Monetary Policy Shocks with External Instruments: A Minimum Distance Approach

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Abstract

This paper replicates the baseline empirical framework of Lakdawala (2019) using an alternative estimation strategy to the standard two-stage SVAR-IV approach. We identify two dimensions of U.S. monetary policy news, a *Target* (short-rate) and a *Path* (forward-guidance) component, through high-frequency external instruments constructed from futures surprises and factor-rotation methods as in Gürkaynak et al. (2005).

Estimation follows the classical minimum distance (CMD) procedure of Angelini and Fanelli (2019), which selects the structural parameters by matching empirical second moments from the data to their model-implied counterparts via a weighted distance criterion. The paper documents the full identification, estimation, and inference pipeline under this CMD implementation, providing a methodological replication of the Lakdawala (2019) setup with a different estimator.

1 Motivation and overview

High-frequency identification has become a standard approach to isolate monetary policy shocks from financial-market reactions around central bank announcements. A central insight of this literature is that policy news is multi-dimensional: announcements can surprise markets both about the current policy rate and about the expected future path of policy (forward guidance). Lakdawala (2019) operationalizes this distinction by constructing two external instruments, a *Target* and a *Path* factor, and estimating a SVAR identified with external instruments (SVAR-IV). The baseline evidence delivers well-known empirical tensions, including a price puzzle and a non-standard response of real activity to the Path shock.

This paper replicates the baseline model of Lakdawala (2019) while changing the estimation strategy. Instead of the customary two-stage SVAR-IV implementation, we estimate the model using the classical minimum distance (CMD) approach proposed by Angelini and Fanelli (2019). CMD selects the structural parameters by matching empirical second moments (computed from the reduced-form innovations of the augmented system) to their model-implied counterparts, minimizing a weighted distance between the two. This provides a unified estimation-and-identification procedure grounded in moment restrictions and naturally accommodates the possibility that the external instruments are measured with error.

Empirically, we construct Target and Path instruments from high-frequency futures surprises using factor extraction and rotation methods in the spirit of Gürkaynak et al. (2005). We assess instrument relevance and separation through first-stage relationships between VAR residuals and the proxies. For inference on impulse responses, we implement a recursive-design wild bootstrap with full re-estimation and CMD re-identification, and we report 90% Sup-t simultaneous confidence bands.

The main findings are as follows. First, the CMD-based implementation reproduces the qualitative baseline patterns of Lakdawala (2019), including a price puzzle and a partially puzzling response of industrial production. Second, consistent with the view that the Path shock may embed a Delphic (information) component, purging the proxy of private-information effects yields a more Odyssean shock that generates contractionary real effects at both short and longer horizons.

The remainder of the paper is organized as follows. Section 2 describes the construction of the external instruments. Section 3 presents the AC-SVAR/CMD estimation framework, the bootstrap-based inference and the baseline impulse responses functions. Section 4 reports the Delphic-Odyssean decomposition. Section 5 concludes.

2 External instruments from high-frequency futures surprises

2.1 High-frequency surprises and factor extraction

Following Gürkaynak et al. (2005), we construct external instruments from high-frequency changes in interest-rate futures in a narrow event window around FOMC announcements. Specifically, for each announcement date t we compute *futures surprises* as changes in prices/yields within a 30-minute window (e.g. $[t^-, t^+]$) centered on the policy communication event. Let $s_t(m)$ denote the surprise at maturity m, for $m \in \{m_1, \dots, m_J\}$, and stack these surprises as

$$s_t \equiv \big(s_t(m_1), \dots, s_t(m_J)\big)' \in \mathbb{R}^J.$$

We summarize the joint term-structure response using principal components:

$$s_t = \Lambda f_t + e_t, \tag{1}$$

where $f_t \in \mathbb{R}^q$ collects the first q principal components. Empirically, the first two components ($q = 2$) account for the vast majority of the variance in s_t, consistent with the idea that policy announcements primarily move yields through two dominant dimensions of news (current stance vs expected path).

2.2 Rotation into Target and Path

The raw factors f_t are not directly interpretable. We therefore apply an identification-oriented rotation to obtain two economically meaningful instruments: a *Target* factor and a *Path* factor. Let

$$z_t \equiv R f_t, \qquad z_t = \begin{bmatrix} z_t^T \\ z_t^P \end{bmatrix},$$

where R is a 2×2 rotation matrix chosen to deliver the following interpretation:

- **Target factor** z_t^T: loads on the short end of the curve and tracks the surprise in the *current-month* futures contract, capturing unexpected changes in the contemporaneous policy rate.

- **Path factor** z_t^P: captures movements in longer-horizon futures surprises that are *orthogonal* to the current-month surprise. Operationally, this means that z_t^P is constructed so that it is uncorrelated with changes in current-month futures contract prices.

This orthogonality is central to our identification strategy. By construction, the rotated Path factor is orthogonal to the Target instrument, but this orthogonality pertains to the relationship between the instruments themselves and does not, by itself, restrict how each instrument loads on the underlying structural shocks.

In the AC-SVAR framework, we formalize identification by imposing economically motivated restrictions on the relevance matrix Φ, which links the proxy variables to the structural shocks according to

$$z_t = \Phi \varepsilon_t^* + v_t, \tag{2}$$

where z_t collects the instruments, ε_t^* denotes the structural shocks of interest, and v_t is an idiosyncratic measurement error orthogonal to the shocks.

We interpret the Target instrument (z_t^T) as a *clean* proxy for the FFR shock (ε_t^T), in the sense that it is orthogonal to the Path shock, i.e. $\mathbb{E}(z_t^T \varepsilon_t^P) = 0$. In contrast, the Path instrument (z_t^P) is a *noisy proxy* that may load on both structural shocks (so that $\phi_{PT} \neq 0$ is admissible), capturing forward-guidance information as well as co-movement with contemporaneous policy-rate innovations.

Accordingly, we adopt a triangular normalization for the relevance matrix Φ, setting $\Phi_{TP} = 0$ to label the shocks consistently with the Target–Path interpretation. This restriction should be interpreted as a normalization/labeling device rather than the sole source of identification, which in our baseline specification is achieved via an impact restriction on B_1.

Ordering the instruments as $z_t = (z_t^T, z_t^P)'$ and the shocks as $\varepsilon_t^* = (\varepsilon_t^T, \varepsilon_t^P)'$, this restriction yields a lower-triangular relevance matrix:

$$\begin{pmatrix} z_t^T \\ z_t^P \end{pmatrix} = \begin{pmatrix} \phi_{TT} & 0 \\ \phi_{PT} & \phi_{PP} \end{pmatrix} \begin{pmatrix} \varepsilon_t^T \\ \varepsilon_t^P \end{pmatrix} + v_t. \tag{3}$$

This Cholesky-type structure serves two purposes. First, it operationalizes the economic interpretation that the Target instrument loads primarily on the contemporaneous policy-rate shock, while allowing the Path instrument to load on both structural innovations. Second, it provides a normalization that uniquely labels the shocks within the minimum-distance estimation procedure.

To ensure a well-defined sign normalization and avoid indeterminacy in the scale of the shocks, we parameterize the diagonal elements of Φ using an exponential transformation,

$$\phi_{TT} = \exp(\gamma_{TT}), \qquad \phi_{PP} = \exp(\gamma_{PP}), \tag{4}$$

which guarantees positive relevance of each instrument for its associated shock. Under this normalization, a positive realization of ε_t^T corresponds to a contractionary policy rate shock, while a positive realization of ε_t^P captures forward-guidance news in the same direction.

Importantly, the first-stage evidence indicates that *both* instruments are informative for movements at longer maturities, as proxied by the 1-year rate residual. This confirms that high-frequency monetary policy surprises, whether captured by the Target or the Path factor, propagate along the yield curve and affect expectations about the future policy path. The distinction between Target and Path shocks therefore does not follow mechanically from reduced-form first-stage correlations with a given maturity, but is instead achieved at the structural level through (i) an impact restriction on B_1 and (ii) a labeling/normalization choice for Φ within the CMD identification.

2.3 Visual summary: instruments

Figure 1 reports the external instruments (Target and Path), mirroring the baseline construction.

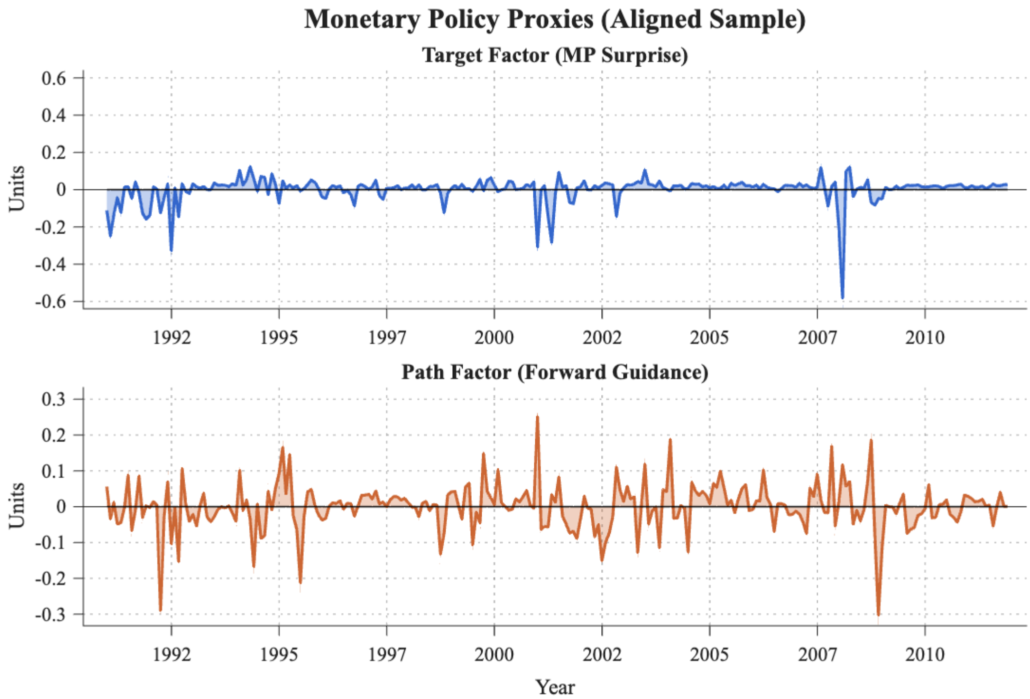

Figure 1: External instruments (Target and Path) constructed from 30-minute high-frequency futures surprises. The Path factor is rotated/orthogonalized so as to be uncorrelated with current-month futures surprises.

2.4 First-stage evidence: relevance and information content

A transparent diagnostic for instrument relevance and the information content of the proxies is provided by first-stage regressions of VAR residuals associated with longer-term interest rates on the Target and Path instruments. Specifically, we regress the residual of the 1-year rate, which primarily reflects surprises at medium-to-long maturities, on (z_t^T, z_t^P), and compare the resulting estimates with the baseline evidence reported in Lakdawala (2019).

Table 1 reports the results. Despite the dependent variable being a proxy for longer-horizon rate movements, the Target factor exhibits a strong and statistically significant loading, while the Path factor displays a smaller and only marginally significant coefficient.

Table 1: First-stage regression (dependent variable: 1-year rate residual). Sample 1991–2011 ($T = 252$).

	Estimate	Std. Error	t-stat
Target factor (z_t^T)	**0.9018**	0.1811	4.98
Path factor (z_t^P)	0.3469	0.1942	1.79
R^2	0.1014	(Paper: 0.101)	
F-statistic	14.06	(Paper: 14.73)	

This pattern is informative. Although longer-maturity rates are expected to reflect forward-guidance news to an important extent, the strong loading of the Target factor indicates that unexpected contemporaneous policy-rate innovations propagate along the yield curve and account for a substantial fraction of movements even at the one-year horizon. At the same time, the positive coefficient on the Path factor confirms that forward-guidance information contributes independently to longer-term rate dynamics.

Importantly, these results are fully consistent with the Cholesky-type restriction imposed on the relevance matrix Φ. The exclusion restriction applies to the mapping from instruments to structural shocks, preventing the Target instrument from loading on the Path shock, rather than to the reduced-form response of longer-term rates, which may reflect both contemporaneous and forward-looking policy components.

3 AC-SVAR representation and minimum-distance estimation

Let $Y_t \in \mathbb{R}^n$ denote the vector of endogenous variables and consider the reduced-form VAR

$$Y_t = \Pi X_t + \Upsilon_y D_{y,t} + u_t, \qquad u_t = B\,\varepsilon_t, \qquad \mathbb{E}(\varepsilon_t \varepsilon_t') = I_n, \tag{5}$$

where $X_t = (Y_{t-1}', \ldots, Y_{t-k}')'$ and u_t are the reduced-form innovations. We partition the structural shocks as

$$\varepsilon_t = \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix}, \qquad \varepsilon_{1,t} \in \mathbb{R}^g, \quad 1 \leq g < n, \tag{6}$$

where $\varepsilon_{1,t}$ are the *instrumented* structural shocks of interest (in our application, the monetary-policy *Target* and *Path* shocks), while $\varepsilon_{2,t}$ collects the remaining shocks.

External instruments are introduced by assuming that there exists an observable $r \times 1$ vector Z_t whose *innovation* component, $v_{Z,t}$, satisfies the relevance and orthogonality conditions. Angelini and Fanelli (2019) formalize this through:

$$v_{Z,t} = R_\Phi\,\varepsilon_t + \omega_t = \Phi\,\varepsilon_{1,t} + \omega_t, \qquad R_\Phi = \begin{pmatrix} \Phi & 0_{r\times(n-g)} \end{pmatrix}, \tag{7}$$

where ω_t is a measurement-error term (uncorrelated with ε_t) and the *relevance matrix* $\Phi \in \mathbb{R}^{r\times g}$ has full column rank, $\operatorname{rank}(\Phi) = g$. Intuitively, instruments must be correlated with $\varepsilon_{1,t}$ and orthogonal to the non-instrumented shocks $\varepsilon_{2,t}$ by construction of R_Φ. This interpretation is precisely where high-frequency identification (HFI) becomes crucial in our application. By construction, the instruments Z_t are built from changes in futures prices measured within a very narrow event window (30 minutes) around FOMC announcements. The identifying premise is that, at such high frequency, the information set relevant for asset price movements is dominated by the monetary policy event itself: macroeconomic fundamentals and other slow-moving state variables cannot react within minutes, and no other systematic macro news is released in the same narrow window. As a result, the measured surprises can be treated as policy-related innovations that are effectively orthogonal to contemporaneous non-policy disturbances.

Formally, HFI justifies viewing $v_{Z,t}$ as a noisy but exogenous proxy for a subset of structural shocks, in the sense that it is correlated with the instrumented shocks $\varepsilon_{1,t}$ (relevance) while being orthogonal to the remaining structural innovations $\varepsilon_{2,t}$ (exogeneity). This is exactly the content of the block structure in $R_\Phi = (\Phi \quad 0_{r\times(n-g)})$: the narrow-window construction supports the assumption that the instruments do not pick up contemporaneous macro shocks other than monetary policy news. In practice, any residual contamination can be interpreted as measurement error and is absorbed by ω_t in (7), while the rank condition $\text{rank}(\Phi) = g$ ensures that the proxies contain enough independent variation to span the g target shocks.

Because empirical instruments may display dynamics and be predictable by lagged macro information, the approach augments the VAR with an auxiliary model for Z_t (so that $v_{Z,t} = Z_t - \mathbb{E}[Z_t \mid \mathcal{F}_{t-1}]$ is the innovation):

$$Z_t = \Theta(L)Z_{t-1} + \Gamma(L)Y_{t-1} + \Upsilon_{z,y}D_{y,t} + \Upsilon_z D_{z,t} + v_{Z,t}. \tag{8}$$

Stack $W_t = (Y_t', Z_t')'$ and define $\eta_t = (u_t', v_{Z,t}')'$. The joint system can be written as an *augmented-constrained* VAR (AC-SVAR), featuring a triangular autoregressive structure (no lags of Z_t enter the Y_t equations). The crucial object is the on-impact mapping for η_t:

$$\begin{pmatrix} u_t \\ v_{Z,t} \end{pmatrix} = \underbrace{\begin{pmatrix} B & 0 \\ R_\Phi & \Sigma_\omega^{1/2} \end{pmatrix}}_{\tilde{G}} \begin{pmatrix} \varepsilon_t \\ \omega_t^* \end{pmatrix}, \tag{9}$$

which implies second-moment restrictions that are the backbone of identification and estimation. In particular, letting $\Sigma_u = \mathbb{E}(u_t u_t')$, $\Sigma_{v_Z,u} = \mathbb{E}(v_{Z,t}u_t')$, and $\Sigma_{v_Z} = \mathbb{E}(v_{Z,t}v_{Z,t}')$, the AC-SVAR restrictions are:

$$\Sigma_u = BB', \qquad \Sigma_{v_Z,u} = \Phi B_1', \qquad \Sigma_{v_Z} = \Phi\Phi' + \Sigma_\omega, \tag{10}$$

where $B_1 \in \mathbb{R}^{n\times g}$ collects the columns of B associated with the instrumented shocks $\varepsilon_{1,t}$. Since $g < n$, the goal is *partial shocks identification*: we only aim at identifying (B_1, Φ) (up to sign normalization), while the remaining columns of B are nuisance parameters.

When $g > 1$ (our case), external instruments alone generally do not pin down the rotation among the g instrumented shocks. A necessary order condition is that at least $\frac{1}{2}g(g-1)$ additional restrictions are imposed on the structural parameters in $G_1 = (B_1', \Phi')'$ (these restrictions can be placed on B_1, on Φ, or split across both).

In our baseline specification with $g = 2$, we achieve *exact identification* by imposing a zero restriction on the impact matrix B_1 in the spirit of Lakdawala (2019): the *Path* shock has no contemporaneous effect on the policy-rate equation (the FFR residual) on impact. This restriction pins down the remaining degree of freedom required for identifying the two shocks.

In addition, we adopt a Cholesky-type normalization for the relevance matrix Φ to obtain a *unique labeling* of the two instrumented shocks and to separate Target from Path in a way consistent with the economic interpretation of the proxies. Ordering instruments as $z_t = (z_t^T, z_t^P)'$ and shocks as $\varepsilon_{1,t} = (\varepsilon_t^T, \varepsilon_t^P)'$, we set

$$\Phi_{TP} = 0,$$

which rules out contemporaneous loading of the *Target* instrument on the *Path* shock while allowing the *Path* instrument to load on both shocks (i.e. $\phi_{PT} \neq 0$). Importantly, this triangular structure should be interpreted as a *normalization/labeling device* rather than the sole source of identification: it selects a particular rotation of the g shocks that is consistent with the intended Target–Path interpretation within the CMD framework.

Define the symmetric $r \times r$ matrix

$$\Xi \;:=\; \Sigma_{v_Z,u}\,\Sigma_u^{-1}\,\Sigma_{u,v_Z}, \tag{11}$$

which has rank g under relevance. Then the AC-SVAR implies the moment conditions

$$\Xi = \Phi\Phi', \qquad \Sigma_{v_Z,u} = \Phi B_1'. \tag{12}$$

These restrictions depend only on (B_1, Φ) and the reduced-form covariances of $(u_t, v_{Z,t})$.

Operationally, we estimate the reduced form of the AC-SVAR (i.e. the VAR for Y_t and the auxiliary model for Z_t), recover residuals $\hat{u}_t$ and $\hat{v}_{Z,t}$, and compute the sample counterparts

$$\widehat{\Sigma}_u,\ \widehat{\Sigma}_{v_Z,u},\ \widehat{\Xi} \quad \text{and hence} \quad \hat{\rho}_T := \Big(\mathrm{vech}(\widehat{\Xi})',\ \mathrm{vec}(\widehat{\Sigma}'_{v_Z,u})'\Big)'.$$

Let θ collect the free elements of (B_1, Φ) under the chosen identifying restrictions. The model-implied counterpart of ρ is the nonlinear mapping

$$\rho(\theta) := \Big(\mathrm{vech}(\Phi\Phi')',\ \mathrm{vec}(\Phi B_1')'\Big)'.$$

The CMD estimator solves

$$\hat{\theta} = \arg\min_{\theta\in\Theta} \Big[\hat{\rho}_T - \rho(\theta)\Big]'\widehat{\Omega}_\rho^{-1}\Big[\hat{\rho}_T - \rho(\theta)\Big], \tag{13}$$

where $\widehat{\Omega}_\rho$ is a consistent estimator of the asymptotic covariance matrix of $\hat{\rho}_T$ (obtained from the reduced-form AC-SVAR). In practice, (13) is minimized numerically (e.g. with `fminunc`), and the solution $\hat{\theta}$ delivers $\widehat{B}_1$ and $\widehat{\Phi}$, hence the impact responses of the g instrumented shocks.

Finally, impulse responses to the instrumented shocks are computed by combining the estimated impact matrix columns $\widehat{B}_1$ with the estimated VAR companion form of Y_t. Inference can be conducted via standard bootstrap methods applied to the AC-SVAR residuals, resampling $(\hat{u}_t, \hat{v}_{Z,t})$ jointly as suggested by the AC-SVAR interpretation.

3.1 Inference: recursive-design wild bootstrap and Sup-t bands

Inference for impulse responses is conducted via a *recursive-design wild bootstrap* with full re-estimation and CMD re-identification. This choice is motivated by the presence of conditional heteroskedasticity and volatility clustering in both the VAR innovations and the external instruments, which is visually apparent in Figure 1 and formally supported by ARCH-type diagnostics. In particular, equation-by-equation ARCH-LM tests based on

$$\hat{u}_{i,t}^2 = \gamma_{i,0} + \gamma_{i,1}\hat{u}_{i,t-1}^2 + \cdots + \gamma_{i,q}\hat{u}_{i,t-q}^2 + e_{i,t}, \tag{14}$$

reject $H_0 : \gamma_{i,1} = \cdots = \gamma_{i,q} = 0$ at conventional levels, indicating time-varying conditional volatility. Wild bootstrap perturbations are well suited to this setting because they preserve the time profile of volatility embedded in the estimated residuals under heteroskedasticity of unknown form (Gonçalves and Kilian, 2004). We adopt a *recursive design* because it generates bootstrap samples that satisfy the estimated VAR dynamics by construction and has been widely used in SVAR applications (Mertens and Ravn, 2013).

Why not a moving-block bootstrap (and why the ordering matters). An alternative is a moving-block bootstrap, which resamples blocks of consecutive observations to mimic serial dependence. In our setting, however, it presents two practical drawbacks. First, block methods require choosing tuning parameters (most importantly the block length), which can materially affect finite-sample performance and tends to reduce efficiency when the effective sample is modest (Gonçalves and Kilian, 2004). Second, because our identification hinges on contemporaneous covariance restrictions between VAR innovations and instruments, the *alignment in time* between (u_t, z_t) is essential: resampling blocks of (u_t, z_t) can preserve dependence, but it also changes the composition of announcement days across blocks and may amplify weak-proxy realizations in bootstrap samples. This concern is not merely hypothetical: the SVAR-IV literature documents that different bootstrap schemes can yield materially different inference, and the role of bootstrap validity and weak-instrument behavior has been debated explicitly in the context of proxy SVARs (Jentsch and Lunsford, 2019; Mertens and Ravn, 2019). For these reasons, we prefer a wild perturbation that keeps the original time ordering intact while allowing for heteroskedasticity.

Let the estimated reduced-form VAR be

$$Y_t = \hat{c} + \sum_{\ell=1}^{p} \hat{A}_\ell Y_{t-\ell} + \hat{u}_t. \tag{15}$$

For each bootstrap replication $b = 1, \ldots, B$, draw i.i.d. Rademacher variables $\eta_t^{(b)} \in \{-1, +1\}$ and define

$$u_t^{*(b)} = \hat{u}_t\, \eta_t^{(b)}, \qquad z_t^{*(b)} = z_t\, \eta_t^{(b)}. \tag{16}$$

We perturb *both* innovations and instruments using the same $\eta_t^{(b)}$ to preserve the contemporaneous second moments that underpin CMD identification. In particular,

$$\mathbb{E}^*\left[u_t^{*(b)} z_t^{*(b)\prime}\right] = \hat{u}_t z_t' \, \mathbb{E}^*\left[\eta_t^2\right] = \hat{u}_t z_t', \tag{17}$$

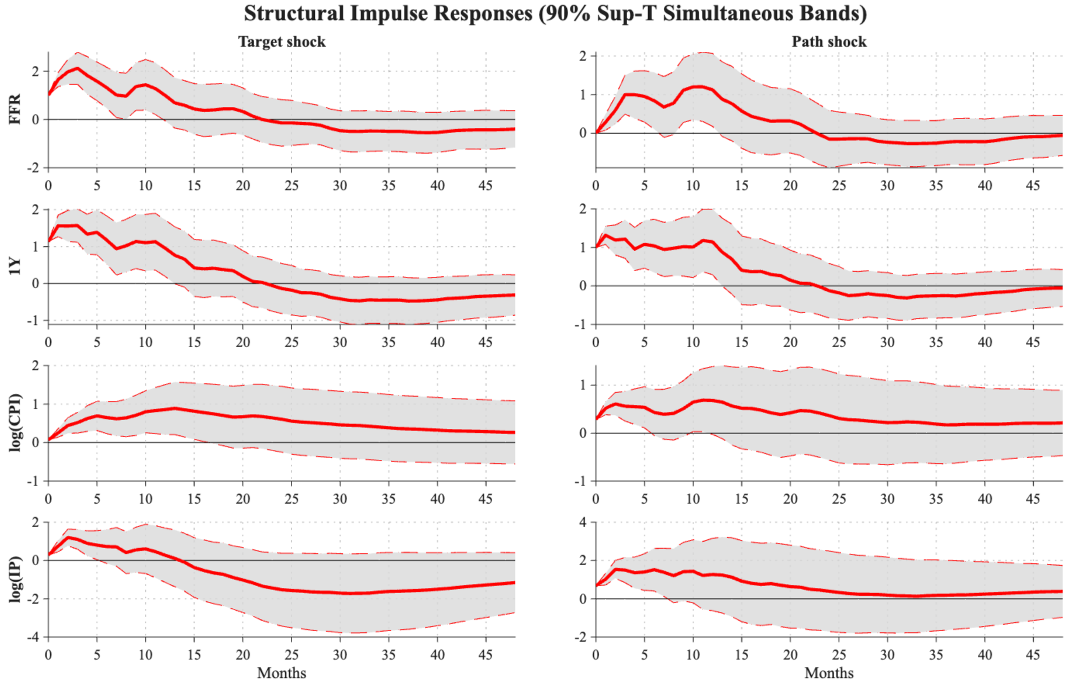

Figure 2: Impulse responses to Target and Path shocks (AC-SVAR/CMD). 90% Sup-t simultaneous confidence bands.

while $\mathbb{E}^*[u_t^{*(b)}] = 0$ and $\mathbb{V}^*(u_t^{*(b)}) = \hat{u}_t\hat{u}_t'$.

Bootstrap data are generated recursively as

$$Y_t^{*(b)} = \hat{c} + \sum_{\ell=1}^{p} \hat{A}_\ell Y_{t-\ell}^{*(b)} + u_t^{*(b)}, \tag{18}$$

using the original initial conditions. Denoting by $\mathcal{F}_{t-1}^*$ the bootstrap information set up to $t-1$, the recursive design implies

$$\mathbb{E}^*\left[Y_t^{*(b)} \mid \mathcal{F}_{t-1}^*\right] = \hat{c} + \sum_{\ell=1}^{p} \hat{A}_\ell Y_{t-\ell}^{*(b)}, \tag{19}$$

$$\mathbb{V}^*\left(Y_t^{*(b)} \mid \mathcal{F}_{t-1}^*\right) = \mathbb{V}^*\left(u_t^{*(b)} \mid \mathcal{F}_{t-1}^*\right) = \hat{u}_t\hat{u}_t'. \tag{20}$$

Hence, the bootstrap process is centered on the estimated reduced-form dynamics and retains the observation-specific volatility profile of the residuals.

Full re-estimation, CMD re-identification, and simultaneous bands. For each bootstrap sample we re-estimate the reduced-form VAR, recompute the second moments entering the CMD objective, and re-identify the model by solving the CMD problem. We then compute bootstrap impulse responses $\widehat{\Psi}_h^{*(b)}$. Finally, we report 90% Sup-t simultaneous confidence bands obtained from the bootstrap distribution of the maximal t-statistic over horizons, ensuring joint coverage of the entire impulse-response path.

3.2 Impulse responses and interpretation

Figure 2 reports impulse responses to the two instrumented monetary policy shocks identified through the AC-SVAR/CMD procedure: the *Target* (short-rate) shock and the *Path* (forward-guidance) shock. Consistent with Lakdawala (2019), both shocks induce an immediate increase in interest rates and are followed, on impact, by a positive response of real activity and prices. A natural interpretation of this short-run co-movement is a general-equilibrium (or information) component: in the data, positive policy-rate surprises tend to occur in states of the world where the economy is already strong and inflationary pressures are building, i.e. when policy tightening coincides with favorable macroeconomic conditions and rising prices. In such episodes, the policy-related news embedded in high-frequency surprises may reflect not only a pure contractionary policy impulse, but also the revelation of the central bank's assessment of stronger underlying fundamentals, which mechanically generates a positive contemporaneous reaction of output and prices.

Identification of the two shocks requires an additional restriction beyond instrument relevance when $g = 2$. In our baseline specification we impose a contemporaneous exclusion restriction on the impact matrix B_1 that aligns with the economic interpretation of forward guidance: the *Path* shock has zero impact effect on the policy-rate equation (the Federal Funds Rate equation) on impact. Formally, letting B_1 collect the first two structural shocks, we set the entry associated with the impact of the Path shock on the FFR residual to zero. This normalization ensures exact identification of the two shocks and is reflected in the impulse responses: the Path shock does not move the policy rate contemporaneously, while it shifts longer maturities through expectations.

Turning to industrial production, the Target shock displays a brief positive response at short horizons, but then becomes contractionary, with the response turning negative at medium horizons (around one year). This pattern is consistent with the view that the short-rate shock captures conventional monetary tightening whose real effects materialize with lags. In contrast, the response of industrial production to the Path shock remains weakly positive (or close to zero) over much of the horizon. This divergence is economically important: one would typically expect forward guidance tightening to be contractionary as well, and the absence of a clear negative response is therefore puzzling. The fact that the Path shock produces a qualitatively different real response than the Target shock suggests that the forward-guidance proxy may embed additional components beyond a pure policy impulse. In particular, the Path factor is the natural candidate to carry an informational (Delphic) component, i.e. news about stronger expected fundamentals that can offset (or dominate) the contractionary effect of a higher expected policy path. This motivates the subsequent decomposition aimed at purging the Path instrument from private-information effects and isolating a more Odyssean component.

4 Results and interpretation

Following Lakdawala (2019), we compare impulse responses to Target and Path shocks. In our baseline estimates, both shocks generate an immediate positive response in industrial production and prices, consistent with a short-run general-equilibrium component and/or informational effects embedded in high-frequency surprises. The Target shock becomes contractionary for real activity at medium horizons (around one year), while the Path shock exhibits a weaker and sometimes positive response of output, echoing the "forward guidance puzzle" documented in the literature.

4.1 Delphic vs. Odyssean decomposition of the Path shock

A key concern is that the Path instrument may contain *Delphic* information: private central-bank information about the macro outlook that moves yields but is not a pure policy shock. Building on the information-channel literature, we "clean" the Path proxy by partialling out a forecast-information component (e.g., based on forecast spreads between central bank staff projections and private forecasts), along the lines of Miranda-Agrippino and Ricco (2021) and the Delphic/Odyssean interpretation in Andrade and Ferroni (2021). Operationally, define:

$$z^P_{t,\text{Odys}} = z^P_t - \widehat{\pi}' x_t, \tag{21}$$

where x_t is a vector of forecast-spread controls and $\widehat{\pi}$ is estimated by OLS. Re-estimating the proxy-SVAR with $z^P_{t,\text{Odys}}$ tends to attenuate the puzzling positive output response, making the Path shock more consistently contractionary. In this way, we obtain a "cleansed" Path-shock instrument that captures only unexpected changes in the monetary policy stance. This is achieved by conditioning on the same information set available to private agents, which we approximate by regressing Blue Chip forecasts on Greenbook forecasts, as in Equation 21. When we re-estimate impulse responses using this "cleansed" Path instrument and compare them with the baseline IRFs, the interpretation becomes clearer: the initial positive response of (log) industrial production in the baseline specification is largely consistent with an information effect, i.e., the disclosure of central-bank private information that leads markets to revise beliefs about the state of the economy at the time of the monetary policy surprise. More broadly, this reading is consistent with the nature of high-frequency instruments constructed from futures prices, which proxy unexpected changes in the pricing of near- and medium-term policy paths. These surprises often reflect a mismatch between the central bank's information set and private-sector expectations about real activity. Once we net out this informational component, the dynamic response to a "pure" forward-guidance (Odyssean) shock becomes contractionary, in line with the intended interpretation of forward guidance as a policy signal about tighter future conditions.

5 Conclusion

This paper provides a methodological replication of Lakdawala (2019) by estimating a two-shock monetary policy proxy-SVAR with an alternative estimator: the classical minimum distance (CMD) procedure of Angelini and Fanelli (2019). Using high-frequency futures surprises around FOMC announcements, we construct Target and Path instruments via factor extraction and rotation in the spirit of Gürkaynak et al. (2005). Identification is implemented in the AC-SVAR representation through second-moment restrictions and a Cholesky-type normalization

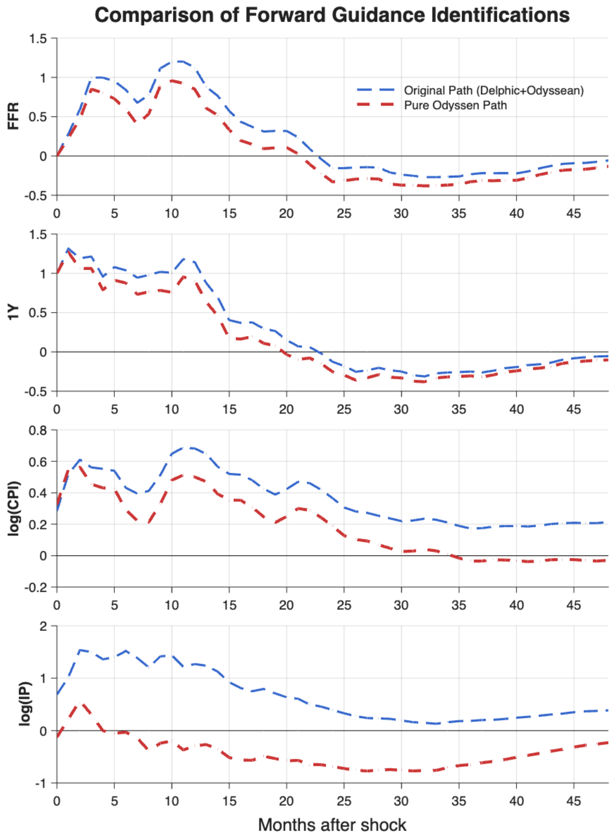

Figure 3: Illustration: IRFs using the mixed Path proxy vs. the cleaned (Odyssean) Path proxy.

of the relevance matrix, which rules out contemporaneous loading of the Target instrument on the Path shock while allowing the Path instrument to retain informational content about both innovations.

Empirically, the CMD-based implementation reproduces the main qualitative patterns documented in the baseline SVAR-IV approach. In particular, the estimated impulse responses display a short-run co-movement of real activity and prices with policy-rate surprises, consistent with the view that high-frequency monetary policy news can embed non-policy information components. While the Target shock becomes contractionary for industrial production at medium horizons, the Path shock exhibits a weaker and sometimes positive real response, echoing the forward-guidance puzzle highlighted in the literature.

Motivated by this evidence, we interpret the Path proxy as the natural carrier of a Delphic (information) component. Once we purge the Path instrument from forecast-related information—thereby isolating a more Odyssean forward-guidance shock—the resulting impulse responses become more consistently contractionary, restoring the expected qualitative effects of monetary tightening at both short and longer horizons.

Overall, the results underscore two broader points. First, the CMD approach provides a coherent and transparent estimation-and-identification pipeline for proxy-SVARs based on second moments, offering a useful alternative to the standard two-stage SVAR-IV implementation. Second, distinguishing between policy and information components is crucial for interpreting forward-guidance shocks identified with high-frequency external instruments. Future work could extend the analysis by exploring alternative information controls, heteroskedasticity-robust inference, and the sensitivity of the Delphic–Odyssean decomposition to different measures of private central-bank information.

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