Monetary Policy Shocks in the Euro Area: Evidence from a FAVAR Model

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Abstract

This study investigates monetary policy transmission in the Euro Area using a Factor-Augmented VAR (FAVAR) Bernanke et al. (2005) framework, estimated on a large monthly dataset (Barigozzi and Lissona, 2024). Latent factors are combined with real GDP, HICP, and a policy rate proxy to assess the stability of the transmission mechanism. Alternative specifications, including standard VARs and shadow-rate variants, are compared against the main model. The analysis shows that the main FAVAR specification successfully resolves the price puzzle: following a contractionary shock, inflation declines significantly after seven months, whereas alternative models exhibit insignificant or weak responses. Overall, the results demonstrate that incorporating latent information alongside core variables is essential to mitigate empirical anomalies and identify plausible transmission mechanisms in the Euro Area.

1 Introduction

Identifying monetary policy shocks and tracing their dynamic effects is challenging when using low-dimensional Vector Autoregression (VAR) models. A well-known limitation in this literature is the *price puzzle* (Sims, 1992)—the empirical finding that inflation increases following a contractionary shock—which is often attributed to omitted information in the policy reaction function. To address this, Bernanke et al. (2005) introduced the Factor-Augmented Vector Autoregression (FAVAR) framework, demonstrating that incorporating latent factors from large datasets substantially improves identification and resolves the anomaly in U.S. data.

This paper applies the FAVAR methodology to the Euro Area, a context complicated by heterogeneous transmission mechanisms and the Zero Lower Bound. The analysis combines latent factors extracted from a large monthly macroeconomic dataset with key observed variables: real GDP, HICP inflation, and the policy interest rate. Several model specifications are compared, including standard VARs, a FAVAR with only the Interest Rate as observable variable (called "Baseline FAVAR") and variants incorporating shadow interest rates. A lag length of seven months is adopted to capture medium-term transmission dynamics while preserving estimation stability.[1]

Results indicate that only the main FAVAR specification—incorporating explicit output, inflation, and the policy rate—successfully resolves the price puzzle: inflation exhibits a significant and persistent decline from the seventh month onward. In contrast, alternative specifications, including those employing shadow rates, produce insignificant or counter-intuitive dynamics. Furthermore, the analysis suggests that at least three latent factors are required to identify statistically significant disinflationary effects. Broadly, the impulse responses of wider macroeconomic aggregates align with theoretical expectations, confirming that a data-rich FAVAR specification is essential for overcoming the empirical shortcomings of small-scale models in the Euro Area.

2 Methodology / Approach

2.1 Econometric Framework

The primary motivation for employing a Factor-Augmented Vector Autoregression (FAVAR) is to address the limited information set inherent in standard VAR models. Small-scale VARs can be "informationally deficient," potentially leading to omitted-variable bias in estimated policy responses. Furthermore, policy institutions monitor large panels of data, and a FAVAR framework allows for the examination of shock transmission at a more disaggregate level, such as specific price sub-indices or sectoral output.

Formalizing the framework of Bernanke et al. (2005), let X_t denote a large $N \times 1$ vector of informational time series and Y_t be an $M \times 1$ vector of observable economic variables (e.g., the policy rate). Assuming that the dynamics of X_t are driven by the observed variables Y_t and a vector of R unobserved latent factors, F_t, via the following *observation equation*:

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + e_t \tag{1}$$

where Λ^f is an $N \times R$ matrix of factor loadings, Λ^y is an $N \times M$ matrix of coefficients, and e_t is an $N \times 1$ vector of uncorrelated idiosyncratic components.

The joint dynamics of the state vector $Z_t = [F_t', Y_t']'$ are governed by the *transition equation*, which takes the form of a VAR structure:

[1] While information criteria suggested fewer lags, a seven-month structure was selected as a compromise between parsimony and the need to capture delayed monetary effects without the over-parameterization issues of longer lag structures (e.g., 13 months) with a dataset with only 311 observations.

$$B(L)\begin{bmatrix}F_t\\Y_t\end{bmatrix} = w_t \tag{2}$$

where $B(L) = B_0 + B_1L + \cdots + B_pL^p$ is a conformable lag polynomial of finite order p (a $(R+M)(R+M)$ matrix operator), and w_t is $(R+M)$-dimensional white noise (see details: Kilian and Lütkepohl (2017) pg 566 cap. 16.2 FAVAR Models).

2.2 Data Description and Variable Selection

The analysis employs a comprehensive monthly dataset of 120 macroeconomic variables for the Euro Area, spanning from January 2000 to November 2025 and sourced from Barigozzi and Lissona (2024). To ensure scale consistency during factor extraction, all series in X_t are standardized to have zero mean and unit variance prior to estimation.

Variable selection follows the framework of Bernanke et al. (2005), adapted to Euro Area data availability. The dataset covers a broad spectrum of economic indicators, including real output, inflation, interest rates, monetary aggregates, consumption, labor market conditions, and asset prices. Where specific U.S. series used in the original study lack harmonized Euro Area equivalents, appropriate proxies are employed to preserve the economic interpretation of the factors.

The explicit variables forming the Y-block are Real GDP, HICP inflation, and the 3-month interbank interest rate (IRT3M). The latter is selected as the proxy for the monetary policy stance rather than the ECB deposit facility rate. This choice avoids the numerical instability associated with extended periods at the zero lower bound and ensures a consistent time series with sufficient variation over the full sample. Shadow rate specifications are employed solely for robustness checks.

2.3 Factor Estimation, Identification and "Cleaning"

Following the approach proposed by Bernanke et al. (2005), the large information set is summarized through a small number of unobserved common factors, which are subsequently included in a VAR framework together with the monetary policy instrument.

Let X_t denote a $N \times 1$ vector collecting the standardized macroeconomic variables observed at time t. The first step consists in extracting r common factors from the full dataset by means of Principal Component Analysis (PCA). Denoting by F_t^{all} the resulting vector of estimated factors:

$$X_t = \Lambda F_t^{all} + e_t, \tag{3}$$

where Λ is the matrix of factor loadings and e_t is an idiosyncratic error term.

However, these factors are not yet suitable for structural analysis, as they may incorporate contemporaneous information about the monetary policy instrument. To address this issue, a second set of factors is extracted from a subset of variables classified as *slow-moving.* These variables are assumed, on economic grounds, not to respond contemporaneously to monetary policy shocks. Let X_t^{slow} denote this subset, and let F_t^{slow} be the corresponding factors obtained via PCA.

To ensure consistency with a recursive identification scheme, the estimated factors F_t^{all} are "cleaned" from the contemporaneous influence of the policy rate. This is achieved by projecting F_t^{all} on the slow-moving factors and the policy instrument i_t:

$$F_t^{all} = \alpha + B_s F_t^{slow} + B_i i_t + u_t \tag{4}$$

where α is an intercept and u_t is an error term. The coefficient B_i captures the component of the estimated factors that is contemporaneously explained by the policy rate.

The cleaned factors are then obtained as

$$\widehat{F}_t = F_t^{all} - B_i i_t \tag{5}$$

By construction, the factors $\widehat{F}_t$ are orthogonal to the contemporaneous monetary policy shock and therefore satisfy the identification assumptions required for the structural FAVAR. These cleaned factors, together with the policy rate, constitute the state vector employed in the subsequent VAR analysis.

2.4 Estimation Strategy

This study employsthe *Two-Step Estimation Method*, which is widely favored in the literature for its computational feasibility. (Bernanke et al. (2005))

Step 1: Factor Extraction. The latent factors F_t are extracted from the informational dataset X_t using Principal Component Analysis (PCA). The principal components correspond to the eigenvectors associated with the largest eigenvalues of the correlation matrix of X_t. Consistent with standard static factor models, the number of factors selected r are sufficient to explain a pre-specified fraction (at least 60%) of the total variance. Since standard PCA estimates do not distinguish between latent factors and observed variables, the observed variables are removed from X_t and the factors are "cleaned" following the procedure in Bernanke et al. (2005) through Eq: (5). This step "partials out" the contribution of the observable policy rate from the principal components, thereby isolating the shocks to latent economic conditions.

Step 2: VAR Estimation. Conditioning on the estimated factors $\hat{F}_t$ as though they were observed variables— the Equation (2) is estimated via Ordinary Least Squares

(OLS) equation-by-equation. The main lag length is set to seven months, in line with the empirical monetary VAR literature.

2.5 Identification of Monetary Policy Shocks

To recover structural monetary policy shocks from the reduced-form errors w_t, a recursive Cholesky decomposition is applied. The ordering of variables in the state vector Z_t is crucial for identification. Following the distinction between "slow-moving" and "fast-moving" variables, and consistent with the standard recursive identification assumptions (Christiano et al., 1999), the following ordering is adopted:

1. **Latent Factors ($\hat{F}_t$):** Ordered first. These represent slow-moving economic conditions (such as real activity) that are assumed not to respond instantaneously to monetary policy shocks within the same period.

2. **Observed Macro Variables:** Real GDP and HICP are ordered second.

3. **3-Months Interest Rates:** Ordered last.

This recursive structure implies that a monetary policy shock has no instantaneous impact on output, prices, or the slow-moving latent factors, consistent with theoretical priors on transmission lags.

2.6 Impulse Responses and Statistical Inference

Impulse responses are computed over a 60-month horizon using a recursive identification scheme. Inference is conducted via a residual-based bootstrap applied to the VAR system, conditional on the estimated latent factors.

The procedure involves generating $10,000$ bootstrap samples by resampling the centered residuals and iterating the VAR dynamics. In each replication, the model parameters are re-estimated to generate a distribution of impulse responses, ignoring the sampling uncertainty associated with the initial factor extraction. Confidence bands are constructed at the 90% level.

2.7 Variance Decomposition and R^2

To quantify the contribution of monetary policy shocks to macroeconomic fluctuations, Forecast Error Variance Decompositions (FEVD) and R^2 goodness-of-fit measures are computed.

The FEVD represents the fraction of the forecast error variance of variable j at horizon h attributable to a specific structural shock k. It is calculated from the orthogonalized impulse responses as:

$$\text{FEVD}_{j,k}(h) = \frac{\sum_{\tau=1}^{h} \text{IRF}_{j,k}(\tau)^2}{\sum_{s=1}^{K}\sum_{\tau=1}^{h} \text{IRF}_{j,s}(\tau)^2},$$

where the denominator sums the contributions of all K structural shocks identifying the system.

Additionally, the information content of the common component is assessed via the R^2 statistic. Since the dataset is standardized, the R^2 obtained from the projection of each variable X_i on the estimated state vector $Z_t = [\hat{F}_t', Y_t']'$ directly measures the share of variance explained by the factors and the observed variables:

$$X_{it} = \lambda_i Z_t + \varepsilon_{it}.$$

3 Empirical Results

3.1 Benchmark Comparison: VAR and FAVAR Models

Figure 1 compares the impulse responses of GDP, HICP, and the policy rate across alternative model specifications. While all models show output contraction after a monetary policy shock, only the main FAVAR—with GDP, HICP, and policy rate as explicit variables—exhibits a statistically significant disinflationary response from the seventh month onward. Alternative models, including the VAR, the FAVAR with only the policy rate, and shadow rate variants, remain statistically insignificant over the same horizon or for the full 60 months.

3.2 The Role of Latent Factors

Figure 2 presents the sensitivity of HICP responses to the number of latent factors included. At least three factors are required to achieve a timely and statistically significant disinflationary effect. Lower-dimensional specifications underestimates the speed and magnitude of the inflation decline, highlighting the importance of incorporating sufficient latent information.

3.3 Transmission Mechanisms in the Euro Area

Factor responses are mapped to observed variables to illustrate the economic transmission of monetary policy shocks (Figure 3). Long-term interest rates, monetary aggregates, and real consumption respond in a manner consistent with standard transmission channels. Stock prices, total employment, the exchange rate, and consumer confidence also react plausibly. Table 1 reports variance decompositions (FEVD) and R^2, showing that the policy shock explains a sizable share of the variation in key variables, particularly GDP, HICP, and the policy rate.

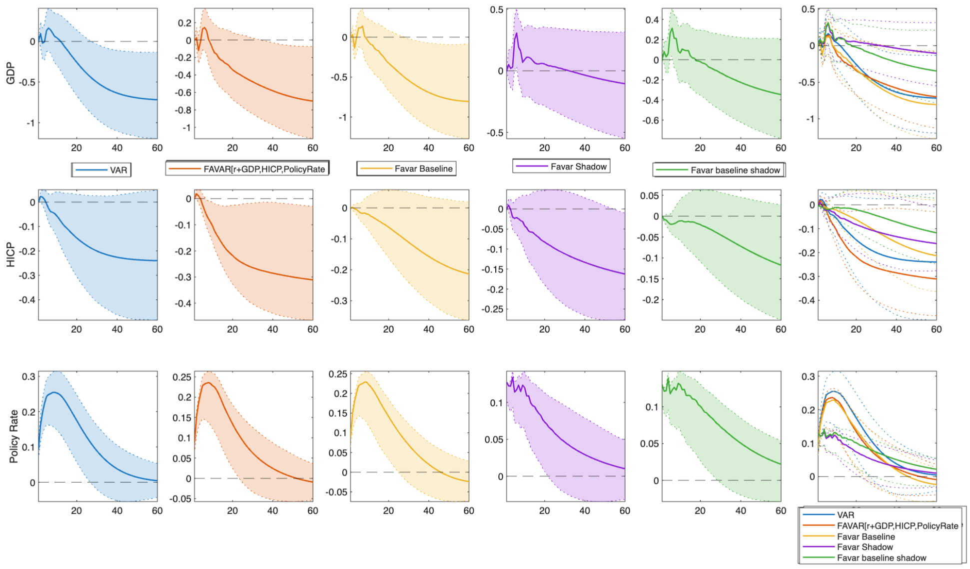


Figure 1: Impulse responses to a monetary policy shock: comparison across VAR, baseline FAVAR, shadow FAVAR, and main FAVAR (7 lags, 90% bootstrap confidence bands). Only the main FAVAR displays significant disinflationary dynamics from the seventh month.

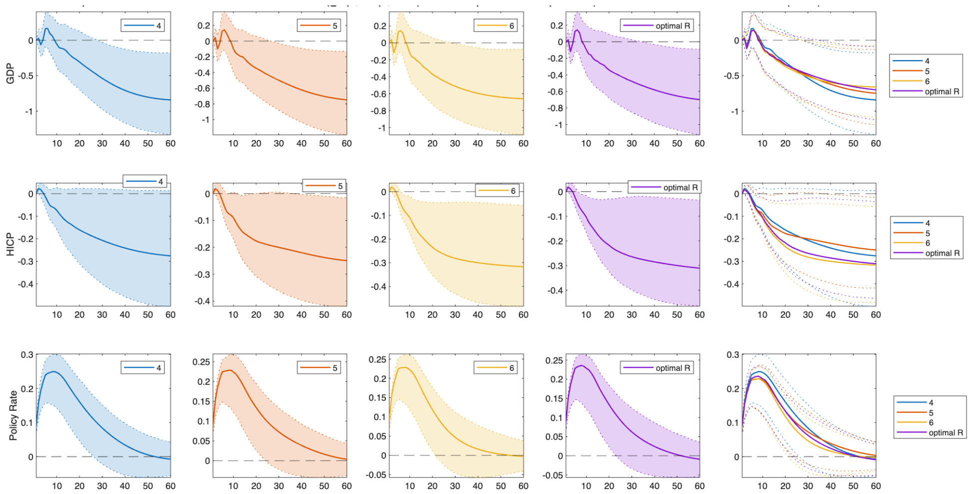


Figure 2: Impulse responses of HICP to a monetary policy shock across different numbers of latent factors.

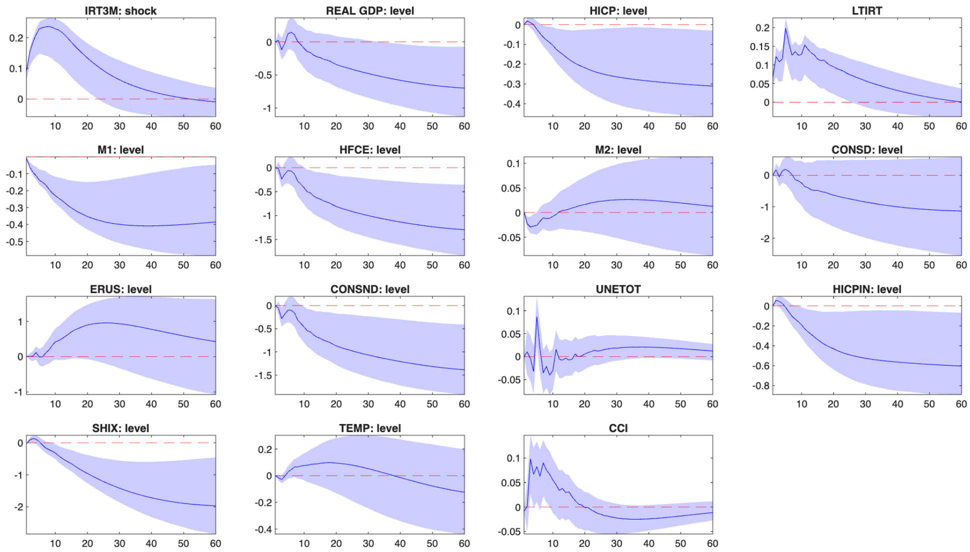


Figure 3: Loaded impulse responses of selected macroeconomic variables to a policy rate shock.

Variable	FEVD (%)	R^2
IRT3M (shock)	0.349	1
REAL GDP	0.028	1
HICP	0.070	1
LTIRT	0.260	0.755
M1	0.132	0.147
HFCE	0.031	0.963
M2	0.041	0.158
CONSD	0.020	0.932
ERUS	0.061	0.163
CONSND	0.034	0.949
UNETOT	0.037	0.421
HICPIN	0.075	0.872
SHIX	0.089	0.074
TEMP	0.029	0.955
CCI	0.076	0.452

Table 1: Forecast error variance decomposition (FEVD) and R^2 for the main FAVAR (7 lags).

4 Robustness

To assess the robustness of the results, several checks varying the VAR lag length and the confidence bands used in the bootstrap procedure are done. In all cases, the qualitative patterns of the impulse responses remain consistent, with the sign of the responses preserved across model specifications. Differences emerge primarily in the statistical significance and smoothness of the IRFs, reflecting changes in the bootstrap variance and confidence intervals.

4.1 Shadow Rate Extension

The shadow policy rate, following Wu and Zhang (2019), is originally available only for the Euro Area from 2004 to 2022. To extend the sample to cover the entire period of the analysis (2000–2024), a splicing procedure is applied, based on the theoretical principle that when the policy rate is positive, the shadow rate should closely track the official policy rate.

Despite this adjustment, the extended shadow rate does not significantly improve the resolution of the price puzzle in this dataset. In particular, the FAVAR specification incorporating the spliced shadow rate exhibits weaker and less persistent disinflationary responses compared to the main FAVAR with three explicit variables (GDP, HICP, policy rate). This outcome suggests that the shadow rate, while conceptually appealing, may not adequately capture the effective stance of monetary policy in the early and late parts of the sample, at least within the Euro Area monthly data employed.

4.2 Comparison Across Models and Lag Lengths

Main Specification: 7 Lags, 68% Confidence Bands Using a lag length of 7 months and 68% bootstrap confidence intervals, the price puzzle is resolved for all models after a few periods, with the main FAVAR remaining the most effective specification. Confidence bands are narrower, making some responses of other variables in the dataset, once mapped via factor loadings, more statistically significant. Figure 4a shows the comparison across models, while Figure 4b illustrates the effect of different numbers of latent factors in the main FAVAR. Figure 4c displays the impulse responses of the dataset variables with the factor loadings applied.

Lag Length 4 (AIC Suggestion) If the VAR lag length is set to 4, which is suggested by the AIC when the maximum lag is 12, the price puzzle is only resolved significantly by the main FAVAR when using 68% confidence bands Figure 5. With 90% bands Figure 6, none of the specifications produce statistically significant disinflationary responses. This emphasizes the importance of a sufficiently long lag length in monthly data to capture the delayed effects of monetary policy.

Lag Length 13 Using 13 lags results in jagged and noisy IRFs, with extremely wide confidence bands in both 68% (Figure 7) and 90% (Figure 8) settings. Consequently, the results are largely uninterpretable, highlighting the practical limitations of long-lag specifications in samples of moderate length (here, 311 monthly observations).

4.3 Summary of Robustness Results

Overall, while the magnitude and smoothness of the IRFs vary across lag lengths and confidence bands, the direction of the responses remains stable. The main FAVAR consistently provides the most significant and economically plausible resolution of the price puzzle.

5 Conclusion

This study investigates the transmission of monetary policy shocks in the Euro Area between 2000 and 2025, applying the Factor-Augmented Vector Autoregression (FAVAR) framework proposed by Bernanke et al. (2005). By leveraging a large dataset of 120 macroeconomic indicators, the analysis tests whether incorporating latent information can resolve standard empirical anomalies often found in small-scale models.

The primary finding indicates that a FAVAR specification including latent factors alongside real GDP, HICP, and the 3-month interbank rate successfully addresses the *price puzzle*. Following a contractionary monetary policy shock, inflation displays a statistically significant decline at medium horizons, a result that standard low-dimensional VARs fail to replicate. This evidence confirms that the informational deficiency of small models—rather than the identification strategy itself—is a primary driver of counter-intuitive empirical results in the Euro Area context. Furthermore, the results suggest that at least three latent factors are required to capture the relevant economic dynamics.

Robustness checks reveal that the findings are sensitive to model parsimony. While the baseline specification with 7 lags yields coherent results with 90% confidence bands, extending the lag length to 13 months leads to estimation instability due to the limited sample size relative to the number of parameters. Additionally, replacing the policy rate with a spliced shadow rate does not improve the identification of the shock, suggesting that in this monthly sample, the interbank rate combined with a rich information set remains a sufficient statistic for the monetary stance.

Overall, this analysis demonstrates that modeling the data-rich environment of the Euro Area is essential for a correct assessment of monetary policy transmission, providing a more reliable tool for analyzing the dynamic response of key macroeconomic aggregates.

References

Barigozzi, M. and Lissona, C. (2024). EA-MD-QD: Large Euro Area and Euro Member Countries datasets for macroeconomic research. Dataset.

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

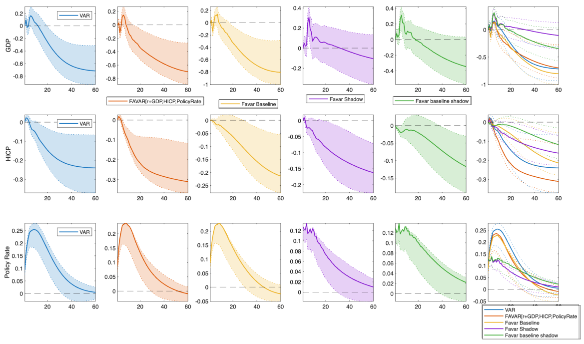
Christiano, L. J., Eichenbaum, M., and Evans, C. L. (1999). Monetary policy shocks: What have we learned and to what end? Elsevier.

Kilian, L. and Lütkepohl, H. (2017). *Structural Vector Autoregressive Analysis*. Cambridge University Press, Cambridge.

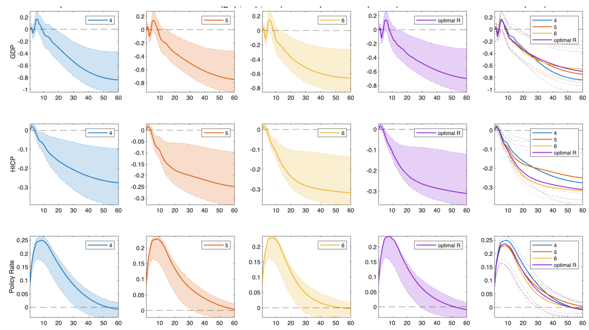
Sims, C. A. (1992). Interpreting the macroeconomic time series facts: The effects of monetary policy. *European Economic Review*, 36(5):975–1000.

Wu, J. C. and Zhang, J. (2019). A shadow rate new keynesian model. *Journal of Economic Dynamics & Control*, 107:103728.

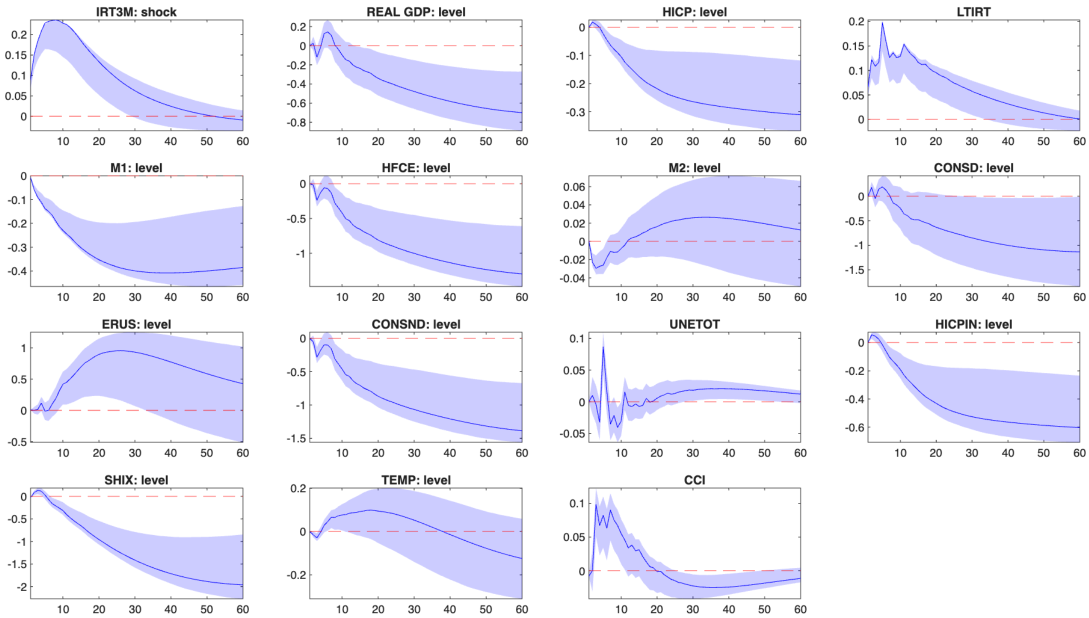
A Additional Figures



(a) Model Comparison

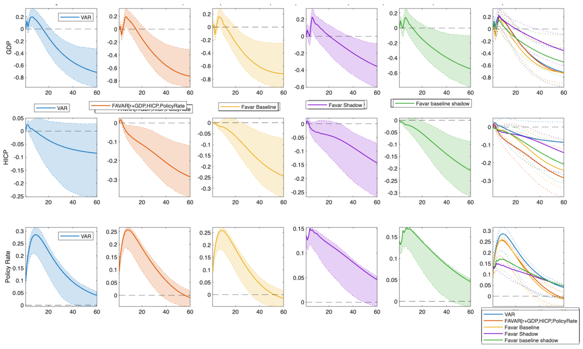


(b) Latent Factors Sensitivity



(c) Loaded impulse responses of macro variables

Figure 4: Robustness: 7 Lags Specification (68% Bands)



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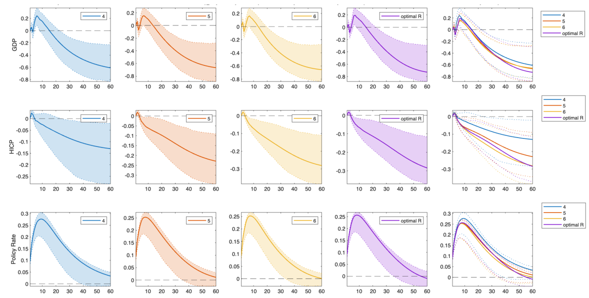
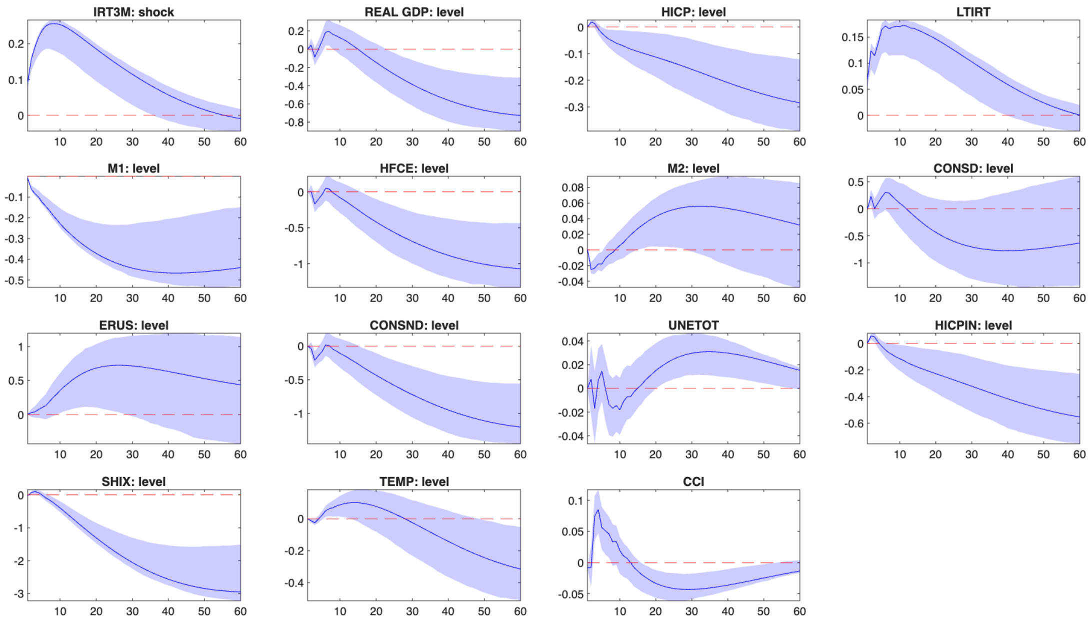
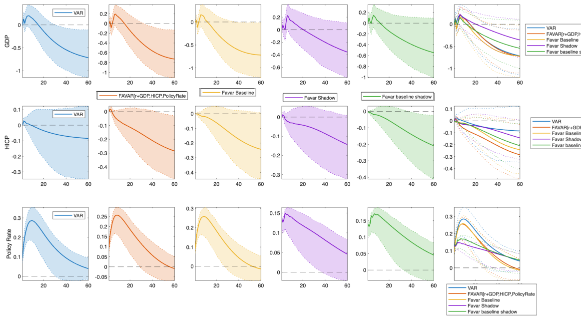


(b) Latent Factors Sensitivity

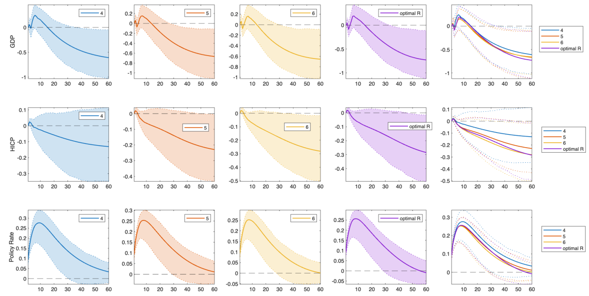


(c) Loaded impulse responses of macro variables

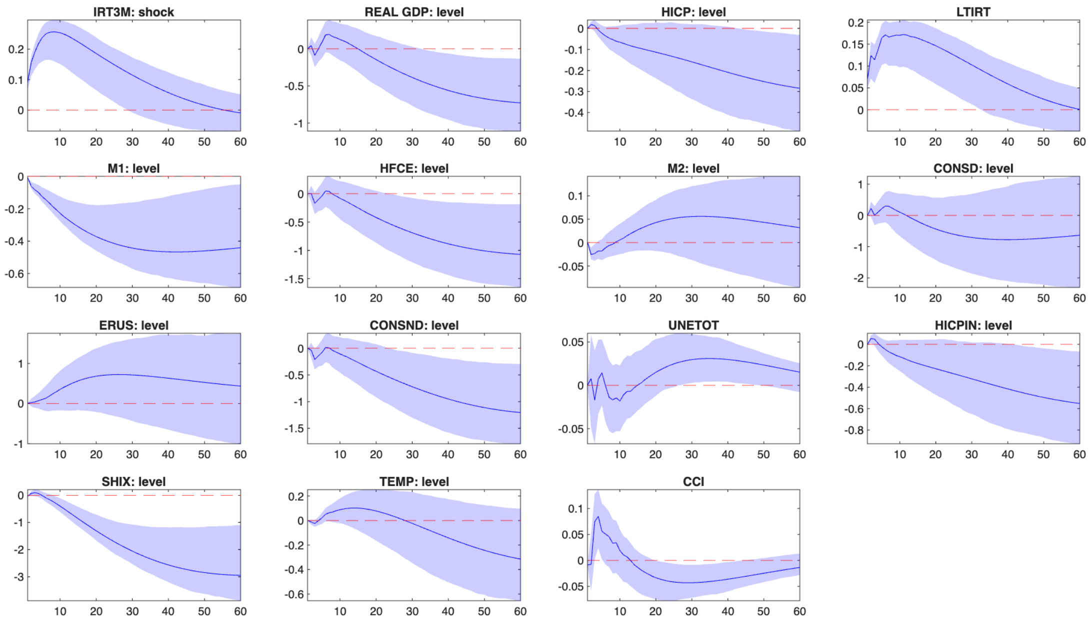
Figure 5: Robustness: 4 Lags Specification (68% Bands)



(a) Model Comparison

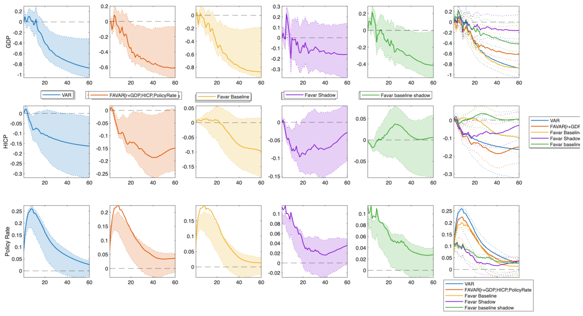


(b) Latent Factors Sensitivity

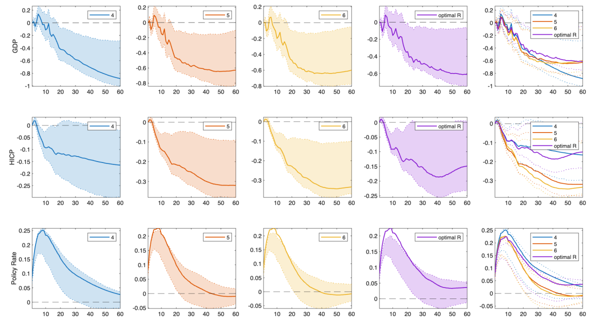


(c) Loaded impulse responses of macro variables

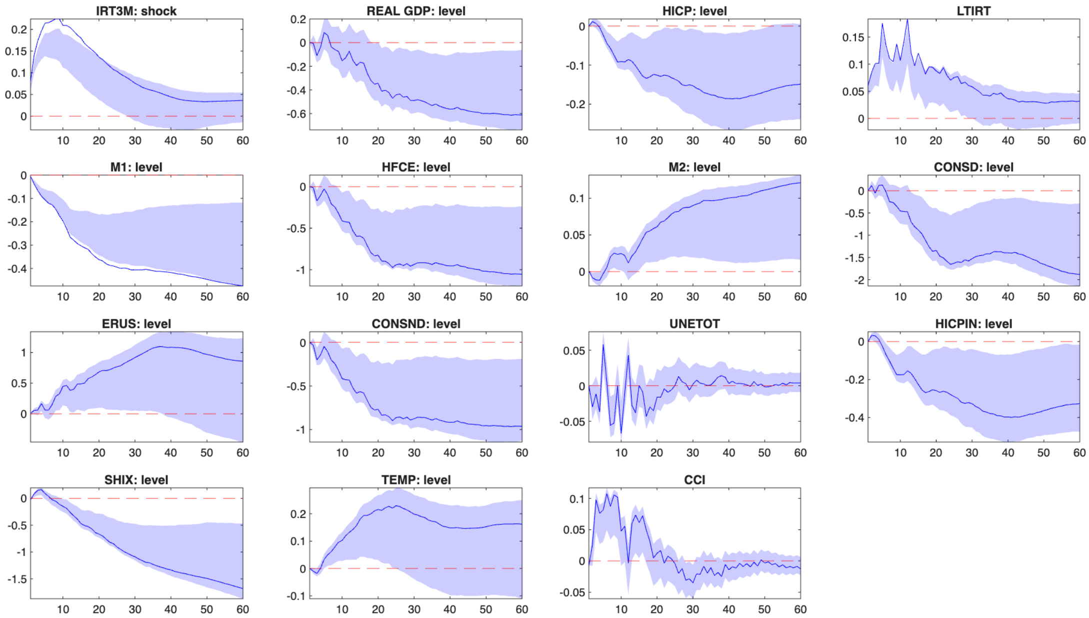
Figure 6: Robustness: 4 Lags Specification (90% Bands)



(a) Comparison across models

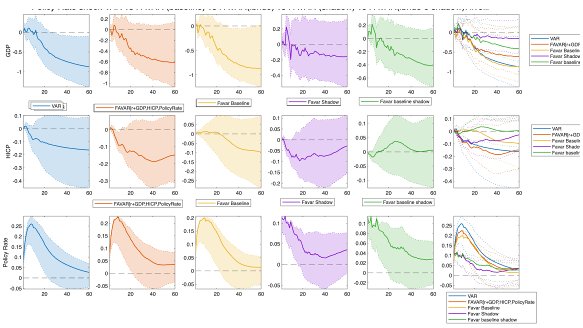


(b) Sensitivity to latent factors

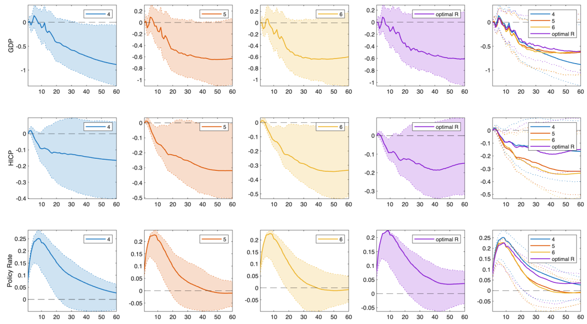


(c) Loaded impulse responses of macro variables

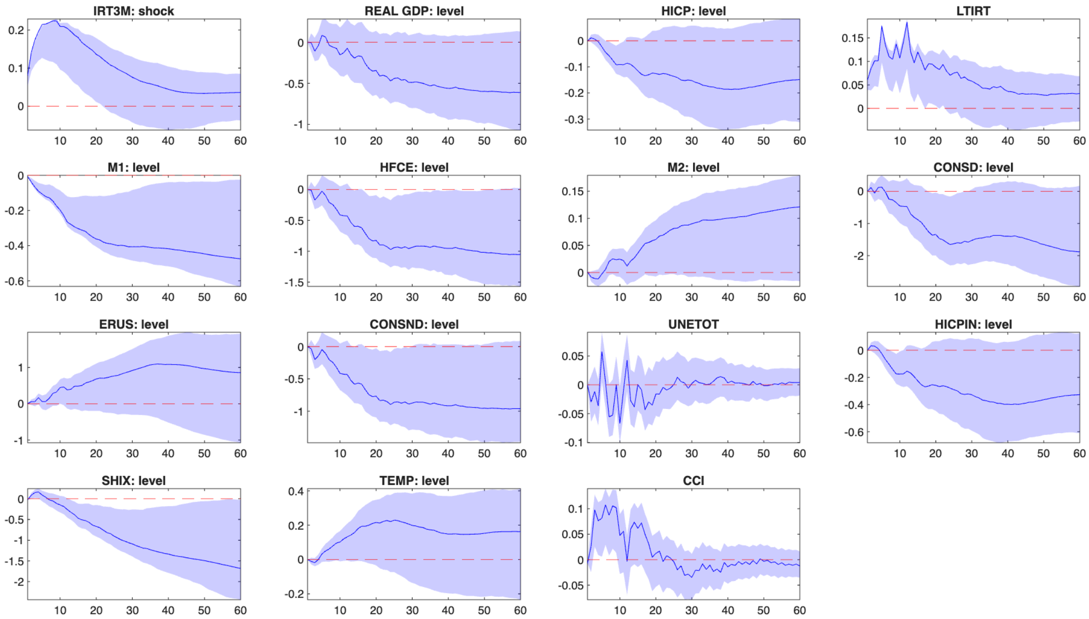
Figure 7: Robustness: 13 Lags Specification (68% Bands)



(a) Comparison across models



(b) Sensitivity to latent factors



(c) Loaded impulse responses of macro variables

Figure 8: Robustness: 13 Lags Specification (90% Bands)