The Term Structure of Monetary Policy News*

Jonathan J. Adams†
Federal Reserve Bank of Kansas City

Philip Barrett‡
International Monetary Fund

June 11, 2025

WORKING PAPER

Link to Most Current Version

Abstract

Empirical monetary policy shocks (EMPS) contain information about monetary policy both today and in the future. We define the *term structure of monetary policy news* as the marginal impact of an EMPS on the policy residual at each horizon. Policy news at different horizons has different effects, so knowing the term structure is necessary in order to use an EMPS to evaluate theory. We develop an IV method to estimate this term structure. We find that most EMPS in the literature convey more information about policy in future than in the present, but there is substantial heterogeneity. We use the estimated term structures to construct synthetic forward guidance and surprise shocks, and estimate their macroeconomic effects. Surprise interest rate hikes exhibit an "output puzzle", but forward guidance about future rate increases is deeply contractionary.

JEL-Codes: E32, E43, E52
Keywords: Monetary Policy Shocks, Forward Guidance, Term Structure

*We thank Regis Barnichon, Huixin Bi, Miguel Faria-e-Castro, Andy Glover, Christian Matthes, and Felipe Saffie, and conference participants at the Spring 2025 Midwest Macro meetings for helpful comments and suggestions. We are also grateful to many authors for releasing their estimated shocks, especially Thomas Drechsel and Eric Swanson who shared early versions of their series with us. The views expressed herein are those of the authors and do not necessarily represent the views of the Federal Reserve Bank of Kansas City or the Federal Reserve System, the IMF, its Executive Board, or IMF management.

†email: adamsjonathanj@gmail.com
‡email: pbarrett@imf.org

1 Introduction

How do central bank decisions affect the economy? Empirical answers to this question require cleanly identified monetary policy shocks. In recent years, clean identification using high frequency data (Gürkaynak et al., 2005) or narrative methods (Romer and Romer, 2004) have yielded an array of high quality estimated empirical monetary policy shocks (EMPS). And while theory gives sharp predictions about the effects of monetary shocks, we can evaluate theory against data only if we know precisely what the EMPS represent.

So what do these EMPS represent? The premise of this paper is that many of these approaches correctly capture the nature of the shock – i.e. an exogenous perturbation to interest rate policy – but they may vary in their information about policy timing. Different EMPS can have different weights on policy surprises versus policy news across many future horizons.[1] This fact poses a challenge when trying to confront theory with data, since models imply that shocks with news at different horizons should have different effects. Does the response to a given EMPS tell us something about the macroeconomic effects of policy? Or just how news and surprise are combined in that particular shock?

Our first contribution is to resolve these questions by developing a method to estimate the *term structure of monetary policy news*. This term structure decomposes an EMPS, revealing how it depends on policy news shocks for every future horizon. This decomposition makes it clear that there is no single variety of a monetary policy shock: a Galí (2008) textbook-style surprise interest rate change is different than a news shock about rates one month in the future. Moreover, a one-month-ahead news shock is different than a two-month-ahead news shock, and so on; as McKay and Wolf (2023) point out, news shock at different horizons are distinct kinds of monetary policy shock. In the data, an EMPS can be a combination of potentially many of these different news shocks. The *term structure of monetary policy news* quantifies what that combination is. But how can it be measured?

Our procedure to estimate the term structure has several stages. In the end, the estimator has a single closed-form expression, but it is helpful to describe it in distinct steps. First, we use plausibly exogenous macroeconomic shocks as instrumental variables in order to identify the monetary policy rule, following insights from Barnichon and Mesters (2020).[2]

[1] This conundrum is well-known. Their creators emphasize that EMPS are not textbook surprises; for example Gertler and Karadi (2015) describe their shock as "a linear combination of exogenous shocks to the current and expected future path of future rates." Swanson (2021) describes the challenge thus: "identifying the effects of forward guidance and LSAP [large scale asset prices] is difficult, because many of the FOMC's announcements provide information about both types of policies simultaneously".

[2] This is a crucial step if there is a non-trivial news component to monetary policy. Many studies use lagged macroeconomic aggregates as instrumental variables to estimate the policy rule, following Clarida et al. (2000). These are valid instruments if monetary policy residuals are unanticipated, but may not be valid instruments if the policy residual is not a true surprise. The central insight of Barnichon and Mesters (2020) is that externally-identified exogenous macroeconomic shocks can be used to identify structural equations when the shocks are orthogonal to the relevant residual. Carvalho and Nechio (2014) argue that instruments

Then, the monetary policy residual is calculated from the estimated rule, and whitened to find the monetary policy innovations. Finally, the innovations are regressed on lags of the EMPS to identify the term structure. It is possible to implement these steps as a single estimator with a simple closed-form expression; we prove that it is unbiased, and derive asymptotic standard errors.

EMPS in the literature are not textbook surprises. We demonstrate our method by estimating the term structure for several well-known narrative and high-frequency EMPS. We find that EMPS are mostly driven by news, capturing forward guidance, rather than immediate policy surprises. However there is substantial heterogeneity across methods.[3] For example, the Bu et al. (2021) shock is dominated by long-term news, while narrative-based EMPS such as those constructed by Aruoba and Drechsel (2024) are closer to a policy surprise or short-run news shock. And while we learn that none of the EMPS correspond to shocks that are neatly interpretable in textbook models, we develop a procedure such that they can be.

The method allows for a valuable application: it is possible to construct a synthetic monetary policy shock with a desired term structure. We show that the impulse response to a linear combination of EMPS is a linear combination of the responses to the component term structures. As a result, we can construct a synthetic MPS that closely approximates a true policy surprise, news about a particular horizon, or any other pattern of forward guidance. We show how this can be used to estimate to macroeconomic effects of specific types of MPS that have no direct analog among EMPS in the literature. But synthetic MPS will have other applications. For example, the method developed in McKay and Wolf (2023) requires a set of monetary news shocks at many horizons in order to estimate policy counterfactuals that are robust to the Lucas critique.

No EMPS is directly comparable to a textbook monetary policy shock, but the synthetic monetary policy surprise is. We estimate the effects of the synthetic surprise on the macroeconomy and find that it does not clearly resemble the textbook effects: after a sudden interest rate increase, prices are roughly unchanged (a "price puzzle") and economic activity increases for several months before contracting (an "output puzzle"). Output puzzles are usually hypothesized to be driven by a central bank information effect (Romer and Romer, 2000), but our synthetic MPS is constructed from EMPS that are ostensibly purged of this effect. This suggests that other forces may be driving output puzzles. In contrast, a synthetic forward guidance shock is immediately and deeply contractionary, reducing output

may not be needed at all, and OLS estimates are reasonably accurate; as a robustness check, we use OLS to estimate the policy rule as well. While OLS may be preferable than IV using traditional lagged macro variables (Carvalho et al., 2021), we find IV using structural shocks to be more robust.

[3] This term structure heterogeneity may partially explain the low correlation in EMPS documented by Brennan et al. (2024).

and inflation significantly on impact.

As intermediate steps, we make two additional contributions. First, we demonstrate the benefits of IV estimation for monetary policy rules. Our policy rule coefficients are surprisingly robust across specifications, and roughly match standard theoretical values (e.g. the inflation coefficient is $\phi_\pi \approx 1.5$). OLS is known to have only a small bias for estimating these rules (Carvalho et al., 2021), but is relatively sensitive to the regression specification, compared to the IV approach. Second, while deriving a penalized version of our estimator for finding smooth term structures, we utilized the Barnichon and Brownlees (2019) "smooth local projections". The estimator is originally written non-linearly, so confidence intervals are usually found by bootstrapping or the delta method. Instead, we show how to rewrite the smooth local projection as a special case of ridge regression, which has known analytical standard errors.

We contribute the literature working to separately estimate the effects of forward guidance (news) versus policy surprises. Gürkaynak et al. (2005) decomposes high frequency MPS into a target factor that moves the current rate, and a path factor that only moves expected future rates. Other papers such as Altavilla et al. (2019), Swanson (2021), and Jarociński (2024) decompose high frequency shocks into additional factors, which have different macroeconomic effects. We show in Section 4 that the shocks resulting from these decompositions are characterized by different news term structures. Campbell et al. (2012) estimate a simple Taylor rule, and use forecasts to decompose the residual into components revealed when the rate is set versus in prior quarters. Hansen and McMahon (2016) use textual analysis to identify components of Fed announcements corresponding to current policy, views about the economy, and forward guidance. Many further papers apply these types of strategies to other settings.

The remainder of the paper is organized as follows. Section 2 contains a motivating example to demonstrate why knowing the term structure of an EMPS is necessary to draw conclusions. Already motivated readers can skip to Section 3, which describes our method in detail. In Section 4 we apply it to estimate the term structures for many EMPS. Section 5 describes and applies the process for constructing synthetic MPS. Section 7 concludes.

2 A Motivating Example

Our motivation is most clearly demonstrated with a concrete example. In this section, we show that for almost all models there is some term structure which can rationalize any given EMPS. Consequently, without some empirical discipline on the term structure of an EMPS, we cannot use them to evaluate theory.

The textbook New Keynesian model is given by

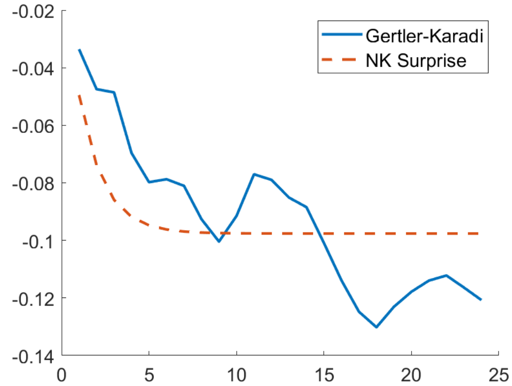
$$\begin{aligned}
&\text{New Keynesian Phillips curve:} && \pi_t = \beta\mathbb{E}[\pi_{t+1}] + \kappa y_t \\
&\text{Euler equation:} && i_t = \mathbb{E}_t[\gamma(y_{t+1} - y_t) + \pi_{t+1}] \\
&\text{Taylor rule:} && i_t = \phi_y y_t + \phi_\pi \pi_t + \nu_t
\end{aligned}$$

where π_t is inflation, y_t is the output gap, and i_t is the nominal interest rate. ν_t is exogenous and white noise. However, we introduce news to this model: ν_t is partially anticipated, given by

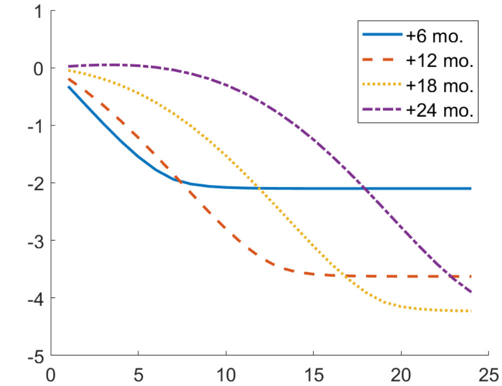
$$\nu_t = \nu_{0,t} + \nu_{1,t-1} + \nu_{2,t-2} + ...$$

where the component $\nu_{h,t-h}$ is learned at time $t - h$. The $\nu_{h,t}$ components are i.i.d. over time and independent of one another. $\nu_{h,t}$ represents a news shock at time t about monetary policy h periods into the future.

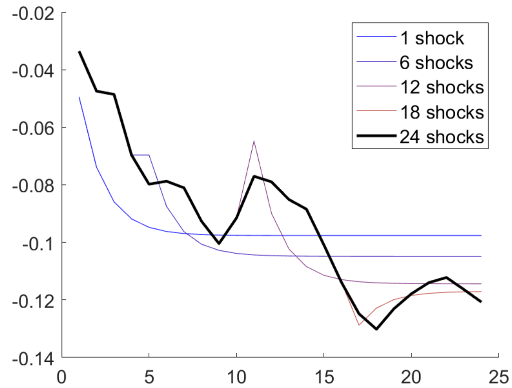
Figure 1a compares the price level IRFs from the New Keynesian model to that of a well-known high frequency EMPS, that of Gertler and Karadi (2015) . The shock causes a gradual deflation over 18 months. In contrast, the standard New Keynesian monetary policy surprise $\nu_{0,t}$ (dashed red line) causes an immediate deflation, then prices rapidly stabilize.



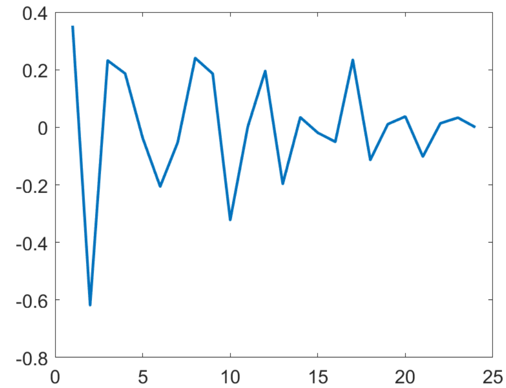
(a) EMPS vs. NK Surprise Shock



(b) NK News Shocks



(c) MPS Approximations



(d) Rationalizing Term Structure

Figure 1: CPI Responses to Monetary Shocks

The EMPS IRF is directly from Gertler and Karadi (2015). IRFs to surprise and news shocks are calculated from a standard calibration (Galí, 2008) of the textbook New Keynesian model. The MPS Approximation IRFs use the first n news shocks to find the linear combination that most closely matches (in terms of least squares) the EMPS IRF. The Rationalizing Term Structure plots the weights on the news shocks that exactly recover the Gertler-Karadi IRF.

But a surprise is not the only kind of monetary policy shock. A news shock $\nu_{h,t}$ has a different effect on prices for every horizon h: an anticipated future tightening causes a smooth deflation. Panel 1b demonstrates, plotting the deflationary effects of news at several semi-annual horizons. Each looks different from a surprise shock, and different from one another. Indeed, they are linearly independent.

The IRF of the Gertler-Karadi shock is perfectly consistent with the New Keynesian model for *some* term structure. In other words, there is some linear combination of surprise and news that exactly replicates the empirical IRF. Panel 1c demonstrates, by approximating the Gertler-Karadi IRF as linear combinations of the first n news horizons. As n

increases, the IRF is approximated more accurately. When 24 shocks are used, the Gertler-Karadi IRF is reproduced perfectly. Panel 1d plots the weights on each news shock in the perfect approximation: this linear combination generates a MPS that would exactly rationalize the Gertler-Karadi IRF in the textbook New Keynesian model. Moreover, if appropriately rescaled, this is the term structure of monetary policy news, which we define formally in the next section.[4]

The lessons from this example are not limited to the Gertler-Karadi EMPS or the basic New Keynesian model. If the term structure of an EMPS is a free variable, we could have argued that any other model (with linearly independent news shock IRFs) was consistent with this EMPS for some term structure. Similarly, we could have found a term structure to rationalize any other EMPS as consistent with the New Keynesian model. The essential point is that without some discipline on the term structure of monetary policy news, *anything goes*.

3 Methodology

This section describes the methodology used to estimate the term structure of monetary policy news. We outline the monetary policy framework, the estimation strategy, and the theoretical properties of the estimator.

3.1 Monetary Policy Framework

We model monetary policy as being determined by a Taylor-type rule:

$$y_t = x_t \phi + r_t \tag{1}$$

where y_t is the policy instrument (typically a short-term rate), r_t is the exogenous monetary policy residual (MPR), x_t is a row vector of endogenous inputs to the policy rule, and ϕ is a vector of coefficients.

We allow interest rate smoothing and the delayed response to endogenous variables in the data generating process for the residuals r_t. This is given by:

$$r_t = \sum_{\ell=1}^{L} (\rho_{y,\ell} y_{t-\ell} + x_{t-\ell} \phi_\ell) + \nu_t \tag{2}$$

[4] It is not smooth of course, as all news shocks have smooth IRFs in the NK model, so jagged linear weights are required to recover the jagged Gertler-Karadi IRF. This also prompts the question: how close can a smooth term structure come to matching the empirical IRF? Is there a tradeoff between smoothness of the term structure and matching the IRF? We return to these questions in Section 6.

Together, equations (1) and (2) nest a very broad set of Taylor rule specifications. These two equations could be combined in one, but splitting them out this way helps highlight how we tackle endogeneity. Endogeneity in Taylor rule estimation is due a *contemporaneous* correlation of x_t with ν_t. Our estimation method addresses this problem by estimating separately the response to contemporaneous endogenous variables and the dynamic correlation of the residuals. And so we formulate the Taylor rule as above.

The monetary policy innovation ν_t is white noise, but not necessarily unforecastable. We write the residual ν_t as a sum of news shocks at H_ν horizons:

$$\nu_t = \nu_{0,t} + \nu_{1,t-1} + \nu_{2,t-2} + ... + \nu_{H_\nu,t-H_\nu} \tag{3}$$

$\nu_{0,t}$ represents the surprise at time t, while $\nu_{h,t-h}$ represents the news component known at time $t-h$. This captures the idea that there may be information today about how policymakers intend to depart from their usual behavior in future. The news shocks are iid Gaussian, distributed $\nu_{h,t} \sim N(0, \sigma_h^2)$.[5]

We model an EMPS as containing some information about news shocks at multiple horizons. There may be many types of EMPS, indexed by $j \in \mathcal{J}$. Each EMPS w_t^j contains information about potentially many future residuals, as well as Gaussian error ξ_t:

$$w_t^j = \sum_{h=0}^{H_w} \beta_h^j \nu_{h,t} + \xi_t^j \tag{4}$$

where ξ_t is orthogonal to the monetary policy innovation ν_{t+h} for all h. ξ_t could be measurement error, but it could also represent other factors captured in the EMPS which do not affect the policy residual, such as a central bank information effect. Equation (4) represents the data-generating process for an EMPS. How does it relate to the term structure?

We define the *term structure of EMPS* j is the effect of the EMPS w_t^j on expectations of the monetary policy innovation ν_t over many horizons:

$$\gamma_h^j \equiv \frac{d\mathbb{E}[\nu_{t+h}|w_t^j]}{dw_t^j}$$

Given the linear DGP in equation (4), the term structure can also be written as a linear relationship between EMPS w_t^j and ν_t:

$$\nu_t = \sum_{h=0}^{H_w} \gamma_h^j w_{t-h}^j + u_t \tag{5}$$

[5] We assume Gaussianity so that we can write linear projections as expectations. This assumption is not necessary for our results; without it, the OLS implementation would be unchanged.

where u_t is a residual. The β_h^j coefficients from equation (4) and γ_h^j coefficients are related by

$$\gamma_h^j = \beta_h^j \frac{Var(\nu_{h,t})}{Var(w_t^j)} \tag{6}$$

Equation (5) encodes the term structure, but cannot be directly estimated since the EMPS w_t^j are data, but the monetary policy innovations ν_t are not. The next section describes how to estimate the term structure using instrumental variables.

3.2 Estimation Strategy

Estimating the γ_h^j coefficients from equation (5) faces several challenges: ν_t is unobserved, it is unknown how it relates to the MPR r_t, and the MPR is not orthogonal to the endogenous variables x_t. To resolve these challenges, our estimation takes a 4-stage approach. An important assumption in our method is the availability of a battery of other well-identifies non-monetary macro shocks, z_t. We discuss these further in Sections 3.3 and 4.1 but for now we take their existence as given. The steps are:

1. Instrument for the endogenous variables x_t in the policy rule, using exogenous macroeconomic shocks z_t that are orthogonal to both u_t and the monetary policy shocks w_t^j.

2. Use the instrumented variables to estimate the policy rule coefficients $\hat{\phi}$ from equation (1). This is standard 2SLS estimation.

3. Calculate the implied residuals $\hat{r}_t$ using the estimated policy coefficients $\hat{\phi}$:

$$\hat{r}_t = y_t - x_t\hat{\phi} \tag{7}$$

   then whiten to find the estimated $\hat{\nu}_t$ innovations. In this step, we can project the residual $\hat{r}_t$ onto lagged values of y_t and x_t:[6]

$$\hat{r}_t = \sum_{\ell=1}^{L} y_{t-\ell}\varrho_{y,\ell} + x_{t-\ell}\varrho_{x,\ell} + \nu_t \tag{8}$$

4. Use the estimated $\hat{\nu}_t$ innovations to estimate the term structure γ_h^j of EMPS j from equation (5).

The 4-stage approach for estimating the γ_h^j coefficients is convenient because it is linear, and there is a closed form expression for the estimator. Proposition 1 gives the expression using the following notation. We stack lags of observables in the row vector

[6] This is preferable to regressing on lags of $\hat{r}_t$ which include estimation error, and also do not give a nice closed form solution for the standard errors.

$\mathbf{x}_t \equiv \begin{pmatrix} y_{t-1} & x_{t-1} & \ldots & y_{t-L} & x_{t-L} \end{pmatrix}$ which includes L lags of y and x. This allows us to write the whitening regression (8) as

$$\hat{r}_t = \mathbf{x}_t \varrho + \nu_t \tag{9}$$

Similarly, we stack lags of EMPS in the vector $\mathbf{w}_t \equiv \begin{pmatrix} w_t^j & w_{t-1}^j & \ldots & w_{t-H_w}^j \end{pmatrix}$ which allows us to write the fourth regression as

$$\hat{\nu}_t = \mathbf{w}_t \gamma + u_t \tag{10}$$

where we have suppressed the j superscript for readability. X, Z, and W are matrices of the endogenous variables, instruments, and EMPS, respectively. Each row corresponds to a time t observation. y and u are vectors of policy observations and equation (5) residuals, respectively. $\mathbf{X}$ denotes the matrix of $\mathbf{x}_t$ observations, and we write the residual projection matrix as $M_{\mathbf{X}} \equiv I - \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'$. Lastly, $P_Z \equiv Z(Z'Z)^{-1}Z'$ denotes the matrix projecting onto the instruments.

Proposition 1 *The 4-stage estimator $\hat{\gamma}$ is given by*

$$\hat{\gamma} = (W'W)^{-1}W'M_{\mathbf{X}}(I - X(X'P_Z X)^{-1}X'P_Z)y$$

Proof: Appendix A

The $\hat{\gamma}$ coefficient vector can be estimated by four independent OLS regressions or in one step, following Proposition 1. Then the β_h^j coefficients can be calculated from the γ_h^j coefficients using equation (6). The closed form expression is also useful because it allows for easy derivation of the estimation properties of our method.

An ancillary benefit of our method is that we get clean estimates of the Taylor rule coefficients, the $\hat{\phi}$. These are given by:

$$\hat{\phi} = (X'P_Z X)^{-1}X'P_Z y \tag{11}$$

The intuition is that by using a battery of non-monetary shocks we can identify the systematic part of the policy rule by isolating variation in x_t independent of monetary policy.

3.3 Theoretical Properties

We prove that if the macroeconomic shocks are valid instruments, then the 4-stage estimation approach is unbiased. The key conditions are that the instruments are orthogonal to all terms on the right-hand side of equation (5): the w_t^j EMPS and the u_t residuals. The first condition is easy to satisfied: z_t can always be orthogonalized with respect to the observed EMPS. The second condition is theoretical: the macroeconomic shocks must not contain any information about the monetary policy residual. This is the typical exclusion restriction, and requires whichever shocks used as instruments to have been carefully identified.

Proposition 2 *If $Z'W = 0$ and $\mathbb{E}[Z'u] = 0$, then the 4-stage estimator is unbiased.*

Proof: Appendix A

The 4-stage estimator also has closed form standard errors. Proposition 3 gives the conditional variance of the estimator, if the same orthogonality assumptions hold for the instruments.

Proposition 3 *If $Z'W = 0$ and $\mathbb{E}[Z'u] = 0$, then the conditional variance of the $\hat{\gamma}$ estimator is*

$$Var\left(\hat{\gamma}|W, X, Z\right) =$$
$$(W'W)^{-1}W'M_{\mathbf{X}}\left(I - X(X'P_ZX)^{-1}X'P_Z\right)\Omega\left(I - X(X'P_ZX)^{-1}X'P_Z\right)' M_{\mathbf{X}}W(W'W)^{-1}$$

where $\Omega = \mathbb{E}[uu']$.

Proof: Appendix A

To actually calculate the standard errors, a consistent estimate of Ω is needed as usual. Because Proposition 1 ensures that γ is estimated consistently, this can be obtained using the estimated residuals $\hat{u}_t$ from equation (10), and then calculating the sample covariance matrix of the residuals with appropriate restrictions.

3.4 Generalization with Smoothing

The final stage of the 4-stage estimator is effectively a local projection (Jorda, 2005) because the EMPS in equation (5) are orthogonal. Local projections have many appealing properties, including that they are unbiased, which allowed us to prove that the entire 4-stage estimator is unbiased (Proposition 2). However, local projection estimates have large errors. Li et al. (2024) show that penalized local projections perform very well; allowing for a small amount of bias can substantially shrink the estimator variance. When considering the bias-variance trade-off, one's objective would have to place almost no weight on minimizing variance in order to prefer unpenalized local projections.

Therefore, we generalize our 4-stage estimator to allow for a penalty to reduce estimator variance. Specifically, in the 4th stage, we estimate a "smooth local projection" (Barnichon and Brownlees, 2019), which approximates an IRF with a set of smooth basis functions. Besides its popularity, this is an appealing method because it can be represented as a ridge regression. This means that we can write the generalized 4-stage estimator in closed form and derive standard errors.

Appendix B describes how to estimate the canonical smooth local projections as a standard ridge regression. In this appendix, Proposition 9 defines the appropriate penalty matrix $\mathbf{P}_B$. The penalty parameter λ controls the degree of smoothing, and is selected by cross-validation. Proposition 4 gives the generalized *smoothed 4-stage estimator*. We call it "generalized", because it nests the original 4-stage estimator (Proposition 1) when the penalty is set to $\lambda = 0$.

Proposition 4 *The smoothed 4-stage estimator $\hat{\gamma}_\lambda$ for penalty parameter λ is given by*

$$\hat{\gamma}_\lambda = \left(W'W + \lambda \mathbf{P}_B\right)^{-1} W' M_{\mathbf{X}} (I - X(X'P_Z X)^{-1} X' P_Z) y$$

and the conditional variance is

$$\begin{aligned} Var(\hat{\gamma}^j | W^j, X, Z, y) = & \left((W^j)' W^j + \lambda \mathbf{P}_B\right)^{-1} (W^j)' \\ & M_{\mathbf{X}} \left(I - X(X'P_Z X)^{-1} X' P_Z\right) \Omega \left(I - X(X'P_Z X)^{-1} X' P_Z\right)' M_{\mathbf{X}} \\ & W^j \left((W^j)' W^j + \lambda \mathbf{P}_B\right)^{-1} B' \end{aligned} \quad (12)$$

Proof: Appendix B.2

We use the smoothed 4-stage estimator throughout the following empirical work.

4 Estimated Term Structures

In this section, we estimate the term structures of popular EMPS using our proposed methodology. We first describe the data used for the estimation, including the different EMPS series and the macroeconomic instruments. Then we present the estimation results, highlighting the heterogeneity in the term structures of different EMPS. We also provide a summary statistic to represent the relative importance of news for each EMPS and discuss the implications of our findings. Finally, we report a summary of the findings of a much more extensive validation exercise in Appendix E using simulated data from a standard New Keynesian model.

4.1 Data

Our method requires two types of data: monetary policy shocks from the literature, and other macroeconomic instruments and series used to estimate the policy rule.

4.1.1 Monetary Policy Shock Data

We estimate the term structure of monetary policy news for a variety of well-known EMPS. They are summarized in Table 1.

Shock Source	Method	Notes	Range
Gertler and Karadi (2015)	HFI	30 min. window around FOMC decisions	1990:M1-2007:M12
Jarociński and Karadi (2020)	HFI	pure monetary shock purged of Fed information	1990:M1-2016:M12
Bundick and Smith (2020)	HFI	2 shocks to term structure uncertainty	1994:M2-2019:M06
Miranda-Agrippino and Ricco (2021)	HFI	Orthogonalized w.r.t. Greenbook forecasts	1991:M1-2009:M12
Bu et al. (2021)	HFI	Alternative without intraday data	1994:M2-2024:M12
Bauer and Swanson (2023)	HFI	Includes Fed minutes and speeches	1988:M2-2023:M12
Swanson (2023)	HFI	Decomposed into 3 types of EMPS	1988:M2-2023:M12
Jarociński (2024)	HFI	Decomposed into 4 types of EMPS	1990:M2-2024:M09
Romer and Romer (2004)	Narrative	Orthogonalized w.r.t. Greenbook forecasts	1983:M1-2007:M12
Aruoba and Drechsel (2024)	Narrative	Natural language processing of Fed docs	1982:M10-2008:M10

Table 1: Monetary Policy Shocks

Many shock series rely on intra-day data for identification, constructing instruments based on high-frequency changes in asset prices around FOMC announcements as a measure of monetary policy surprises. A classic example, Gertler and Karadi (2015) use 3-month-ahead federal funds futures rates. This horizon covers multiple FOMC meetings, and is interpreted as capturing both current rate decisions and forward guidance. Bauer and Swanson (2023) refines standard high-frequency methods by including additional policy events (e.g. speeches and press conferences) to the usual FOMC announcements to add observations, while also orthogonalizing with respect to high frequency data to ensure that the EMPS series is unforecastable. Swanson (2023) applies these refinements to the Swanson (2021) methodology, which uses multiple asset prices to construct three distinct EMPS (the "target rate", "forward guidance" and "large-scale asset purchases" (LSAP)) that correspond roughly to effects at short, medium, and long-term yields.

One concern with high-frequency EMPS is that it includes a "Fed information effect" (Romer and Romer, 2000; Nakamura and Steinsson, 2018) where the central bank reveals private information about the state of the economy, which is independent of its policy residuals. We include two EMPS series that attempt to isolate the information effects from true policy shocks. Jarociński and Karadi (2020) measure high-frequency changes in interest rates and stock prices, and use sign-restrictions to isolate information from policy shocks, assuming that information moves rates and stock prices in the same direction, while policy has opposite effects. Miranda-Agrippino and Ricco (2021) identify a pure policy shock by orthogonalizing the EMPS with respect to internal Fed forecasts.

We also use two shocks identified with narrative methods. The classic Romer and Romer

(2004) shock (updated by Wieland and Yang (2020)) identifies policy actions motivated by the Fed's policy stance, rather than reactions to contemporaneous economic data, by orthogonalizing with respect to internal forecasts. In a modern refinement, Aruoba and Drechsel (2024) incorporate substantially more information, via natural language processing of internal Fed documents. Then they orthogonalize interest rate changes with respect to both forecasts and the text-based time series.

4.1.2 Data for Estimating the Monetary Policy Rule

In our baseline method, we specify the monetary policy rule (1) with the Effective Federal Funds rate as the policy variable, and with unemployment and PCE inflation on the right-hand side.

Shock Source	Method	Notes	Range
Government Spending Shocks			
Romer and Romer (2016)	Narrative	Social Security expansions	1951:M1-1991:M12
Fieldhouse et al. (2018)	Narrative	Government housing purchases	1952:M11-2014:M12
Oil Shocks			
Känzig (2021)	HFI	Oil supply news	1975:M1-2023:M6
Baumeister and Hamilton (2019)	SVAR	Oil supply, consumption/inventory demand	1975:M2-2024:M3
Other Shocks			
Kim et al. (2022)	External	ACI severe weather shocks	1964:M4-2019:M5
Adams and Barrett (2024)	SVAR	Shocks to inflation expectations	1979:M1-2024:M5

Table 2: Structural Shock Instruments

To address endogeneity concerns in estimating the Taylor rule, we employ instrumental variables (IVs) drawn from the literature. Over the last decade, the collection of well-identified macroeconomic shocks has expanded substantially. However, our options are limited because we require monthly series. Still, we were able to collect six monthly instruments that represent a diverse variety of shocks. They are summarized in Table 2.

Our first two instruments are related to government expenditures. We utilize the narrative measure of transfer payment shocks constructed by Romer and Romer (2016). This measure uses historical accounts of Social Security benefits to identify changes in transfer payments that are not a systematic response to macroeconomic conditions. To capture government spending shocks, we use the Fieldhouse et al. (2018) narrative instrument constructed from significant regulatory events impacting federal housing agency mortgage holdings. This series captures the ex ante impact of policy changes on the capacity of agencies to purchase mortgages. It focuses on non-cyclically motivated policy interventions by the federal government, excluding changes resulting from the agencies' regular response to market developments. These non-cyclically motivated policy shifts provide a source of exogenous variation in credit supply within the mortgage market.

Our next two instruments capture exogenous variations in the oil market. First, we use oil supply news shocks identified through high frequency changes in oil futures prices around OPEC production announcements (Känzig, 2021). Second, we employ structural oil shocks identified from a structural VAR by Baumeister and Hamilton (2019). This approach distinguishes contemporaneous shocks to oil supply and shocks to oil demand, and, unlike other methods, does not require that there is no short-run response of oil supply to the price.

We take severe weather shocks from the Actuaries Climate Index, a meteorological time series for severe weather. We take this series as exogenous, and use as shocks the statistical innovations calculated by Kim et al. (2022).

Finally, we use the Adams and Barrett (2024) inflation expectation shocks. This series is derived from a structural VAR that identifies exogenous shocks to inflation forecasts. To do so, the approach identifies the dimension of the VAR statistical innovation that causes survey forecasts to deviate from the rational expectation. In models where belief distortions are exogenous and stochastic, this method identifies the exogenous shock. Where data are unavailable for instruments we treat them as zeroes.

4.2 Estimation Results

In this section, we present the estimated term structures of each EMPS both numerically and graphically.

4.2.1 Estimated Taylor Rules

This section describes the first 2 stages of our 4-stage estimator: estimating the Taylor Rule. We find that the use of structural shocks as IVs leads to remarkably robust estimates for the inflation coefficient, especially compared to OLS approaches. Our estimated values are largely consistent with typical calibrations in theoretical models, with an inflation coefficient of roughly 1.5 across multiple specifications.

The results of the Taylor rule esitmation are shown in Table 3. In most cases we specify the FFR to depend on currently monthly inflation and real activity, as well as lags of the Taylor rule residual. In the baseline specification (first column), we use two variables in x_t: inflation, for which our preferred measure is the 12-month growth rate in the PCE index; and activity, for which we use Christiano-Fitzgerald filtered real GDP. We estimate the term structure up to two years after the shock, so $H_w = 24$. When whitening the monetary policy residuals, we orthogonalize with respect to six lags, setting $L = 6$.[7] Because instruments can have persistent effects, we include six lags of the IVs.[8] Table 3 also includes many alternative measures of real activity. Whether we use GDP growth, an alternative filter, industrial production, or unemployment affects the estimated coefficient on real activity, as expected. However, the inflation coefficients are largely unchanged, and generally satisfy the Taylor principle, that $\phi_\pi > 1$. We also include some specifications where we introduce additional variables. Including the excess bond premium has little effect. In constrast, the introduction of inflation forecasts (as measured either by the Michigan Survey or the Cleveland Fed) is the only specification we have found that substantially changes the size of the inflation coefficient. This is not surprising, as expectations in the data are highly correlated with current inflation, and if the Fed responds to both similarly, rules with different coefficients might be almost observationally equivalent.

We also consider alternative inflation measures. These results are reported in Table 4. All 12-month inflation measures tend to satisfy the Taylor principle. When we use 1-month measures, we find smaller coefficients. And using core PCE, which the Federal Reserve considers a better indicator than headline PCE of medium-term inflationary pressures, even the one-month measure conforms to the Taylor principle.

In Appendix C, we report several more variations. First, we allow for alternative lag lengths. Second, we drop various IVs from our estimation to ensure that no single category in Table 2 is driving our results. And third, our baseline Taylor rule is estimated using data beginning in January 1975 and omits the zero-lower-bound (ZLB) and Covid periods, but we consider alternative choices. Our Taylor estimates appear robust to all of these checks, except for the inclusion of the ZLB period, which is not totally surprising since policy rates are pinned to zero during this period, and thus invariant to macroeconomic conditions.

These regular results from the structural IV estimation contrast sharply with OLS estimates. OLS estimates from the literature vary considerably, and our findings are no different. We ran several OLS specifications, and the coefficient estimates are highly sensitive to specification choice. As an example, we also report in Appendix C OLS results with small differences in the lag structure, and found estimates that are highly dissimilar from each other, let alone our IV results. In contrast, our IV method produces results which are stable across multiple specifications and consistent with theory.

[7] We vary these choices in robustness checks.

[8] We estimate monthly GDP using a Kalman Smoother which matches the quarterly NIPA data and monthly consumption series.

	Baseline	GDP growth	IP	Unemployment	Add EBP	Add π_1^e, Clev.	Add π_1^e, Mich.
12-month PCE Inflation, demeaned	1.552***	1.559***	1.567***	1.370***	1.555***	-0.377***	2.629***
	(0.036)	(0.035)	(0.038)	(0.042)	(0.034)	(0.046)	(0.142)
GDP, CF-low-pass, demeaned	0.747***				0.739***	0.106	0.125
	(0.084)				(0.081)	(0.076)	(0.092)
GDP growth, annualized, demeaned		0.032***					
		(0.010)					
Industrial Production, CF low-pass filter			-0.099***				
			(0.031)				
Unemployment rate, departures from quadratic trend				0.005***			
				(0.000)			
Excess bond premium, demeaned					-0.180		
					(0.156)		
Cleveland Fed inflation expectations, 1 year, demeaned						2.025***	
						(0.061)	
Michigan inflation expectations, 1 year, demeaned							-1.836***
							(0.187)
Residual autocorrelation	0.95	0.95	0.96	0.96	0.95	0.91	0.91
R^2	0.37	0.45	0.43	0.40	0.36	0.78	0.48
Observations	569	569	569	569	569	485	533

Table 3: Estimated Taylor Rule Parameters: Different real variables

Table reports the estimated Taylor rule parameters from the second stage of the four-stage method using instrumental variables. Residual autocorrelation is the first order autocorrelation of the monetary policy residual, r_t. R^2 is calculated as the fraction of variance in the policy rate explained by the contemporaneous systematic part of monetary policy, $x_t\phi$, and so $1 - R^2$ is that explained by the monetary policy residual, r_t. Standard errors are reported in parentheses.

	Baseline	Inf. only	1m Inf.	1m, Inf. only	Core PCE	Core PCE, 1m	CPI
12-month PCE Inflation, demeaned	1.552***	1.540***					
	(0.036)	(0.038)					
1-month PCE Inflation, demeaned			0.649***	0.647***			
			(0.079)	(0.081)			
12-month Core PCE Inflation, demeaned					2.066***		
					(0.044)		
1-month Core PCE Inflation, demeaned						1.600***	
						(0.105)	
12-month CPI inflation, demeaned							1.155***
							(0.030)
GDP, CF-low-pass, demeaned	0.747***		-0.039		1.047***	0.577**	0.645***
	(0.084)		(0.143)		(0.092)	(0.232)	(0.079)
Residual autocorrelation	0.95	0.96	0.88	0.88	0.94	0.63	0.95
R^2	0.37	0.46	0.20	0.21	0.35	0.20	0.38
Observations	569	569	569	569	569	569	569

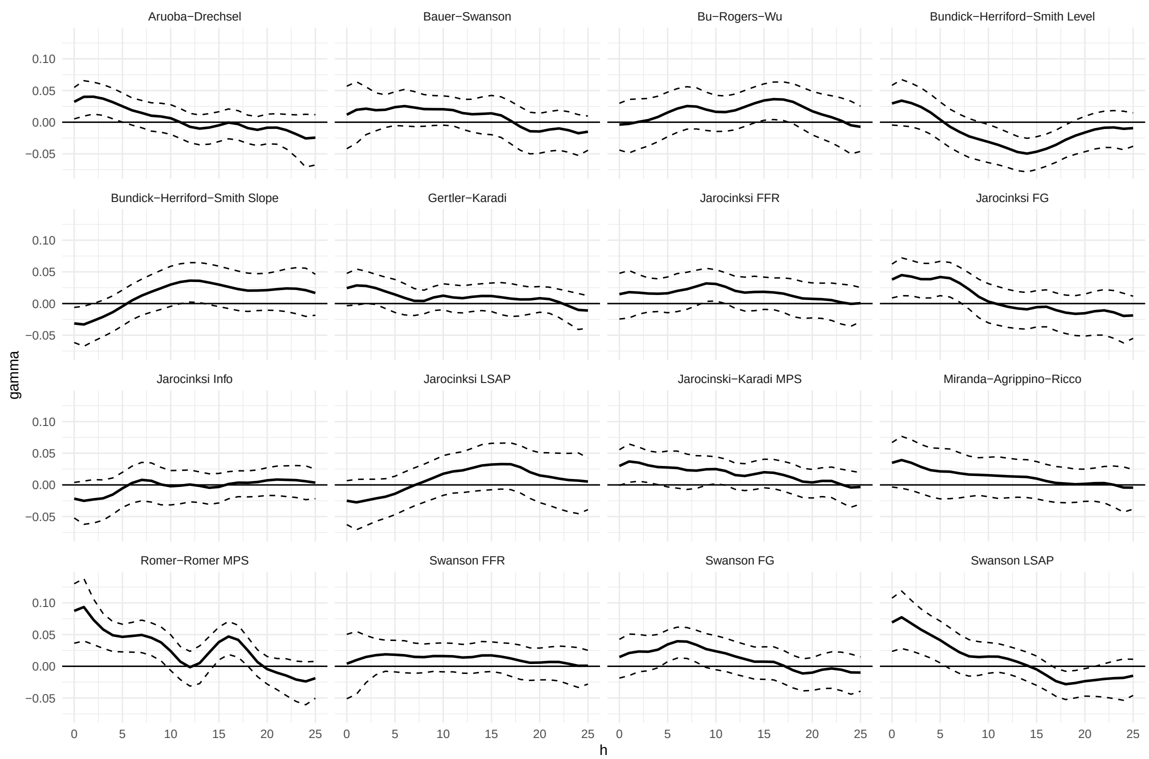
Table 4: Estimated Taylor Rule Parameters: Different inflation measures

Table reports the estimated Taylor rule parameters from the second stage of the four-stage method using instrumental variables. Residual autocorrelation is the first order autocorrelation of the monetary policy residual, r_t. R^2 is calculated as the fraction of variance in the policy rate explained by the contemporaneous systematic part of monetary policy, $x_t\phi$, and so $1 - R^2$ is that explained by the monetary policy residual, r_t. Standard errors are reported in parentheses.

4.2.2 Estimated Term Structures

Figure 2 plots the estimated term structure of monetary policy news for each EMPS. The further a term structure curve deviates from zero, the more information the EMPS has about monetary policy at that horizon. The figure immediately reveals heterogeneity across the shocks. Some have spikes at low horizons, others have most of their weight in the middle, and most – but not all – decay to zero at long horizons.

It is striking that all shocks have a non-trivial term structure at horizons longer than $h = 0$. That is, even well-identified shocks typically include information about both monetary surprises and forward guidance. For shocks derived from high-frequency methods, this might arise either because Fed announcements genuinely do include correlated information, or because the high frequency variables used to inform the magnitude of the shock are inherently forward-looking.



Dashed lines show 95 percent confidence intervals.

Figure 2: Estimated Term Structures

Figure shows the estimated γ_h^j coefficients, i.e. the impact of each identified monetary policy shock h periods later on the monetary policy innovation $\hat{\nu}_{t+h}$.

When interpreting the term structures in Figure 2 it is helpful to have a summary statistic which represents the relative importance of news for a given EMPS. To do so, we use the R_k^2 statistic, which captures how much of the information in an EMPS is due to news at horizon k.

Proposition 5 *The share R_k^2 of variation in monetary policy innovation ν_t that is explained by an EMPS at horizon k is*

$$R_k^2 \equiv \frac{Var(\nu_t | w_{t-k}^j)}{Var(\nu_t | \{w_{t-h}^j\}_{h=0}^{H_w})} = \frac{(\gamma_k^j)^2}{\sum_{h=0}^{H_w} (\gamma_h^j)^2}$$

Proof: Appendix A

Table 5 reports several of these statistics for each monetary policy shock, calculated using the smoothed 4-stage estimator.[9] The first column is $R_{0:1}^2$, which is the share of the EMPS that is due to an "immediate" change in the monetary policy innovation, i.e. either in the current or next month. There is substantial heterogeneity. The EMPS that are most driven by the immediate horizons are the Romer and Romer (2004) narrative shocks and the Swanson (2023) LSAP shock. This latter shock may appear unintuitive, but serves as an informative example. The LSAP shock has – by design – little effect on short-run interest rates. But it has a sizeable and negative effect on short-run real activity, so in the estimated Taylor rule, a large change in real activity without a corresponding change in the FFR requires a movement in the monetary policy residual. In contrast, the LSAP shock identified by Jarociński (2024), which uses a similar estimation methods but different data, shows considerable information content at longer horizons.

To summarize the forward guidance content of the EMPS, we calculate three components. The second column of Table 5 reports the sum of R_k^2 for $2 \leq k \leq 6$. This is *short-run news*, which is realized in the remaining half year after the immediate horizons. Column 3 reports *medium-run news*, which sums the R_k^2 statistic for next half year (months $7 - 12$), and the final column reports *long-run news*, which occurs over the following year.

Paradoxically, some of the EMPS that are least like a surprise are the Swanson (2023) and Jarociński (2024) Federal Funds Rate (FFR) shocks: nearly all of their variation is due to news.[10] How is it possible that possible that the Swanson and Jarociński FFR shocks

[9] We set the smoothing parameter to $\lambda = 30$. This was chosen by initially minimizing the rolling out-of-sample errors for each EMPS separately. That is, for each of a large set of values of λ we estimate $\hat{\gamma}_\lambda$ repeatedly on a series of extending subsets of the data, each beginning at the (same) sample start date but but incrementing the end month by one for each element of the series. For each data subset (the minimum subset length is 10 years) we compute the out-of-sample errors on equation (10) for the first 12 months after the end date. We then choose the value of λ which minimizes the average error across the extending windows. This approach is analogous to cross-validation, in that is minimizes the out-of-sample errors, but it preserves the time series structure of the data. But because this results in terms structures which depend differently on smoothing across the different EMPS. And so for comparability we set a common value for λ in our baseline results, which is close to the average of the EMPS-specific optimal values. We consider alternate values of λ in the robustness checks found in Section 6.

[10] We show in a variety of robustness checks in Section 6 that across all specifications, these shocks are

Shock	$R^2_{0:1}$	$R^2_{2:6}$	$R^2_{7:12}$	$R^2_{13:24}$
Bu-Rogers-Wu	0.00	0.07	0.23	0.69
Swanson FFR	0.03	0.34	0.31	0.32
Swanson FG	0.06	0.43	0.44	0.07
Jarocinksi FFR	0.07	0.18	0.53	0.23
Bauer-Swanson	0.07	0.34	0.33	0.25
Bundick-Herriford-Smith Level	0.10	0.09	0.26	0.56
Jarocinksi LSAP	0.12	0.15	0.13	0.60
Bundick-Herriford-Smith Slope	0.13	0.09	0.28	0.50
Jarocinski-Karadi MPS	0.20	0.39	0.26	0.15
Jarocinksi FG	0.23	0.54	0.11	0.12
Aruoba-Drechsel	0.27	0.50	0.05	0.18
Gertler-Karadi	0.30	0.42	0.09	0.19
Miranda-Agrippino-Ricco	0.34	0.42	0.18	0.06
Romer-Romer MPS	0.35	0.34	0.14	0.17
Swanson LSAP	0.36	0.44	0.05	0.15
Jarocinksi Info	0.39	0.44	0.04	0.13

Table 5: Decomposition of Term Structure by Horizon

Table reports the R^2_k measures in Proposition 5, summed over monthly horizons denoted in subscripts. For example, $R^2_{2:6}$ is the total variation in the Taylor residual attributable to 2- to 6-month news in a given identified monetary policy shock.

are mostly news, when they are identified as the *only* dimension of the data in which short-term rates move after a Fed event? The answer is that while such a shock includes all high-frequency FFR surprises, it is not purged of forward guidance. And the information conveyed by Fed communication is mostly forward guidance, which thus dominates the information content of the high frequency identified shocks. While what these papers identify as target rate shocks are not exorcised of forward guidance, they do at least concentrate their news term structures into the current year. In Section 5, we demonstrate how to use the estimated term structures to remove the remaining forward guidance information in these EMPS.

4.3 Validation

To check our method, we also run a Monte Carlo exercise, testing our method on simulated data in small and large samples. Appendix E reports the results in detail, but the key findings are 1) that our method delivers unbiased estimates of both the Taylor rule coefficients

majority news. However, the extremely low immediate information content ($R^2_{0:1}$) estimated for these two specific shocks in our baseline approach is probably not robust: many alternative specifications give larger values between 0.10 to 0.20.

and the term structure of EMPSs in small samples, and 2) that the confidence intervals for the term structure are accurate even with weak instruments for macroeconomic shocks. We also compare our results to OLS estimates and show that the latter perform poorly in small samples. Although biases in Taylor rule estimation are economically small, confidence intervals are spuriously tight. The mapping from Taylor coefficients to the term structure is sensitive to this, leading to highly unreliable inference when using OLS estimates.

Our findings mirror those of Carvalho et al. (2021), who find that the bias in OLS is small enough to be economically meaningless and, in small samples, preferable to traditionally-used GMM using lagged endogenous variables as instruments. One way to interpret these results in common with ours to think of them as picking different points on the trade-off between bias and maximizing informative variation. Lagged variable GMM reduces endogeneity bias but throws away informative contemporaneous covariation of interest rates and macro variables. OLS exploits this variation but at the price of biased Taylor rule coefficients. Carvalho et al. (2021) show that this price is one typically worth paying in applied work. Our method gives the best of both worlds. It exploits contemporaneous variation in the endogenous variables, but by isolating only the variation due to non-monetary shocks it completely corrects for endogeneity bias. As a result, it delivers unbiased estimates of both the term structure and the Taylor rule coefficients, as well as accurate inference, even in small samples and, for the term structure at least, even with weak instruments.

5 Synthetic Monetary Policy Shocks

This section explains how to construct a synthetic monetary policy shock with a desired term structures, and then does so for several examples, including a synthetic surprise.

5.1 Method

The EMPS that we estimate in the data have a variety of news term structures. Calculating these term structures is innately useful, because it allows us to interpret the shocks in standard DSGE models. However, we can also use the results from multiple EMPS to construct *synthetic* shocks with a new term structure. This allows us to study the effects of MPS of particular interest that are not directly estimated in the data.

Let $\vec{\gamma}^j$ denote the vector of *normalized* term structure coefficients for EMPS j, estimated from Proposition 1, where the EMPS has been normalized so that $Var(w_t^j) = 1$.

Proposition 6 *For a linear combination of EMPS $w_t^c = \lambda_a w_t^a + \lambda_b w_t^b$, the resulting term structure of monetary policy news $\vec{\gamma}^c$ is proportional to the linear combination of term* *structures:*

$$\vec{\gamma}^c \propto \lambda_a \vec{\gamma}^a + \lambda_b \vec{\gamma}^b$$

Proof: Appendix A

Proposition 6 is useful because it allows us to construct a synthetic MPS with a desired term structure by finding the appropriate linear combination of existing EMPS. This is a valuable property because it allows us to study specific types of monetary policy shocks that are relevant to theoretical models but not directly estimated in the data. For example, one might be interested in studying the effects of a true monetary surprise, as in Figure 1a. But we learned in Section 4.2 that the EMPS all feature news at multiple horizons. To estimate the effects of a surprise, we need to construct a synthetic MPS with a term structure $\vec{\gamma}^0 = \begin{pmatrix} 1 & 0 & 0 & ... \end{pmatrix}'$. Or, if we wanted to study a pure 1-period-ahead news shock, we would construct a synthetic MPS with term structure $\vec{\gamma}^1 = \begin{pmatrix} 0 & 1 & 0 & ... \end{pmatrix}'$. Indeed, the term structure of any h-period-ahead news shock is simply the corresponding basis vector. Proposition 7 states when this is feasible.

Proposition 7 *EMPS with normalized term structures in the set $\mathcal{J} = \{\vec{\gamma}^j\}$ can be used to construct any synthetic MPS s with term structure*

$$\vec{\gamma}^s \in span\left(\{\vec{\gamma}^j\}_{j\in\mathcal{J}}\right)$$

This property follows directly from Proposition 6. An immediate corollary is:

Corollary 1 *If $\mathcal{J}$ contains $H_w + 1$ EMPS with linearly independent term structures, then a synthetic MPS can be constructed with any term structure of horizon length up to H_w.*

In practice, the number of linearly independent EMPS may be less than the IRF horizon $H_w + 1$. In this case, the span of the term structures is a lower-dimensional vector space. The synthetic MPS can be constructed with any term structure in that space. If the term structure of interest (e.g. $\vec{\gamma}^0$) is not in the space, it must be approximated. The following Proposition explains how to do so.

Proposition 8 *Let $\Gamma_{\mathcal{J}}$ denote the matrix of normalized term structures for the linearly independent set $\mathcal{J}$ of observed EMPS, and let $\vec{\gamma}^i$ denote the term structure of interest. The term structure of the synthetic MPS $\vec{\gamma}^s$ that is closest to $\vec{\gamma}^i$ (in the Euclidean norm) is given by*

$$\vec{\gamma}^s = \Gamma_{\mathcal{J}}(\Gamma'_{\mathcal{J}}\Gamma_{\mathcal{J}})^{-1}\Gamma'_{\mathcal{J}}\vec{\gamma}^i$$

Proof: Appendix A

5.2 Synthetic Surprise and News

To estimate synthetic MPS, we take a step to improve parsimony. Many of the EMPS are estimated in a similar way, and have relatively colinear term structures; Figure 3 presents their absolute correlations. Therefore, we selected a subset of six EMPS that are relatively dissimilar, as measured by the average Euclidean distance to the other vectors $\vec{\gamma}^j$. The EMPS we use for the synthetic exercise are: Aruoba-Drechsel, Bauer-Swanson, Miranda-Agrippino and Ricco, Jarociński-Karadi, and the Swanson and Jarociński FFR shocks. These shocks are also orthogonalized in some way to be purged of information effects, which makes the results simpler to interpret. In Appendix D, we repeat this exercise, constructed from alternative subsets.

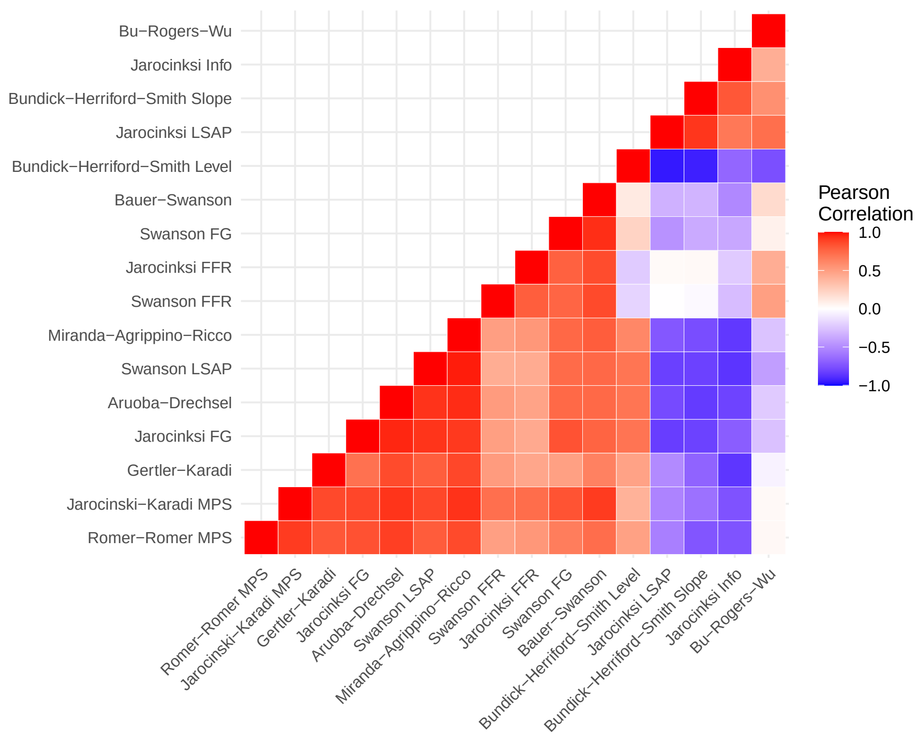


Figure 3: Term Structure Correlations

Figure shows absolute cross-correlations of the estimated term structures of candidate EMPS, ordered from least to most dissimilar top to bottom.

Using the six empirical shocks, we construct three synthetic MPS: an immediate interest rate tightening, short-term forward guidance, and long-term forward guidance. Each synthetic MPS is targeted to be an equally-weighted collection of news shocks at similar horizons. Since so many shocks come from high-frequency methods and because the relevant policy announcements can range from the first to the last day of ht month, we define the immediate shock as news about the current month and 1 month ahead. The short-term forward guidance shock contains news in the 2-6-month-ahead window and the long-term forward guidance shock contains news about the remaining year and a half.

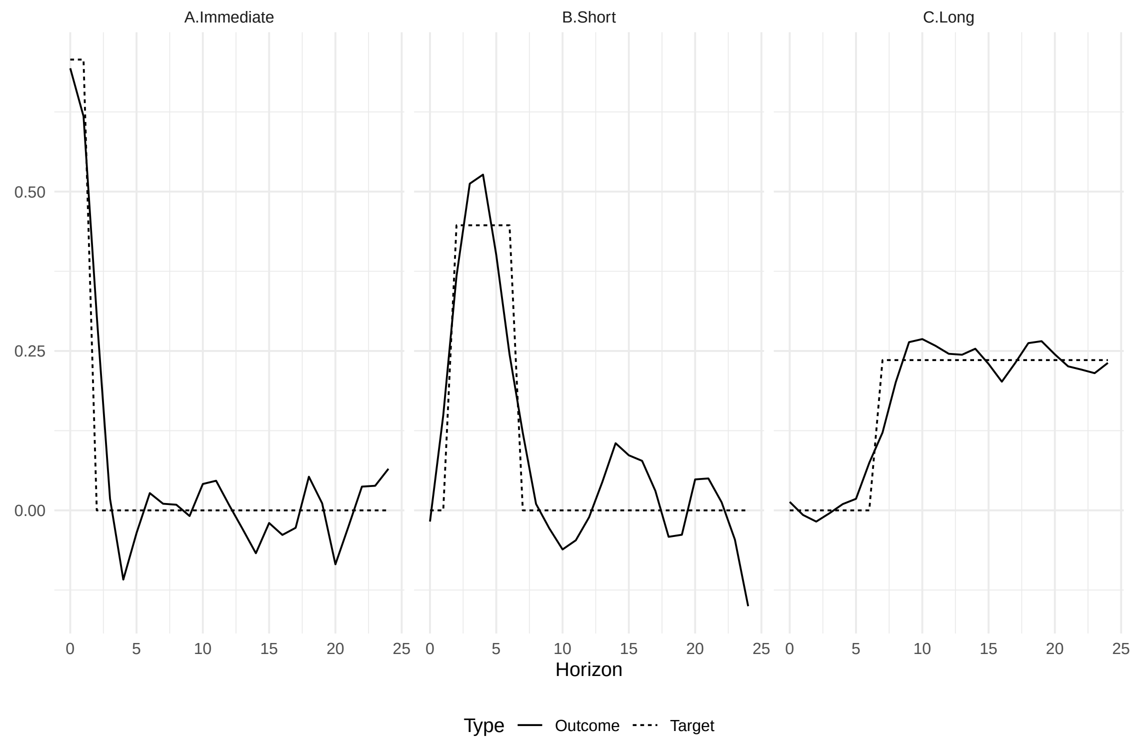


Figure 4: Target and Matched Synthetic MPS Term Structures

Figure shows target and matched term structures for synthetic policy shocks, $\vec{\gamma}^s$ and $\vec{\gamma}^i$ respectively.

Figure 6 plots the term structures for these synthetic MPS. The dotted lines are the target term structures, i.e. vector $\vec{\gamma}^i$ in the notation of Proposition 8. Because we use only six empirical shocks, we cannot match these targets exactly. But we get close: the solid lines in Figure 6 are the actual term structures of our synthetic MPS, which approximately match the targets. A solid line corresponds to the vector $\vec{\gamma}^s$ in Proposition 8.[11]

We estimate the effects of the synthetic MPS on the macroeconomy using a proxy VAR. Specifically, we estimate a standard VAR similar to Gertler and Karadi (2015), which includes 1-year yields, log CPI, log industrial production, and the excess bond premium (EBP). We then construct the responses to synthetic shocks by projecting each synthetic

[11]Note that the target term structures combine news over multiple horizons; this contrasts to the single horizon examples described in Section 5.1. We found that the empirical MPS are much worse at accurately approximating single horizon news (i.e. standard basis vectors) than the multiple-horizon targets that we adopted.

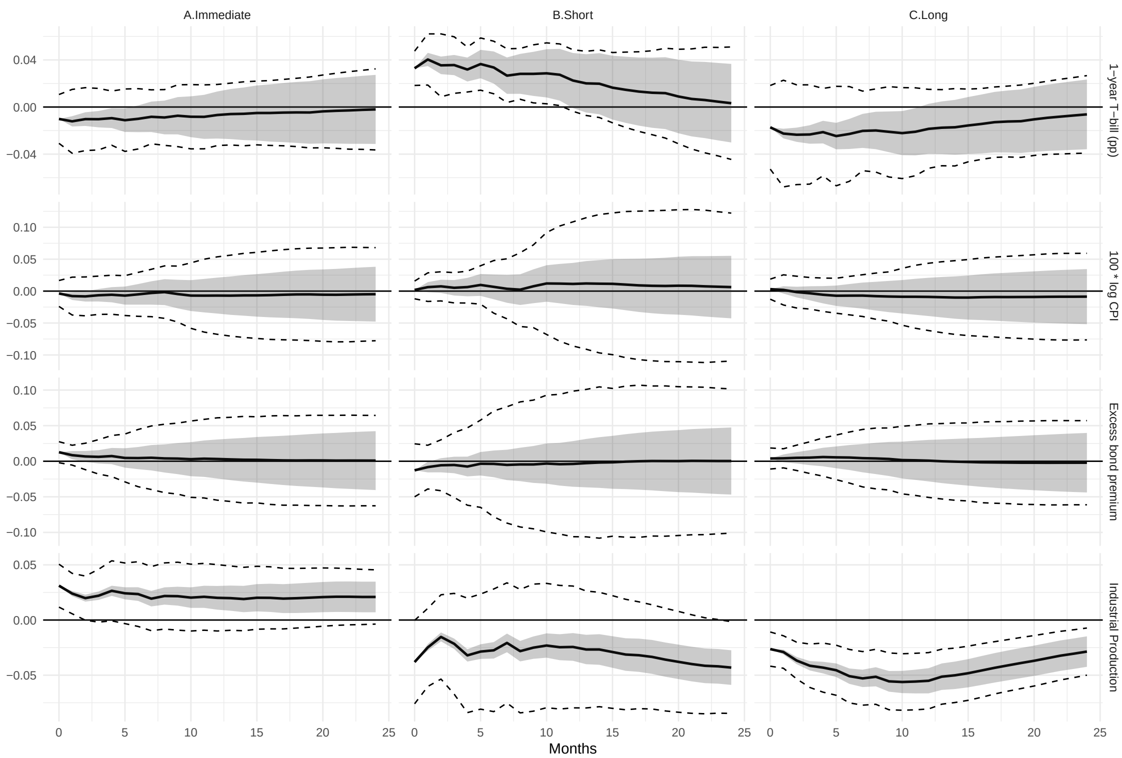


Figure 5: Impulse Responses to Synthetic Shocks

Figure shows impulse responses from a VAR to synthetic monetary policy shocks, whose term structures of monetary policy news appear in Figure 6. The first column shows responses to the immediate shock, which has news on impact and in the first following month. The second column shows responses to the short-run news shock, which has news about months $2-6$. The third column shows responses to the long-run news shock, which has news about months $7-24$. The shaded region indicates the 90% confidence interval conditional on the impact values; the dotted lines indicate the 90 % confidence intervals accounting for impact uncertainty. The VAR lag length is 11 and is chosen by AIC.

shock onto the reduced form residuals. This gives us the appropriate weighting on the reduced form shocks consistent with a synthetic term structure shock. An advantage of this approach is that we can apply the same method to the EMPS shock series, projecting them onto a common reduced-form VAR. This allows us to compare the impact of the shocks alone, holding the VAR autocovariances, and hence the dynamics of macroeconomic propagation, fixed.

Figure 5 presents the estimated IRFs to the immediate, short-term, and long-term synthetic MPS. At first glance, the immediate shock might resemble a textbook MPS – rates go down and real activity rises – however, the signs are both inconsistent with the New Keynesian prediction. The immediate shock is a synthetic monetary policy *tightening*. This is a shock that flattens the yield curve; the 1-year rate declines even though the synthetic shock increases the Federal funds rate. At the same time, this shock causes an

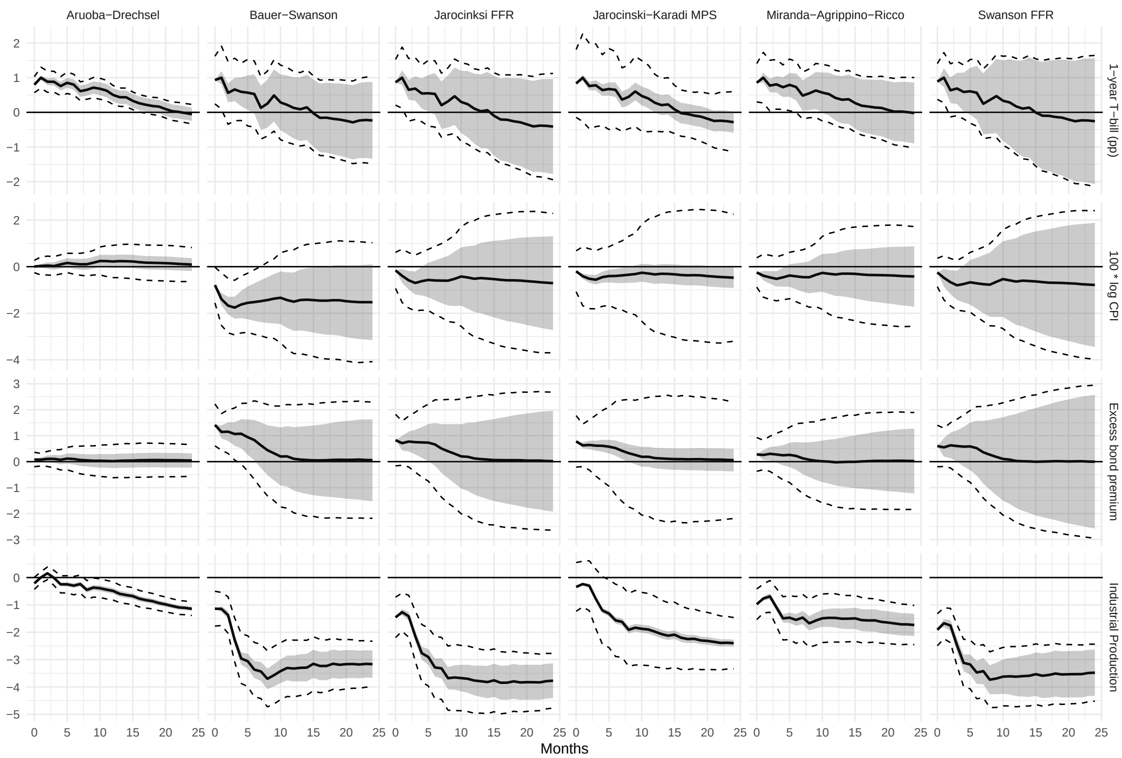


Figure 6: Impulse Responses to Estimated MPS

Figure shows impulse responses from a VAR to each of the underlying empirical MPS. Each column shows the response to a different shock. The shaded region indicates the 90% confidence interval conditional on the impact values; the dotted lines indicate the 90 % confidence intervals accounting for impact uncertainty. The VAR lag length is 11 and is chosen by AIC.

immediate economic expansion.

The short-run news shock resembles the familiar, conventional monetary policy contraction: interest rates increase, while prices and real activity both fall. In contrast, the long-run news shock counterintuitively decreases rates in the short run. However, this effect is not inconsistent with the textbook model: the forward guidance shock is contractionary, so short-term monetary policy is endogenously stimulative through the Taylor rule. Generally, none of the shocks have any statistically discernible impact on prices, something that is largely inherited from the underlying EMPS.

These results reveal that empirical MPS contain heterogeneous effects from news at different horizons, but this heterogeneity is unobserved without breaking apart the term structure into its components. To illustrate this finding, Figure 6 plots the IRFs for each component EMPS, as estimated by the same standard VAR. The empirical MPS are relatively homogeneous: they all predict higher rates, reduced real activity, and zero or modest deflation. So how can the synthetic shocks be inconsistent with these broad patterns? After all, the synthetic shock IRFs in Figure 5 are simply a linear combination of the empirical shock IRFs in Figure 6; why don't they inherit the main qualitative effects?[12] The key is that they are not a *convex* combination, and the IRFs to these 6 shocks span a wide variety of possible outcomes beyond contraction, deflation, and higher rates.

We learn that the relatively homogeneous empirical MPS are mixing heterogeneous effects of different news horizons. The standard rate increases are driven by *short-run news.* The standard deflation is driven entirely by *long-run news.* And the rapid contractions are not a property of *immediate news.* How are we able to uncover these lessons? Because even though they are qualitatively similar, quantitative variation in the EMPS IRFs are associated with variation in their term structures of monetary policy news.

Some of these results are consistent with the standard New Keynesian model, while some are puzzling. For example, it is typical that future monetary policy contractions can cause rates to decline in anticipation. However, the short-run expansionary effect of an immediate shock is hard to explain with the textbook model. Historically this type of "output puzzle" has been hypothesized to be caused by central bank information effects, i.e. the Fed's actions reveal its private information about the economy. However, the EMPS that we employ are all orthogonalized to some degree, and yet still feature an output puzzle from the immediate synthetic shock. Moreover, when we repeat our synthetic shock exercise using a smaller set of EMPS that are explicitly purged of the Fed information effect (Appendix D), the immediate synthetic MPS still causes short-run expansions. We also repeat the exercise with a larger set of EMPS to more closely match the target term structure; the results still resemble our baseline. This suggests that central bank information effects may not be the only explanation for observed output puzzles.

6 Robustness

In this section, we describe how our results depend on several assumptions made in our approach.

First, we adopted many alternative approaches for our IV estimation of the Taylor rule. We discuss these in depth in Section 4.2.1, and include further robustness checks in Appendix C. We found relatively robust estimates of the Taylor rule, particularly the inflation coefficient. But how sensitive are our term structure estimates to these assumptions?

To answer this question (and others that follow) we re-estimated our main term structure summary under several alternative specifications. Figure 7 reports how the estimated term structure for each EMPS depends on our the variables included in the Taylor Rule, x_t.

[12] For this reason, the synthetic shocks' wide confidence intervals in Figure 5 are inherited from the EMPS' wide confidence intervals in Figure 6.

Each panel is associated with a single EMPS, and each column in the panel is a different specification. Within each column, the bars add up to one, and each bar represents the share of the term structure that is due to news at each horizon: impact, short, medium, and long. These are the same statistics as are reported in Table 5. This figure shows that the estimated term structures are relatively consistent across specifications. For EMPS whose news is concentrated at low horizons in our baseline estimation, this also tends to be true for other specifications. For example, the Aruoba-Drechsel shock is mostly short-horizon news for all specifications. In contrast, the Bu-Rogers-Wu shock is mostly long horizon news for all specifications. The most substantial exceptions are the Swanson and Jarociński HFI Fed Funds shocks, which are almost entirely forward guidance in the baseline, but less so when alternative measures of real activity are used.

In Figure 8, we repeat this exercise, varying the sample and estimation methods. One obvious concern about our results is that the smoothing process we apply to the term structure is driving our finding that EMPS typically have long-term effects. After all, smoothing dampens high-frequency fluctuations and so could downplay the impact of the EMPS at short horizons, risking a spurious finding that EMPS effects are at longer horizons than they actually are. Figure 8 shows that this is not the case. There, we report results for two versions, titled "low smoothing" and "no smoothing", which respectively set the smoothing parameter to $\lambda = 10$ (approximately the lowest value across the baseline estimates for the different EMPS) and $\lambda = 0$. For even small values, the smoothing parameter does not meaningfully change our results, although when smoothing is eliminated entirely, several shocks lose most of their immediate news content. So, if anything, term structure smoothing is reallocating effects from longer horizons to shorter. Changes in the instrument lags have little effect on our results, but changes in sample period do. In particular, including periods where the Federal Reserve was constrained by the zero lower bound on interest rates yields quite different results. This is likely less a product of a true change in the term structure of monetary policy shocks, and rather a product of the Taylor rule breaking down in this period – when the ZLB binds, the Fed no longer responds to marginal changes in inflation or output.

7 Conclusions

In this paper, we address two important questions about the identification of monetary policy shocks.

The first is: how should we compare different estimated monetary policy shocks? The framework we develop in this paper is based on the idea that identified monetary policy shocks identify a common type of exogenous disturbance, but vary in its anticipated timing.

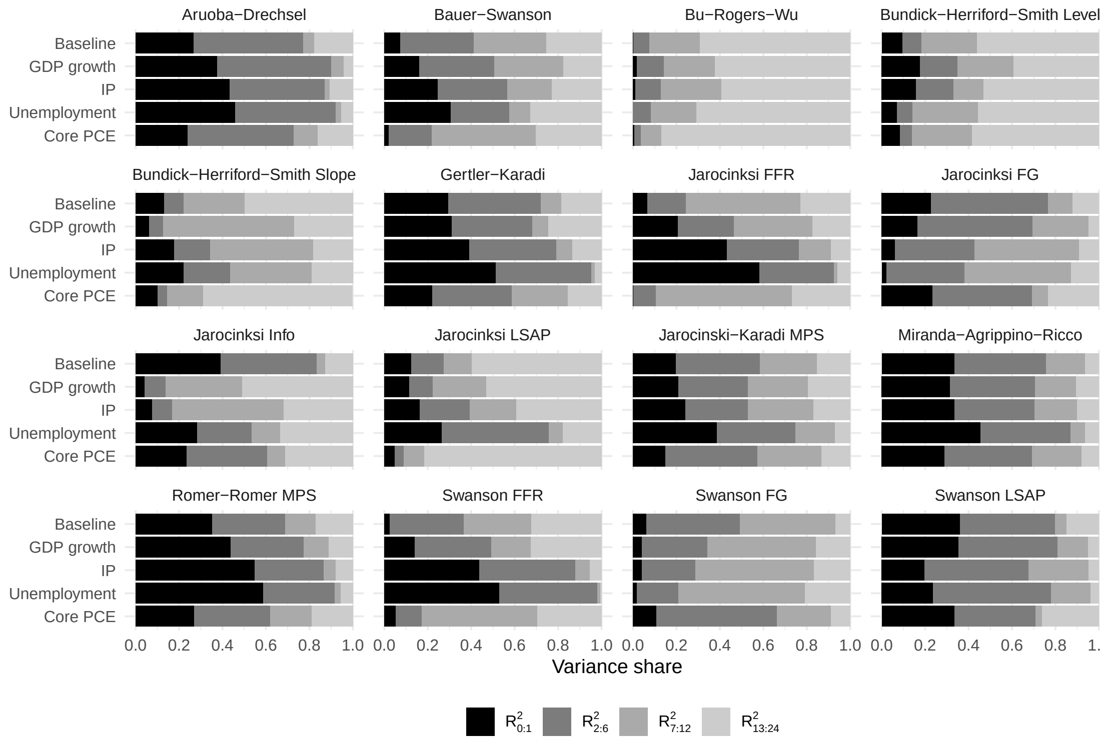


Figure 7: Term Structure Variance Decomposition: Robustness to Taylor rule variables.

Figure shows the how the variance decomposition changes for different versions of the estimated term structure. "Baseline" corresponds to the numbers in Table 5. Different versions (labeled on the x axis) correspond to the alternate Taylor rule estimation methods with the same names as in Tables 3 to 8.

By applying this method to identify the differences in sixteen well-known monetary shock series, we decompose each into its surprise and news components, the latter at multiple horizons. We find that most of these shocks have large news components.

Second, how can we map between empirical shocks and theory? By projecting fixed h-period ahead impulses onto imperfectly correlated empirical shocks, we can construct the responses to news shocks at multiple horizons as a linear combination of estimated impulse responses. In doing so, we are able to characterize the empirical responses of shocks which comport with theory. We show that positive monetary surprises are contractionary and deflationary, but that news at longer horizons increases output, employment, and prices. At very long horizons the effect of monetary policy news is negligible.

These results suggest several directions for future research. Most obviously, they provide a framework for evaluating future monetary policy shocks, allowing them to be compared to those already in the literature. However, our specific findings also give some guidance on how empirical identification of MPS might most valuably proceed. In particular, our

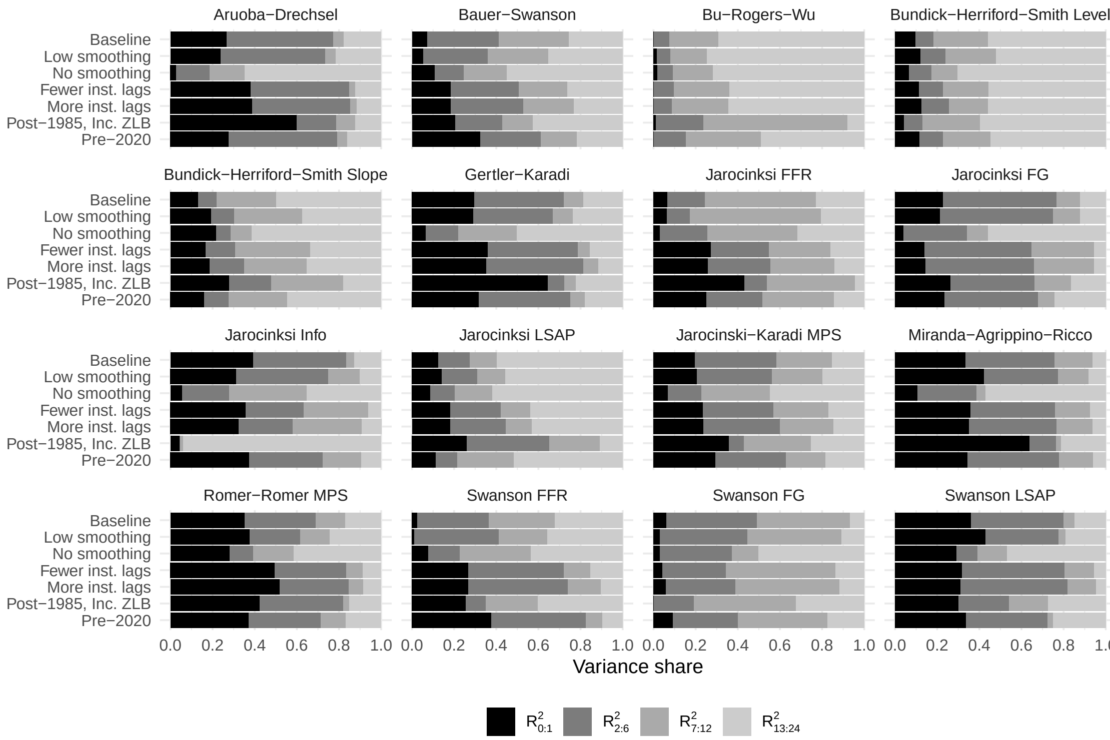


Figure 8: Term Structure Variance Decomposition: Robustness to sample and estimation method

Figure shows the how the variance decomposition changes for different versions of the estimated term structure. "Baseline" corresponds to the numbers in Table 5. Different versions (labeled on the x axis) correspond to the alternate Taylor rule estimation methods with the same names as in Tables 3 to 8.

results show that there is still much to be done to systematically capture monetary policy surprises distinct from news about the future. Beyond this, our findings on the measured effect of news shocks at multiple horizons set an empirical benchmark for future models to reflect.

References

Adams, Jonathan J. and Philip Barrett, "Shocks to inflation expectations," *Review of Economic Dynamics*, October 2024, *54*, 101234.

Altavilla, Carlo, Luca Brugnolini, Refet S. Gürkaynak, Roberto Motto, and Giuseppe Ragusa, "Measuring euro area monetary policy," *Journal of Monetary Economics*, December 2019, *108*, 162–179.

Aruoba, S. Borağan and Thomas Drechsel, "Identifying Monetary Policy Shocks: A Natural Language Approach," May 2024.

Barnichon, Regis and Christian Brownlees, "Impulse Response Estimation by Smooth Local Projections," *The Review of Economics and Statistics*, July 2019, *101* (3), 522–530.

_ **and Geert Mesters**, "Identifying Modern Macro Equations with Old Shocks*," *The Quarterly Journal of Economics*, November 2020, *135* (4), 2255–2298.

Bauer, Michael D. and Eric T. Swanson, "A Reassessment of Monetary Policy Surprises and High-Frequency Identification," *NBER Macroeconomics Annual*, May 2023, *37*, 87–155. Publisher: The University of Chicago Press.

Baumeister, Christiane and James D. Hamilton, "Structural Interpretation of Vector Autoregressions with Incomplete Identification: Revisiting the Role of Oil Supply and Demand Shocks," *American Economic Review*, May 2019, *109* (5), 1873–1910.

Brennan, Connor M., Margaret M. Jacobson, Christian Matthes, and Todd B. Walker, "Monetary Policy Shocks: Data or Methods?," November 2024.

Bu, Chunya, John Rogers, and Wenbin Wu, "A unified measure of Fed monetary policy shocks," *Journal of Monetary Economics*, March 2021, *118*, 331–349.

Bundick, Brent and A. Lee Smith, "The Dynamic Effects of Forward Guidance Shocks," *The Review of Economics and Statistics*, December 2020, *102* (5), 946–965.

Campbell, Jeffrey R., Charles L. Evans, Jonas D. M. Fisher, Alejandro Justiniano, Charles W. Calomiris, and Michael Woodford, "Macroeconomic Effects of Federal Reserve Forward Guidance [with Comments and Discussion]," *Brookings Papers on Economic Activity*, 2012, pp. 1–80. Publisher: Brookings Institution Press.

Carvalho, Carlos and Fernanda Nechio, "Do people understand monetary policy?," *Journal of Monetary Economics*, September 2014, *66*, 108–123.

— , — , **and Tiago Tristão**, "Taylor rule estimation by OLS," *Journal of Monetary Economics*, November 2021, *124*, 140–154.

Clarida, Richard, Jordi Galí, and Mark Gertler, "Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory," *The Quarterly Journal of Economics*, February 2000, *115* (1), 147–180.

Fieldhouse, Andrew J, Karel Mertens, and Morten O Ravn, "The Macroeconomic Effects of Government Asset Purchases: Evidence from Postwar U.S. Housing Credit Policy*," *The Quarterly Journal of Economics*, August 2018, *133* (3), 1503–1560.

Galí, Jordi, *Monetary policy, inflation, and the business cycle: an introduction to the new Keynesian framework and its applications*, Princeton University Press, 2008.

Gertler, Mark and Peter Karadi, "Monetary Policy Surprises, Credit Costs, and Economic Activity," *American Economic Journal: Macroeconomics*, January 2015, *7* (1), 44–76.

Gürkaynak, Refet S., Brian Sack, and Eric Swanson, "The Sensitivity of Long-Term Interest Rates to Economic News: Evidence and Implications for Macroeconomic Models," *American Economic Review*, March 2005, *95* (1), 425–436.

Hansen, Stephen and Michael McMahon, "Shocking language: Understanding the macroeconomic effects of central bank communication," *Journal of International Economics*, March 2016, *99*, S114–S133.

Jarociński, Marek, "Estimating the Fed's unconventional policy shocks," *Journal of Monetary Economics*, May 2024, *144*, 103548.

— **and Peter Karadi**, "Deconstructing Monetary Policy Surprises—The Role of Information Shocks," *American Economic Journal: Macroeconomics*, April 2020, *12* (2), 1–43.

Jorda, Oscar, "Estimation and Inference of Impulse Responses by Local Projections," *American Economic Review*, March 2005, *95* (1), 161–182.

Kim, Hee Soo, Christian Matthes, and Toan Phan, "Severe weather and the macroeconomy," *Federal Reserve Bank of Richmond Working Papers, 21-14R*, 2022.

Känzig, Diego R., "The Macroeconomic Effects of Oil Supply News: Evidence from OPEC Announcements," *American Economic Review*, April 2021, *111* (4), 1092–1125.

Li, Dake, Mikkel Plagborg-Møller, and Christian K. Wolf, "Local projections vs. VARs: Lessons from thousands of DGPs," *Journal of Econometrics*, March 2024, p. 105722.

McKay, Alisdair and Christian K Wolf, "What can time-series regressions tell us about policy counterfactuals?," *Econometrica*, 2023, *91* (5), 1695–1725.

Miranda-Agrippino, Silvia and Giovanni Ricco, "The Transmission of Monetary Policy Shocks," *American Economic Journal: Macroeconomics*, July 2021, *13* (3), 74–107.

Nakamura, Emi and Jón Steinsson, "High-Frequency Identification of Monetary Non-Neutrality: The Information Effect," *The Quarterly Journal of Economics*, August 2018, *133* (3), 1283–1330.

Romer, Christina D. and David H. Romer, "Federal Reserve Information and the Behavior of Interest Rates," *American Economic Review*, June 2000, *90* (3), 429–457.

_ **and** _ , "A New Measure of Monetary Shocks: Derivation and Implications," *American Economic Review*, September 2004, *94* (4), 1055–1084.

_ **and** _ , "Transfer Payments and the Macroeconomy: The Effects of Social Security Benefit Increases, 1952-1991," *American Economic Journal: Macroeconomics*, October 2016, *8* (4), 1–42.

Swanson, Eric T., "Measuring the effects of federal reserve forward guidance and asset purchases on financial markets," *Journal of Monetary Economics*, March 2021, *118*, 32–53.

_ , "The Macroeconomic Effects of the Federal Reserve's Conventional and Unconventional Monetary Policies," August 2023.

Wieland, Johannes F. and Mu-Jeung Yang, "Financial Dampening," *Journal of Money, Credit and Banking*, 2020, *52* (1), 79–113. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jmcb.12681.

A Proofs

Proposition 1. The OLS estimator for the third stage regression (9) is

$$\hat{\varrho} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\hat{R} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'(y - X\hat{\phi})$$

so $\hat{\nu}$ is given by

$$\hat{\nu} = \hat{R} - \mathbf{X}\hat{\varrho}$$

$$= (y - X\hat{\phi}) - \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'(y - X\hat{\phi}) = M_{\mathbf{X}}(y - X\hat{\phi})$$

The OLS estimator for the fourth stage regression (10) is

$$\hat{\gamma} = (W'W)^{-1}W'\hat{\nu} = (W'W)^{-1}W'M_{\mathbf{X}}(y - X\hat{\phi})$$

Finally, the 2SLS estimator is $\hat{\beta} = (X'P_Z X)^{-1}X'P_Z y$, so $\hat{\gamma}$ can be written

$$\hat{\gamma} = (W'W)^{-1}W'M_{\mathbf{X}}(y - X(X'P_Z X)^{-1}X'P_Z y)$$

■

Proposition 2. The following expectations are conditional on the data:

$$\mathbb{E}[\hat{\gamma}] = \mathbb{E}\left[(W'W)^{-1}W'M_{\mathbf{X}}(y - X\hat{\phi})\right]$$

$$= \mathbb{E}\left[(W'W)^{-1}W'M_{\mathbf{X}}(X\phi + R - X\hat{\phi})\right]$$

$$= \mathbb{E}\left[(W'W)^{-1}W'M_{\mathbf{X}}R\right] + \mathbb{E}\left[(W'W)^{-1}W'M_{\mathbf{X}}X(\phi - \hat{\phi})\right]$$

$$= \mathbb{E}\left[(W'W)^{-1}W'\nu\right] + \mathbb{E}\left[(W'W)^{-1}W'M_{\mathbf{X}}X(\phi - \hat{\phi})\right]$$

$$= \mathbb{E}\left[(W'W)^{-1}W'(W\gamma + u)\right] + \mathbb{E}\left[(W'W)^{-1}W'M_{\mathbf{X}}X(\phi - \hat{\phi})\right]$$

$$= \gamma + \mathbb{E}\left[(W'W)^{-1}W'M_{\mathbf{X}}X(\phi - \hat{\phi})\right]$$

which uses that W and u are orthogonal.

The 2SLS error $\phi - \hat{\phi}$, is given by

$$\phi - \hat{\phi} = \phi - (X'P_Z X)^{-1}X'P_Z y$$

$$= \phi - (X'P_Z X)^{-1}X'P_Z(X\phi + W\gamma + u)$$

$$= -(X'P_Z X)^{-1}X'P_Z(W\gamma + u) \tag{13}$$

Substitute this back in:

$$\mathbb{E}\left[\hat{\gamma}\right] = \gamma - \mathbb{E}\left[(W'W)^{-1}W'M_{\mathbf{X}}X(X'P_ZX)^{-1}X'P_Z(W\gamma + u)\right]$$

By assumption, Z is orthogonal to both W and u, so the equation becomes

$$\mathbb{E}\left[\hat{\gamma}\right] = \gamma$$

■

Proposition 3. The conditional variance of the estimator is

$$\begin{aligned}
Var\left(\hat{\gamma}|W,X,Z\right) &= Var\left(\hat{\gamma} - \gamma|W,X,Z\right) \\
&= Var\left((W'W)^{-1}W'M_{\mathbf{X}}(y - X\hat{\beta}) - \gamma|W,X,Z\right) \\
&= Var\left((W'W)^{-1}W'M_{\mathbf{X}}(X\beta + \gamma W + u - X\hat{\beta}) - \gamma|W,X,Z\right) \\
&= Var\left((W'W)^{-1}W'M_{\mathbf{X}}(X(\beta - \hat{\beta}) + u)|W,X,Z\right)
\end{aligned}$$

u is not orthogonal to the IV error $\beta - \hat{\beta}$, which is given by equation (13). Substitute it in:

$$Var\left(\hat{\gamma}|W,X,Z\right) = Var\left((W'W)^{-1}W'M_{\mathbf{X}}(-X(X'P_ZX)^{-1}X'P_Z(W\gamma + u) + u)|W,X,Z\right)$$

$$= (W'W)^{-1}W'M_{\mathbf{X}}Var\left(\left(I - X(X'P_ZX)^{-1}X'P_Z\right)u - X(X'P_ZX)^{-1}X'P_ZW\gamma|W,X,Z\right)M_{\mathbf{X}}W(W'W)^{-1}$$

We can separate the interior term because u and W are orthogonal, i.e. $\mathbb{E}[W\gamma u'] = 0$:

$$\begin{aligned}
&Var\left(\left(I - X(X'P_ZX)^{-1}X'P_Z\right)u - X(X'P_ZX)^{-1}X'P_ZW\gamma|W,X,Z\right) \\
&= Var\left(\left(I - X(X'P_ZX)^{-1}X'P_Z\right)u|W,X,Z\right) + Var\left(X(X'P_ZX)^{-1}X'P_ZW\gamma|W,X,Z\right)
\end{aligned}$$

The first term is given by

$$Var\left(\left(I - X(X'P_ZX)^{-1}X'P_Z\right)u|W,X,Z\right) = \left(I - X(X'P_ZX)^{-1}X'P_Z\right)\Omega\left(I - X(X'P_ZX)^{-1}X'P_Z\right)'$$

using $\Omega = \mathbb{E}[uu']$. And the second term is simply

$$Var\left(X(X'P_ZX)^{-1}X'P_ZW\gamma|W,X,Z\right) = 0$$

Accordingly, we can construct the entire variance matrix by

$$Var\left(\hat{\gamma}|W,X,Z\right) = \\ (W'W)^{-1}W'M_{\mathbf{X}}\left(I - X(X'P_ZX)^{-1}X'P_Z\right)\Omega\left(I - X(X'P_ZX)^{-1}X'P_Z\right)' M_{\mathbf{X}}W(W'W)^{-1}$$

■

Proof of Proposition 6. By equation (4), the EMPS w_t^c can be written as

$$\begin{aligned} w_t^c &= \lambda_a w_t^a + \lambda_b w_t^b \\ &= \lambda_a \sum_{h=0}^{H_{w^a}} \beta_h^a \nu_{h,t} + \lambda_a \xi_t^a + \lambda_b \sum_{h=0}^{H_{w^b}} \beta_h^b \nu_{h,t} + \lambda_b \xi_t^b \\ &= \sum_{h=0}^{H_{w^c}} \beta_h^c \nu_{h,t} + \xi_t^c \end{aligned}$$

where $\beta_h^c = \lambda_a \beta_h^a + \lambda_b \beta_h^b$, $H_{w^c} = \max\{H_{w^a}, H_{w^b}\}$ and $\xi_t^c = \lambda_a \xi_t^a + \lambda_b \xi_t^b$ is orthogonal to $\nu_{h,t}$ for all h. By equation (6), the term structure coefficients are given by

$$\begin{aligned} \gamma_h^c &= \left(\lambda_a \beta_h^a + \lambda_b \beta_h^b\right) \frac{Var(\nu_{h,t})}{Var(w_t^c)} \\ &= \lambda_a \gamma_h^a \frac{Var(w_t^a)}{Var(w_t^c)} + \lambda_b \gamma_h^b \frac{Var(w_t^b)}{Var(w_t^c)} \end{aligned}$$

When $Var(w_t^a)$ and $Var(w_t^b)$ are normalized to 1, the vector form of this equation is

$$\begin{aligned} \vec{\gamma}^c = \lambda_a \vec{\gamma}^a \frac{1}{Var(w_t^c)} + \lambda_b \vec{\gamma}^b \frac{1}{Var(w_t^c)} \\ \propto \lambda_a \vec{\gamma}^a + \lambda_b \vec{\gamma}^b \end{aligned}$$

■

Proof of Proposition 8. The synthetic MPS $\vec{\gamma}^s$ must be in the span of the observed EMPS term structures, i.e. the columns of $\Gamma_{\mathcal{J}}$. The vector in this span minimizing $\||\vec{\gamma}^i - \vec{\gamma}\|_2$ is the projection of $\vec{\gamma}^i$ onto the span of the columns of $\Gamma_{\mathcal{J}}$. This is given by the familiar expression

$$\vec{\gamma}^s = \Gamma_{\mathcal{J}}(\Gamma'_{\mathcal{J}}\Gamma_{\mathcal{J}})^{-1}\Gamma'_{\mathcal{J}}\vec{\gamma}^i$$

■

Proof of Proposition 5. By equation (5), the ν_t variance conditional on w^j_{t-k} is

$$Var(\nu_t|w^j_{t-k}) = Var(\sum_{h=0}^{H_w} \gamma^j_h w^j_{t-h} + u_t|w^j_{t-k})$$

$$= Var(\gamma^j_h w^j_{t-k}|w^j_{t-k}) = (\gamma^j_k)^2 Var(w^j_t)$$

because the past EMPS is homoskedastic white noise, and orthogonal to u_t. Similarly, the total variance conditional on the history of EMPS is

$$Var(\nu_t|\{w^j_{t-h}\}^{H_w}_{h=0}) = Var(\sum_{h=0}^{H_w} \gamma^j_h w^j_{t-h} + u_t|\{w^j_{t-k}\}^{H_w}_{k=0})$$

$$= \sum_{h=0}^{H_w} Var(\gamma^j_h w^j_{t-h}) = \left(\sum_{h=0}^{H_w} (\gamma^j_h)^2\right) Var(w^j_t)$$

Combining these two equations gives the ratio

$$\frac{Var(\nu_t|w^j_{t-k})}{Var(\nu_t|\{w^j_{t-h}\}^{H_w}_{h=0})} = \frac{(\gamma^j_k)^2}{\sum_{h=0}^{H_w} (\gamma^j_h)^2}$$

■

B Smooth Term Structures

This appendix describes how to estimate the smoothed term structures, analogous to the smooth local projections of Barnichon and Brownlees (2019). First we derive how to estimate smooth local projections in closed form. In particular, we show that there is a shortcut such that transformation with B-splines is not needed at all; the local projection can be estimated by ridge regression using a suitable penalty matrix. Then we show how to apply the smoothing in the context of our broader method.

B.1 Smooth Local Projections

Consider the following local projection for $h = 0, 1, ..., H$:

$$y_{t+h} = w_t \gamma_h + \epsilon_{h,t+h}$$

where y_{t+h} is the outcome variable of interest, w_t is an exogenous shock, and $\epsilon_{h,t+h}$ is the error term. If w_t is white noise, then the local projection coefficients can be estimated from the following regression:

$$y_t = \sum_{h=0}^{H} \gamma_h w_{t-h} + \epsilon_t \tag{14}$$

The smooth local projection approach is to approximate the γ_h coefficients with B-splines, which are indexed piecewise polynomial functions $B_0(h), B_1(h), ..., B_K(h)$. The coefficients are given by

$$\gamma_h = \sum_{0}^{K} \alpha_k B_k(h)$$

where α_k are coefficients to be estimated. We can rewrite the local projection regression as

$$y_t = \sum_{h=0}^{H} \sum_{0}^{K} \alpha_k B_k(h) w_{t-h} + \epsilon_t$$

$$= \sum_{0}^{K} \alpha_k v_{t-h} + \epsilon_t$$

where

$$v_{t-h} = \sum_{h=0}^{H} B_k(h) w_{t-h} \tag{15}$$

is a *smoothed* version of the shock. The coefficients α_k can be estimated by OLS.

A vector respresentation is useful. Let $\vec{w}_t$ be the $H+1$-dimensional row vector of shocks at time t, and $\vec{v}_t$ be the $H+1$-dimensional row vector of smoothed shocks at time t. They are related by

$$\vec{v}_t = \vec{w}_t B$$

where B is the $(H+1) \times (H+1)$ matrix of B-spline basis functions, sampled at appropriate points to recover equation (15). Stack the vectors into matrices, so that V is the $T \times (H+1)$ matrix of smoothed shock vectors, W is the $T \times (H+1)$ matrix of shock vectors, and y is the $T \times 1$ vector of outcomes. The smooth local projection regression is written

$$y = V\alpha + \epsilon$$

where α is the $K+1$-dimensional vector of coefficients, and ϵ is the $T \times 1$ vector of errors. The coefficients from the original form $Y = W\gamma + \epsilon$ can be recovered by

$$\gamma = B\alpha$$

because $WB = V$.

Barnichon and Brownlees (2019) estimate the smooth local projections by ridge regression. An appropriate penalty term gives the interpretation that the local projection is shrunk towards a lower order polynomial. The ridge regression estimator is

$$\begin{aligned}\hat{\alpha} &= \arg\min_{\alpha} (y - V\alpha)' (y - V\alpha) + \lambda\alpha'\mathbf{P}\alpha \\ &= \left(V'V + \lambda\mathbf{P}\right)^{-1} V'Y\end{aligned}$$

where λ is a positive shrinkage parameter, and $\mathbf{P}$ is the penalty matrix. λ can be chosen by cross-validation. For the canonical smooth local projections the penalty matrix is

$$\mathbf{P} = \mathbf{D}_r'\mathbf{D}_r$$

where $\mathbf{D}_r$ is the rth difference matrix.

Because the estimated original coefficients are related by $\hat{\gamma} = B\hat{\alpha}$, there is a short-cut to smooth local projections that skips the transformation step entirely:

Proposition 9 *The smooth local projection coefficient vector $\hat{\gamma}$ can be found by estimating equation* (14) *by ridge regression with penalty matrix*

$$\mathbf{P}_B = (B^{-1})'\mathbf{P}B^{-1}$$

so that the estimate is given by

$$\hat{\gamma} = \left(W'W + \lambda\mathbf{P}_B\right)^{-1} W'y$$

Proof. The relationship $\hat{\gamma} = B\hat{\alpha}$ and the expression for the ridge regression estimator $\hat{\alpha}$ imply

$$\begin{aligned}\hat{\gamma} &= B\left(V'V + \lambda\mathbf{P}\right)^{-1} V'y \\ &= B\left(B'W'WB + \lambda\mathbf{P}\right)^{-1} B'W'y \\ &= \left(W'W + \lambda(B^{-1})'\mathbf{P}B^{-1}\right)^{-1} W'y\end{aligned}$$

The definition $\mathbf{P}_B = (B^{-1})'\mathbf{P}B^{-1}$ gives the proposed expression, which is equivalent to the ridge regression estimator with penalty matrix $\mathbf{P}_B$. ■

Ridge regression also has closed form standard errors. The conditional variance of the ridge regressor is

$$Var(\hat{\alpha}|V) = \sigma^2\left(V'V + \lambda\mathbf{P}\right)^{-1} V'V\left(V'V + \lambda\mathbf{P}\right)^{-1}$$

where σ^2 is the error variance. Returning to the original coefficients, the conditional variance is

$$\begin{aligned}Var(\hat{\gamma}|V) &= \sigma^2 B\left(V'V + \lambda\mathbf{P}\right)^{-1} V'V\left(V'V + \lambda\mathbf{P}\right)^{-1} B' \\ Var(\hat{\gamma}|W) &= \sigma^2 B\left(B'W'WB + \lambda\mathbf{P}\right)^{-1} B'W'WB\left(B'W'WB + \lambda\mathbf{P}\right)^{-1} B' \\ &= \sigma^2\left(W'W + \lambda(B^{-1})'\mathbf{P}B^{-1}\right)^{-1} W'W\left(W'W + \lambda(B^{-1})'\mathbf{P}B^{-1}\right)^{-1}\end{aligned}$$

B.2 Smoothed Term Structures

We can apply the smooth local projection method to the term structure estimation. The final step of the four-stage procedure is to regress the estimated policy residuals $\hat{\nu}_t$ onto lags of the EMPS w_t^j. The smooth local projection method is directly applicable to equation (5). The regression is

$$\begin{aligned}\nu_t &= \sum_{h=0}^{H_w} \gamma_h^j w_{t-h}^j + u_t \\ &= \sum_{h=0}^{H_w}\sum_{0}^{K} \alpha_k^j B_k(h) w_{t-h}^j + u_t \\ &= \sum_{0}^{K} \alpha_k^j v_{t-h}^j + u_t\end{aligned}$$

where again v_{t-h}^j is the smoothed shock.

The ridge regression estimator for the vector of α_k^j coefficients is

$$\hat{\alpha}^j = \left((V^j)'V^j + \lambda\mathbf{P}\right)^{-1}(V^j)'\hat{\nu}$$

The penalty matrix $\lambda\mathbf{P}$ is the same as in the previous section. The coefficients are related to the term structure coefficients by

$$\hat{\gamma}^j = B\hat{\alpha}^j$$

and the vector $\hat{\nu}$ is given in matrix notation by $\hat{\nu} = M_{\mathbf{X}}(I - X(X'P_Z X)^{-1}X'P_Z)y$, so the smoothed term structure estimator is

$$\hat{\gamma}^j = B\left((V^j)'V^j + \lambda\mathbf{P}\right)^{-1}(V^j)'M_{\mathbf{X}}(I - X(X'P_Z X)^{-1}X'P_Z)y$$

with conditional variance

$$Var(\hat{\gamma}^j|V^j, X, Z, y) = B\left((V^j)'V^j + \lambda\mathbf{P}\right)^{-1}(V^j)'Var(\hat{\nu}|X, Z, y)V^j\left((V^j)'V^j + \lambda\mathbf{P}\right)^{-1}B'$$

$$\begin{aligned} &= B\left((V^j)'V^j + \lambda\mathbf{P}\right)^{-1}(V^j)' \\ &\qquad M_{\mathbf{X}}\left(I - X(X'P_Z X)^{-1}X'P_Z\right)\Omega\left(I - X(X'P_Z X)^{-1}X'P_Z\right)'M_{\mathbf{X}} \\ &\qquad V^j\left((V^j)'V^j + \lambda\mathbf{P}\right)^{-1}B' \end{aligned} \quad (16)$$

Following the proof of Proposition 3 in Appendix A.

In terms of untransformed shocks, the estimator is

$$\hat{\gamma}^j = \left(W'W + \lambda\mathbf{P}_B\right)^{-1}W'M_{\mathbf{X}}(I - X(X'P_Z X)^{-1}X'P_Z)y$$

and the conditional variance is

$$\begin{aligned} Var(\hat{\gamma}^j|W^j, X, Z, y) &= \left((W^j)'W^j + \lambda\mathbf{P}_B\right)^{-1}(W^j)' \\ &\qquad M_{\mathbf{X}}\left(I - X(X'P_Z X)^{-1}X'P_Z\right)\Omega\left(I - X(X'P_Z X)^{-1}X'P_Z\right)'M_{\mathbf{X}} \\ &\qquad W^j\left((W^j)'W^j + \lambda\mathbf{P}_B\right)^{-1}B' \end{aligned} \quad (17)$$

where again $\mathbf{P}_B = (B^{-1})'\mathbf{P}B^{-1}$.

C Further Taylor Rule Specification Alternatives

Consistent estimation of the Taylor rule is crucial for our esitmation exercise. In Section 4.2.1 we explored how robust our esitmates are to alternative measures of inflation and real activity. In this appendix, we explore further alternative specifications.

Table 6 presents how the results depend on the number of lags used included in the rule, while Table 7 presents how our results depend on the sample period used. Our results are broadly robust across these choices, except in the extreme case where we both begin the sample after 1985 and include the zero-lower-bound (ZLB) period.

In our baseline IV estimation, we used three types of structural shocks as instruments, listed in Table 2. In case one of the instruments fails the exclusion restrictions, we also repeat our analysis with different subsets of instruments. The inflation coefficient in the Taylor Rule is robust to these choices, although the GDP coefficient changes substantially.

Finally, we include a variety of OLS estimates for the Taylor rule, to compare our approach with the typical method in the literature. These are reported in table 9 which reveals that OLS estimates are highly attenuated compared to our IV results. In addition to the expected bias, OLS estimates are also highly sensitive to changes in the regression specification.

D Alternative Synthetic Shocks

In Section 5, we used a set of modern EMPS to construct the synthetic MPS. In this appendix, we repeat the exercise with alternative sets of EMPS. Broadly speaking, the estimated IRFs look similar to the baseline case: the long-run news shock reduces rates in the short run, only the long-run news shock causes deflation, and the immediate policy shock causes an expansion on impact with contraction following after roughly half a year.

In our first alternative, we employ a smaller set of EMPS, restricted to a few shocks that are explicitly designed to remove a Fed information effect. None of these EMPS individually feature an output puzzle (Figure 10) and yet the synthetic surprise – which is just a linear combination of these EMPS – does, although only in the short-run when compared to our baseline (Figure 9). Moreover, with this smaller set, the short-run news shock now has a brief expansionary effect as well. On net, the output puzzle gets less severe with this smaller set of ingredient shocks.

In our second alternative, we employ an expanded set of EMPS. This is because the baseline set of shocks does not perfectly approximate the target synthetic shock structure (Figure 2), and we would like to check if our conclusions hold up when we improve the approximation fit. In this expanded set include the classic Romer-Romer and Gertler-

	Baseline	Fewer inst. lags	More inst. lags	n_{H_ν}=12	$L=1$	$L=12$	$L=23$
12-month PCE Inflation, demeaned	1.552***	1.603***	1.291***	1.558***	1.552***	1.552***	1.552***
	(0.036)	(0.045)	(0.031)	(0.037)	(0.041)	(0.035)	(0.029)
GDP, CF-low-pass, demeaned	0.747***	0.279**	0.261***	0.767***	0.747***	0.747***	0.747***
	(0.084)	(0.118)	(0.032)	(0.085)	(0.087)	(0.084)	(0.075)
Residual autocorrelation	0.95	0.96	0.96	0.95	0.95	0.95	0.95
R^2	0.37	0.43	0.49	0.36	0.37	0.37	0.37
Observations	569	565	575	581	569	569	569

Table 6: Estimated Taylor Rule Parameters: Different lag lengths

Table reports the estimated Taylor rule parameters from the second stage of the four-stage method using instrumental variables. Residual autocorrelation is the first order autocorrelation of the monetary policy residual, r_t. R^2 is calculated as the fraction of variance in the policy rate explained by the contemporaneous systematic part of monetary policy, $x_t\phi$, and so $1 - R^2$ is that explained by the monetary policy residual, r_t. Standard errors are reported in parentheses.

	Baseline	Inc. ZLB	Post-1985, Inc. ZLB	Pre-2020
12-month PCE Inflation, demeaned	1.552***	1.230***	0.508***	1.466***
	(0.036)	(0.030)	(0.030)	(0.031)
GDP, CF-low-pass, demeaned	0.747***	-0.092***	0.147**	0.735***
	(0.084)	(0.035)	(0.058)	(0.071)
Residual autocorrelation	0.95	0.98	0.99	0.96
R^2	0.37	0.49	0.20	0.54
Observations	569	569	449	521

Table 7: Estimated Taylor Rule Parameters: Different samples

Table reports the estimated Taylor rule parameters from the second stage of the four-stage method using instrumental variables. Standard errors are reported in parentheses.

	Baseline	Fewer MPS	More MPS	Omit gov.	Omit oil	Omit other
12-month PCE Inflation, demeaned	1.552***	1.552***	1.552***	1.669***	1.540***	1.669***
	(0.029)	(0.029)	(0.029)	(0.036)	(0.082)	(0.036)
GDP, CF-low-pass, demeaned	0.747***	0.747***	0.747***	-0.059	1.701***	-0.059
	(0.074)	(0.074)	(0.074)	(0.064)	(0.210)	(0.064)
Residual autocorrelation	0.95	0.95	0.95	0.96	0.91	0.96
R^2	0.37	0.37	0.37	0.43	0.01	0.43
Observations	569	569	569	569	569	569

Table 8: Estimated Taylor Rule Parameters: Different instruments

Table reports the estimated Taylor rule parameters from the second stage of the four-stage method using instrumental variables. Residual autocorrelation is the first order autocorrelation of the monetary policy residual, r_t. R^2 is calculated as the fraction of variance in the policy rate explained by the contemporaneous systematic part of monetary policy, $x_t\phi$, and so $1 - R^2$ is that explained by the monetary policy residual, r_t. Standard errors are reported in parentheses.

	Baseline	OLS	OLS, no RHS int. rate	OLS, 1 lagged int. rate	OLS, no lags	OLS, 6 lags	OLS, 6 lags no int. rate
12-month PCE Inflation, demeaned	1.552***	0.096	0.307	0.096	0.307	0.096	0.307
	(0.036)	(0.087)	(0.518)	(0.087)	(0.518)	(0.087)	(0.518)
GDP, CF-low-pass, demeaned	0.747***	0.136**	0.245*	0.136**	0.245*	0.136**	0.245*
	(0.084)	(0.069)	(0.140)	(0.069)	(0.140)	(0.069)	(0.140)
Residual autocorrelation	0.95	-0.00	0.96	-0.00	0.96	-0.00	0.96
R^2	0.37	0.99	0.55	0.99	0.55	0.99	0.55
Observations	569	582	582	582	582	582	582

Table 9: Estimated Taylor Rule Parameters: OLS estimates

Table reports the estimated Taylor rule parameters from the second stage of the four-stage method using instrumental variables. Residual autocorrelation is the first order autocorrelation of the monetary policy residual, r_t. R^2 is calculated as the fraction of variance in the policy rate explained by the contemporaneous systematic part of monetary policy, $x_t\phi$, and so $1 - R^2$ is that explained by the monetary policy residual, r_t. Standard errors are reported in parentheses.

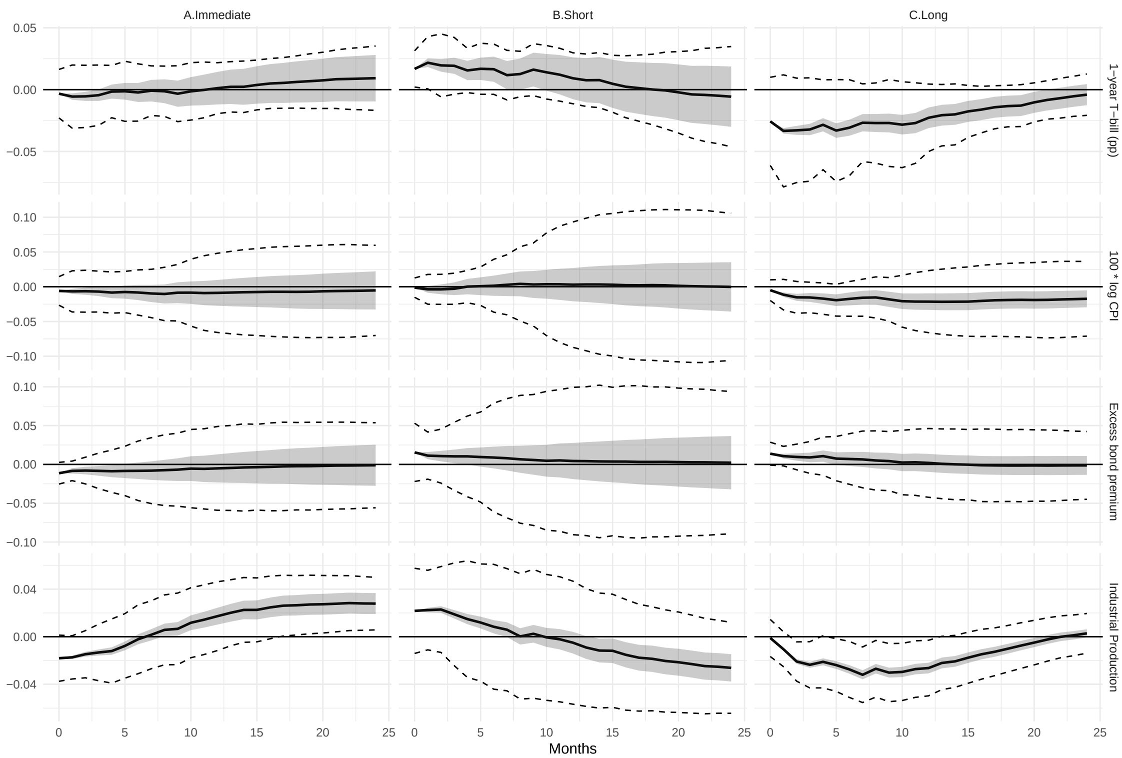


Figure 9: Impulse Responses to Synthetic Shocks (Smaller Set)

Figure shows impulse responses from a VAR to synthetic monetary policy shocks. The first column shows responses to the immediate shock, which has news on impact and in the first following month. The second column shows responses to the short-run news shock, which has news about months $2-6$. The third column shows responses to the long-run news shock, which has news about months $7-24$. The shaded region indicates the 90% confidence interval conditional on the impact values; the dotted lines indicate the 90 % confidence intervals accounting for impact uncertainty. The VAR lag length is 11 and is chosen by AIC.

Karadi shocks, which are not as effectively purged of central bank information as the more recent shock series, and thus yield differently shaped IRFs (Figure 12). Again, the implied synthetic shocks resemble the baseline results, with one exception. Now, the long-run news shock is entirely expansionary.

E Monte Carlo Validation

To validate our method and to check some of its properties, we conduct a Monte Carlo experiment. We simulate data from the motivating three-equation New Keynesian model from Section 2, extended to include additive shocks to the Euler equation (a "demand" shock) and the Phillips curve (a "supply" shock). We also simulate two instruments for each of the two non-monetary shocks, one strong and one weak. We then assess our method

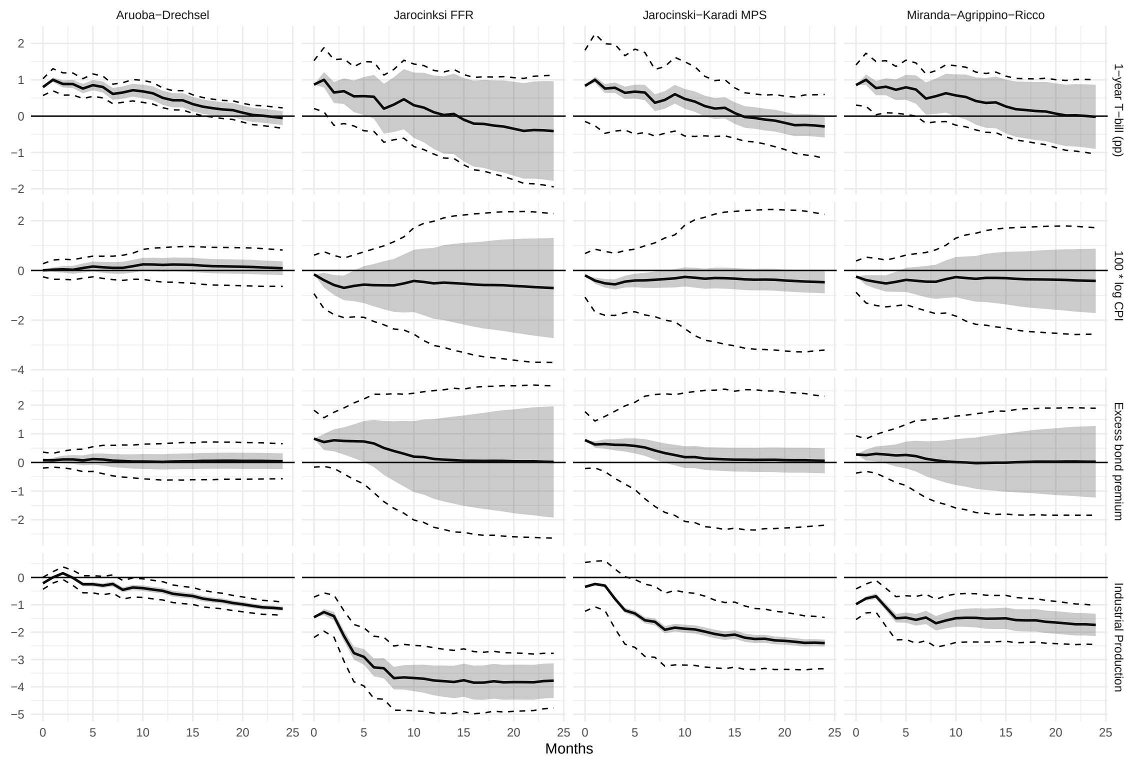


Figure 10: Impulse Responses to Estimated MPS (Smaller Set)

Figure shows impulse responses from a VAR to each of the underlying empirical MPS. Each column shows the response to a different shock. The shaded region indicates the 90% confidence interval conditional on the impact values; the dotted lines indicate the 90 % confidence intervals accounting for impact uncertainty. The VAR lag length is 11 and is chosen by AIC.

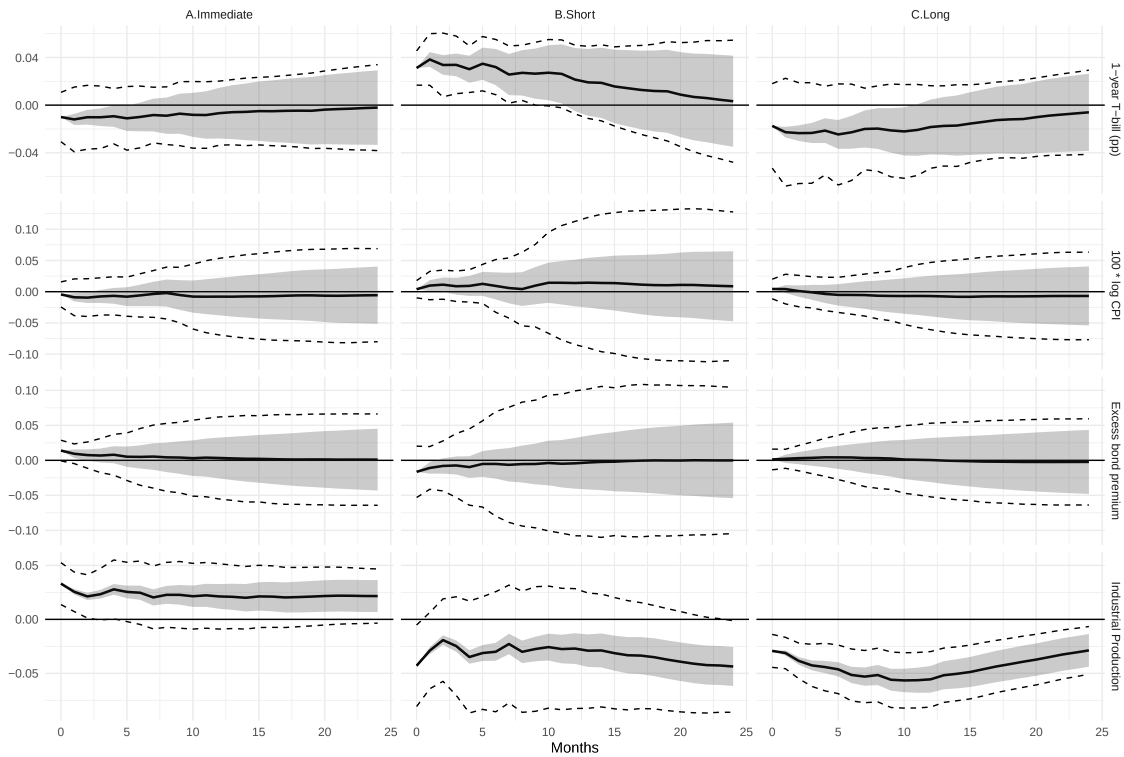


Figure 11: Impulse Responses to Synthetic Shocks (Expanded Set)

Figure shows impulse responses from a VAR to synthetic monetary policy shocks. The first column shows responses to the immediate shock, which has news on impact and in the first following month. The second column shows responses to the short-run news shock, which has news about months $2-6$. The third column shows responses to the long-run news shock, which has news about months $7-24$. The shaded region indicates the 90% confidence interval conditional on the impact values; the dotted lines indicate the 90 % confidence intervals accounting for impact uncertainty. The VAR lag length is 11 and is chosen by AIC.

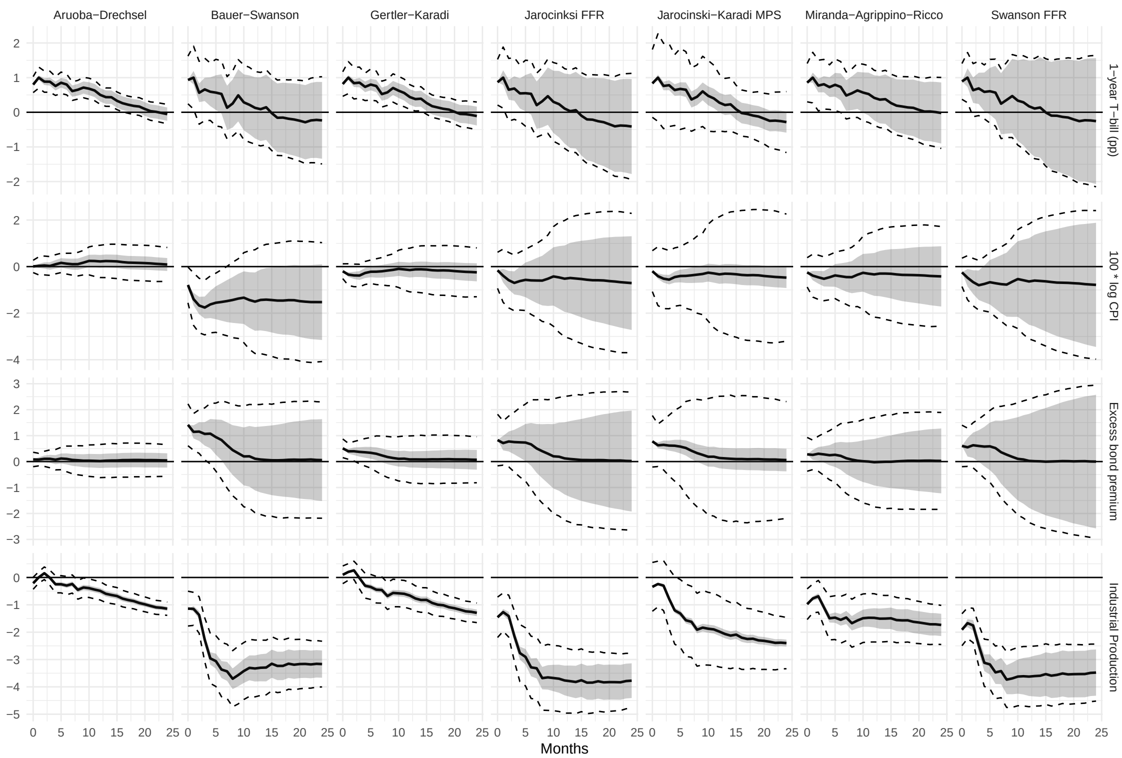


Figure 12: Impulse Responses to Estimated MPS (Expanded Set)

Figure shows impulse responses from a VAR to each of the underlying empirical MPS. Each column shows the response to a different shock. The shaded region indicates the 90% confidence interval conditional on the impact values; the dotted lines indicate the 90 % confidence intervals accounting for impact uncertainty. The VAR lag length is 11 and is chosen by AIC.

against these data in two distinct exercises: a long-sample assessment using 25,000 periods of simulated data; and a short-sample assessment using fewer periods.

Since the aim here is to test our method, rather than shock identification per se, we assume that the target empirical monetary shock is noisy (so $var\xi_t^j > 0$) and inherently monetary in nature, but that it has a non-trivial term structure (so $\beta_h^j \neq 0$ for some $h > 0$). Then the subsequent exercises answer the question: if a shock were identified perfectly, under what conditions would we correctly measure its term structure?

Parameter	Interpretation	Value	Parameter	Interpretation	Value
$1-\alpha$	Returns to scale	0.67	β	Utility discount factor	0.997
ρ_a	Technology shock persistence	0.98	ρ_r	Interest rate smoothing in Taylor rule	0.49
ρ_z	Demand shock persistence	0.56	ρ_{zpc}	Supply shock persistence	0.49
σ	Risk aversion	1.0	φ	Labor supply elasticity	1.0
ϕ_π	Taylor rule inflation coefficient	1.5	ϕ_π	Taylor rule output gap coefficient	0.125
θ	Calvo parameter	0.75	Demand elasticity	6.0	
			$\{\beta_i\}_{i=0}^{L-1}$	EMPS lag structure	1
L	EMPS lag length	4	$var\xi$	MPS measurement error variance	0.003^2
$var\nu_0$	EMPS surprise variance	0.003^2	$var\nu_1$	EMPS 1-period news variance	0.0008^2
$var\nu_3$	EMPS 1-period news variance	0.0001^2	$var\nu_4$	EMPS 1-period news variance	0.00003^2

Table 10: Parameters of the Monte Carlo Simulation

Table shows parameters used for simulations drawn from a calibrated version of the standard three-line New Keynesian model of Galí (2008).

E.1 Large Sample Properties

Table 11 reports the results of this first exercise, using standard parameters for the Taylor rule, an arbitrary declining term structure for the monetary policy shock, γ_i, and an AR(1) residual. The model parameters otherwise match a standard monthly calibration (see Table 10 for details). The specification in column (1) uses all four instruments, including the two strong ones. In this case, estimation recovers the correct parameters almost perfectly. With large enough sample and strong enough instruments, our method works.

In columns (2)-(3) we consider alternatives when multiple strong instruments are not available. In column (2), the case where we have only instruments for the demand shock, but one is strong.[13] Although the point estimates are not as accurate as in the case with strong instruments for multiple shocks, the standard errors are appropriately wider, in that the true value of the parameters lies within two standard errors in all cases. In column (3) we include *only* weak instruments, although since one is a supply shock and one a demand shock there they cover more dimensions of variation in the data. Unsurprisingly, with only weak instruments, performances is worse. However, in column (4) we allow for the most

[13] We need to use at lease two instruments to estimate a Taylor rule with two contemporaneous variables. With fewer instruments than endogenous variables, the fitted endogenous regressors in the second stage are colinear.

obvious practical fix, just including lags of the weak instruments. The intuition is that past shocks can have distinct effects on contemporaneous endogenous variables. In this case, adding just six lags results in improved performance for almost all point estimates, and confidence intervals which continue to nest the true parameters.

		Model	Four-stage IV				OLS			
			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Taylor Rule	ϕ_π	1.500	1.501	1.566	1.524	1.519	1.417	1.405	1.404	1.404
			(0.003)	(0.062)	(0.026)	(0.021)	(0.003)	(0.003)	(0.003)	(0.003)
	ϕ_y	0.125	0.128	0.120	0.146	0.137	0.093	0.084	0.084	0.084
			(0.002)	(0.008)	(0.013)	(0.009)	(0.001)	(0.001)	(0.001)	(0.001)
Term Structure	γ_0	0.435	0.435	0.434	0.450	0.443	0.402	0.394	0.393	0.392
			(0.004)	(0.005)	(0.013)	(0.009)	(0.004)	(0.004)	(0.004)	(0.004)
	γ_1	0.109	0.109	0.117	0.109	0.110	0.106	0.106	0.104	0.104
			(0.003)	(0.008)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
	γ_2	0.017	0.020	0.016	0.021	0.020	0.017	0.016	0.016	0.016
			(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
	γ_3	0.004	0.009	0.011	0.008	0.009	0.009	0.009	0.007	0.007
			(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Residual lag length, L			1	1	1	1	1	1	6	24
Demand instrument			2	2	1	1				
Supply instruments			2	0	1	1				
Instrument lags			0	0	0	6				
F-test, first stage, π_t			374.2	7.7	26.2	7.3				
F-test, first stage, y_t			102.2	37.5	9.1	3.2				
Lagged y_t							No	Yes	Yes	Yes

Table 11: Monte Carlo Simulation: Long sample

Table reports the results of two estimating the term structure to 25,000 periods of simulated data using a New Keynesian model with a well-identified monetary policy shock. Columns (1) to (4) use our four-stage IV approach, and columns (5) to (8) estimating the Taylor rule by OLS. In all cases where only one instrument is used, it is the weakest one available.

In columns (5) to (8) we repeat this exercise for OLS estimation. In all cases, OLS is inaccurate in large samples and provides misleadingly narrow confidence intervals. As is well-known, OLS estimates of Taylor rules are inconsistent, and so even including extensive lagged endogenous variables and interest rates as controls does not fix this problem.

In summary, our four-stage IV method works in large samples. It is best with strong instruments but including instruments lags in the first stage can help offset some of the problems of instrument weakness. Even the worse version of the IV approach is superior to the best OLS method.

E.2 Small Sample Properties

We now report the performance of our method on repeated small samples. To avoid a profusion of specifications, we select three models, a "strong instruments" IV, a "weak instruments" IV, and a long-lagged OLS. These versions, which correspond to columns (1), (4), and (8) of Table 11, represent reasonable best- and worst-cases for the IV and the best case for OLS in practice.

Figure 13 reports the distribution of the estimates for the Taylor rule coefficients, for repeated samples of 250, 500 (which is close to our sample size), and 750 observations. This shows that if strong instruments are available, then our four-stage method is unbiased and relatively powerful even in small samples. When instruments are weak, the method is much less powerful. In general, the distribution of OLS is tight, but it is biased and to a non-trivial extent in samples of size relevant to our work.

It is important to note that the results presented here do not contradict Carvalho et al. (2021). There, the authors argue that Taylor rule estimation by OLS is, in most reasonable cases, better than GMM using lagged endogenous variables. Although they are inconsistent, the small-sample bias of OLS estimates Taylor rule is proportional to the variance of endogenous variable due to the monetary shock. Since this is small, the resulting bias is also small. One intuition for their findings is that lagged-variable GMM addresses endogeneity but only by throwing out contemporaneous co-variation of endogenous variables and the policy rate (except for that due to autocorrelation). In contrast, OLS uses information about the current period, but at the price of endogeneity bias. The key result of Carvalho et al. (2021) is that this is usually a price worth paying. Our method gives the best of both worlds. It exploits contemporaneous variation in the endogenous variables, but by isolating only the variation due to non-monetary shocks it corrects for endogeneity bias. This also has important implications for some of the limitations of OLS laid out by Carvalho et al. (2021), who show that both OLS and lagged-variable GMM perform increasingly poorly for either persistent monetary shocks or for Taylor rule coefficients near to unity. Neither of these limitations apply to our method. And, as we will see in the next paragraph, these properties matter when estimating the term structure of monetary policy.

Figure 14 shows the same distribution of point estimates in the repeated samples for the estimated term structure. When assessed in this way, the four-stage IV estimator performs well even when instruments are weak, producing better estimates of the term structure compared to OLS *even* in cases where the IV Taylor rule estimates are clearly inferior. This is particularly true for γ_0, arguably the most important entry in the term structure. The intuition is that because the term structure of the EMPS is the projection of the whitened estimated Taylor rule residuals onto the EMPS, and because the endogenous variables are autocorrelated, the estimated residuals are correlated with the whitening regressors. As a result, the relationship between $\hat{\phi}$ and $\hat{\gamma}$ is effectively concave.[14] The confidently incorrect Taylor rule estimates from OLS are heavily penalized by this convexity and so are projected

[14]This concavity can be seen in the slight skews for the smallest sample sizes in Figure 14.

onto term structure estimates far from the truth. In contrast, the IV estimates are more spread out and so the mapping to $\hat{\gamma}$ is,on average, more forgiving.

Another important measure of the accuracy of test statistics is the coverage ratio. To assess this, we compute for each simulation the p-value of a hypothesis test with the true null. If the distribution of these p-values is uniform, then the test will have good coverage ratios at all confidence intervals. Note that this is a joint test of both the point estimate and its variance. From a practical perspective is the gold standard for creating useful estimators: if an estimate delivers uniform p-values, it says that one can do reasonably accurate inference about the data generating process, *even if the if the point estimates are inaccurate*.

Figures 15 and 16 report the distribution of p-values for the estimated Taylor rule coefficients and the monetary policy term structure respectively. Throughout, the four-stage IV estimates are relatively close to the diagonal. Performance is better, of course, when instruments are strong or when the sample size is larger. But for samples similar to the size we use, the results are generally good, although with some bias for estimates of γ_0. In contrast, confidence intervals based on OLS cannot be trusted for any parameters for small sample sizes or for ϕ_π, ϕ_y, or γ_0 at any sample size.

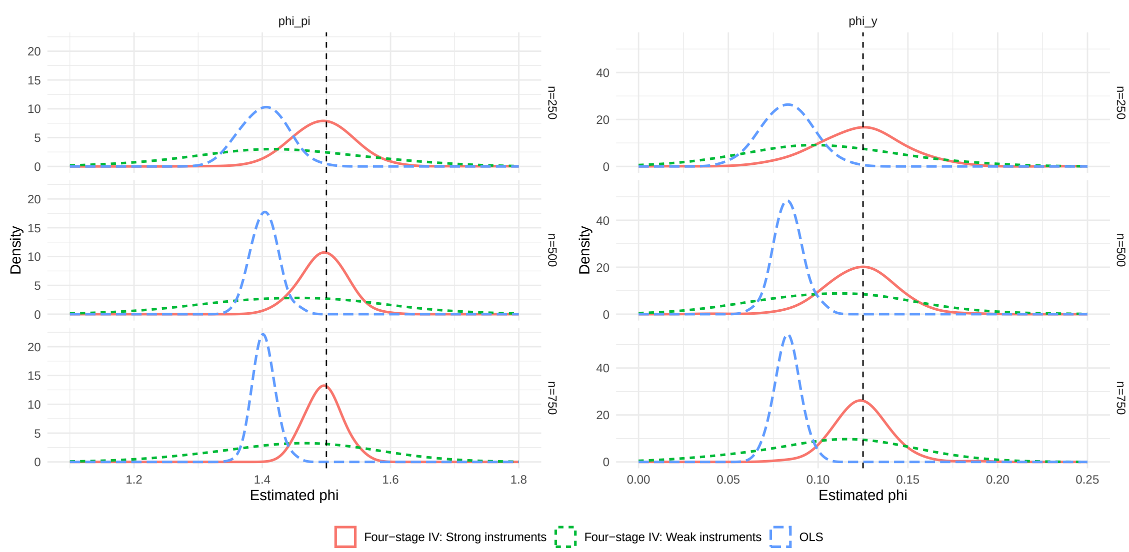


Figure 13: Short sample simulation: Distribution of estimated Taylor Rule coefficients

Figure shows the distribution of the estimated Taylor rule coefficients at different sample sizes. Calculations drawn from disjoint subsamples of a 100,000 period simulation.

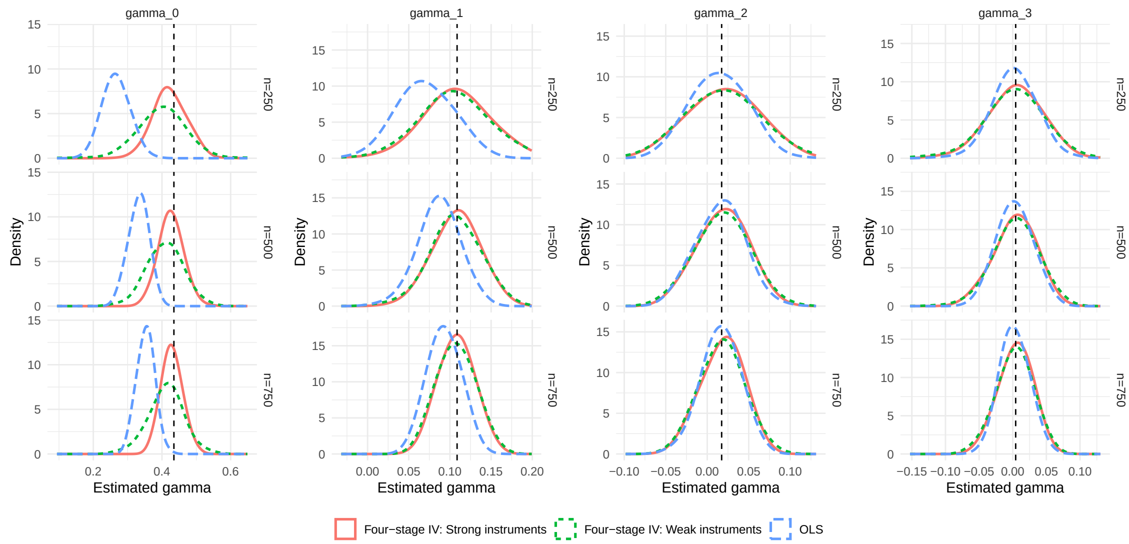


Figure 14: Short sample simulation: Distribution of estimated term structure of monetary policy.

Figure shows the distribution of the estimated monetary policy term structure at different sample sizes. Calculations drawn from disjoint subsamples of a 20,000 period simulation.

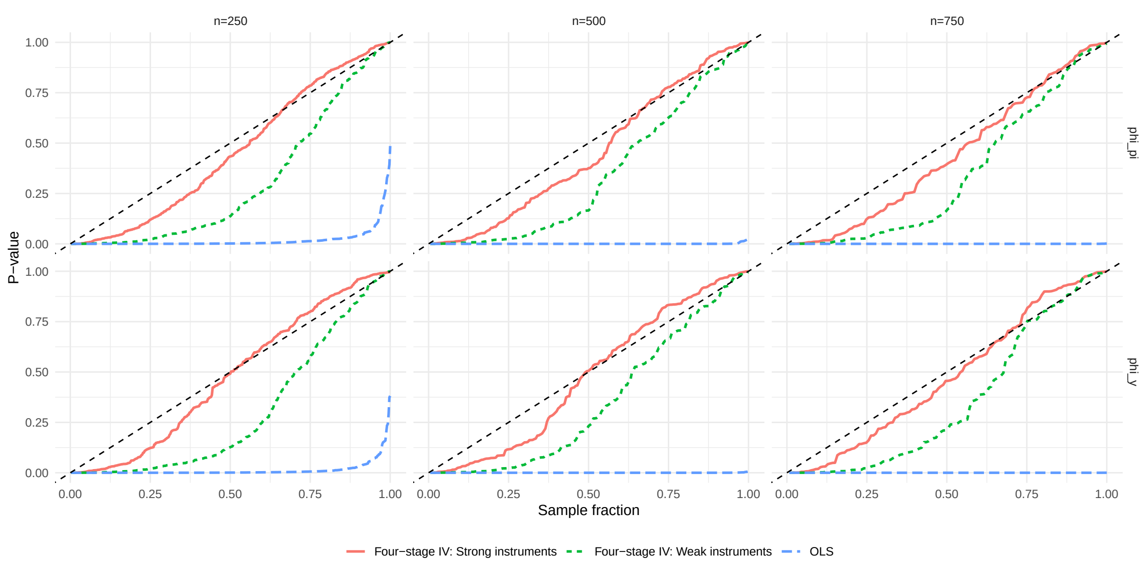


Figure 15: Short sample simulation: Distribution of p-values for Taylor Rule coefficients

Figure shows the distribution of the p-value of the true model parameter for Taylor rule coefficients at different sample sizes, using small-sample point estimates and standard errors. Perfect coverage ratios would produce diagonal lines. Calculations drawn from disjoint subsamples of a 20,000 period simulation.

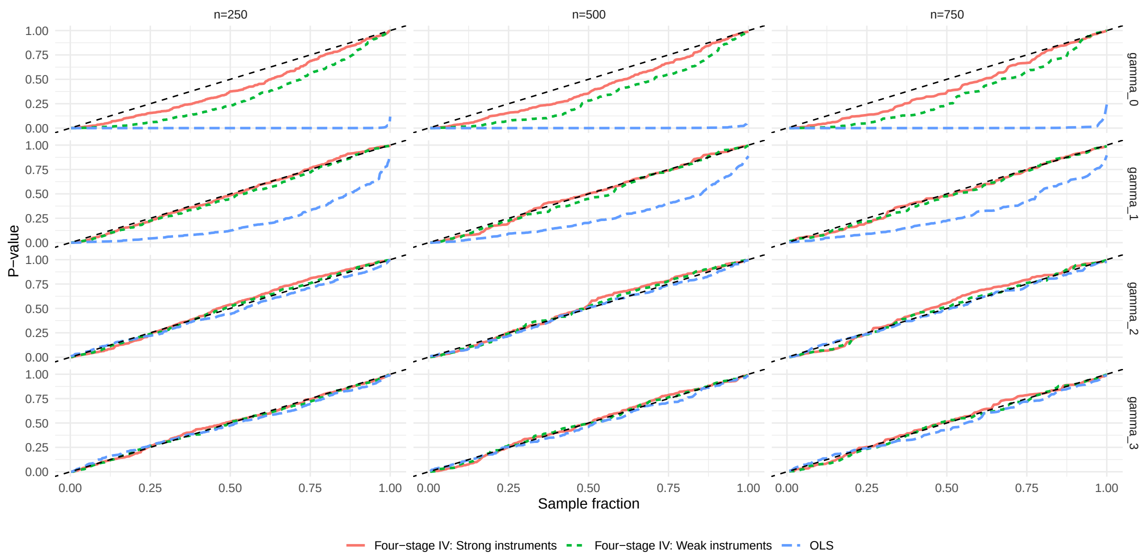


Figure 16: Short sample simulation: Distribution of p-values for term structure of monetary policy.

Figure shows the distribution of the p-value of the true model parameter for term structre of monetary policy at different sample sizes, using small-sample point estimates and standard errors. Perfect coverage ratios would produce diagonal lines. Calculations drawn from disjoint subsamples of a 20,000 period simulation.