unine
Université de Neuchâtel
Institut de recherches économiques

IRENE Working Paper 26-06

Multiple monetary policy shocks from daily data: A heteroskedasticity IV approach

Marc Burri and Daniel Kaufmann

Multiple monetary policy shocks from daily data: A heteroskedasticity IV approach*

Marc Burri† Daniel Kaufmann‡ §

2 April 2026

Abstract: We extend the heteroskedasticity IV estimator of Rigobon and Sack (2004) from one to multiple monetary policy shocks by imposing recursive zero restrictions on the impact matrix. Unlike high-frequency identification, the approach requires neither intraday tick data nor precise announcement timestamps, making it applicable to countries or historical periods where such data are unavailable. Applied to US FOMC announcements, we find causal effects similar to those of high-frequency identification. The heteroskedasticity-based instrument passes weak-instrument tests for the target shock, whereas high-frequency surprises fail. For the path shock, we also find strong heteroskedasticity-based instruments in key specifications, and we show that the underlying shocks are similar to those based on high-frequency identification.

JEL classification: C3, E3, E4, E5

Keywords: Monetary policy shocks, causal effects, forward guidance, heteroskedasticity, high-frequency, instrumental variables

*We thank Gianluca Benigno, Kenza Benhima, Aurélien Eyquem, Jean-Marie Grether, Kevin Kotzé, Leif Anders Thorsrud, Jean-Paul Renne, Eric Swanson, Mark Watson, Linyan Zhu, as well as participants at the SSES Annual Congress, the Workshop on Applied Macroeconomics and Monetary Policy in St. Gallen, the University of Fribourg Research Seminar, and the University of Lausanne research seminar for helpful discussions and comments. Daniel Kaufmann gratefully acknowledges financial support from the Swiss National Bank. A previous version of this paper circulated under the title "Causal effects of multiple monetary policy dimensions: A heteroskedasticity IV approach".

†University of Neuchâtel, Institute of Economic Research, Rue A.-L. Breguet 2, CH-2000 Neuchâtel, marc.burri91@gmail.com

‡University of Neuchâtel, Institute of Economic Research, Rue A.-L. Breguet 2, CH-2000 Neuchâtel, daniel.kaufmann@unine.ch

§KOF Swiss Economic Institute, ETH Zurich

1 Introduction

We propose a heteroskedasticity-based instrumental variables (HET-IV) approach to identify the causal effects of monetary policy target and path shocks from daily financial market data. The approach extends the IV estimator of Rigobon and Sack (2004) from one to multiple shocks by imposing recursive zero restrictions on the impact matrix along the term structure of interest rates, which mirror those used for constructing multi-dimensional high-frequency instruments (HF-IV) (see, e.g., Gürkaynak et al., 2005, Swanson, 2021). Unlike HF-IV, the approach does not require intraday tick data or knowledge of the exact timing of announcements, making it applicable to countries and historical periods where such information is unavailable. The recursive IV structure yields a closed-form estimator to which the weak-instrument tests of Lewis and Mertens (2025) apply directly, enabling straightforward instrument-strength evaluation for multi-dimensional shocks identified through HET-IV.

Related work identifies multiple monetary policy shocks using GMM estimators (Rigobon, 2003), non-Gaussianity (Jarociński, 2024), multi-dimensional HF-IVs (Swanson, 2021, Altavilla et al., 2019), or combining external instruments, heteroskedasticity, and parameter restrictions (Schlaak et al., 2023, Carriero et al., 2024, Jarocinski and Karadi, 2025).[1] We add to this literature by proposing a closed-form IV estimator, exploiting the change in the variance-covariance matrix of daily financial variables combined with recursive zero restrictions to disentangle multiple monetary policy shock dimensions. Although high-frequency data sets become increasingly available for various countries (Altavilla et al., 2019, Acosta et al., 2025, Braun et al., 2024, Emeksiz et al., 2026), data are often only available over relatively short sample periods. Because daily data are available over longer sample periods, our approach is especially useful when analyzing causal effects of monetary policy or other announcements through their financial market effects over longer historical episodes.

[1] Another strand of the literature uses heteroskedasticity to obtain overidentified models, such that the validity of traditional identifying assumptions can be tested (see, e.g., Lütkepohl and Schlaak, 2022, Schlaak et al., 2023).

Applying the approach to US FOMC announcements, we find causal effects similar to those based on HF-IVs by Swanson (2021). A key advantage of HET-IV is its strong instrument performance: for the target shock, the heteroskedasticity- and autocorrelation-robust (HAR) test statistic of Montiel Olea and Pflueger (2013) ranges from 31.8 to 141.4 in various specifications, well above the critical value of 23.1, whereas the HF-IV fails the same test (5.4 to 19.7). For the path shock, results are more mixed. The HET-IVs pass the weak instrument tests in some key specifications, and the results are close in others. Meanwhile, the HF-IVs pass all weak instrument tests for the path shock. This is reflected in slightly wider confidence intervals of the impulse responses for the path shock based on HET-IV. However, the point estimates are close, and we generally cannot reject the null hypothesis of equality of the responses based on HET-IV and HF-IV. While Lewis (2022) documents that HET-IVs based on high-frequency data yield stronger instruments compared to daily data, our results suggest that daily data can still yield strong multi-dimensional instruments on longer sample periods.

In what follows, Section 2 presents the model. Section 3 reports the application. Section 4 concludes.

2 Estimation and identification with HET-IV

2.1 Model

Suppose that we observe N financial market variables (y_t), for which the data-generating process reads:

$$\begin{aligned} y_t &= \alpha + \Psi\varepsilon_t + \Gamma v_t + \Phi(L)x_{t-1} \quad \text{for } t \in P \qquad (1) \\ y_t &= \alpha + \Gamma v_t + \Phi(L)x_{t-1} \quad \text{for } t \in C \ , \end{aligned}$$

where α is a vector of constants, ε_t is a vector of E structural shocks on policy event days (P), and v_t is a vector of R other shocks on policy event as well as control days (P and C). We assume that all shocks are serially and mutually uncorrelated. Furthermore, Γ and Ψ denote impact matrices of dimensions $N \times R$ and $N \times E$, respectively. Finally, x_{t-1} is a vector of pre-determined control variables, which may include lags of y_t, and $\Phi(L)$ is a conformable lag polynomial.

2.2 Estimation and identification

It is well known that, if the monetary policy shock is one-dimensional ($E = 1$), we can estimate Ψ up to a scale using the following instrumental variable (Rigobon and Sack, 2004, Lewis, 2022):[2]

$$Z_{1t} = \left[\mathbf{1}(t \in P)\frac{T}{T_P} - \mathbf{1}(t \in C)\frac{T}{T_C} \right] u_{1t} \ ,$$

where, without loss of generality, we treat variable y_{1t} as the endogenous variable, u_{1t} is the residual of y_{1t} with $u_t = y_t - \Phi(L)x_{t-1}$, $\mathbf{1}(t \in P)$ and $\mathbf{1}(t \in C)$ denote indicator functions that equal one on policy event and control days, respectively, and zero otherwise, and T, T_P, and T_C are the number of total, policy event and control days.[3]

However, for $E > 1$, the standard IV fails. Let Z_{et} be the heteroskedasticity-based instrument constructed using the residual for variable e in Model (1). In addition, let Ψ_{ie} denote the i^{th} row and e^{th} column of Ψ. Finally, let u_i and Z_e denote the column vectors of all observations of the residual i and instrument e, respectively.

Proposition 1. *For $E > 1$ and $e = 1 \ldots E$*

$$\Psi_{ie}^{IV} = [Z_e' u_e]^{-1} Z_e' u_i$$

[2] See also Online Appendix B.2.

[3] We follow Lewis (2022) and construct the HET-IV from consistently estimated residuals. Therefore, the standard errors of the IV estimator are subject to a generated-regressor problem. The magnitude of the problem decreases with sample size. In our application with daily data, due to the large sample size this problem is negligible.

is an inconsistent estimator of Ψ_{ie}.

Proof. See Online Appendix B.3. □

Intuitively, using only one IV, independent of which variable we use to construct it, is inconsistent because multiple shocks affect the endogenous variables on event days and the instrument is correlated with all of those shocks.

However, using additional identifying assumptions, a modified HET-IV consistently estimates each column of Ψ up to a scale.

Assumption 1. *The leading* $E \times E$ *principal submatrix of* Ψ *is lower-triangular.*

Proposition 2. *Under Assumption 1, the last element of*

$$\Psi_{ie}^{IV} = [(Z_1 \ \dots \ Z_e)'(u_1 \ \dots \ u_e)]^{-1}(Z_1 \ \dots \ Z_e)'u_i$$

is a consistent estimator of Ψ_{ie} *up to a scale.*

Proof. See Online Appendix B.4. □

This implies that we can recursively estimate each column of Ψ up to a scale. To estimate the column e, we use the first e instruments for the first e endogenous variables. Intuitively, the second instrument is correlated with both, the first and second structural shock. Therefore, only using the second instrument does not allow us to disentangle the two dimensions. By including the first instrument, which is by assumption only correlated with the first shock, we control for the variation in the second variable that is caused by the first shock.

3 Multi-dimensional monetary policy shocks in the US

We apply our approach to US data because we can compare the results to existing multi-dimensional high-frequency surprises.

3.1 Identifying assumptions

The order of the variables in y_t is key for identification. We impose recursive zero restrictions along the term structure of interest rates: a target shock affects all financial market variables on impact, whereas a path shock does not affect the short-term interest rate contemporaneously. These restrictions mirror the factor rotation approach used in standard HF-IV schemes (Gürkaynak et al., 2005, Swanson, 2021), giving the shocks a similar economic interpretation as their HF-IV counterparts.[4]

3.2 Data

In y_t we include a short- and medium-term interest rate, as well as a corporate bond spread, an effective exchange rate, stock prices, and the VIX.[5] As control variables (x_{t-1}) we include one lag of the same variables and the implied treasury yield skewness by Bauer and Chernov (2024).[6] All interest rates, spreads and the VIX are included in first-differences. All other variables are included in log-differences multiplied by 100. The exchange rate is defined as one unit of foreign currency measured in USD (a decline is an appreciation of the Dollar). As policy events, we use FOMC announcement dates by Bauer and Swanson (2022) starting in 1988 and extend them until the end of 2022. All other weekdays, excluding holidays, are used as control days.

[4] Altavilla et al. (2019) additionally differentiate between press releases, which may comprise a target shock, and press conferences, which may comprise a path shock.

[5] The data sources are given in Online Appendix A.

[6] We include this variable because Bauer and Swanson (2022) have shown it to predict high-frequency monetary policy surprises.

3.3 Dynamic causal effects

We estimate dynamic causal effects in a long-difference local projection framework (Jordà, 2005).[7] Specifically, for each horizon $h = 0, 1, \ldots, H$, outcome variable $i = 1, \ldots, N$, and shock dimension $e = 1, \ldots, E$ we estimate:

$$y_{i,t+h} - y_{i,t-1} = \alpha_{ieh} + \sum_{j=1}^{e} \psi_{ijh} \left(i_{j,t} - i_{j,t-1} \right) + \Phi_{ieh} x_{t-1} + u_{ie,t+h} \,, \tag{2}$$

where i_{et} is the interest rate corresponding to shock e, treated as endogenous and instrumented by Z_{et} from Proposition 2. That is, for $e = 1$ we include the short-term interest rate instrumented by Z_{1t} and for $e = 2$ we include the short-term and medium-term interest rate instrumented by Z_{1t} and Z_{2t}. The impulse response of variable i to shock e at horizon h is $\hat{\psi}_{ieh}$, where we normalize the estimate to a 25 basis point increase in the corresponding interest rate at $h = 0$. Inference is based on HC standard errors (Montiel Olea et al., 2025).

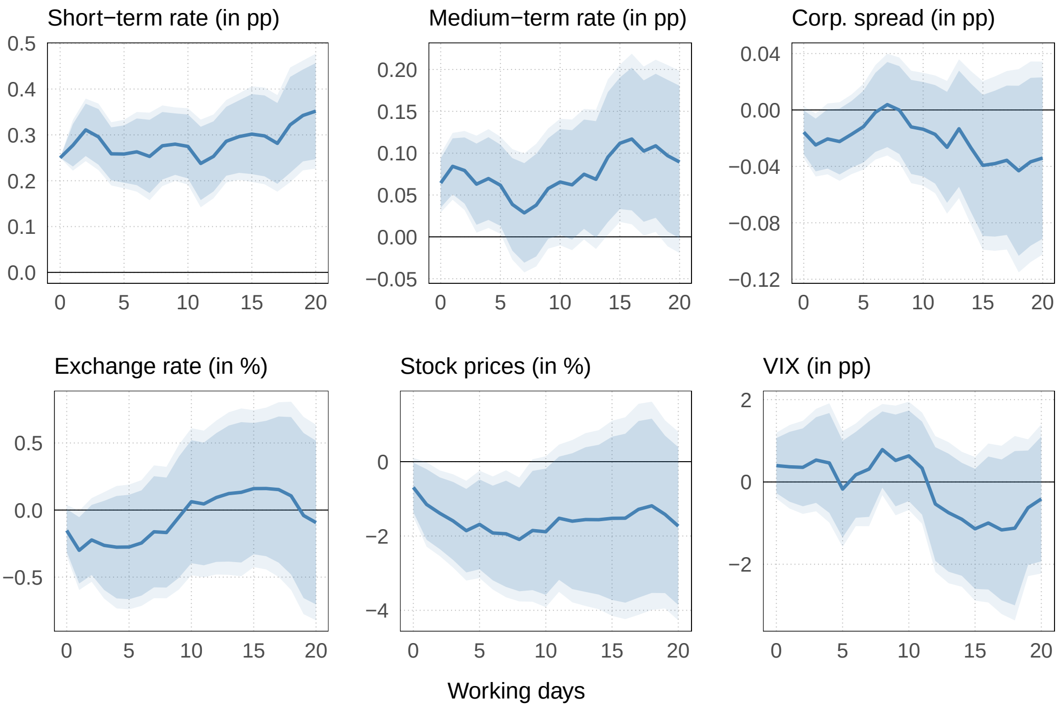
Figure 1 panel (a) shows the causal effect of a target shock, for which the instrument is constructed based on the short-term interest rate. A 25 bp increase in the short-term interest rate, caused by a target shock, leads to a smaller increase in medium-term interest rates, a decline in the corporate bond spread, an appreciation of the US Dollar, and a decline in stock prices. Meanwhile, the VIX does not show a statistically significant response.

The path shock shown in panel (b) has qualitatively similar effects on most variables. However, there are two important differences. First, the short-term interest rate does not change, as assumed, on impact. Meanwhile, the 25 bp increase in the medium-term interest rate leads to a stronger response of all other variables compared to the target shock. In particular, the US Dollar appreciates more and stock prices fall more. In addition, the VIX shows a statistically

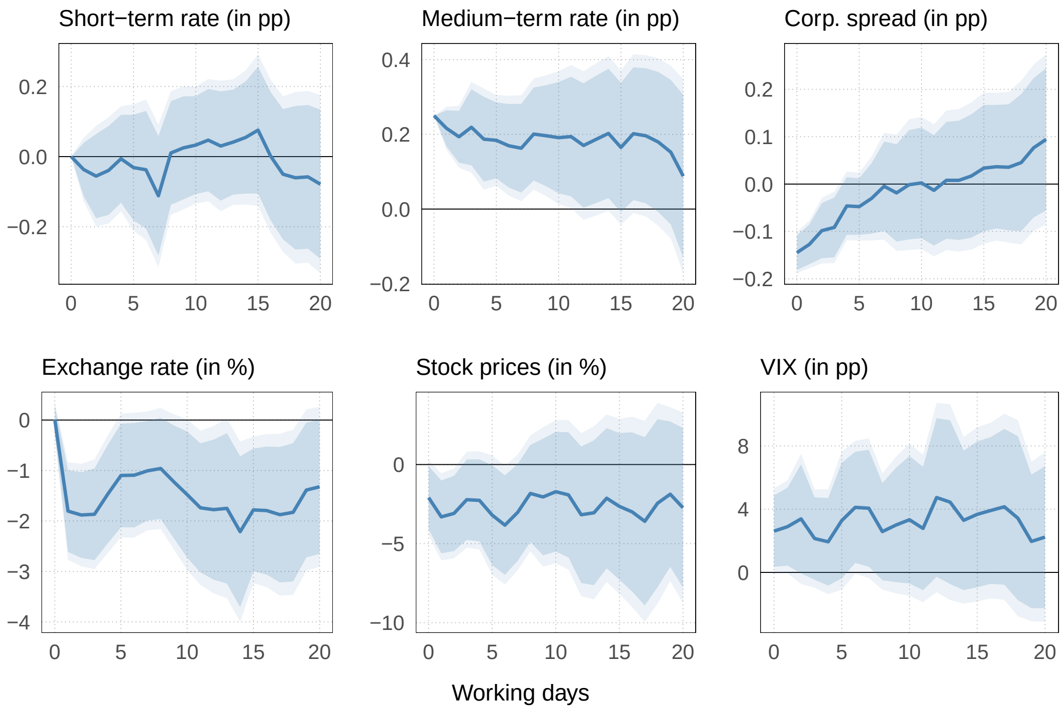
[7] Compared to a level specification, this framework is more robust when estimating persistent responses (see Piger and Stockwell, 2025). Compared to a VARs, local projections are more robust with respect to model-misspecification (see Montiel Olea et al., 2024). See Montiel Olea et al. (2025) for an overview of the advantages and disadvantages of local projections and VARs.

Fig. 1: Dynamic causal effects using HET-IVs

(a) Target shock



(b) Path shock



Notes: Impulse responses to a target (panel a) and path (panel b) monetary policy shock identified via HET-IV. The responses are normalized to a 25 bp increase in the short-term and medium-term interest rate, respectively. The horizontal axis measures working days (excluding weekends and holidays). The model is estimated in first (log-)differences, but the impulse responses are cumulated. Therefore, all interest rate responses are measured in percentage points and the exchange rate responses are measured in percent. The shaded areas show 90% and 95% confidence intervals, which are based on HC standard errors.

significant increase.

3.4 Comparison with high-frequency identification and weak-instrument tests

We estimate dynamic causal effects using FFR and forward guidance surprises by Swanson (2021) as instruments and compare them to heteroskedasticity-based responses (see Figure 2).[8]

For the path shock (panel b), we find very similar point estimates. We also bootstrapped p-values for a test of equality of the impulse responses identified via HF-IV and HET-IV.[9] In the vast majority of horizons, we do not reject the null hypothesis of equality of the responses. Interestingly, the impact effect of the HF-IV path shock on the short-term interest rate is not statistically significantly different from zero. This lends additional credibility to our recursive identifying assumption when using HET-IV.

Differences are more pronounced for the target shock, where responses using the HF-IV are larger in absolute value. Again, we formally test equality of the impulse responses. Even though the HF-IV confidence intervals are wider, we reject the null of equality somewhat more often than for the path shock. We therefore next turn to the question, why the differences are more pronounced for the target shock.

We present weak-instrument tests, which additionally explain the difference in confidence interval width across approaches. The tests follow Montiel Olea and Pflueger (2013), Lewis (2022) and Lewis and Mertens (2025) and account for heteroskedasticity and autocorrelation.[10]

Table 1 reports HAR weak-instrument tests for the target shock. Because results may differ depending on the choice of the endogenous variable, we present various specifications. Panel (a) shows that the heteroskedasticity-based instrument passes the test comfortably for all

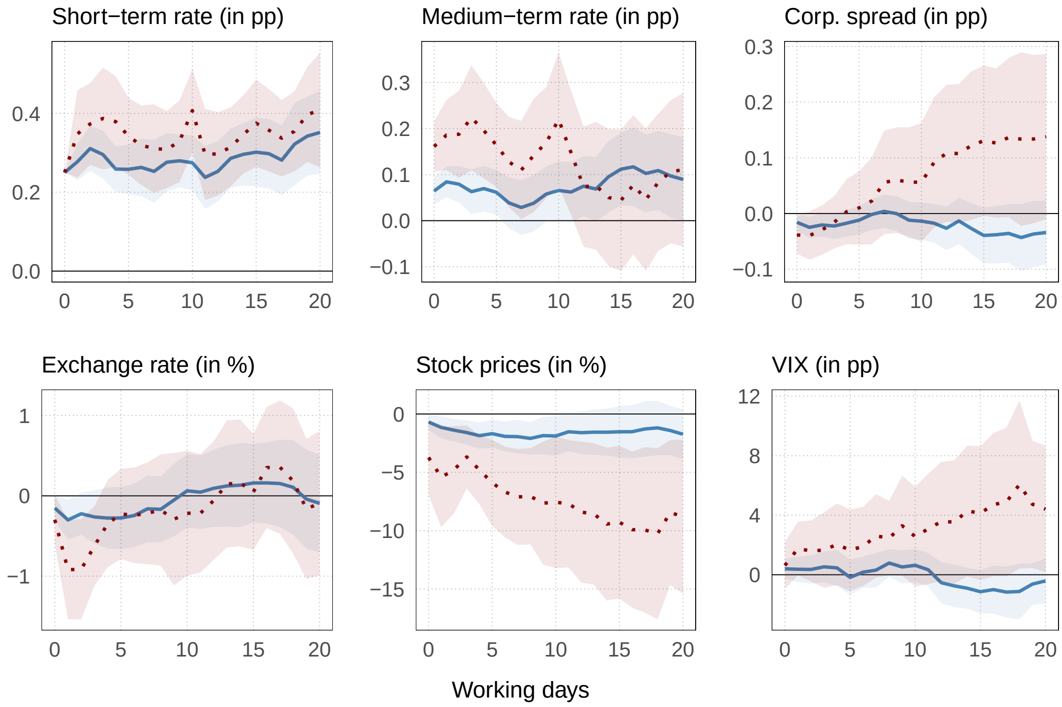
[8] We do so by estimating an equation similar to Equation (2). There are two differences. First, we use the HF-IVs. Second, we do not impose the recursive zero restriction. Online Appendix C shows that the results remain virtually identical when imposing the zero restriction.

[9] See Online Appendix C.

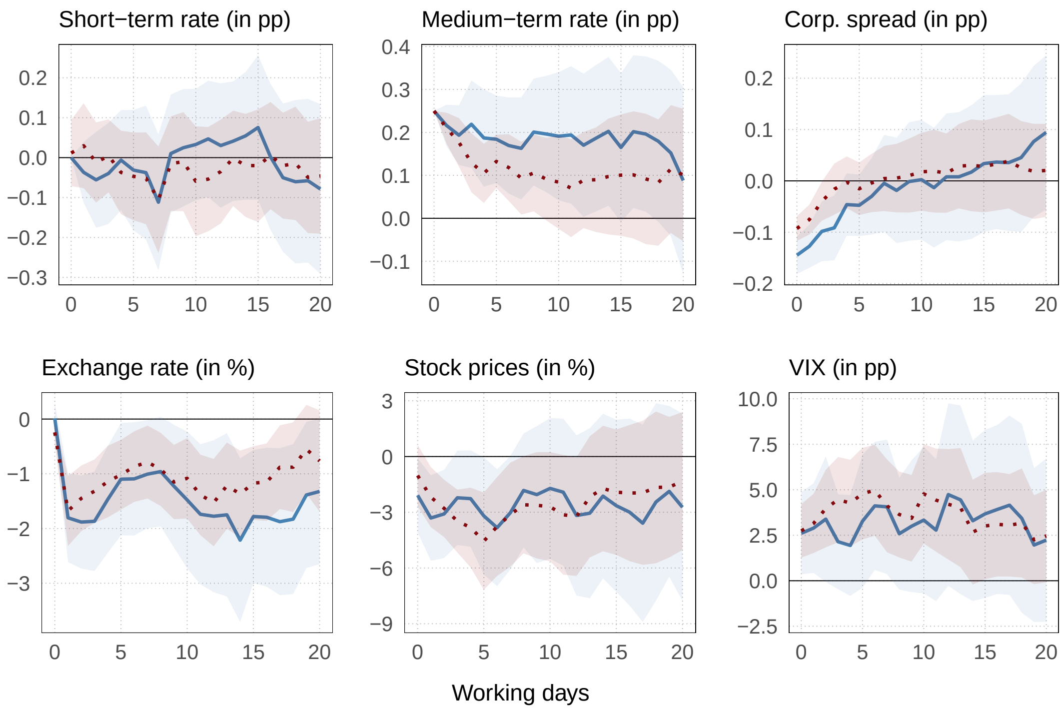
[10] For the path shock, they also give indirect evidence of whether two dimensions exist. If no path shock exists in addition to a target shock, the first instrument already captures the relevant variation, and adding a second instrument contains no additional information.

Fig. 2: Comparison of HET-IVs with HF-IVs

(a) Target shock



(b) Path shock



Notes: Impulse responses to a target (panel a) and path (panel b) monetary policy shock identified via HF-IV (red dotted line) and HET-IV (blue solid line). Shaded areas show 90% confidence intervals (blue shading for HET-IV, red for HF-IV), based on HC standard errors. See also notes to Figure 1.

Tab. 1: Weak-instrument tests for target shocks

(a) HET-IV

	FFR	3M	6M	Average
Test statistic	54.0	31.8	78.5	141.4
Critical value	23.1	23.1	23.1	23.1

(b) HF-IV

	FFR	3M	6M	Average
Test statistic	5.4	16.3	19.7	12.0
Critical value	23.1	23.1	23.1	23.1

Notes: Weak-instrument tests based on the HAR test statistic by Montiel Olea and Pflueger (2013) and Lewis (2022). Each column varies the endogenous variable. For heteroskedasticity-based identification, we also vary the variable to construct the instrument. For high-frequency identification, we always use the FFR surprises by Swanson (2021). The significance level is set to 5% and the tolerance level to 10%.

Tab. 2: Weak-instrument tests for path shocks

(a) HET-IV

	Path shock			
Target shock	2Y	3Y	5Y	Average
FFR	27.0	26.2	27.9	27.5
Critical value	28.4	27.5	26.9	27.6
3M	17.6	18.3	21.3	19.8
Critical value	28.5	28.2	27.6	28.0
6M	22.1	22.0	19.9	22.6
Critical value	28.7	28.7	27.6	28.2
Average	29.5	26.6	26.4	28.1
Critical value	28.9	28.5	27.3	28.3

(b) HF-IV

	2Y	3Y	5Y	Average
Test statistic	127.8	125.4	77.4	120.4
Critical value	23.1	23.1	23.1	23.1

Notes: Weak instrument tests allowing for heteroskedasticity and autocorrelation. Panel (a) uses the test for multiple instruments and multiple endogenous regressors by Lewis and Mertens (2025). Each row varies the endogenous variable and instrument for the first dimension (target shock). Each column varies the endogenous variable and instrument for the second dimension (path shock). Panel (b) uses the test for one instrument and one endogenous regressor by Montiel Olea and Pflueger (2013). For high-frequency identification, we always use the forward guidance surprises by Swanson (2021). The significance level is set to 5% and the tolerance level to 10%.

short-term interest rate specifications, with test statistics of 31.8–141.4 against a critical value of 23.1. Panel (b) reveals a stark contrast: high-frequency FFR surprises fail the same test across all specifications (test statistics 5.4–19.7). This weak-instrument problem under high-frequency identification directly explains the wider confidence intervals seen in Figure 2 and differences of the point estimates.[11]

Table 2 reports tests for the joint two-dimensional case using the Lewis and Mertens (2025) test. The strength of the HET-IV for the second dimension depends on the choice of the HET-IV for the first dimension. We therefore report multiple combinations. Panel (a) shows that the instruments jointly pass in two specifications (FFR–5Y and Average–2Y), with near-critical values in several others (FFR–2Y, FFR–Average, Average–Average). These mixed results are relevant for applied researchers, who aim to obtain strong instruments for multiple monetary policy shocks: the target shock is robustly identified, while path-shock inference is more sensitive to the choice of the endogenous variable. For completeness, Panel (b) reports that the high-frequency forward guidance surprises easily pass the one-dimensional Montiel Olea and Pflueger (2013) test.

To further examine whether the two approaches identify similar underlying shocks, we predict the shocks using the Kalman-filter approach by Burri and Kaufmann (2025).[12] For HET-IV, the target and path shocks are virtually uncorrelated (0.05) as we would expect. In addition, the HET-IV path shock is highly correlated with the HF-IV path shock (0.84), confirming that both approaches identify similar underlying shocks. The HET-IV and HF-IV target shocks exhibit a lower correlation (0.71), reflecting the weak instrument problem for the HF-IV.

[11] Lewis (2022) shows that in an application using data from Nakamura and Steinsson (2018) daily data yield weaker heteroskedasticity-based instruments than intraday data. While we do not dispute this result, which is intuitive and convincing, panel (a) of Table 1 demonstrates that heteroskedasticity-based instruments can be strong even at daily frequency. However, the results are not directly comparable with Lewis (2022) or Nakamura and Steinsson (2018) because we use a longer sample, examine multiple monetary policy shock dimensions, and control for lags of dependent variables. The latter may be especially important as daily financial market data and high-frequency surprises may be correlated with information available on FOMC announcement days (Bauer and Swanson, 2023, 2022).

[12] The results are shown in Online Appendix C

4 Conclusions

We propose a heteroskedasticity IV approach to identify the causal effects of multiple monetary policy shocks from daily financial market data. The closed-form recursive estimator extends Rigobon and Sack (2004) to multiple dimensions and enables direct weak-instrument testing via Lewis and Mertens (2025). Applied to US FOMC announcements, the approach yields causal effects similar to high-frequency identification while outperforming it on instrument-strength tests for the target shock. Although the identification of the path shock is weaker for HET-IV compared to HF-IV, we still obtain similar point estimates for the impulse responses, and similar shock predictions, suggesting the resulting bias is relatively small. Key extensions—separately identifying information effects (Nakamura and Steinsson, 2018) and measuring impacts on low-frequency macroeconomic variables via the predicted shock series of Burri and Kaufmann (2025)—are left for future research.

References

Acosta, M., Ajello, A., Bauer, M., Loria, F., and Miranda-Agrippino, S. (2025). Financial market effects of FOMC communication: Evidence from a new event-study database. Working Paper 2025-30, Federal Reserve Bank of San Francisco.

Altavilla, C., Brugnolini, L., Gürkaynak, R. S., Motto, R., and Ragusa, G. (2019). Measuring euro area monetary policy. *Journal of Monetary Economics*, 108:162–179, DOI: 10.1016/j.jmoneco.2019.08.016.

Bauer, M. and Chernov, M. (2024). Interest rate skewness and biased beliefs. *The Journal of Finance*, 79(1):173–217, DOI: 10.1111/jofi.13276.

Bauer, M. D. and Swanson, E. T. (2022). A reassessment of monetary policy surprises and high-frequency identification. In Eichenbaum, M., Hurst, E., and Ramey, V. A., editors, *NBER Macroeconomics Annual 2022, volume 37*. University of Chicago Press.

Bauer, M. D. and Swanson, E. T. (2023). An alternative explanation for the "Fed information effect". *American Economic Review*, 113(3):664–700, DOI: 10.1257/aer.20201220.

Braun, R., Miranda-Agrippino, S., and Saha, T. (2024). Measuring monetary policy in the UK: The UK monetary policy event-study database. *Journal of Monetary Economics*, DOI: 10.1016/j.jmoneco.2024.103645.

Burri, M. and Kaufmann, D. (2025). Measuring monetary policy shocks. Working Paper 24-03, IRENE Institute of Economic Research, University of Neuchâtel.

Carriero, A., Marcellino, M., and Tornese, T. (2024). Blended identification in structural VARs. *Journal of Monetary Economics*, 146:103610, DOI: 10.1016/j.jmoneco.2024.103610.

Emeksiz, Ece Ozge Kamber, G., Otten, J., and Pasricha, G. K. (2026). Still packing a punch: Monetary policy transmission in a new cross-country high-frequency dataset. IMF Working Paper 2026/018, International Monetary Fund.

Gürkaynak, R. S., Sack, B., and Swanson, E. (2005). Do actions speak louder than words? The response of asset prices to monetary policy actions and statements. *International Journal of Central Banking*, 1(1).

Jarocinski, M. and Karadi, P. (2025). Disentangling monetary policy, central bank information, and fed response to news shocks. Discussion Paper DP19923, CEPR.

Jarociński, M. (2024). Estimating the Fed's unconventional policy shocks. *Journal of Monetary Economics*, 144:103548, DOI: 10.1016/j.jmoneco.2024.01.001.

Jordà, O. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, 95(1):161–182, DOI: 10.1257/0002828053828518.

Lewis, D. J. (2022). Robust inference in models identified via heteroskedasticity. *The Review of Economics and Statistics*, 104(3):510–524, DOI: 10.1162/rest_a_00963.

Lewis, D. J. and Mertens, K. (2025). A robust test for weak instruments for 2SLS with multiple endogenous regressors. *The Review of Economic Studies*, DOI: 10.1093/restud/rdaf103.

Lütkepohl, H. and Schlaak, T. (2022). Heteroscedastic proxy vector autoregressions. *Journal of Business & Economic Statistics*, 40(3):1268–1281, DOI: 10.1080/07350015.2021.1920962.

Montiel Olea, J. L. and Pflueger, C. (2013). A robust test for weak instruments. *Journal of Business & Economic Statistics*, 31(3):358–369, DOI: 10.1080/00401706.2013.806694.

Montiel Olea, J. L., Plagborg-Møller, M., Qian, E., and Wolf, C. K. (2024). Double robustness of local projections and some unpleasant varithmetic. Working Paper 32495, National Bureau of Economic Research, DOI: 10.3386/w32495.

Montiel Olea, J. L., Plagborg-Møller, M., Qian, E., and Wolf, C. K. (2025). Local projections or VARs? A primer for macroeconomists. In *NBER Macroeconomics Annual 2025*, volume 40. University of Chicago Press.

Nakamura, E. and Steinsson, J. (2018). High-frequency identification of monetary non-neutrality: The information effect. *The Quarterly Journal of Economics*, 133(3):1283–1330, DOI: 10.1093/qje/qjy004.

Piger, J. and Stockwell, T. (2025). Differences from differencing: Should local projections with observed shocks be estimated in levels or differences? *Journal of Applied Econometrics*, DOI: 10.1002/jae.70003.

Rigobon, R. (2003). Identification through heteroskedasticity. *The Review of Economics and Statistics*, 85(4):777–792.

Rigobon, R. and Sack, B. (2004). The impact of monetary policy on asset prices. *Journal of Monetary Economics*, 51(8):1553–1575, DOI: 10.1016/j.jmoneco.2004.02.004.

Schlaak, T., Rieth, M., and Podstawski, M. (2023). Monetary policy, external instruments, and heteroskedasticity. *Quantitative Economics*, 14(1):161–200, DOI: doi.org/10.3982/QE1511.

Swanson, E. T. (2021). Measuring the effects of Federal Reserve forward guidance and asset purchases on financial markets. *Journal of Monetary Economics*, 118:32–53, DOI: 10.1016/j.jmoneco.2020.09.003.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used Claude, Writefull, and Copilot in order to obtain feedback on structure and grammar, and support with coding in R. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Online Appendix

A Data

The data stem from Burri and Kaufmann (2025). To make the paper self-contained, the sources are reported in Table 3. To capture the information across a wider variety of financial market variables, and potentially reduce some noise in the individual series, we compute averages over multiple series. The short-term rate averages the FFR, and the 3M and 6M treasury bill rates. The medium-term interest rate averages the 2Y, 3Y and 5Y treasury bond yields. The stock price index averages the S&P 500, as well as the NASDAQ Composite Index and the NASDAQ 100 Index. The former receives a weight of 0.5, and the other two each receive a weight of 0.25. The corporate bond spread averages the series for AAA and BAA rated bonds. All results remain robust using various versions of the individual series.

B Technical appendix

In what follows, we discuss the identification and estimation of the impact matrix Ψ in Model (1) using heteroskedasticity-based IVs.

B.1 Preliminaries

We use the following notation. We denote the variances of the structural shocks as $\sigma^2_{e\varepsilon}$, $e = 1 \dots E$, and σ^2_{rv}, $r = 1 \dots R$. Ψ_i and Γ_i are the corresponding impact vectors on variable $i = 1 \dots N$. Furthermore, u_i denotes a column vector of residuals of a regression of variable y_i on the control variables. Also, we use $u_{it\in P}$, $u_{it\in C}$ to denote column vectors containing only observations on policy event days, and other days, respectively. $\mathbb{COV}[u_i, u_j]_{t\in P}$, $\mathbb{COV}[u_i, u_j]_{t\in C}$ are the corresponding covariances. Finally, we use $\tilde{\mathbb{V}}[u_i] = \mathbb{V}[u_i]_{t\in P} - \mathbb{V}[u_i]_{t\in C}$ and $\tilde{\mathbb{COV}}[u_i, u_j] = \mathbb{COV}[u_i, u_j]_{t\in P} - \mathbb{COV}[u_i, u_j]_{t\in C}$ to denote the difference in the variance and

Tab. 3: Data

Category	**Source**	**Variants**	**Time stamp**	**Comments**
Treasury bill yields	Board of Governors	3M, 6M, 1Y, 2Y, 3Y, 5Y, 7Y, 10Y, 30Y	4pm EST	www.federalreserve.gov/releases/h15/. We do not use the 1M and 20Y yields as they comprise missing data
Federal Funds Rate	Board of Governors		4pm EST	www.federalreserve.gov/releases/h15/
Nominal effective exchange rate	Board of Governors		Noon EST	www.federalreserve.gov/releases/h10/. We linked the discontinued series with FRED identifier DTWEXM with DTWEXAFEGS. Also, we define the NEER as one unit of foreign currency in terms of USD. Therefore, a decline in the exchange rate is an appreciation of the USD.
Stock prices	S&P Dow Jones, NASDAQ OMX	S&P 500, NASDAQ	4pm EST	tradingview.com/symbols/SPX/. FRED variable keys: NASDAQCOM, NASDAQ100
VIX	CBOE		Close	FRED variable keys: VIXCLS, VXOCLS
Corporate bond spreads	Moody's	AAA, BAA	Unclear	FRED variable keys: DAAA, DBAAA. We computed the spreads as the difference to the 10Y government bond yield
Treasury yield skewness	Bauer and Chernov (2024)		End-of-day	The underlying data are treasury futures and options from CME group. Starts in 1988
Monetary policy surprises	Swanson (2021)	FFR, forward guidance	Event window	The surprises do not cover the entire sample of FOMC announcements by Bauer and Swanson (2022)
FOMC announcements	Bauer and Swanson (2022)			From 1988-2019. We use the days on which there is a monetary policy surprise
FOMC announcements	Board of Governors			From 2020-2022, own data collection from www.federalreserve.gov/monetarypolicy/fomccalendars.htm

covariance, respectively, on policy event and other days.

We will repeatedly use the standard heteroskedasticity-based IV by Rigobon and Sack (2004):

$$Z_{it} = \left[\mathbf{1}(t \in P)\frac{T}{T_P} - \mathbf{1}(t \in C)\frac{T}{T_C} \right] u_{it} \ , \tag{3}$$

where $\mathbf{1}(t \in P)$, $\mathbf{1}(t \in C)$ denote indicator function that equal one one policy event and control days, respectively, and T, T_P, and T_C are the number of total, policy event and control days.

In addition, we will use the fact that the following term converges in probability to the difference in the covariance between residual for variable i and j, on policy event and other days (see Rigobon and Sack, 2004):

$$\begin{aligned} \frac{1}{T}Z_i' u_j &= \frac{1}{T_P}u_{it\in P}' u_{jt\in P} - \frac{1}{T_C}u_{it\in C}' u_{jt\in C} \\ &\xrightarrow{p} \mathbb{COV}[u_i, u_j]_{t\in P} - \mathbb{COV}[u_i, u_j]_{t\in C} \\ &= \tilde{\mathbb{COV}}[u_i, u_j] \ , \end{aligned} \tag{4}$$

and, therefore:

$$\frac{1}{T}Z_i' u_i \xrightarrow{p} \tilde{\mathbb{V}}[u_i] \ .$$

B.2 Standard HET-IV if $E = 1$

To make the paper self-contained, we show consistency of the standard heteroskedasticity-based IV for $E = 1$, a well-known result from Rigobon and Sack (2004).

Proof. Assume that we use u_1 to construct Z_1 based on Equation (3). The standard heteroskedasticity-IV estimator of the impact effect on the variable i reads:

$$\begin{aligned}\Psi_{i1}^{IV} &= \frac{\frac{1}{T}Z_1'u_i}{\frac{1}{T}Z_1'u_1} \\ &\xrightarrow{p} \frac{\tilde{\mathbb{COV}}[u_1,u_i]}{\tilde{\mathbb{V}}[u_1]} \quad ,\end{aligned}$$

where we used Equation (4) for convergence in probability. Using Model (1) and $E = 1$ we obtain:

$$\begin{aligned}\tilde{\mathbb{COV}}[u_1,u_i] &= \Psi_{11}\Psi_{i1}\sigma_{1\varepsilon}^2 + \Gamma_1\Sigma_v\Gamma_i' - \Gamma_1\Sigma_v\Gamma_i' = \Psi_{11}\Psi_{i1}\sigma_{1\varepsilon}^2 \\ \tilde{\mathbb{V}}[u_1] &= \Psi_{11}^2\sigma_{1\varepsilon}^2 + \Gamma_1\Sigma_v\Gamma_1' - \Gamma_1\Sigma_v\Gamma_1' = \Psi_{11}^2\sigma_{1\varepsilon}^2\end{aligned}$$

It follows that:

$$\Psi_{i1}^{IV} \xrightarrow{p} \frac{\Psi_{11}\Psi_{i1}\sigma_{1\varepsilon}^2}{\Psi_{11}^2\sigma_{1\varepsilon}^2} = \frac{\Psi_{i1}}{\Psi_{11}} \propto \Psi_{i1}$$

□

Therefore, IV consistently estimates Ψ up to a scale, assuming that $\Psi_{11} \neq 0$. The latter corresponds to the identifying assumption that the variance of u_1 increases on days with policy event days compared to control days.

B.3 Standard HET-IV if $E > 1$

Proposition 1 states that if $E > 1$ the standard heteroskedasticity-IV does not consistently estimate any column of Ψ up to a scale.

Proof. Without loss of generality, assume that we use u_1 to construct Z_1 based on Equation (3).

The standard heteroskedasticity-IV estimator of the impact effect on the variable i reads:

$$\begin{aligned}\Psi_{i1}^{IV} &= \frac{\frac{1}{T}Z_1'u_i}{\frac{1}{T}Z_1'u_1} \\ &\xrightarrow{p} \frac{\tilde{\mathbb{COV}}[u_1, u_i]}{\tilde{\mathbb{V}}[u_1]} \ ,\end{aligned}$$

where we used Equation (4) for convergence in probability. Using Model (1) we obtain:

$$\begin{aligned}\tilde{\mathbb{COV}}[u_1, u_i] &= \sum_{e=1}^{E} \Psi_{1e}\Psi_{ie}\sigma_{e\varepsilon}^2 + \Gamma_1\Sigma_v\Gamma_i' - \Gamma_1\Sigma_v\Gamma_i' = \sum_{e=1}^{E} \Psi_{1e}\Psi_{ie}\sigma_{e\varepsilon}^2 \\ \tilde{\mathbb{V}}[u_1] &= \sum_{e=1}^{E} \Psi_{1e}^2\sigma_{e\varepsilon}^2 + \Gamma_1\Sigma_v\Gamma_1' - \Gamma_1\Sigma_v\Gamma_1' = \sum_{e=1}^{E} \Psi_{1e}^2\sigma_{e\varepsilon}^2\end{aligned}$$

Therefore,

$$\Psi_{i1}^{IV} \xrightarrow{p} \frac{\sum_{e=1}^{E} \Psi_{1e}\Psi_{ie}\sigma_{e\varepsilon}^2}{\sum_{e=1}^{E} \Psi_{1e}^2\sigma_{e\varepsilon}^2} \not\propto \Psi_{i1} \ ,$$

which shows that IV does not consistently estimate the causal effect of shock ε_{1t} on variable i up to a scale. □

Remark 1. *Although IV is inconsistent, there exists a GMM estimator exploiting multiple equations of the system to consistently estimate the columns of the impact matrix (see Rigobon, 2003, Rigobon and Sack, 2004, Lewis, 2022).*

B.4 Modified HET-IV if $E > 1$

Proposition 2 states that, if we are willing to impose additional restrictions, our modified heteroskedasticity-based IV-approach consistently estimates each column of Ψ up to a scale.

Let $\Psi_{1:e,1:e}$ denote the leading principal submatrix of Ψ. In addition, Σ_ε denotes the diagonal variance-covariance matrix of the structural shocks ε_t.

Proof. Suppose we use $u_1, \ldots u_e$ to construct instruments $Z_1, \ldots Z_e$ based on Equation (3). The modified heteroskedasticity-based IV estimator of the impact of shock e on variable i reads:

$$
\begin{aligned}
\Psi_{ie}^{IV} &= [(Z_1 \;\ldots\; Z_e)'(u_1 \;\ldots\; u_e)]^{-1}(Z_1 \;\ldots\; Z_e)'u_i \\
&\xrightarrow{p} \begin{bmatrix} \tilde{\mathbb{V}}[u_1] & \tilde{\mathbb{COV}}[u_1,u_2] & \cdots & \tilde{\mathbb{COV}}[u_1,u_e] \\ \tilde{\mathbb{COV}}[u_1,u_2] & \tilde{\mathbb{V}}[u_2] & & \\ \vdots & & \ddots & \\ \tilde{\mathbb{COV}}[u_1,u_e] & \cdots & & \tilde{\mathbb{V}}[u_e] \end{bmatrix}^{-1} \begin{bmatrix} \tilde{\mathbb{COV}}[u_1,u_i] \\ \tilde{\mathbb{COV}}[u_2,u_i] \\ \vdots \\ \tilde{\mathbb{COV}}[u_e,u_i] \end{bmatrix} ,
\end{aligned}
$$

where we used Equation (4) for convergence in probability. Using Model (1) we obtain:

$$
\begin{aligned}
\Psi_{ie}^{IV} &\xrightarrow{p} [\Psi_{1:e,1:e}\Sigma_\varepsilon\Psi'_{1:e,1:e}]^{-1}\Psi_{1:e,1:e}\Sigma_\varepsilon\Psi'_i \\
&= \Psi'^{-1}_{1:e,1:e}\Sigma_\varepsilon^{-1}\Psi^{-1}_{1:e,1:e}\Psi_{1:e,1:e}\Sigma_\varepsilon\Psi'_i \\
&= \Psi'^{-1}_{1:e,1:e}\Psi'_i \;.
\end{aligned}
$$

Under Assumption 1, $\Psi_{1:e,1:e}$ is lower-triangular, such that $\Psi'^{-1}_{1:e,1:e}$ is upper-triangular with lower right element equal to $1/\Psi_{ee}$. Therefore, the e^{th} row of $\Psi'^{-1}_{1:e,1:e}\Psi_i$ is $\Psi_{ie}/\Psi_{ee} \propto \Psi_{ie}$. □

For illustration, consider estimating the response to the first structural shock ($e = 1$) on variable i:

$$
\begin{aligned}
\Psi_{i1}^{IV} &= [Z_1'u_1]^{-1}Z_1'u_i \\
&\xrightarrow{p} \frac{\tilde{\mathbb{COV}}[u_1,u_i]}{\tilde{\mathbb{V}}[u_1]} \;.
\end{aligned}
$$

Using Model (1) and Assumption 1 we obtain:

$$\begin{aligned}\tilde{\mathbb{V}}[u_1] &= \Psi_{11}^2\sigma_{1\varepsilon}^2 \\ \tilde{\mathbb{COV}}[u_1,u_i] &= \Psi_{11}\Psi_{i1}\sigma_{1\varepsilon}^2 \ .\end{aligned}$$

Therefore,

$$\frac{\tilde{\mathbb{COV}}[u_1,u_i]}{\tilde{\mathbb{V}}[u_1]} = \frac{\Psi_{11}\Psi_{i1}\sigma_{1\varepsilon}^2}{\Psi_{11}^2\sigma_{1\varepsilon}^2} = \frac{\Psi_{i1}}{\Psi_{11}} \propto \Psi_{i1} \ .$$

This follows directly from the fact that only the first shock appears in the first equation of Model (1). For the first equation, the modified IV corresponds to the standard IV estimator by Rigobon and Sack (2004).

Let us consider estimating the response to the second structural shock ($e = 2$) on variable i:

$$\begin{aligned}\Psi_{i2}^{IV} &= [(Z_1 \ \ Z_2)'(u_1 \ \ u_2)]^{-1}(Z_1 \ \ Z_2)'u_i \\ &\xrightarrow{p} \begin{bmatrix} \tilde{\mathbb{V}}[u_1] & \tilde{\mathbb{COV}}[u_1,u_2] \\ \tilde{\mathbb{COV}}[u_1,u_2] & \tilde{\mathbb{V}}[u_2]\end{bmatrix}^{-1} \begin{bmatrix}\tilde{\mathbb{COV}}[u_1,u_i] \\ \tilde{\mathbb{COV}}[u_2,u_i]\end{bmatrix} \ .\end{aligned}$$

Using Model (1) and Assumption 1 we obtain:

$$\begin{aligned}\tilde{\mathbb{V}}[u_1] &= \Psi_{11}^2\sigma_{1\varepsilon}^2 \\ \tilde{\mathbb{V}}[u_2] &= \Psi_{21}^2\sigma_{1\varepsilon}^2 + \Psi_{22}^2\sigma_{2\varepsilon}^2 \\ \tilde{\mathbb{COV}}[u_1,u_i] &= \Psi_{11}\Psi_{i1}\sigma_{1\varepsilon}^2 \\ \tilde{\mathbb{COV}}[u_2,u_i] &= \Psi_{21}\Psi_{i1}\sigma_{1\varepsilon}^2 + \Psi_{22}\Psi_{i2}\sigma_{2\varepsilon}^2 \ .\end{aligned}$$

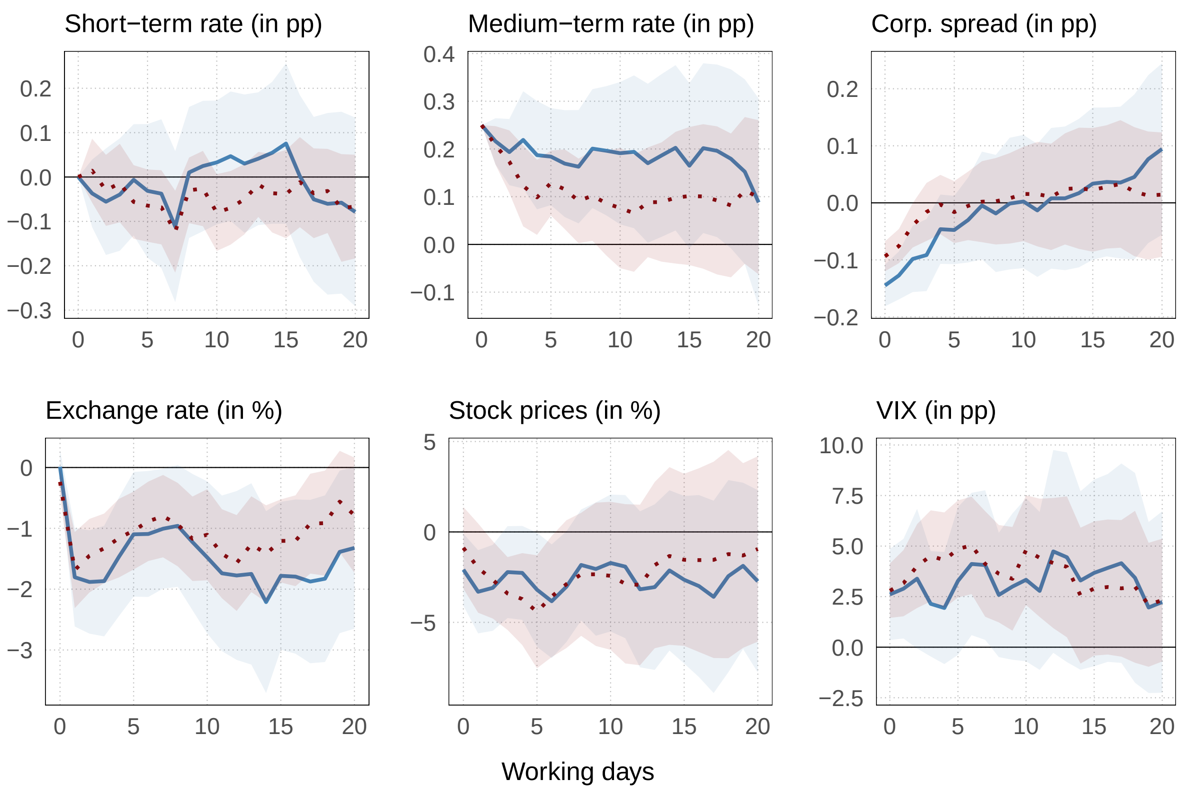
Therefore, after some algebra, we obtain:

$$\Psi_{i2}^{IV} \xrightarrow{p} \begin{bmatrix} \frac{\Psi_{i1}}{\Psi_{11}} - \frac{\Psi_{21}\Psi_{i2}}{\Psi_{11}\Psi_{22}} \\ \frac{\Psi_{i2}}{\Psi_{22}} \end{bmatrix},$$

which shows that the last row of the IV estimator consistently estimates the second column of the impact matrix up to a scale, where the response is normalized by Ψ_{22}.

C Additional results

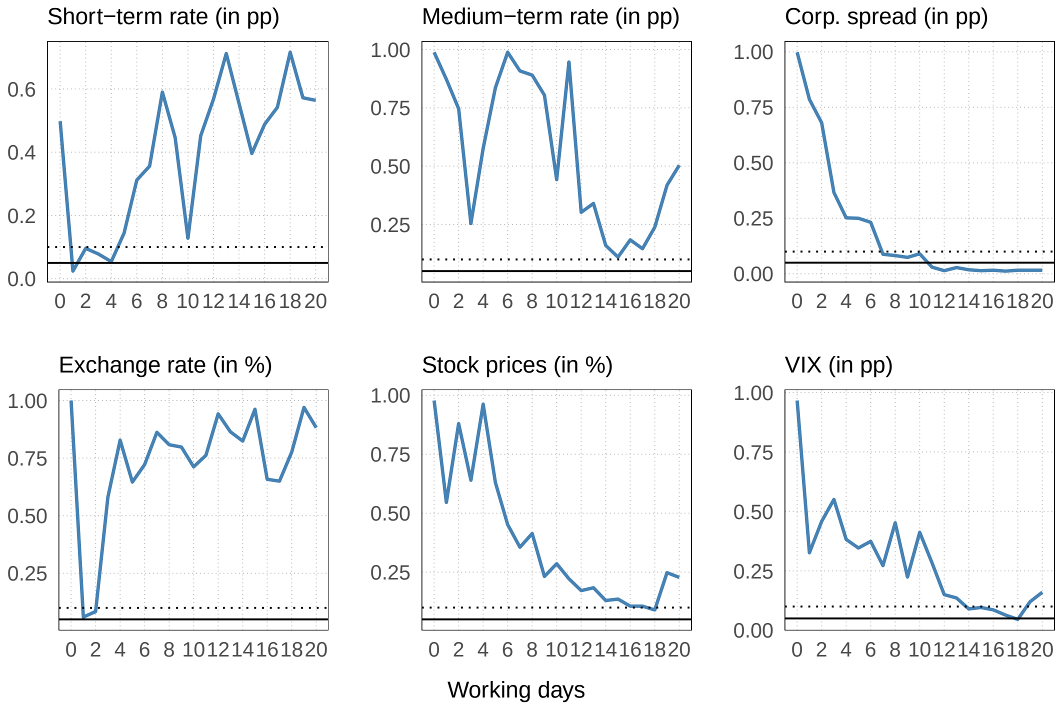
Fig. 3: Comparison of HET-IVs with HF-IVs adding recursive zero restriction



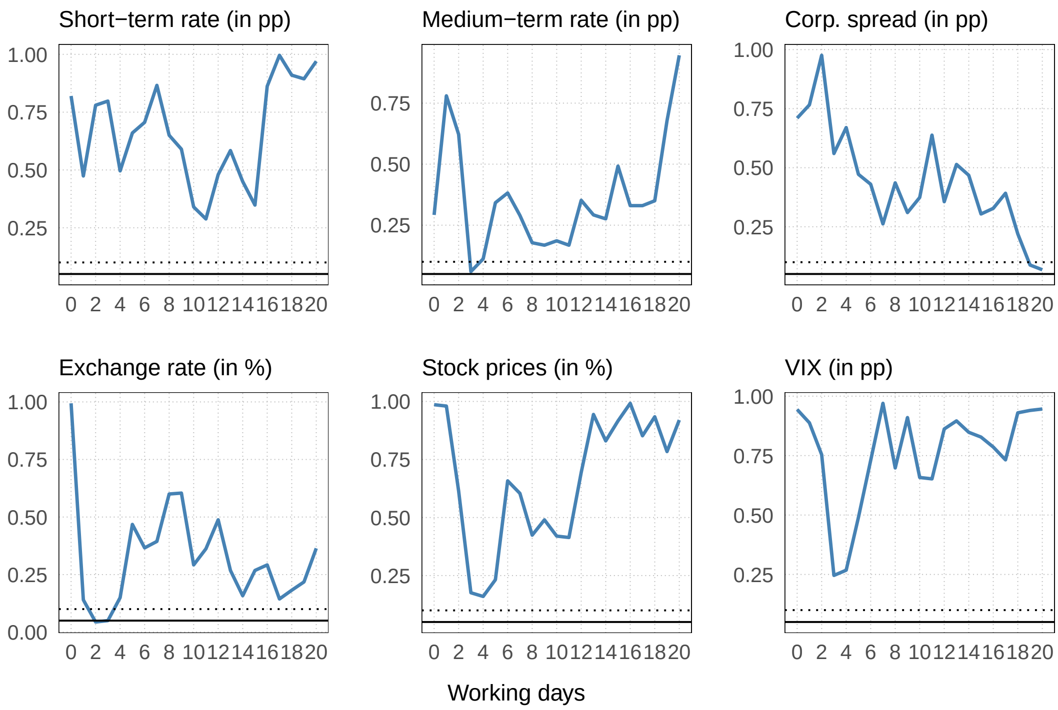
Notes: Impulse responses to a path monetary policy shock identified via HF-IV (red dotted line) and HET-IV (blue solid line). The specification imposes the recursive zero restriction also on the HF-IV path shock. Shaded areas show 90% confidence intervals (blue shading for HET-IV, red for HF-IV), based on HC standard errors. See also notes to Figure 1.

Fig. 4: Test for equality of impulse responses (p-values)

(a) Target shock



(b) Path shock



Notes: Bootstrapped p-values for a test of equality of impulse responses estimated using HET-IV and HF-IV. The horizontal lines denote the 5% (black solid line) and 10% (blue dotted line) confidence level. The horizontal axis measures working days (excluding weekends and holidays).

Tab. 4: Correlations of shock predictions

	HET-IV		HF-IV		HF-IV recursive	
	Target	Path	Target	Path	Target	Path
HET-IV						
Target	1.00					
Path	0.05	1.00				
HF-IV						
Target	0.71	0.40	1.00			
Path	0.10	0.84	0.37	1.00		
HF-IV recursvie						
Target	0.71	0.40	1.00	0.37	1.00	
Path	0.07	0.84	0.34	1.00	0.34	1.00

Notes: Correlations of shock predictions following Burri and Kaufmann (2025) based on the estimated impact matrix using the Kalman filter.