Monetary Policy Shocks and Consumer Expectations in the Euro Area

Martin Geiger (Liechtenstein Institute),
Daniel Gründler (University of Innsbruck),
Johann Scharler (University of Innsbruck)

Motivation

- Great relevance of private sector expectations for monetary policy transmission.
- Effectiveness of policy depends private sector understanding of how monetary policy works.
- While EA member countries are subject to common monetary policy, its transmission is heterogeneous.
- Expectation formation might be characterized by similar heterogeneities.
- **Our contribution: We study how consumers in the euro area adapt their macroeconomic expectation in response to monetary policy and if their beliefs about the transmission mechanism are heterogeneous across countries.**

Survey Data

- We use the monthly consumer survey data from the Joint Harmonized EU Programme of Business and Consumer Surveys (BCS).

- Conducted based on a harmonized questionnaire in all EU member countries. A sample typically exceeds 1 000 respondents per month and country.

- Two questions to measure consumer price expectations, unemployment expectations and consumption plans:

  - *By comparison with the past 12 months, how do you expect that consumer prices will develop in the next 12 months? They will...*

  - *How do you expect the number of people unemployed in this country to change over the next 12 months? The number will...*

- Given the qualitative nature of the survey answers, we use scores to aggregate the data.

Model Estimation

We estimate a factor-augmented VAR (FAVAR) model including a large dataset x_t, consisting of $M = 181$ time series from 2003M1 to 2019M4,from which we extract $L = 8$ factors, based on the information criterion of Bai and Ng (2002). We model the joint dynamics of these factors and the policy surprise m_t as

$$y_t = c + \sum_{j=1}^{p} B_j y_{t-j} + u_t, \qquad (1)$$

where $y_t = [m_t, f_t']'$ and f_t is a $L \times 1$ vector of factors, c is a vector of constants, the B_j are matrices of autoregressive coefficients, and $u_t \sim \mathcal{N}(0, \Sigma)$ is a vector of error terms. In our baseline model, we set $p = 6$.

We use a Gibbs Sampler for drawing for posterior simulation. For the VAR coefficients, we choose a Minnesota prior with relatively loose tightness parameters.

Factor Analysis

The observed series in x_t are related to the common factors and idiosyncratic components according to:

$$x_t = \lambda_f f_t + \lambda_m m_t + e_t, \tag{2}$$

where λ_m, which is $M \times 1$, and λ_f, which is $M \times L$, contain the loadings on m_t and f_t, respectively. We use the method proposed by Boivin and Giannoni (2007) to estimate the factors.

Table 1: Variance in data explained by factors

	F1	F2	F3	F4	F5	F6	F7	F8	Σ
% explained	22.3	13.7	9.9	7.3	4.8	3.5	3.1	2.0	66.6

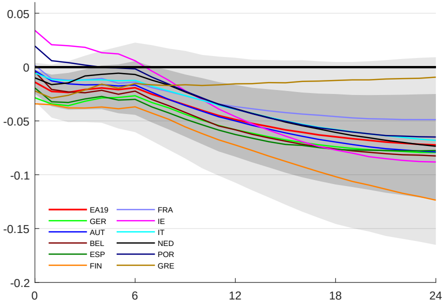
Notes: The table presents the percentage share of the variation in our dataset (without instrument) explained by each of the 8 factors we use in our analysis.

Monetary policy shock identification

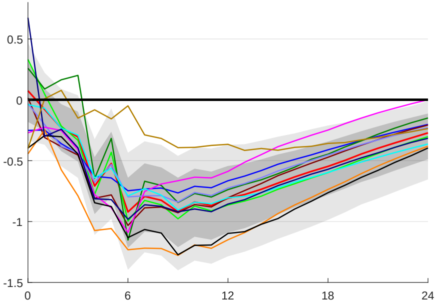
- We use a high-frequency approach to identify the monetary policy shock.
- Assumption: Changes in interest rates and equity prices within a 30 minute window around monetary policy announcements will only be affected by the announcement and thus can be interpreted as broad policy surprises.
- Thus, these surprises should be correlated with policy and information shocks but not with other shocks.
- Next step is to decompose the interest rate surprise into two orthogonal parts, to purge the policy surprise against information effects.
- We interpret the component characterised by a negative co-movement of interest rate surprises and stock market surprises as a pure policy surprise.
- As the only observed variable, we order the instrument first in the FAVAR and use the Cholesky decomposition to calculate responses of the factors. Afterwards, we multiply with the factor loadings to recover the responses of the underlying variables.

Country IRFs, HICP and consumer price expectations

Panel (A): HICP

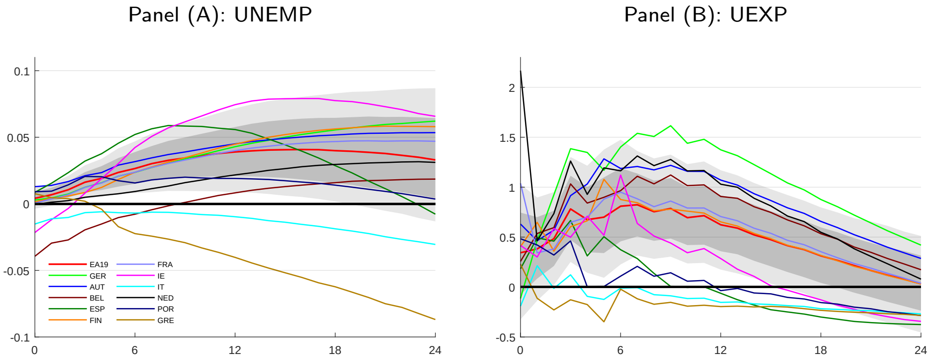


Panel (B): PEXP



Notes: Panel (A) illustrates pointwise median IRFs of the HICP to a pure monetary policy shock for all member countries in the sample including the EA aggregate. Panel (B) presents pointwise median IRFs of consumer price expectations to a pure monetary policy shock for the same countries. The shaded areas in both panels refer to the 68% and 90% credible set of the EA response.

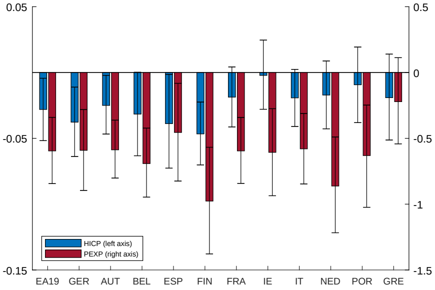
Country IRFs, unemployment rate and unemployment expectations



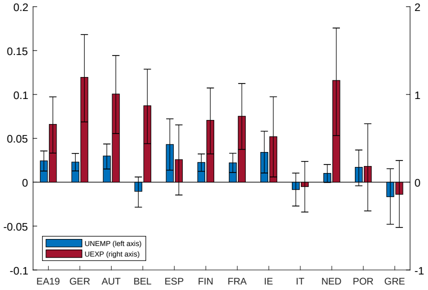
Notes: Panel (A) illustrates pointwise median IRFs of the unemployment rate to a pure monetary policy shock for all member countries in the sample including the EA aggregate. Panel (B) presents pointwise median IRFs of unemployment expectations to a pure monetary policy shock for the same countries. The shaded areas in both panels refer to the 68% and 90% credible set of the EA response.

Averaged impulse response functions

Panel (A): Prices



Panel (B): Unemployment



Notes: Panel (A) shows bar plots of the median responses of the HICP (blue) and consumer price expectations to a pure monetary policy shock across different euro area member countries. The bars are calculated as the average response of horizons 0 to 12. Panel (B) presents the corresponding responses of the unemployment rate (blue) and unemployment expectations to a pure monetary policy shock across different euro area member countries. The whiskers refer to the 68% credible sets.

Coefficients of variation

(A) Macroeconomic Variables

Variable	$h = 0$	$h = 6$	$h = 12$
HICP	5.77	2.95	1.74
	(3.39, 17.41)	(1.60, 9.02)	(1.05, 4.22)
Unemployment rate	14.06	3.42	3.26
	(7.41, 42.79)	(2.39, 5.82)	(2.10, 6.41)

(B) Survey variables

Variable	$h = 0$	$h = 6$	$h = 12$
Price expectations	11.67	1.30	0.95
	(5.88, 36.52)	(1.02, 1.81)	(0.79, 1.33)
Unemployment expectations	8.24	2.34	3.00
	(4.02, 26.47)	(1.63, 3.97)	(1.93, 5.16)

Notes: The table shows the coefficient of variation for the responses of various variables calculated using the pointwise median responses at horizons $h = 0$, $h = 6$, and $h = 12$, together with the 68% credible set in brackets. Panel (A) shows results for macroeconomic variables and Panel (B) presents results for survey variables. The coefficient of variation is calculated as the standard deviation of the member country response with respect to the euro area aggregate response. The responses are scaled such that the euro area aggregate response equals 1 in modulus.

Conclusion

- We use a FAVAR model to investigate the effects of common euro area monetary policy on consumer expectations in the euro area and its member countries.
- In response to a monetary policy shock, euro area consumers tend to revise their macroeconomic expectations in line with standard macroeconomic models.
- Also, their expectation revisions match the responses of actual macroeconomic variables.
- Consumer price expectations respond relatively homogeneous across countries, while consumers adapt their unemployment expectations more heterogeneously after a monetary policy shock.
- These findings suggest that the ECB is relatively successful in managing expectations and explaining their policies.

References

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

Boivin, J., Giannoni, M.P., 2007. Global forces and monetary policy effectiveness, in: International Dimensions of Monetary Policy. University of Chicago Press, pp. 429–478.

Jarocinski, M., Karadi, P., 2020. Deconstructing monetary policy surprises – the role of information shocks. American Economic Journal: Macroeconomics 12, 1–43. doi:10.1257/mac.20180090.

Korobilis, D., 2013. Assessing the transmission of monetary policy using time-varying parameter dynamic factor models. Oxford Bulletin of Economics and Statistics 75, 157–179.

Appendix: Rotational Sign Restrictions

Following Jarocinski and Karadi (2020), let M be a $T \times 2$ matrix containing monthly aggregated high frequency changes in the policy rate, i, and the S&P500, s, which we want to decompose into two orthogonal components mp and cbi.

As a first step, we calculate the QR-decomposition of M, such that:

$$M = QR, \qquad Q'Q = I_2, \qquad R = \begin{pmatrix} r_{11} > 0 & r_{12} \\ 0 & r_{22} > 0 \end{pmatrix}, \tag{A.3}$$

Next, we rotate the orthogonal components in Q using the following rotation matrix:

$$P = \begin{pmatrix} cos(\alpha) & sin(\alpha) \\ -sin(\alpha) & cos(\alpha) \end{pmatrix}, \tag{A.4}$$

where α is calculated as $\alpha = arccos(\sqrt[2]{\frac{var(mp_{pm})}{var(i)}})$. This rotation ensures that the surprises we calculate can be interpreted as policy and information surprises, i.e., they fulfil the sign restrictions mentioned above.

Appendix: Rotational Sign Restrictions

We use the poor man's sign restriction approach to recover mp_{pm}. More precisely, set i to 0 for each observation where i and s have the same sign and interpret the resulting vector as policy surprises mp_{pm}. We then calculate the share of the variance in mp_{pm} in the total variance of i and take the square root of it to calculate α.

Finally, we use the following matrix D to scale the policy and the information surprise such that they add up to the broad policy surprise i:

$$D = \begin{pmatrix} r_{11} cos(\alpha) & 0 \\ 0 & r_{22} sin(\alpha) \end{pmatrix}, \tag{A.5}$$

Combining these three steps, we can calculate the orthogonalized instruments as $[mp, cbi] = QPD$.

Appendix: Priors

More precisely, we specify a Minnesota type prior for the means and variances of the VAR coefficients. More precisely, we assume $\beta \sim \mathcal{N}(\underline{\beta}, \underline{V})$, where:

$$\underline{\beta} = 0_K, \tag{A.6}$$

$$\underline{V_{kk}} = \frac{\alpha \sigma_i}{r^2 \sigma_j}, \quad i, j = 1, ..., N; kk = 1, ..., K, \tag{A.7}$$

where 0_K is a $K-$dimensional vector of zeros and $\underline{V}$ is a $K \times K$ diagonal matrix with diagonal elements $\underline{V_{kk}}$. σ_i and σ_j are estimated as the residuals of univariate autoregressions with p lags for each variable in y_t and r is the lag order of each coefficient. Finally, we set the tightness parameter $\alpha = 0.2$. For the intercepts in Equation (1), we choose a loose prior, setting the corresponding diagonal elements in $\underline{V}$ to 100^2.

For the VAR covariance matrix, we specify $\Sigma \sim iW(\underline{\Sigma}, \underline{\nu})$, where:

$$\underline{\sigma_i} = 0_K, \tag{A.8}$$

$$\underline{\nu} = N + 2, \tag{A.9}$$

where $\underline{\Sigma}$ is a $N \times N$ diagonal matrix and σ_i its diagonal elements.

Appendix: Gibbs Sampler

First, let $z_t = [I_N, I_N \otimes y'_{t-1}, ..., I_N \otimes y'_{t-p}]'$, where $N = 1 + L$ and $\beta = (c', vec(B'_1)', ..., vec(B'_p)')'$, and rewrite the model in Equation (1) more compactly as:

$$y_t = z'_t \beta + u_t, \tag{A.10}$$

where z_t is $K \times N$, $K = (Np + 1)N$, β is $K \times 1$ and u_t is $N \times 1$. We use a Gibbs Sampler to sequentially draw from $p(\beta|y, \Sigma)$ and $p(\Sigma|y, \beta)$. Thereby, $p(\beta|y, \Sigma) = N(\overline{\beta}, \overline{V})$, where

$$\overline{V} = (\underline{V}^{-1} + \sum_{t=1}^{T} z'_t \Sigma^{-1} z_t)^{-1}, \tag{A.11}$$

$$\overline{\beta} = \overline{V}(\underline{V}^{-1}\underline{\beta} + \sum_{t=1}^{T} z'_t \Sigma^{-1} y_t), \tag{A.12}$$

and $p(\Sigma|y, \beta) = iW(\overline{S}, \overline{\nu})$, with

$$\overline{\nu} = T + \underline{\nu}, \tag{A.13}$$

$$\overline{S} = \underline{S} + \sum_{t=1}^{T} (y_t - z'_t \beta)(y_t - z'_t \beta)'. \tag{A.14}$$

Appendix: Gibbs Sampler

In addition to the FAVAR equation parameters β and Σ, we draw the parameters of the factor equation, λ and R, at each iteration. For this purpose, we rewrite Equation (2) as:

$$x_t = \lambda y_t + e_t, \tag{A.15}$$

where $\lambda = [\lambda_m \, \lambda_f]$ contains the factor loadings. For each row λ_j, $j = 1, ..., M$, the posterior is $\lambda_j \sim \mathcal{N}(\overline{\lambda_j}, \overline{W})$, with

$$\overline{W} = (\underline{W}^{-1} + R_{jj}^{-1} y' y)^{-1}, \tag{A.16}$$

$$\overline{\lambda_j} = (\overline{W}(\underline{W}^{-1} y' x_j))', \tag{A.17}$$

where x_j contains observations $t = 1, ..., T$ of the j^{th} variable in x and $\underline{W} = 4I_N$.

Appendix: Gibbs Sampler

The diagonal elements in R are the variances of the idiosyncratic components in the factor equation. The first element on the main diagonal of R is set to zero and for the remaining $j = 1, ..., M$ diagonal elements we assume $R_{jj} \sim iG(\overline{r_1}, \overline{r_2})$, where

$$\overline{r_1} = \underline{r_1}/2 + T/2, \tag{A.18}$$

$$\overline{r_2} = (\underline{r_2}/2 + (x_j - y\lambda_j')'(x_j - y\lambda_j')/2)^{-1}. \tag{A.19}$$

We set the prior shape parameter in Equation (A.18) to $\underline{r_1} = 0.01$ and the prior scale parameter in Equation (A.19) to $\underline{r_2} = 0.01$, where the latter implies a loose prior (see e.g. Korobilis, 2013).

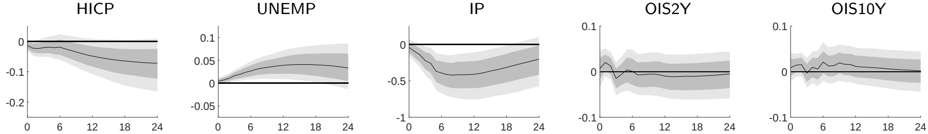
Appendix: Factor Estimation

As an initial estimate of the factors, we calculate the first 8 principal components from the dataset x_t and denote them as $\tilde{f}_t^0$. Note that although the policy surprise is treated as a common factor in the factor equation (2), it is not included in the principal components analysis. Hence, without any correction, its influence would be captured by the estimated principal components. Therefore, we follow the iterative procedure proposed in Buch et al. (2014) and Boivin and Giannoni (2007) to remove the policy surprise from the factor space. It can be summarized as follows:

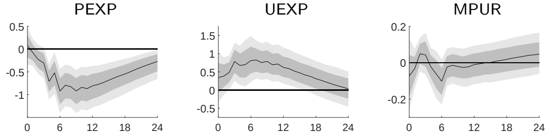
1. Regress x_t on $\tilde{f}_t^0$ and m_t to obtain initial estimates of the factor loadings $\tilde{\lambda}_m^0$ and $\tilde{\lambda}_f^0$.
2. Based on these estimates, calculate $\tilde{x}_t^0 = x_t - \tilde{\lambda}_m^0 m_t$, i.e. remove the part in x_t explained by the observed factor.
3. Extract a new set of L principal components $\tilde{f}_t^1$ from $\tilde{x}_t^0$ and go back to step 1 until convergence is achieved
4. We consider this process as being converged if the sum of squared residuals of $x_t = \tilde{\lambda}_f^j \tilde{f}_t^j + \tilde{\lambda}_m^j m_t + e_t$, where j denotes the current iteration number, changes by less than 0.000001 compared to the previous iteration.

Appendix: IRFs, euro area aggregates

(A) Macroeconomic variables



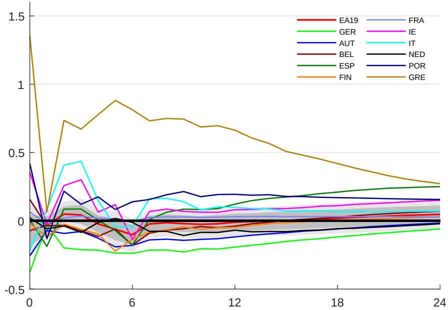
(B) Survey measures



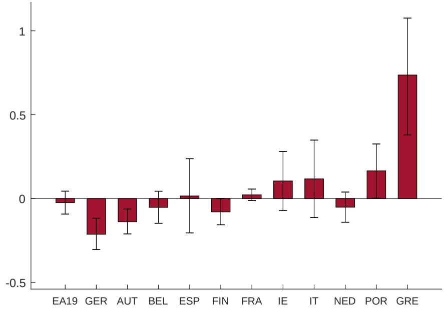
Notes: The figure shows pointwise median impulse response functions (black line) of euro area aggregate variables over a 2-year horizon as well as 68% and 90% credible sets (shaded areas) to a contractionary monetary policy shock. Panel (A) presents responses of macroeconomic variables and the responses of survey variables are shown in Panel (B).

Appendix: Country IRFs, consumption plans

Panel (A)



Panel (B)



Notes: Panel (A) illustrates pointwise median IRFs of planned consumer major purchases to a pure monetary policy shock for all member countries in the sample including the EA aggregate. The shaded areas refer to the 68% and 90% credible set of the EA response. Panel (B) shows bar plots of the median responses of planned consumer major purchases to a pure monetary policy shock, calculated as the average of horizons 0 to 12. The whiskers refer to the 68% credible sets.