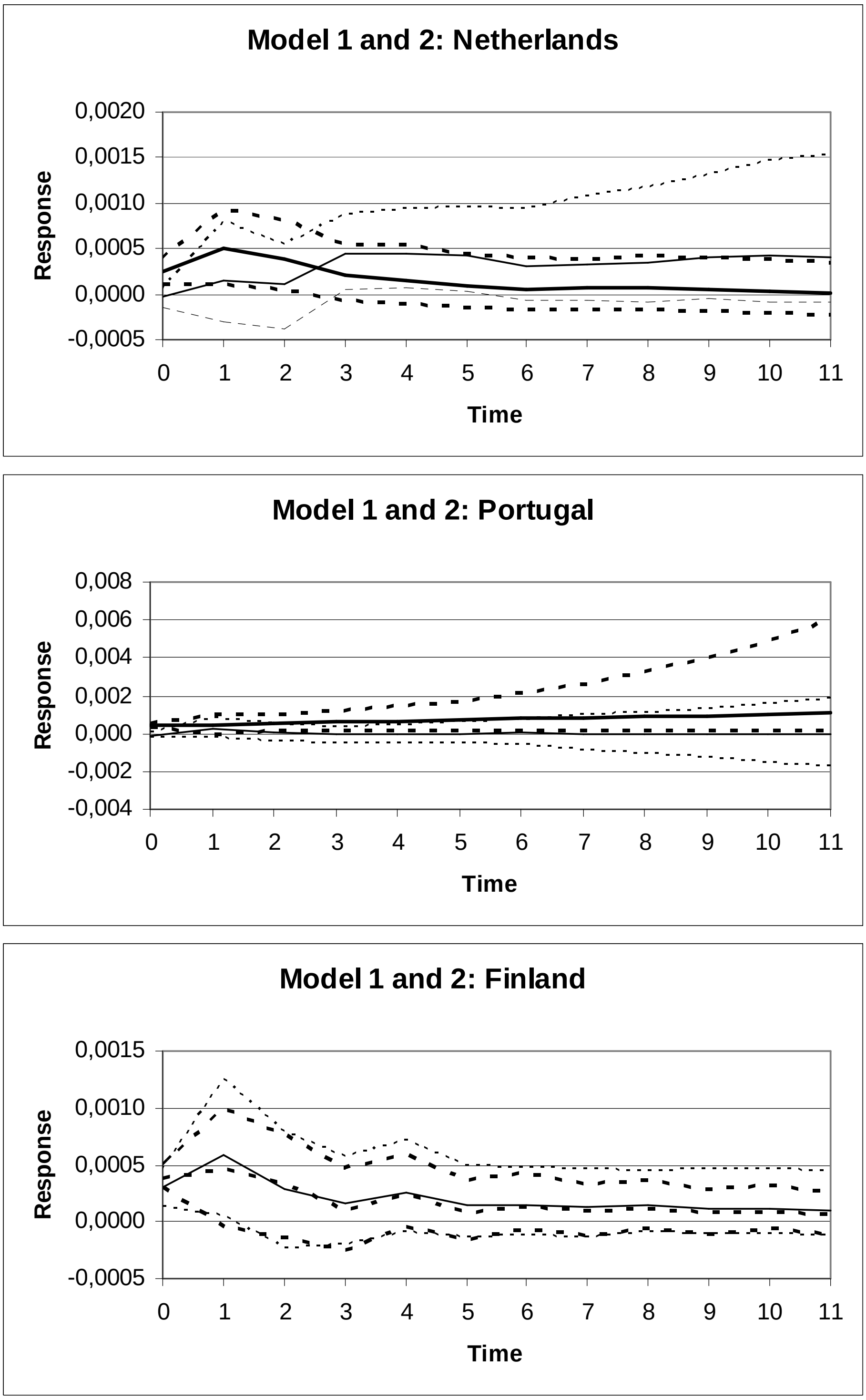


FIGURE 1. Impulse Responses for Structural VAR Models (Thick lines are for *Model* 1 and thinner lines are for *Model* 2.)

The impulse responses show that in general, the effects of inflation to a shock to a common monetary policy are similar across the EMU countries. That is, our data lends strong support for the impulse responses being zero. This result contradicts the results of Peersman (2004). The major reason for the difference between his and our results could be our standard treatment of unit root price series; we use the difference series $\Delta \ln P_t$, while Peersman uses level series. Note also that standard bootstrapped confidence intervals may give a too optimistic view of precision due to the assumption of stationary data generating processes, which does not hold in the case when the variables are modelled in levels.

Taking a closer look at the drawn impulse responses, we see that immediate asymmetric inflation responses exist in the cases of Belgium, France, and Finland. However, since these responses die out during the first period, we should be very careful to state that the ECB's monetary policy causes asymmetric price responses in the Euro area. One reason for the result that inflation responses are similar across countries is of course the relatively wide error bands of the reported impulse responses. However, in most of the cases, the point estimates (medians) are also quite close to the zero.

Finally, Table 4 in the Appendix (Section D) shows the point estimates (median) of hyperparameter λ_2. In general, the hyperparameters are estimated relatively large, suggesting that prior restrictions derived from the theoretical model should not be set too tight. Thus, our choice to use SVAR rather than an alternative approach, where the parameters of the DSGE model are estimated directly, seems to be supported by the data.

2.3.3. Robustness of the Results

To control the robustness of the results we derive impulse responses from the reduced-form VAR models. We identify the VAR models using recursive approach with different ordering of variables. Estimated reduced form VAR is given by

$$B(L)y(t) + D = v(t),$$

where $y(t)$ is an $(m\times1)$ vector of observations, $B(L)$ is an $(m\times m)$ matrix polynomial of lag operator L with lag length p and non-negative powers, D is a constant vector, $B(0) = I$, and a vector of error terms $v(t)$ is assumed to be normally distributed with zero mean and Ω covariance matrix. In the linear multivariate model above, we use normal likelihood, traditional Jeffreys' priors for the parameters, and lower triangular identification restrictions to generate identified impulse responses from the model. Find more discussion on Jeffreys' priors in multivariate regressions in Zellner (1971).

Section B in the Appendix gives alternative orderings of variables of the estimated reduced form VAR models. The lag lengths used in the reduced-form VAR models for different variable orderings are listed in Table 5 in the Appendix (Section C).

Figure F reports the impulse responses of the Cholesky identified VAR models with different ordering of variables. In general, we find moderate support in the data for symmetry of inflation responses. To be more concrete, the differences of the response of inflation in the individual country with the area-wide inflation (excluding domestic) response are flat except in the cases of Spain, Portugal, the Netherlands, and France, for which the Cholesky identification yields asymmetric behaviour of inflation responses. However, the Cholesky identification produces spurious results for the ECB's reaction function under Taylor rule based ordering of variables, which we use. Specifically, Taylor rule parameter estimates indicate counterintuitive monetary policy. That is, according to our estimation results (not reported here to save space), the ECB would target for lower (higher) interest rates under a high (low) inflation and output period. Thus, in our case we have to be very cautious about the results based on exactly identified VAR models.

2.5. Conclusions

In this paper, we have used structural VAR models to calculate the impulse responses of the difference of the response of inflation in the individual country with the area-wide inflation (excluding domestic inflation) response. We modelled the actual EONIA interest rate with the Taylor rule to describe the ECB's monetary policy. We acquired our prior knowledge of parameters from the underlying New-Keynesian open economy macro model and applied it in the estimation. We find that using economic theory to specify an econometric model is crucial since e.g. a traditional exactly identified recursive approach produces spurious parameter estimates in our case.

To enable us to make an exact inference in a non-linear model environment we apply posterior based analysis. Our new results, based on the posterior distribution of impulse responses, indicate that the consumer price inflation responses to an unanticipated monetary policy shock are symmetric in the Euro-area countries. Thus, it seems fair to say that responses of inflation in individual countries to monetary policy conducted by the ECB do not cause undesired real income differences between EMU countries.

FIGURES

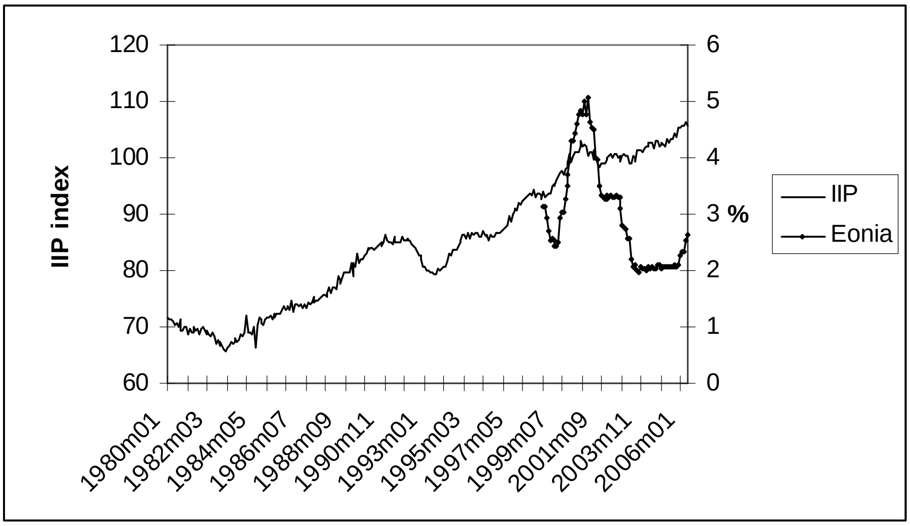


Figure A: Industrial Production Index (IIP) for the EMU area and the EONIA interest rate series

Table 1: Correlations between constructed and actual IIP series

Correlations between log-differences of the constructed IIP and actual IIP series for the EMU area.

BEL	GER	SPA	FRA	IRE	ITA	LUX	NETH	AUST	POR	FIN
0.80	0.67	0.77	0.75	0.79	0.78	0.79	0.78	0.79	0.78	0.79

Sample 1980/m2 – 2006/m4

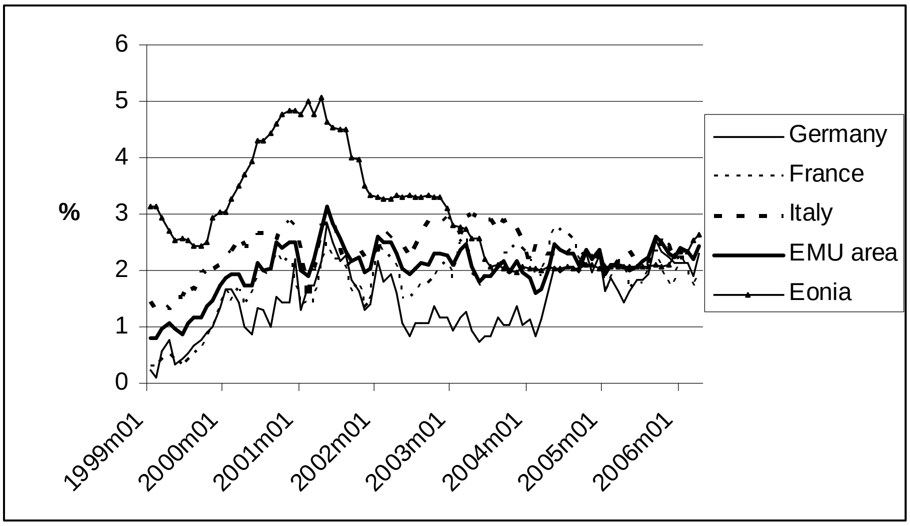


Figure B: Actual annual HICP inflations for Germany, France, Italy, the EMU area, and the EONIA interest rate series

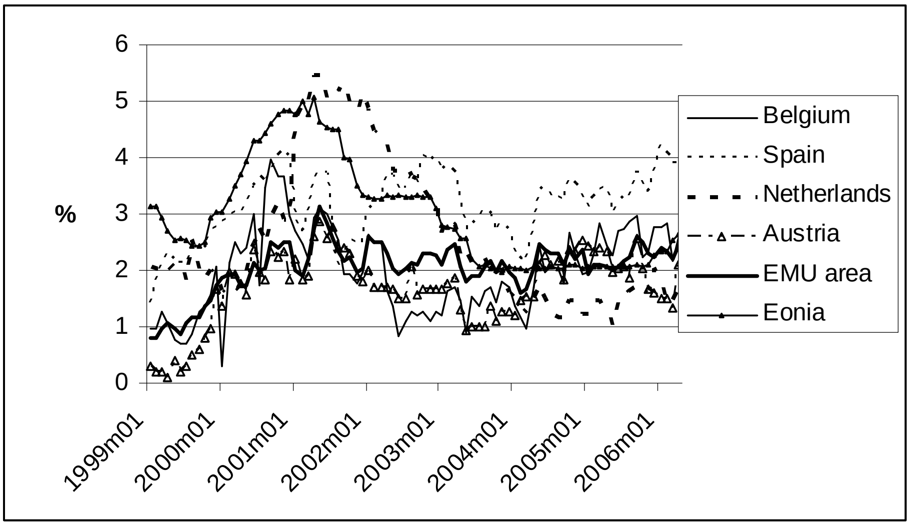


Figure C: Actual annual HICP inflations for Belgium, Spain, the Netherlands, Austria, the EMU area, and the EONIA interest rate series

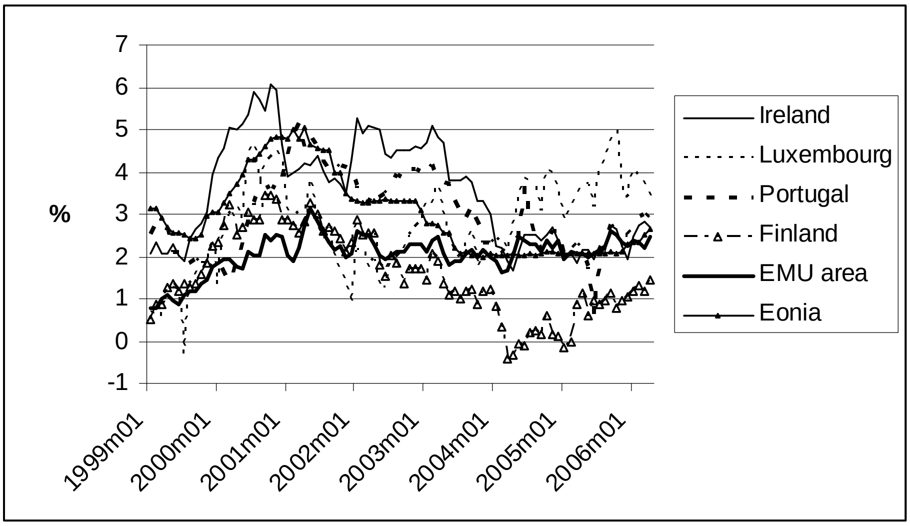


Figure D: Actual annual HICP inflations for Ireland, Luxembourg, Portugal, Finland, the EMU area, and the EONIA interest rate series

Table 2: Correlations between the constructed and actual HICP series

Correlations between log-differences of the constructed HICP and actual HICP series for the EMU area.

BEL	GER	SPA	FRA	IRE	ITA	LUX	NETH	AUST	POR	FIN
0.98	0.88	0.98	0.97	0.98	0.96	0.98	0.98	0.98	0.98	0.98

Sample 1999/m1 – 2006/m4

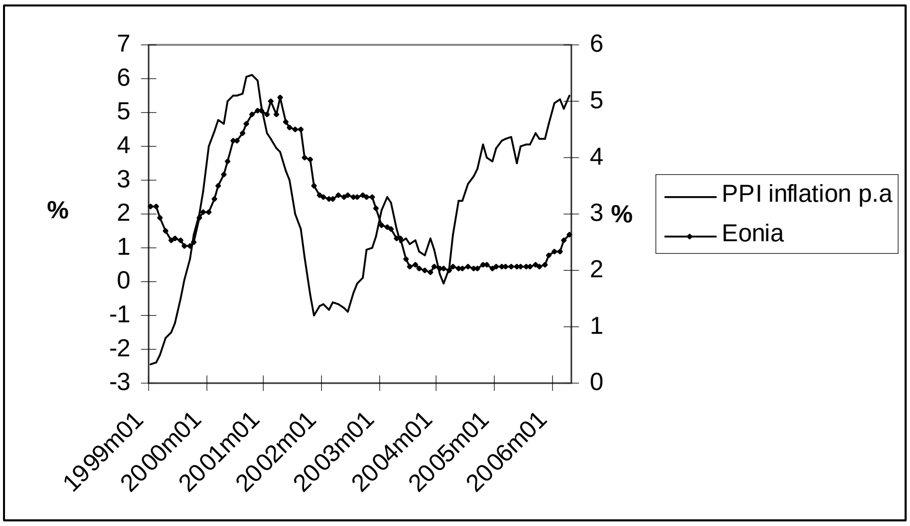


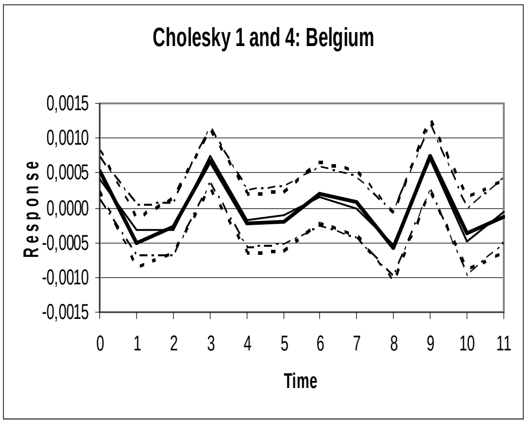
Figure E: Annual Producer Price inflation for the EMU area and the EONIA interest rate series (Left y-axis is for annual PPI inflation values)

Table 3: Correlations between the constructed and actual PPI series

Correlations between log-differences of the constructed PPI and actual PPI series for the EMU area.

BEL	GER	SPA	FRA	IRE	ITA	LUX	NETH	AUST	POR	FIN
0,997	0,97	0,85	0,84	0,88	0,83	0,88	0,85	0,87	0,87	0,88

Sample 1999/m1 – 2006/m4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0,0000
-0,0005
-0,0010
-0,0015
Response
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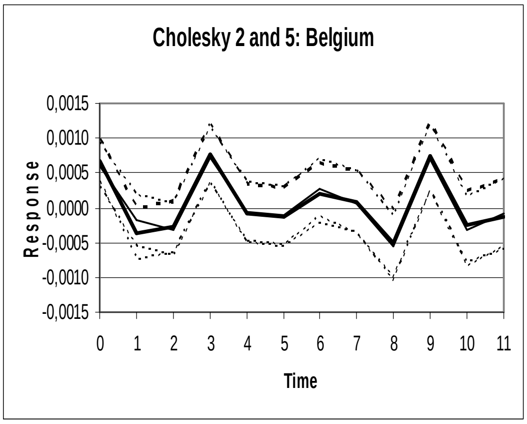
Time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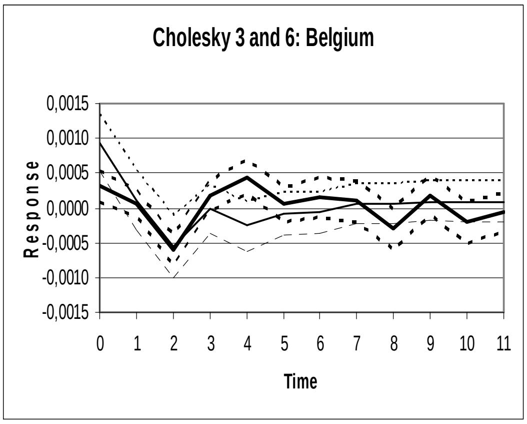
Time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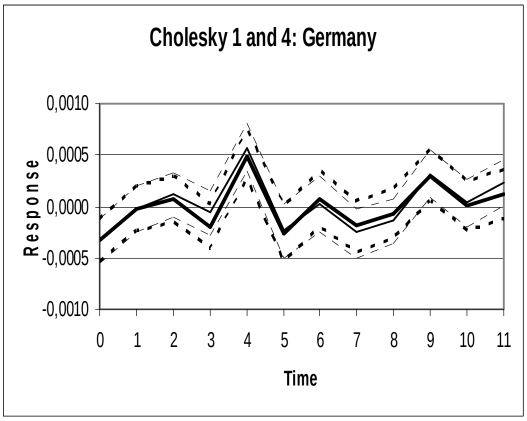
Time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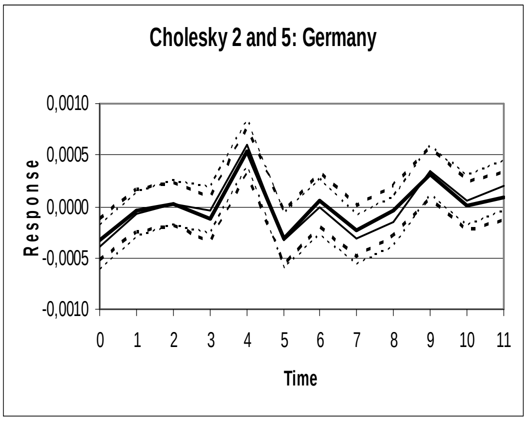
Response
0 1 2 3 4 5 6 7 8 9 10 11
Time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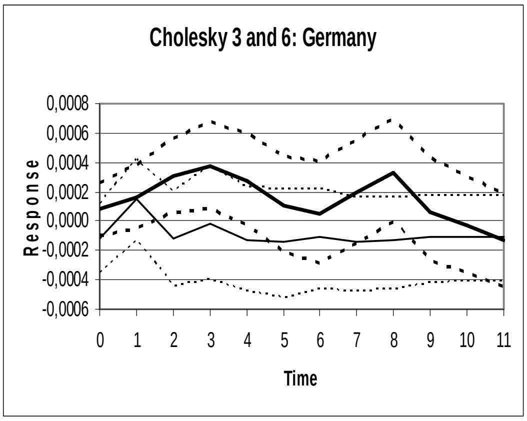
Time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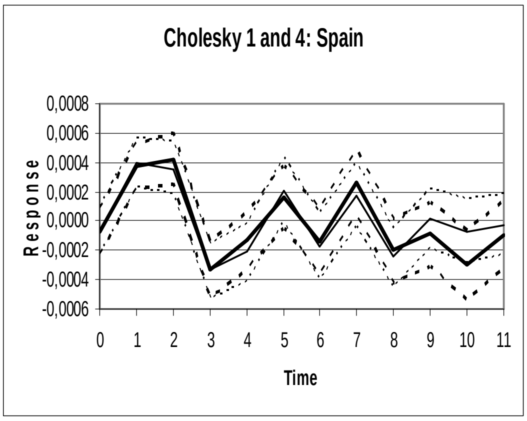
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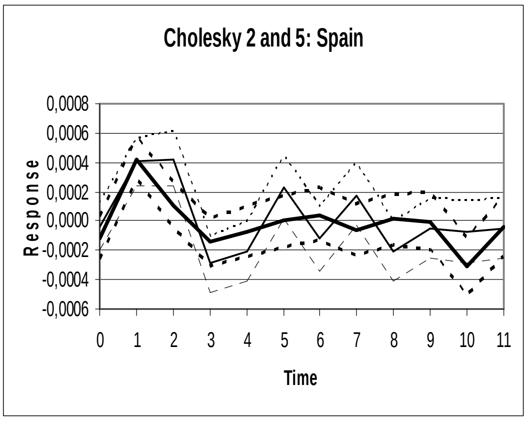
Time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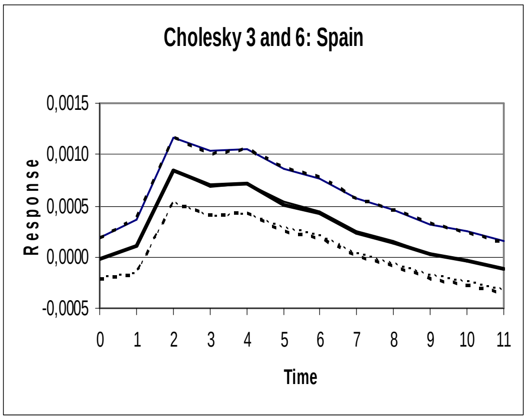
Time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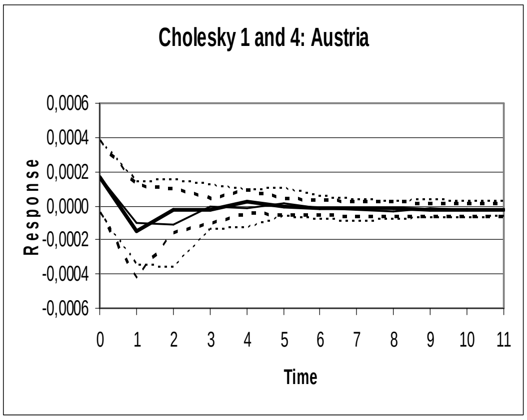
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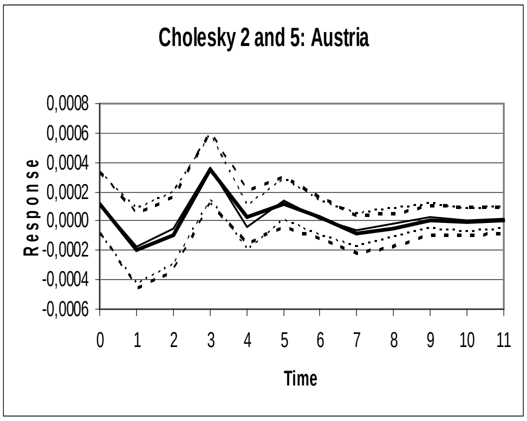
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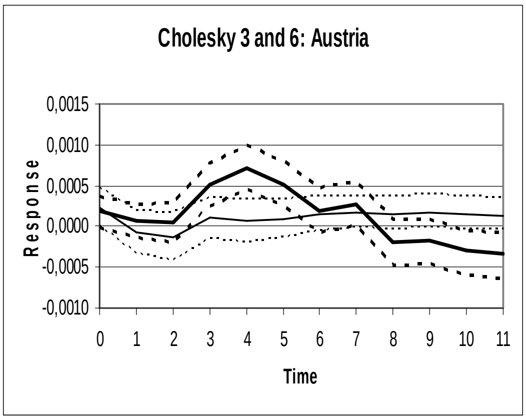
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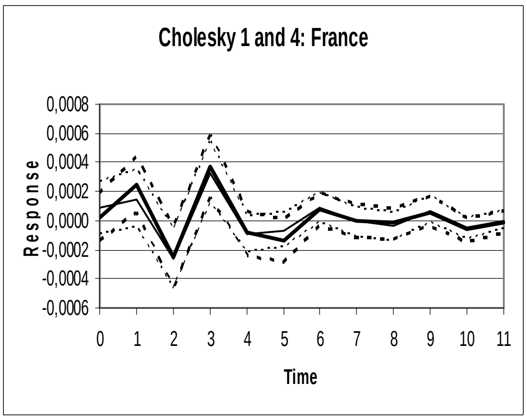
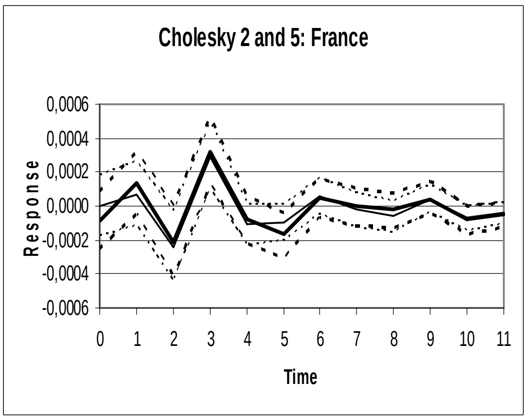
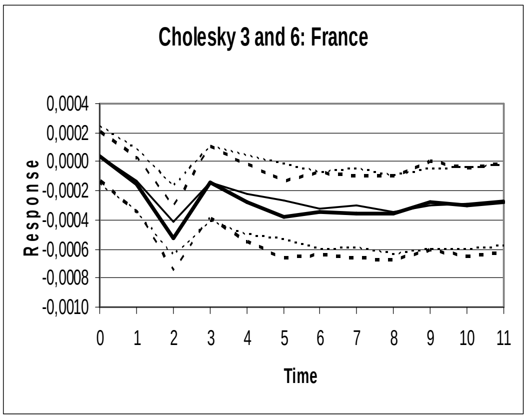
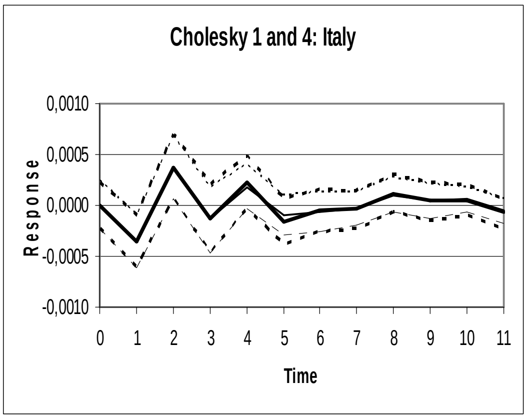
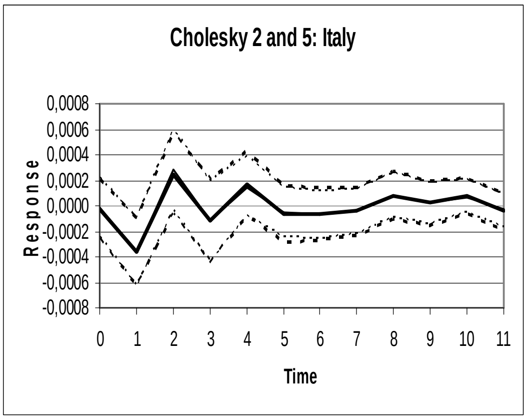
-0,0010
Response
0 1 2 3 4 5 6 7 8 9 10 11
Time

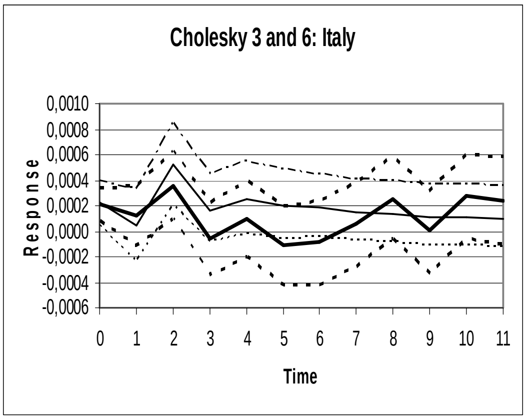

Cholesky 1 and 4: France
0,0008
0,0006
0,0004
0,0002
0,0000
-0,0002
-0,0004
-0,0006
Response
0 1 2 3 4 5 6 7 8 9 10 11
Time

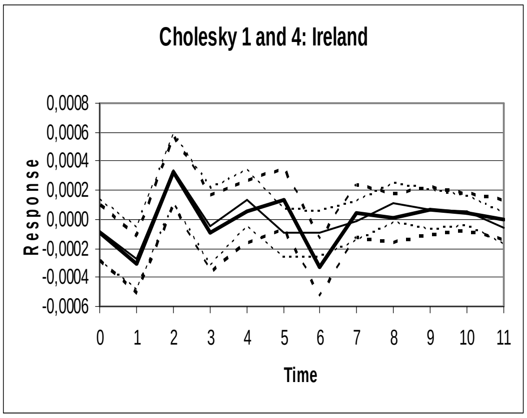

Cholesky 2 and 5: France
0,0006
0,0004
0,0002
0,0000
-0,0002
-0,0004
-0,0006
Response
0 1 2 3 4 5 6 7 8 9 10 11
Time

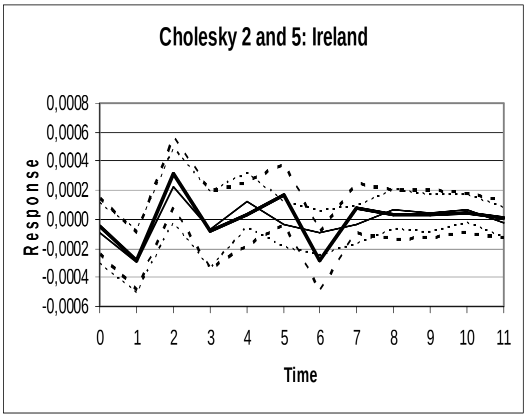

Cholesky 3 and 6: France
Response
Time

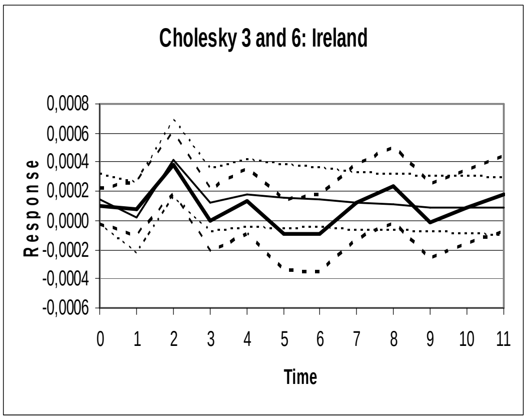

Cholesky 1 and 4: Italy
Response
Time

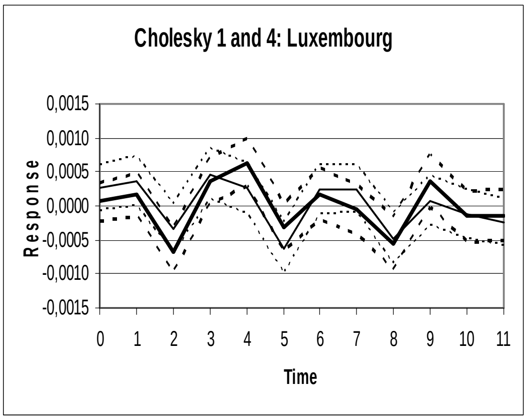

Cholesky 2 and 5: Italy
Response
Time

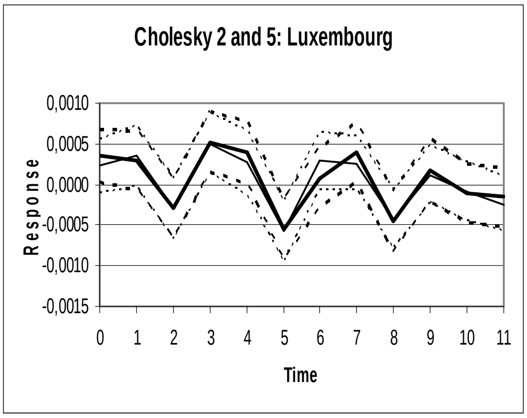

Cholesky 3 and 6: Italy
Response
Time


Cholesky 1 and 4: Ireland
Response
Time


Cholesky 2 and 5: Ireland
Response
Time


Cholesky 3 and 6: Ireland
Response
Time


Cholesky 1 and 4: Luxembourg
Response
Time


Cholesky 2 and 5: Luxembourg
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-0,0010
-0,0015
Response
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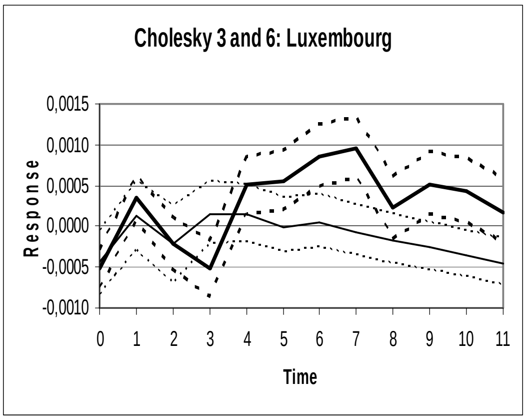
Time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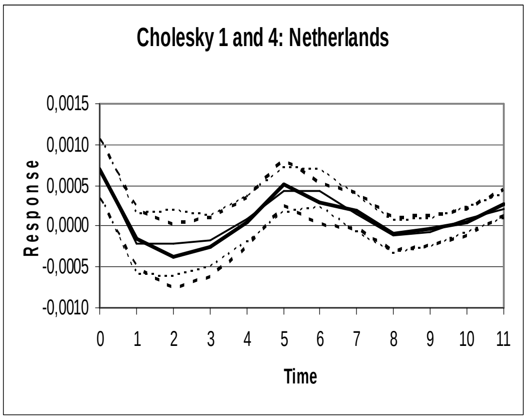
0,0010
0,0005
0,0000
-0,0005
-0,0010
Response
0 1 2 3 4 5 6 7 8 9 10 11
Time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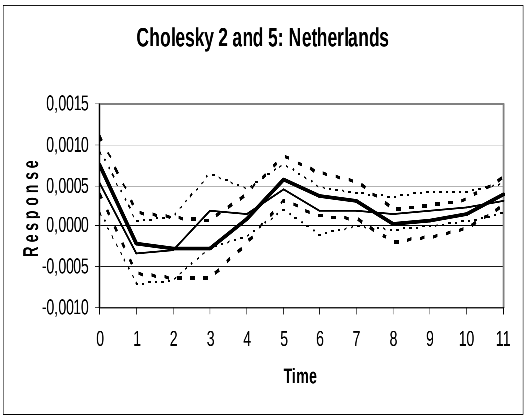
0,0005
0,0000
-0,0005
-0,0010
Response
0 1 2 3 4 5 6 7 8 9 10 11
Time


Cholesky 2 and 5: Netherlands
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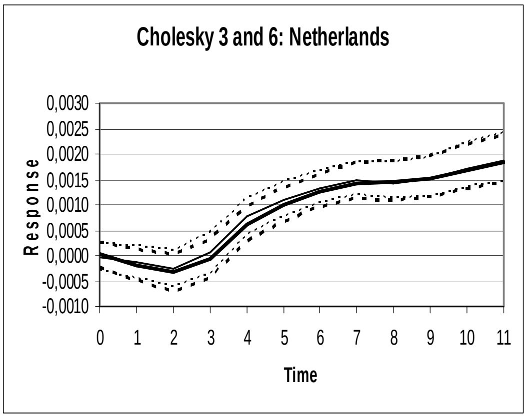
0,0010
0,0005
0,0000
-0,0005
-0,0010
Response
0 1 2 3 4 5 6 7 8 9 10 11
Time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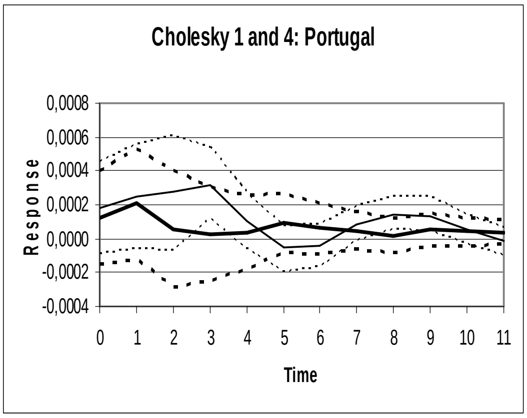
0,0020
0,0015
0,0010
0,0005
0,0000
-0,0005
-0,0010
Response
0 1 2 3 4 5 6 7 8 9 10 11
Time


Cholesky 1 and 4: Portugal
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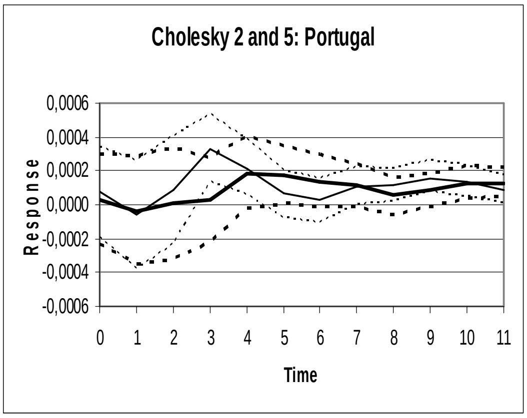
0,0006
0,0004
0,0002
0,0000
-0,0002
-0,0004
Response
0 1 2 3 4 5 6 7 8 9 10 11
Time


Cholesky 2 and 5: Portugal
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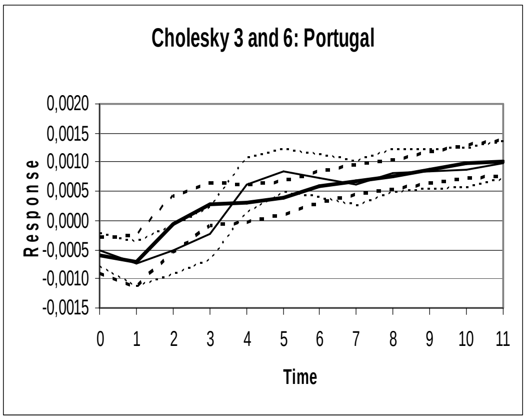
0,0002
0,0000
-0,0002
-0,0004
-0,0006
Response
0 1 2 3 4 5 6 7 8 9 10 11
Time


Cholesky 3 and 6: Portugal
0,0020
0,0015
0,0010
0,0005
0,0000
-0,0005
-0,0010
-0,0015
Response
0 1 2 3 4 5 6 7 8 9 10 11
Time

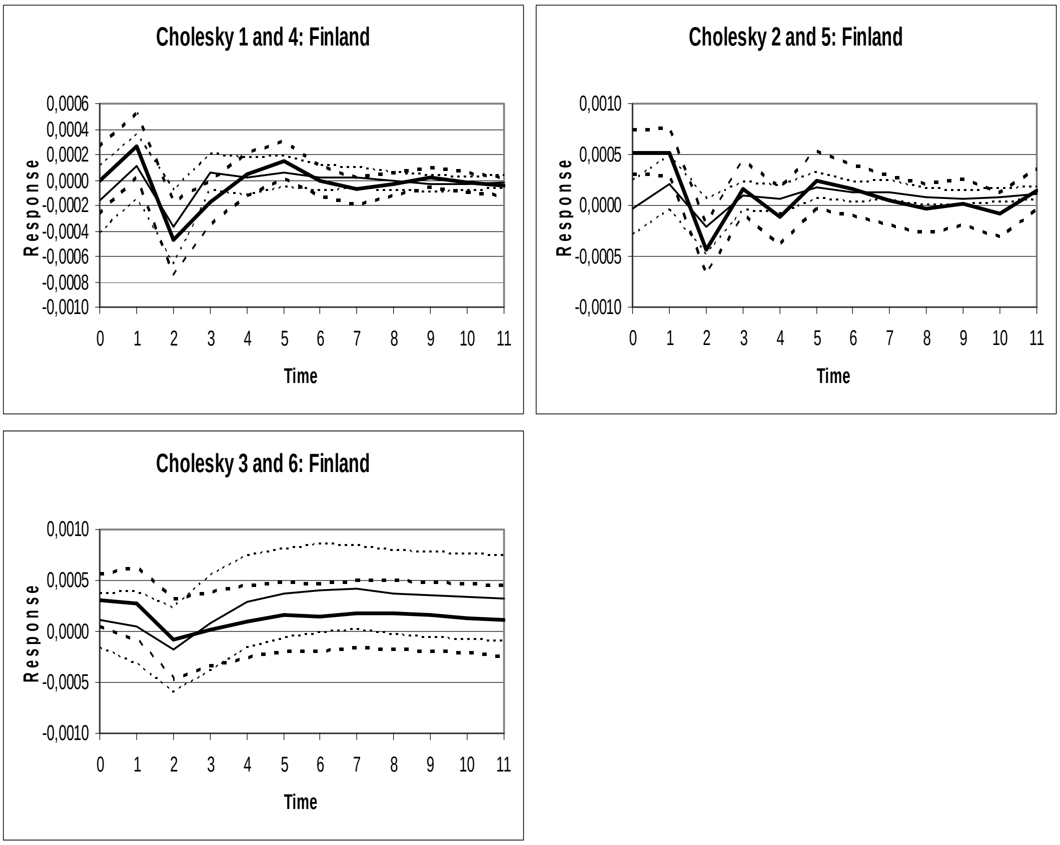


Figure F. Impulse Responses for Reduced Form VAR Models. The thick lines are for the variable ordering scheme mentioned first in the title.

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APPENDIX

A. Derivation of Equations (20)-(23)

We can write Equation (10) in a form

$$\pi_t = \beta E_t\{\pi_{t+1}\} - \alpha\beta E_t\{\hat{s}_{t+1}\} + \alpha\beta\cdot\hat{s}_t + \alpha\hat{s}_t - \alpha\hat{s}_{t-1} + \lambda\left(1+\frac{\phi\omega}{\sigma}\right)\hat{s}_t + \lambda(\phi+\sigma)\hat{y}_t^* - \lambda(1+\phi)z_t$$
$$= \beta E_t\{\pi_{t+1}\} - \alpha\beta E_t\{\hat{s}_{t+1}\} + \lambda_1\cdot\hat{s}_t - \alpha\hat{s}_{t-1} + \lambda(\phi+\sigma)\hat{y}_t^* - \lambda(1+\phi)z_t,$$

where $\lambda_1 = [\alpha\beta + \alpha + \lambda(1+\phi\omega/\sigma)]$.

Using Equations (15) and (18) together with the definition for marginal cost of a small open economy, we get

$$\pi_t = \beta\sum_{i=0}^{p} b_{i,1}\pi_{t-i} + \beta\sum_{i=0}^{p} b_{i,2}m\hat{c}_{t-i} - \alpha\beta\sum_{i=0}^{p} b_{i,7}\hat{s}_{t-i} + \lambda_1\cdot\hat{s}_t - \alpha\hat{s}_{t-1} + \lambda(\phi+\sigma)\hat{y}_t^* - \lambda(1+\phi)z_t$$
$$= \beta\sum_{i=0}^{p} b_{i,1}\pi_{t-i} + \beta(\phi+\sigma)\sum_{i=0}^{p} b_{i,2}\hat{y}_{t-i}^* + \beta(1+\phi\omega/\sigma)\sum_{i=0}^{p} b_{i,2}\hat{s}_{t-i} - \beta(1+\phi)\sum_{i=0}^{p} b_{i,2}z_{t-i}$$
$$-\alpha\beta\sum_{i=0}^{p} b_{i,7}\hat{s}_{t-i} + \lambda_1\cdot\hat{s}_t - \alpha\hat{s}_{t-1} + \lambda(\phi+\sigma)\hat{y}_t^* - \lambda(1+\phi)z_t$$
$$\Leftrightarrow$$
$$(1-c_{0,1})\pi_t - c_{0,2}\hat{y}_t^* - d_{0,3}\hat{s}_t = \sum_{i=1}^{p} c_{i,1}\pi_{t-i} + \sum_{i=1}^{p} c_{i,2}\hat{y}_{t-i}^* + \sum_{i=1}^{p} d_{i,3}\hat{s}_{t-i} - \sum_{i=0}^{p} c_{i,4}z_{t-i},$$

where $c_{i,1} = \beta\cdot b_{i,1}$ for (i = 0, …, p),
$c_{0,2} = (\beta b_{0,2} + \lambda)(\phi+\sigma)$,
$c_{i,2} = \beta(\phi+\sigma)\cdot b_{i,2}$ for (i = 1, …, p),
$d_{i,3} = \beta(1+\phi\omega/\sigma)b_{i,2} - \alpha\beta b_{i,7}$ for (i = 2, …, p)
$d_{0,3} = \beta(1+\phi\omega/\sigma)b_{0,2} - \alpha\beta b_{0,7} + \lambda_1$
$d_{1,3} = \beta(1+\phi\omega/\sigma)b_{1,2} - \alpha\beta b_{1,7} - \alpha$,
$c_{i,4} = -\beta b_{i,2}(1+\phi)$ for (i = 1, …, p) and $c_{0,4} = -(\beta b_{0,2} + \lambda)(1+\phi)$.

Denote $\hat{s}_t = s_t - s = \log S_t - \log S$, then

$$(1-c_{0,1})\pi_t - c_{0,2}\hat{y}_t^* - c_{0,3}s_t = c_1 + \sum_{i=1}^{p} c_{i,1}\pi_{t-i} + \sum_{i=1}^{p} c_{i,2}\hat{y}_{t-i}^* + \sum_{i=1}^{p} c_{i,3}s_{t-i} - \sum_{i=0}^{p} c_{i,4}z_t$$

Above is Equation (20) where

$c_{i,3} = d_{i,3}$ for (i = 0, …, p) and $c_1 = -s\left(d_{0,3} + \sum_{i=1}^{p} d_{i,3}\right)$.

Add Equation (16) and the definition for marginal cost into Equation (11) and obtain

$$\pi_t^* = \beta \sum_{i=0}^{p} b_{i,3}\pi_t^* + \beta \sum_{i=0}^{p} b_{i,4} m\hat{c}_t^* + \lambda(\phi+\sigma)\hat{y}_t^* - \lambda(1+\phi)z_t^*$$

$$= \beta \sum_{i=0}^{p} b_{i,3}\pi_{t-i}^* + \beta(\phi+\sigma)\sum_{i=0}^{p} b_{i,4}\hat{y}_{t-i}^* - \beta(\phi+1)\sum_{i=0}^{p} b_{i,4} z_{t-i}^* + \lambda(\phi+\sigma)\hat{y}_t^* - \lambda(1+\phi)z_t^*$$

$$\Leftrightarrow$$

$$(1-c_{0,5})\pi_t^* - c_{0,6}\hat{y}_t^* = \sum_{i=1}^{p} c_{i,5}\pi_{t-i}^* + \sum_{i=1}^{p} c_{i,6}\hat{y}_{t-i}^* - \sum_{i=0}^{p} c_{i,7} z_{t-i}^*$$

Above is Equation (21). Now

$c_{i,5} = \beta b_{i,3}$ for (i = 0, …, p),
$c_{i,6} = \beta(\phi+\sigma)b_{i,4}$ for (i = 1, …, p),
$c_{0,6} = (\beta b_{0,4} + \lambda)(\phi+\sigma)$,
$c_{i,7} = -\beta b_{i,4}(\phi+1)$ for (i = 0, …, p)
and
$c_{0,7} = -(\beta b_{0,4} + \lambda)(\phi+1)$.

Combining Equations (13) and (17), we obtain

$$\hat{y}_t^* = \sum_{i=0}^{p} b_{i,5}\hat{y}_{t-i}^* + \sum_{i=0}^{p} b_{i,6} r_{t-i}^* - \sum_{i=0}^{p} b_{i,6} E_t\{\pi_{t+1}^*\} - \frac{1}{\sigma}\left(r_t^* - E_t\{\pi_{t+1}^*\}\right)$$

$$= \sum_{i=0}^{p} b_{i,5}\hat{y}_{t-i}^* + \sum_{i=1}^{p} b_{i,6} r_{t-i}^* - \sum_{i=0}^{p} b_{i,6}\pi_{t-i}^* - \left(\frac{1}{\sigma} - b_{0,6}\right) r_t^* + \left(\frac{1}{\sigma} - b_{0,6}\right) E_t\{\pi_{t+1}^*\}.$$

Define $\sigma_1 = 1/\sigma - b_{0,6}$. Then, add Equation (16) and the definition for marginal cost into the above to get

$$= \sum_{i=0}^{p} b_{i,5}\hat{y}_{t-i}^* + \sum_{i=1}^{p} b_{i,6} r_{t-i}^* - \sum_{i=0}^{p} b_{i,6}\pi_{t-i}^* - \sigma_1 r_t^* + \sigma_1 \sum_{i=0}^{p} b_{i,3}\pi_{t-i}^* + \sigma_1 \sum_{i=0}^{p} b_{i,4} m\hat{c}_{t-i}^*$$

$$= \sum_{i=0}^{p} b_{i,5}\hat{y}_{t-i}^* + \sum_{i=1}^{p} b_{i,6} r_{t-i}^* - \sum_{i=0}^{p} (b_{i,6} + \sigma_1 b_{i,3})\pi_{t-i}^* - \sigma_1 r_t^* + \sigma_1(\phi+\sigma)\sum_{i=0}^{p} b_{i,4}\hat{y}_t^* - \sigma_1(\phi+1)\sum_{i=0}^{p} b_{i,4} z_t^*$$

$$= \sum_{i=0}^{p} (b_{i,5} + \sigma_1(\phi+\sigma)b_{i,4})\hat{y}_{t-i}^* + \sum_{i=1}^{p} b_{i,6} r_{t-i}^* - \sum_{i=0}^{p} (b_{i,6} + \sigma_1 b_{i,3})\pi_{t-i}^* - \sigma_1 r_t^* - \sigma_1(\phi+1)\sum_{i=0}^{p} b_{i,4} z_t^*$$

$$\Leftrightarrow$$

$$(1-c_{0,8})\hat{y}_t^* - c_{0,9} r_t^* - c_{0,10}\pi_t^* = \sum_{i=1}^{p} c_{i,8}\hat{y}_{t-i}^* + \sum_{i=1}^{p} c_{i,9} r_{t-i}^* + \sum_{i=1}^{p} c_{i,10}\pi_{t-i}^* + \sum_{i=0}^{p} c_{i,11} z_{t-i}^*$$

Above is Equation (22). Now

$c_{i,8} = b_{i,5} - \sigma_1(\phi+\sigma)b_{i,4}$ for (i = 0, …, p),

$c_{i,9} = b_{i,6}$ for (i = 1, …, p),
$c_{i,10} = -(b_{i,6} + \sigma_1 b_{i,3})$ for (i = 0, …, p),
$c_{i,11} = -\sigma_1(\phi+1)b_{i,4}$ for (i = 0, …, p),
and
$c_{0,9} = b_{0,6} - \sigma_1$.

Then combine Equations (14) and (18) to get

$$\hat{s}_t = \frac{\beta}{\mu}\sum_{i=0}^{p} b_{i,7}\hat{s}_{t-i} + \frac{1}{\mu}\hat{s}_{t-1} + \frac{\lambda(1+\phi)}{\mu}\left(z_t - z_t^*\right)$$
$$\Leftrightarrow$$
$$\left(1 - c_{0,12}\right)s_t = c_2 + \sum_{i=1}^{p} c_{i,12}s_{t-i} + c_{13}\left(z_t - z_t^*\right)$$

Above is Equation (23). Now $c_{i,12} = b_{i,7}\beta / \mu$ for (i = 0, 2, 3, …, p),

$c_{1,12} = (1+\beta)/\mu$ and $c_2 = -s\left(1 + \mu + \beta\sum_{i=0}^{p} b_{i,7}\right)/\mu$.

B. The Ordering of Variables in Reduced Form VAR Models

In the different versions of the VAR model in Equation (33), we define the vectors of observations as

$${}^1y_t = \begin{pmatrix} \pi_t^* \\ \hat{y}_t^* \\ i_t^* \\ s_t \\ \pi_t \end{pmatrix}, \qquad {}^2y_t = \begin{pmatrix} \pi_t^* \\ \Delta \log Y_t^* \\ i_t^* \\ s_t \\ \pi_t \end{pmatrix}, \qquad {}^3y_t = \begin{pmatrix} a\pi_t^* \\ \Delta_{12} \log Y_t^* \\ i_t^* \\ s_t \\ a\pi_t \end{pmatrix},$$
$${}^4y_t = \begin{pmatrix} \pi_t^* \\ \hat{y}_t^* \\ i_t^* \\ \pi_t \end{pmatrix}, \qquad {}^5y_t = \begin{pmatrix} \pi_t^* \\ \Delta \log Y_t^* \\ i_t^* \\ \pi_t \end{pmatrix}, \quad \text{and} \quad {}^6y_t = \begin{pmatrix} a\pi_t^* \\ \Delta_{12} \log Y_t^* \\ i_t^* \\ a\pi_t \end{pmatrix}.$$

Variable $a\pi_t^*$ is the annual HICP inflation of the large country and $\Delta \log Y_t^*$ and $\Delta_{12} \log Y_t^*$ refer to monthly and annual growth of the large country's industrial product output, respectively. The reduced VAR model specified with ${}^1y_t$ is set to have a direct comparison between the structural form VARs. Accordingly, a reduced form VAR of ${}^2y_t$ and ${}^3y_t$ will be estimated to have a comparison between ${}^1y_t$ and a structure form VAR. Models for ${}^4y_t$ - ${}^6y_t$ are specified and estimated to investigate how the terms of trade s_t variable affects the model dynamics in the impulse response sense of HICP inflation differences to an unanticipated expansionary monetary policy shock.

C. Summary Statistics for SVAR models

Table 4: SVAR models' lag lengths and convergence diagnostics of Model 1 and Model 2 for individual countries

Information on structural model lag lengths and convergence diagnostics

	Belgium		Germany		Spain		Austria	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
lag (*p*)	6	6	6	6	8	8	2	2
Number of draws	250,000	50,000	250,000	50,000	250,000	50,000	250,000	50,000
Acceptance ratio	29%	26%	28%	27%	21%	23%	20%	29%
Burn-in period	10,000	5,000	10,000	5,000	10,000	5,000	10,000	5,000
Thinning interval	100	100	100	100	100	100	100	100
Geweke z-statistics								
$a_{0,11}$	-1.5	1.5	-0.1	1.1	0.1	0.2	-0.6	-0.2
$a_{0,21}$	0.2	0.9	-1.5	-0.8	0.1	1.2	-1.4	-0.5
$a_{0,12}$	1.2	0.0	0.9	-0.1	0.6	1.3	-1.6	-0.8
$a_{0,22}$	-0.2	1.4	-0.9	0.5	-0.4	0.0	-0.6	-0.1
$a_{0,42}$	-0.6	-0.1	-1.5	0.1	0.1	-1.1	-0.3	0.6
$a_{0,23}$	-0.4	0.7	0.4	1.3	-0.0	-1.3	1.1	0.6
$a_{0,33}$	-0.2	-0.9	0.2	0.1	-0.3	1.6	-0.7	-0.3
$a_{0,44}$	0.1	0.6	-1.3	0.1	-0.4	1.3	-0.2	0.8
$a_{0,45}$	0.6	0.1	1.6	1.0	1.0	-1.0	-0.7	-0.5
$a_{0,55}$	-1.2	-1.0	-1.2	-0.5	1.6	-0.1	-0.0	-1.7
λ_2	0.6	NA	0.9	NA	-1.5	NA	-0.2	NA
Median of λ_2	169.4	NA	21.6	NA	40.0	NA	39.2	NA
Mean of λ_2	195.4	NA	34.6	NA	58.2	NA	51.6	NA

	France		Italy		Ireland		Luxembourg	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
lag (*p*)	4	4	7	7	4	4		
Number of draws	250,000	50,000	250,000	50,000	250,000	50,000	250,000	50,000
Acceptance ratio	20%	30%	20%	29%	25%	31%	28%	28%
Burn-in period	10,000	5,000	10,000	5,000	10,000	5,000	10,000	5,000
Thinning interval	100	100	100	100	100	100	100	100
Geweke z-statistics								
$a_{0,11}$	0.1	-0.3	-1.1	-0.8	-0.3	-0.3	-0.0	0.9
$a_{0,21}$	0.2	-0.6	-0.3	0.7	-0.1	-0.1	-0.9	0.5
$a_{0,12}$	0.2	0.2	0.2	-1.6	-0.4	-0.4	-0.7	-0.2
$a_{0,22}$	0.2	-0.2	-0.7	-0.8	-0.7	-0.7	-0.1	1.2
$a_{0,42}$	-0.0	0.2	-0.2	-0.5	0.1	0.1	-1.5	-0.6
$a_{0,23}$	0.6	-0.1	-1.3	1.0	0.2	0.2	0.5	0.0
$a_{0,33}$	0.6	-1.0	0.3	-0.4	-0.9	-0.9	-0.8	-1.1
$a_{0,44}$	-0.6	-1.1	-1.1	1.0	-0.3	-0.3	-0.1	-0.7
$a_{0,45}$	-0.3	-0.6	-0.4	-0.9	-0.3	-0.3	0.3	-0.5
$a_{0,55}$	-0.4	0.2	-0.8	0.3	-1.4	-1.4	-1.3	-1.6
λ_2	0.8	NA	0.1	NA	-0.1	NA	-0.3	NA
Median of λ_2	51.4	NA	29.1	NA	141.1	NA	16.2	NA
Mean of λ_2	68.2	NA	47.1	NA	162.4	NA	28.6	NA

	The Netherlands		Portugal		Finland	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
lag (p)	3	3	3	3	3	3
Number of draws	250,000	50,000	250,000	50,000	250,000	50,000
Acceptance ratio	19%	17%	19%	27%	24%	29%
Burn-in period	10,000	5,000	10,000	5,000	10,000	5,000
Thinning interval	100	100	100	100	100	100
Geweke z-statistics						
$a_{0,11}$	-1.4	-0.7	1.1	1.4	1.1	-1.5
$a_{0,21}$	-1.6	1.3	0.5	-1.5	1.6	-0.1
$a_{0,12}$	0.8	-1.3	0.8	1.7	0.4	0.8
$a_{0,22}$	-1.4	-0.6	1.0	1.8	0.8	-1.4
$a_{0,42}$	-0.1	0.9	0.6	-1.3	-0.5	-1.0
$a_{0,23}$	-0.4	-1.0	0.7	-0.5	-1.0	1.1
$a_{0,33}$	-0.4	1.2	-1.2	0.7	0.2	1.0
$a_{0,44}$	0.1	-0.6	-0.3	0.1	1.4	-0.9
$a_{0,45}$	-1.4	0.5	0.8	-0.3	-1.2	0.7
$a_{0,55}$	0.0	-0.3	0.2	-0.0	-1.3	0.3
λ_2	-0.7	NA	-0.1	NA	-1.3	NA
Median of λ_2	318.0	NA	77.8	NA	18.2	NA
Mean of λ_2	336.7	NA	95.2	NA	32.1	NA

Table 5: Reduced form VAR lag lengths

Information on reduced form VAR models lag lengths

Country	Estimated lag length (p)					
Belgium	6	6	9	6	6	3
Germany	7	7	10	7	7	4
Spain	8	10	3	8	8	3
Austria	2	4	7	3	4	3
France	4	4	5	4	4	5
Italy	4	4	7	4	4	3
Ireland	4	4	7	4	4	3
Luxembourg	7	6	7	6	6	3
The Netherlands	3	3	4	3	4	4
Portugal	3	3	3	3	3	5
Finland	3	6	3	3	3	4