The Term Structure of Monetary Policy News*

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May 17, 2025

WORKING PAPER

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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 are contractionary, but not immediately. Forward guidance about future rate increases is deeply contractionary on impact.

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

*We thank Regis Barnichon, Huixin Bi, Miguel Faria-e-Castro, 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.
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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 decomposes an EMPS into news about monetary policy residuals at every horizon. The procedure utilizes plausibly exogenous macroeconomic shocks as instrumental variables in order to identify the monetary policy rule, following insights from Barnichon and Mesters (2020).[2] 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. The resulting estimator has a simple closed-form expression; we prove that it is unbiased, and derive asymptotic standard errors. This simplicity is preserved when we extend the estimator to smooth through noise in the term structure, using a form of ridge regression following Barnichon and Brownlees (2019). An ancillary benefit of our method is that it produces estimates of the Taylor rule coefficients which are both very stable over alternate specifications and almost alwyas satisfy the Taylor principle.

We demonstrate our method by estimating the term structure for several well-known

[1] This conundrum is well-known. Their creators emphasize that EMPS are not textbook surprises; instead, they "include shocks to forward guidance" (Gertler and Karadi, 2015). 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] Many studies use lagged macroeconomic aggregates as instrumental variables to estimate the policy rule, following Clarida et al. (2000). These may not be valid instruments if the policy residual is serially correlated; 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 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.

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, Jarociński (2024) decomposes monetary policy events into several dimensions: the Jarosiński large scale asset purchases (LSAP) shock is dominated by long-run news, while the Jarociński target rate shock contains the least information about long-run forward guidance. 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 (sMPS) that closely approximates a true policy surprise, news about a particular horizon, or any other pattern of forward guidance.

The synthetic monetary policy surprise is directly comparable to a textbook monetary policy shock. 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) or a "Fed Response to News" (Bauer and Swanson, 2023a), but our synthetic MPS is constructed from EMPS that are ostensibly purged of these two effects. This suggests that other forces may be driving output puzzles. In contrast, a synthetic forward guidance shock is immediately and deeply contractionary, reducing output and inflation significantly on impact.

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

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

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 how the estimated IRF to an EMPS can be rationalized by *some* term structure of monetary policy news, even if the it does not resemble the IRF to a true policy surprise.

The textbook New Keynesian model is given by

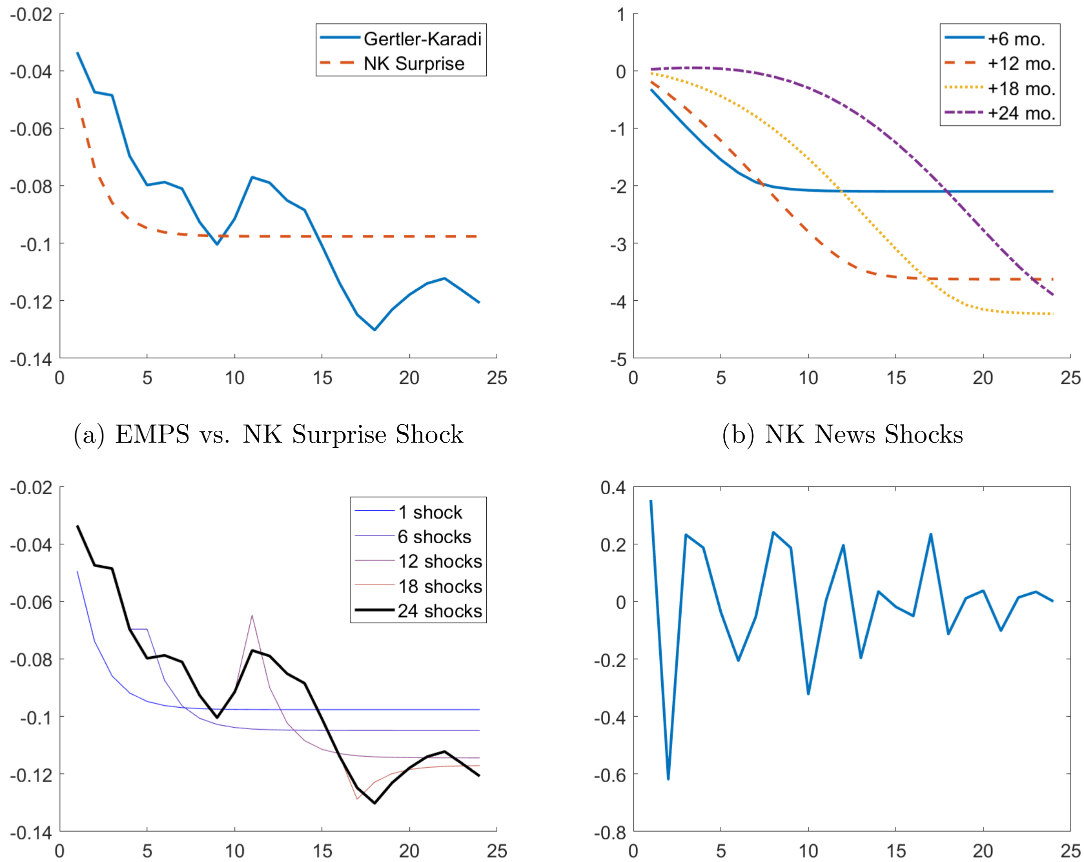
$$\begin{aligned} &\text{New Keynesian Phillips curve:} && \pi_t = \beta\mathbb{E}[\pi_{t+1}] + \kappa y_t \\ &\text{Euler equation:} && i_t = \mathbb{E}_t[\gamma(y_{t+1} - y_t) + \pi_{t+1}] \\ &\text{Taylor rule:} && i_t = \phi_y y_t + \phi_\pi \pi_t + \nu_t \end{aligned}$$

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 1 compares the price level IRFs from the New Keynesian model to that of a high frequency EMPS. The effect of the Gertler and Karadi (2015) EMPS on prices is plotted in Panel 1a (solid blue line). 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-year 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 shape also represents a term structure of monetary policy news, which we define formally in the next section. 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 is the point of the exercise; any estimated IRF can be rationalized in the NK model by some (possibly extreme) term structure.[4]

This example demonstrates that it is meaningless to use an EMPS to evaluate a model without knowing the news term structure associated with that EMPS. Without further analysis, we cannot know to what extent impulse responses are informative about how true policy shocks transmit versus how news and surprise are combined in the individual EMPS.

The reverse is also true: a given EMPS cannot be described as exhibiting a price or output "puzzle" with respect to some model on the basis of the IRF alone. Why? Because there is some combination of news shocks that can justify any inflation response. In order to evaluate a model based on an EMPS, it is necessary to estimate its term structure of monetary policy news.

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

[4]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.

a vector of coefficients. Residuals r_t may be autocorrelated:

$$r_t = \sum_{\ell=1}^{L} \rho_{r,\ell} r_{t-\ell} + \nu_t \tag{2}$$

The monetary policy innovation (MPI) 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]

Note that the formulation laid out in equations (1) and (2) is quite flexible. In particular, lagged variables may be included directly in the vector of Taylor rule variables x_t. And even when x_t is purely contemporaneous, the persistence of the Taylor rule residual imparts a more restrictive dependence of the policy rule on lagged macro variables, with lagged responses to different variables in constant proportion across horizons:[6]

$$y_t = x_t \phi + \sum_{l=1}^{L} \rho_{r,l} y_{t-l} - \sum_{l=1}^{L} \rho_{r,l} \phi' x_{t-l} + \nu_t$$

We model an EMPS as containing some (but not all) 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 MPI 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 stucture of EMPS j* is the effect of the EMPS w_t^j on expectations

[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.

[6]The constant proportion restriction is not essential; we write it this way because it is may be familiar to those accustomed to textbook models. More generally, an arbitrary lag structure is allowed by simply including lagged variables in the x_t vector. Our empirical method described in Section 3 allows for a general representation without requiring proportional coefficients.

of the MPI 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 the MPI ν_t:

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

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 MPI 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:

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 rule:

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

   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 i_t and x_t:[7]

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

[7] 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.

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 $\mathbf{x}_t \equiv \begin{pmatrix} y_{t-1} & x_{t-1} & ... & y_{t-L} & x_{t-L} \end{pmatrix}$ 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 $\mathbf{w}_t \equiv \begin{pmatrix} w_t^j & w_{t-1}^j & ... & w_{t-H_w}^j \end{pmatrix}$ 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*

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

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 me get clean estimates of the Taylor rule coefficients, the $\hat{\phi}$. THese are given by:

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

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

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

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. Finally, we provide a summary statistic to represent the relative importance of news for each EMPS and discuss the implications of our findings.

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	2 shocks: pure monetary and Fed information	1990:M1-2016:M12
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 (2023b)	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:M9
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 (2023b) 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 CPI inflation on the right-hand side. The policy residual is allowed to be autocorrelated, so in effect interest rate decisions depend on lagged variables as well.

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.

4.2 Estimation Results

In this section, we present the estimated terms 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.

We start by reporting the estimated Taylor rule parameters from the second stage of our method, which 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 terms structure up to two years after the shock, so $H_w = 24$. When whitening the monetary policy residuals, we orthogonalize with respect to as many, also choosing $L = 24$. 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. 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. In contrast, including the excess bond premium has little effect.

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 varying widely, 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 resutls which are stable across multiple specifications and consistent with theory.

[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***
	(0.029)	(0.028)	(0.032)	(0.033)	(0.027)	(0.036)	(0.099)
GDP, CF-low-pass, demeaned	0.747***				0.739***	0.106*	0.125**
	(0.074)				(0.070)	(0.063)	(0.062)
Cleveland Fed inflation expectations, 1 year, demeaned						2.025***	
						(0.049)	
Excess bond premium, demeaned					-0.180		
					(0.141)		
GDP growth, annualized, demeaned		0.032***					
		(0.009)					
Industrial Production, CF low-pass filter			-0.099***				
			(0.024)				
Michigan inflation expectations, 1 year, demeaned							-1.836***
							(0.141)
Unemployment rate, departures from quadratic trend				0.005***			
				(0.000)			
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.

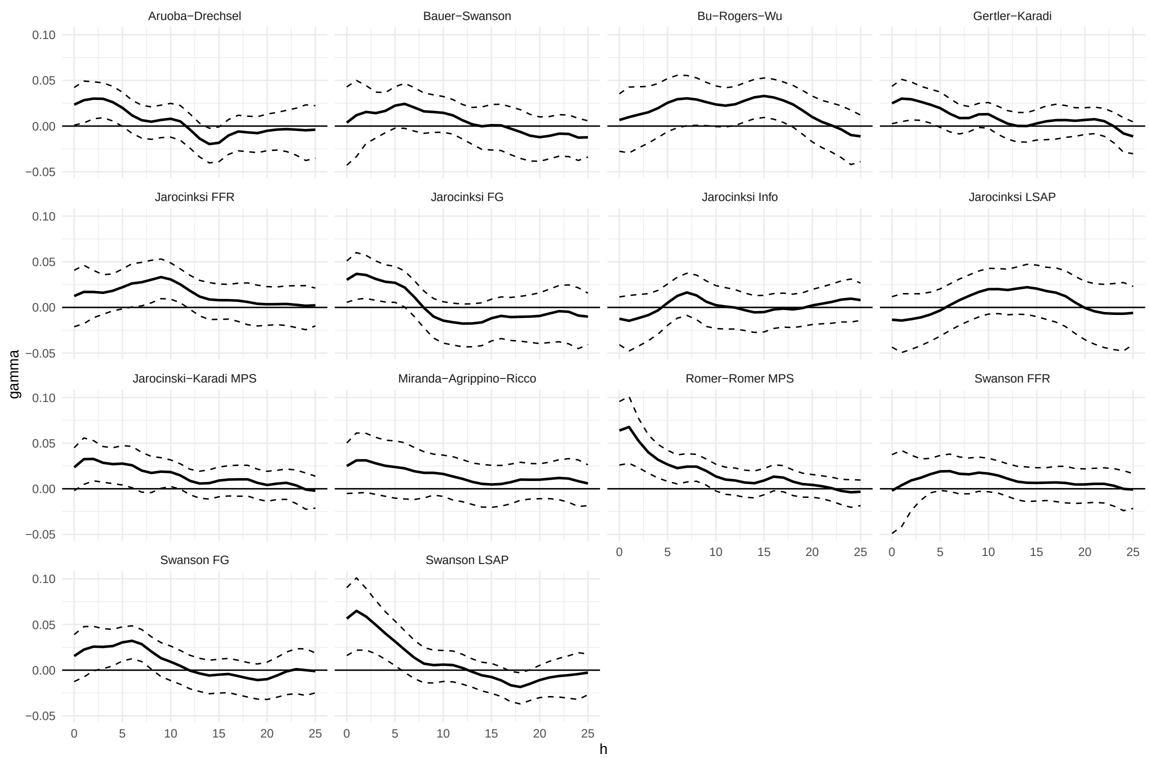
	Baseline	Inf. only	1m Inf.	1m, Inf. only	Core PCE	Core PCE, 1m	CPI
12-month PCE Inflation, demeaned	1.552***	1.540***					
	(0.029)	(0.033)					
1-month Core PCE Inflation, demeaned						1.600***	
						(0.094)	
1-month PCE Inflation, demeaned			0.649***	0.647***			
			(0.071)	(0.075)			
GDP, CF-low-pass, demeaned	0.747***		-0.039		1.047***	0.577***	0.645***
	(0.074)		(0.126)		(0.085)	(0.205)	(0.067)
12-month Core PCE Inflation, demeaned					2.066***		
					(0.036)		
12-month CPI inflation, demeaned							1.155***
							(0.022)
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.



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 $\hat{\nu}_{t+h}$.

It is helpful to have a summary statistic to represent 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 of MPI variation R_k^2 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 $R^2_{0:1}$, 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 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.

Shock	$R^2_{0:1}$	$R^2_{2:6}$	$R^2_{7:12}$	$R^2_{13:24}$
Swanson FFR	0.01	0.40	0.47	0.13
Bu-Rogers-Wu	0.01	0.19	0.33	0.47
Bauer-Swanson	0.04	0.45	0.32	0.18
Jarocinksi FFR	0.06	0.27	0.61	0.06
Jarocinksi LSAP	0.08	0.08	0.36	0.48
Swanson FG	0.11	0.59	0.23	0.07
Jarocinski-Karadi MPS	0.20	0.51	0.21	0.08
Miranda-Agrippino-Ricco	0.21	0.46	0.21	0.13
Aruoba-Drechsel	0.23	0.52	0.04	0.21
Jarocinksi Info	0.24	0.26	0.31	0.19
Jarocinksi FG	0.26	0.48	0.11	0.15
Gertler-Karadi	0.30	0.53	0.11	0.07
Swanson LSAP	0.41	0.50	0.02	0.07
Romer-Romer MPS	0.49	0.37	0.11	0.04

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, $R^2_{1:3}$ is the total variation in the Taylor residual attributable to 1- to 3-month news in a given identified monetary policy shock.

To summarize the forward guidance content of the EMPS, we calculate three components. The second column of Table 5 reports the sum of R^2_k for $2 \leq k \leq 6$. This is *short-run*

[9] The smoothing parameter λ is chosen for each EMPS by maximizing the out-of-sample errors for an extending window. 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.[10] For each data subset, 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. We consider alternate values of λ in the robustness checks found in Section 6.

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, the EMPS that is least like a surprise is the Swanson (2023) Federal Funds Rate (FFR) shock: nearly all of its variation is due to news.[11] How is it possible that possible that the Swanson FFR shock is mostly news, when it is identified in Swanson (2023) as the *only* dimension of the data in which short-term rates move after a Fed event? The answer is that while it 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. However, even though they does not isolate pure policy surprises, the Swanson (2023) and Jarociński (2024) decompositions are effective at sorting based on long-run news: in both cases, the FFR shock is the one with the small long-run news component. What these papers identify as target rate shocks are not purged of forward guidance, but they do 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.

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*

[11] We show in a variety of robustness checks in Section 6 that across all specifications, these shocks are majority news. However, the extremely low immediate information content ($R_{0:1}^2$) 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.

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 disimilar, 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, the Swanson FFR shock, and the Jarociński FFR and forward guidance shocks. Additionally, we selected shocks that are 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.

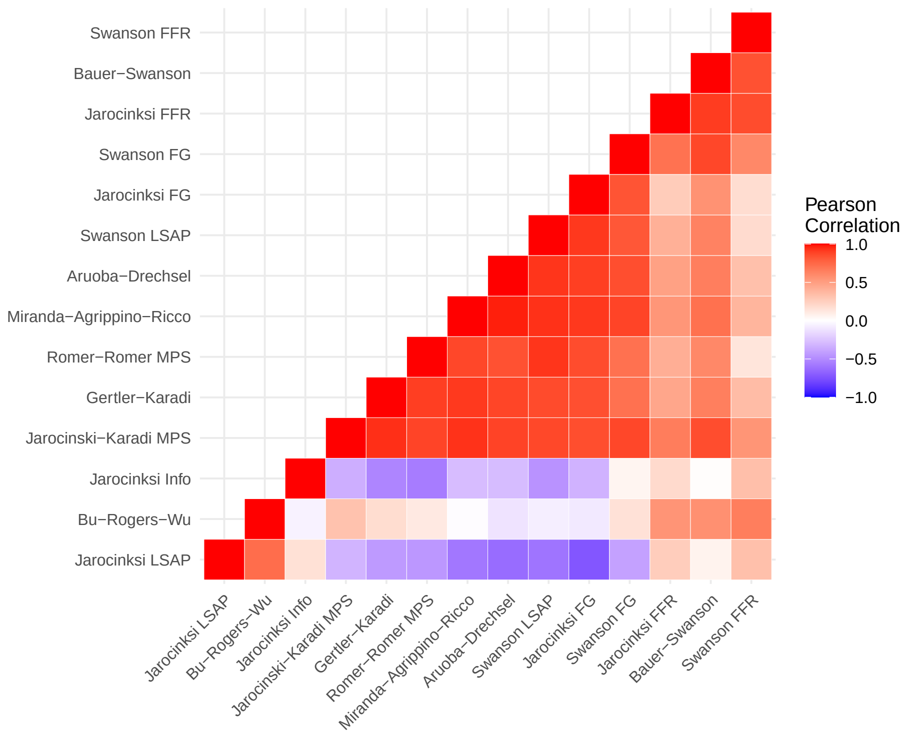


Figure 3: Term Structure Correlations

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. For example, the immediate shock contains 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.

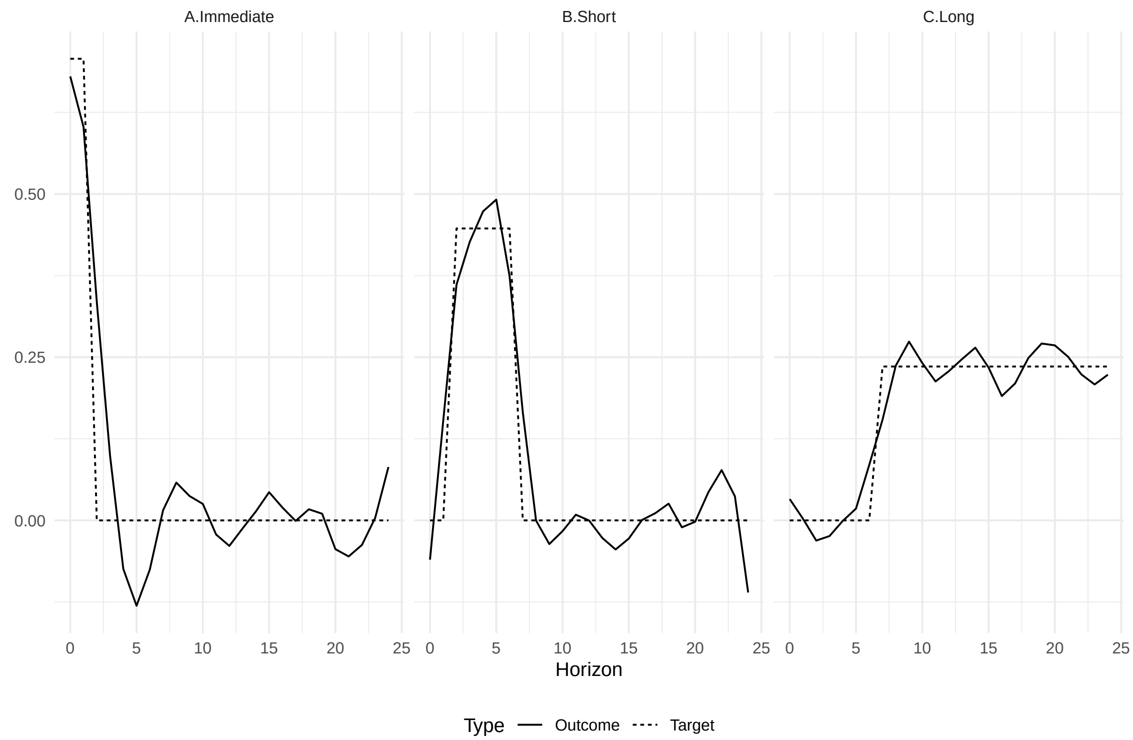


Figure 4: Target and Matched Synthetic MPS Term Structures

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 eight 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.[12]

We estimate the effects of the synthetic MPS on the macroeconomy. To do so, we include each synthetic MPS in 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). The synthetic MPS is taken as exogenous, so we order it first in the VAR, and estimate IRFs by causal ordering.

[12]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.

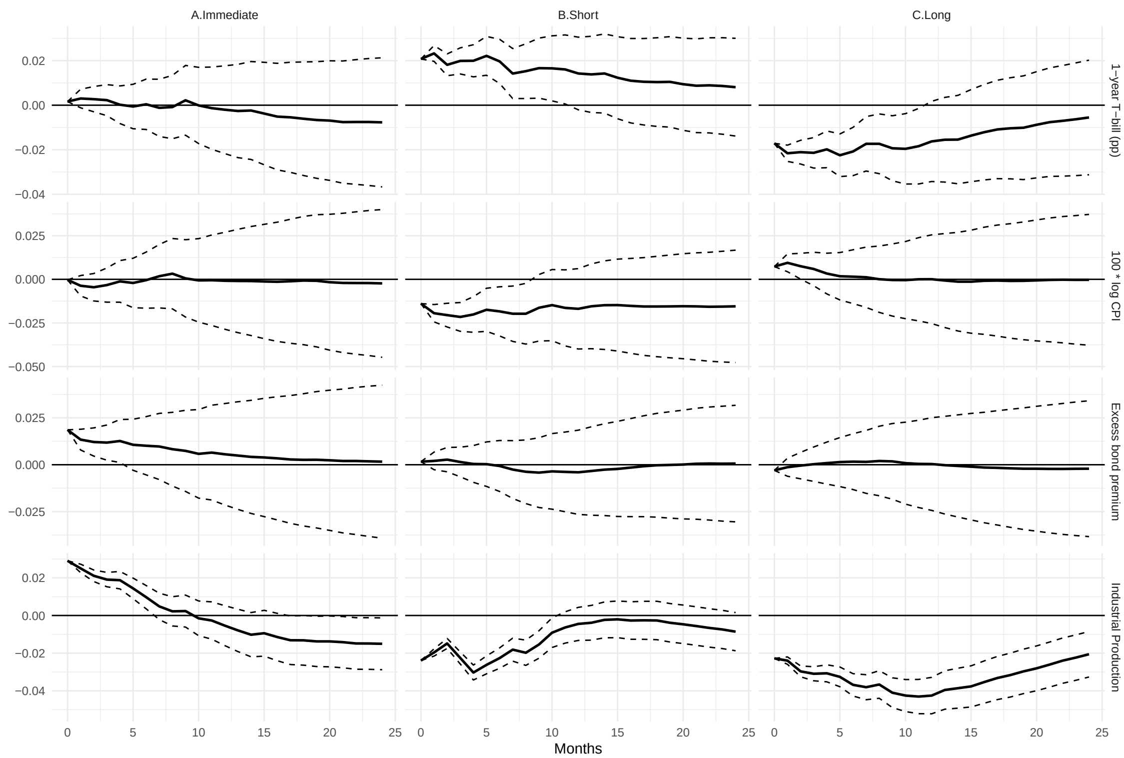


Figure 5: Impulse Responses to Synthetic Shocks

Figure shows impulse responses from a VAR to synthetic monetary policy shocks. Each column shows the response at a different news horizons $h = 0$ through $h = 12$. Lag length chosen by AIC.

Figure 5 presents the estimated IRFs to the immediate, short-term, and long-term synthetic MPS. The immediate shock does not clearly resemble a textbook MPS. Rates rise, but inflation is unaffected. Eventually the shock is contractionary, but only after three quarters of a year; on impact, the shock is expansionary. In contrast, short-run and long-run news shocks are clearly contractionary on impact, and for many months afterwards. However, these two types of synthetic news shocks also differ substantially.

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 enws 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.

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 rela-

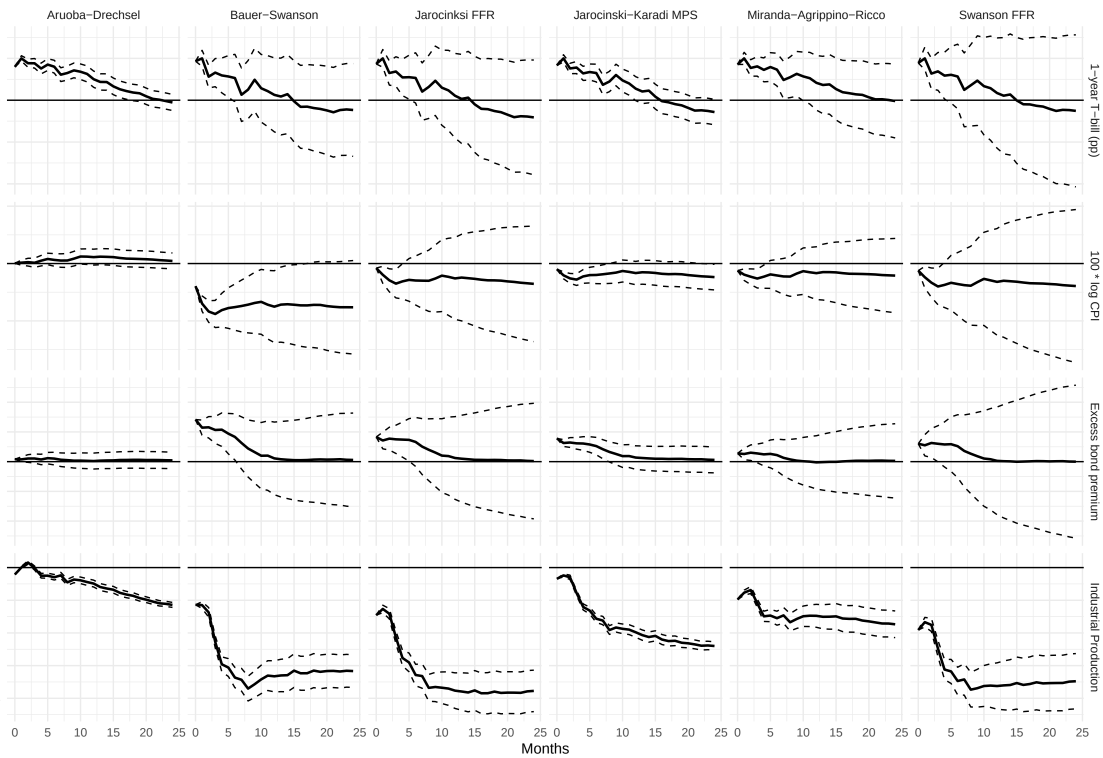


Figure 6: Impulse Responses to Estimated MPS

Figure shows impulse responses from a VAR to each of the underlying empirical MPS. Each column shows the response to a different shock. Lag length chosen by AIC.

tively homogeneous: they all predict higher rates, reduced real activity, and zero or modest deflation. So 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. But 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.[13] However, the short-run expansionary effect of an

[13]See Appendix E, where we document how our synthetic MPS behave in the New Keynesian model from

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 only using EMPS that are explicitly purged of the Fed information effect (Appendix D), immediate sMPS still causes short-run expansions. 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. 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 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

Section 2.

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. 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.

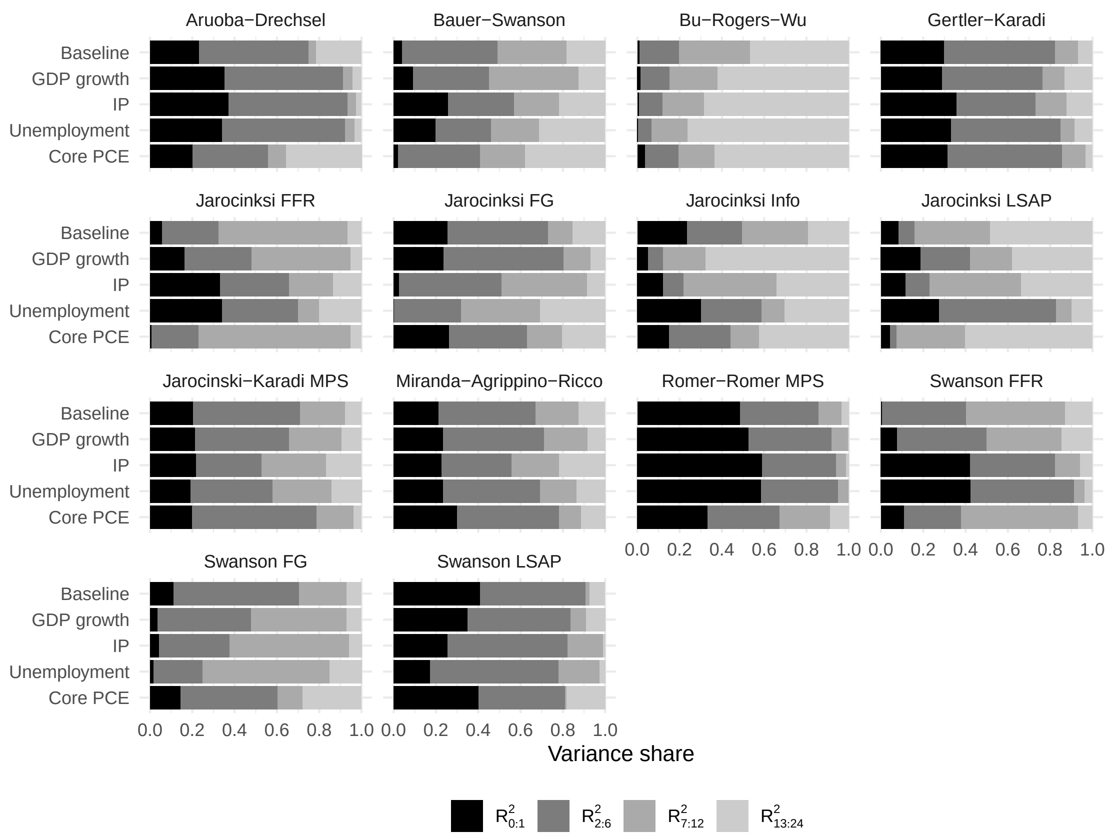


Figure 7: Term Structure Variance Decomposition: Robustness to Taylor rule variables.

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.

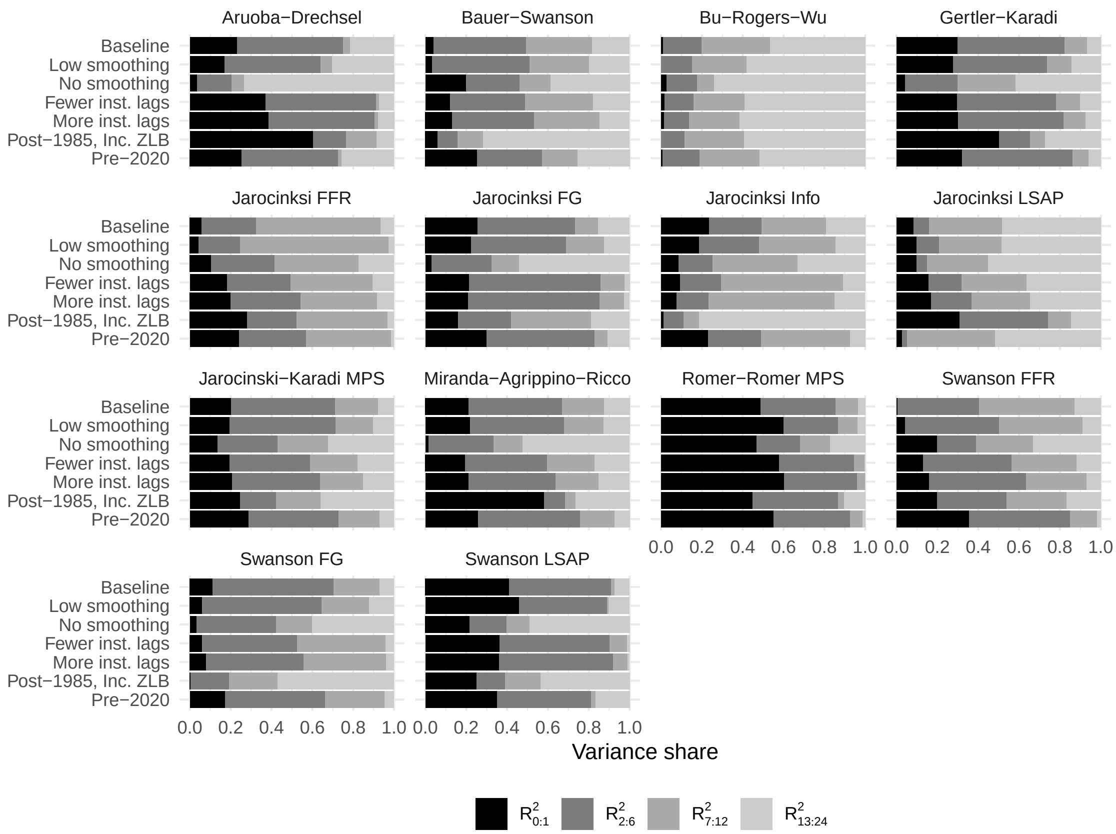


Figure 8: Term Structure Variance Decomposition: Robustness to sample and estimation method

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.

7 Conclusions

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

The first is: how should we compare the 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. By applying this method to identify the differences in nine 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 the 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.

Third, how can we make sense of these findings? As this is principally an empirical paper, we do not provide a full answer to this question. However, we do show that our results are not entirely at odds with standard macroeconomic theory. A standard New Keynesian framework can provide results which are at least qualitatively consistent with our findings.

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 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 effect of news shocks at multiple horizons set a target for future models to aim at.

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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:

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

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

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

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

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

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

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

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

■

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 MPI variance condition 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

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

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

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

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

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, and the expansionary effect is even longer-lived than in 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 more 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
12-month PCE Inflation, demeaned	1.552***	1.603***	1.291***	1.558***
	(0.029)	(0.036)	(0.025)	(0.034)
GDP, CF-low-pass, demeaned	0.747***	0.279***	0.261***	0.767***
	(0.074)	(0.100)	(0.025)	(0.083)
Residual autocorrelation	0.95	0.96	0.96	0.95
R^2	0.37	0.43	0.49	0.36
Observations	569	565	575	581

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***
	(0.029)	(0.026)	(0.026)	(0.024)
GDP, CF-low-pass, demeaned	0.747***	-0.092***	0.147***	0.735***
	(0.074)	(0.030)	(0.052)	(0.060)
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***	0.111	0.360	0.266***	0.074	0.082	0.467
	(0.029)	(0.102)	(0.557)	(0.088)	(0.502)	(0.081)	(0.507)
GDP, CF-low-pass, demeaned	0.747***	0.142**	0.315**	0.161**	0.258*	0.133*	0.219
	(0.074)	(0.061)	(0.138)	(0.070)	(0.140)	(0.070)	(0.139)
Residual autocorrelation	0.95	-0.01	0.97	0.32	0.97	-0.01	0.96
R^2	0.37	0.99	0.67	0.98	0.50	0.99	0.56
Observations	569	563	563	583	583	581	581

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.

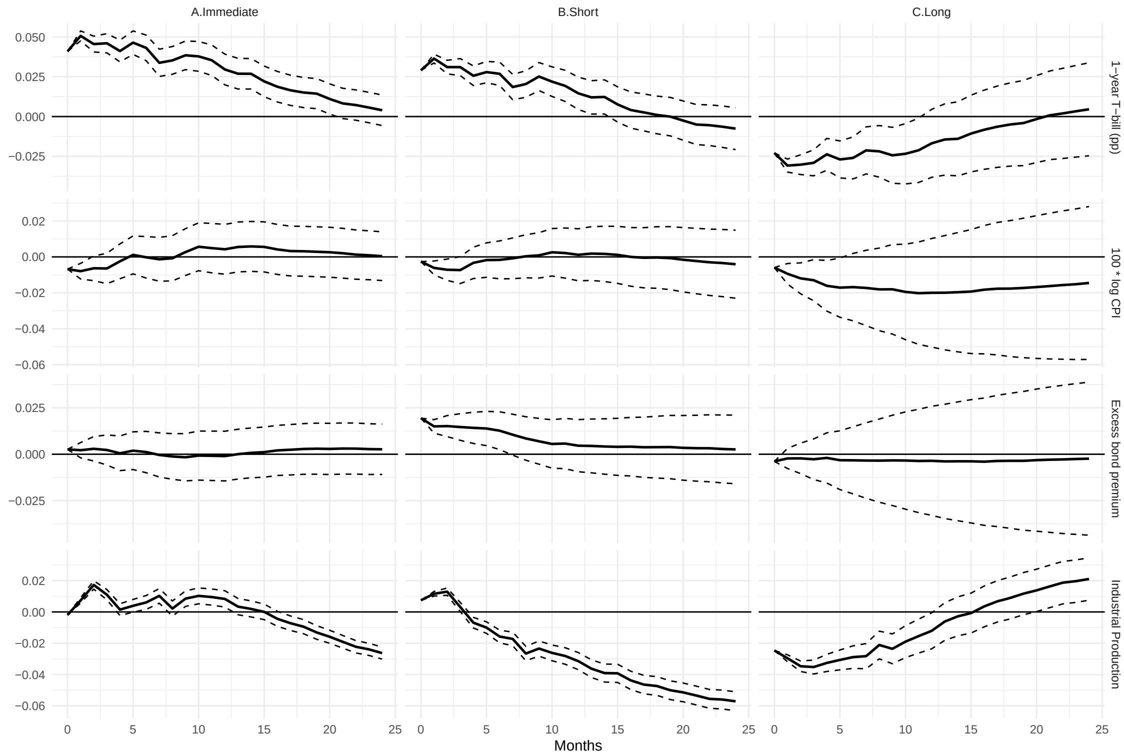


Figure 9: Impulse Responses to Synthetic Shocks (Smaller Set)

Figure shows impulse responses from a VAR to synthetic monetary policy shocks. Each column shows the response at a different news horizons $h = 0$ through $h = 12$. Lag length 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. As in the smaller set alternative, the immediate shock creates a long expansion, and the short-run news shock is also expansionary. This suggests that output puzzles are even more prevalent than in our baseline analysis.

E Synthetic Monetary Policy Shocks in the New Keynesian Model

Section 5 studied three types of synthetic MPS: immediate shocks (news about the policy residual on impact and 1 month ahead), short-run news (months 2 to 7), and longer-run news (8 to 25). These term structures are summarized in Figure 6. This appendix summarizes how these synthetic shocks affect the standard New Keynesian model outlined in Section 2.

Each column of Figure 6 plots the IRFs of a different synthetic MPS. The first row

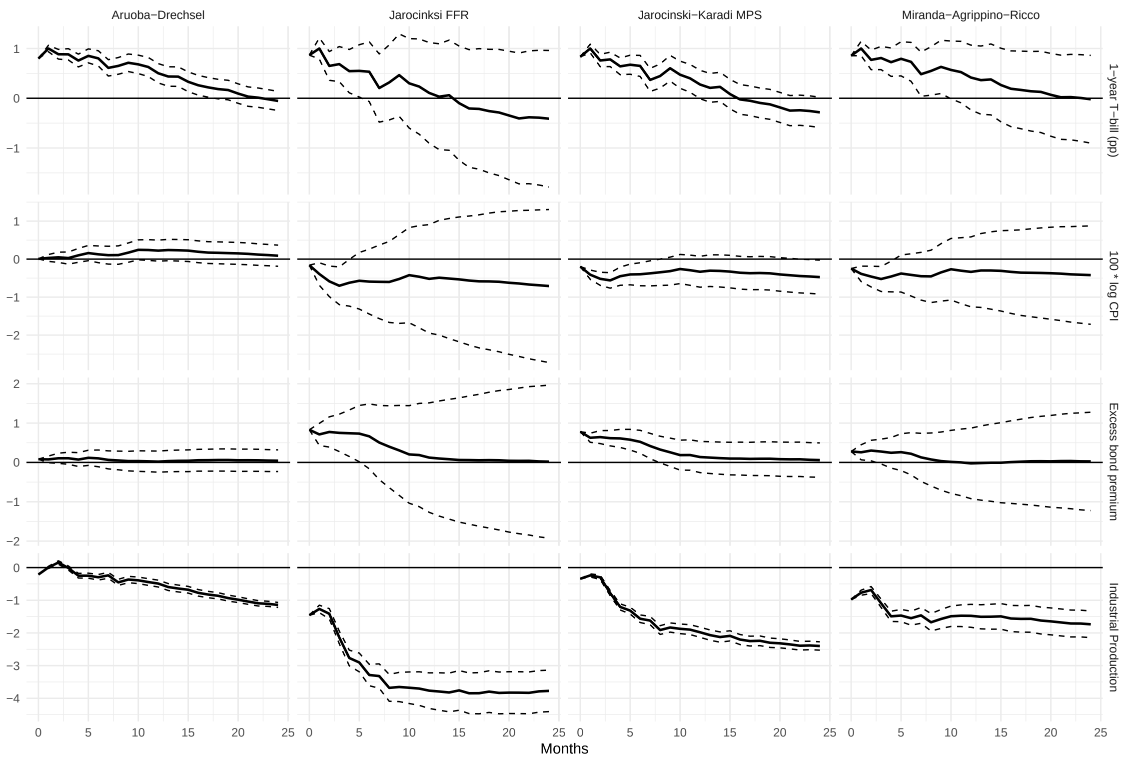


Figure 10: Impulse Responses to Estimated MPS (Smaller Set)

Figure shows impulse responses from a VAR to each of the underlying empirical MPS. Each column shows the response to a different shock. Lag length chosen by AIC.

plots the price level responses; as usual the textbook New Keynesian model features strong forward guidance effects: the longer the news horizon, the larger the resulting deflation. None of these IRFs are consistent with the data, where EMPS have little effect on prices. The second row plots the interest rate response, which roughly matches those estimated in the data: immediate shocks cause interest rate hikes, but long-run news causes short-run interest rate declines. However, it is hard to declare success regarding the interest rate behavior, when the other endogenous variables are inconsistent between the model and the data. For example, the third row plots the GDP response, where an immediate shock causes an immediate contraction, while the long-run news causes a short-run expansion before the contraction arrives. This is the opposite the data (Figure 5) where it is the immediate shocks that lead to a short-run expansion.

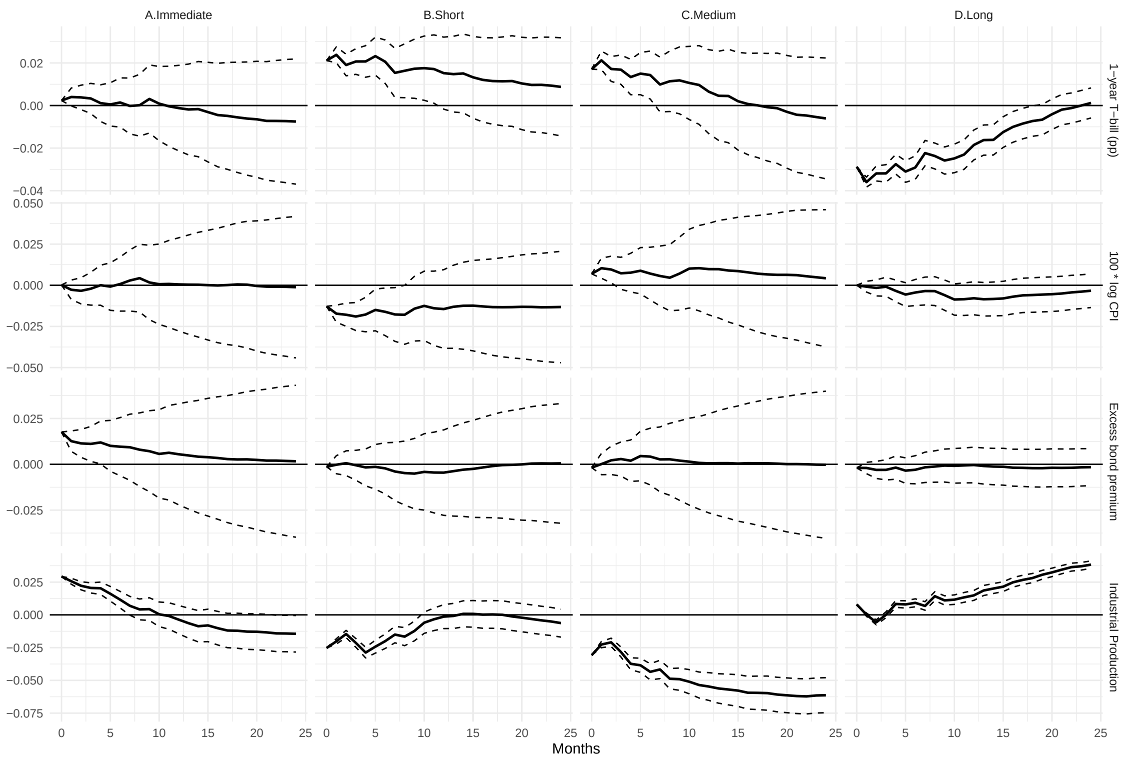


Figure 11: Impulse Responses to Synthetic Shocks (Expanded Set)

Figure shows impulse responses from a VAR to synthetic monetary policy shocks. Each column shows the response at a different news horizons $h = 0$ through $h = 12$. Lag length chosen by AIC.

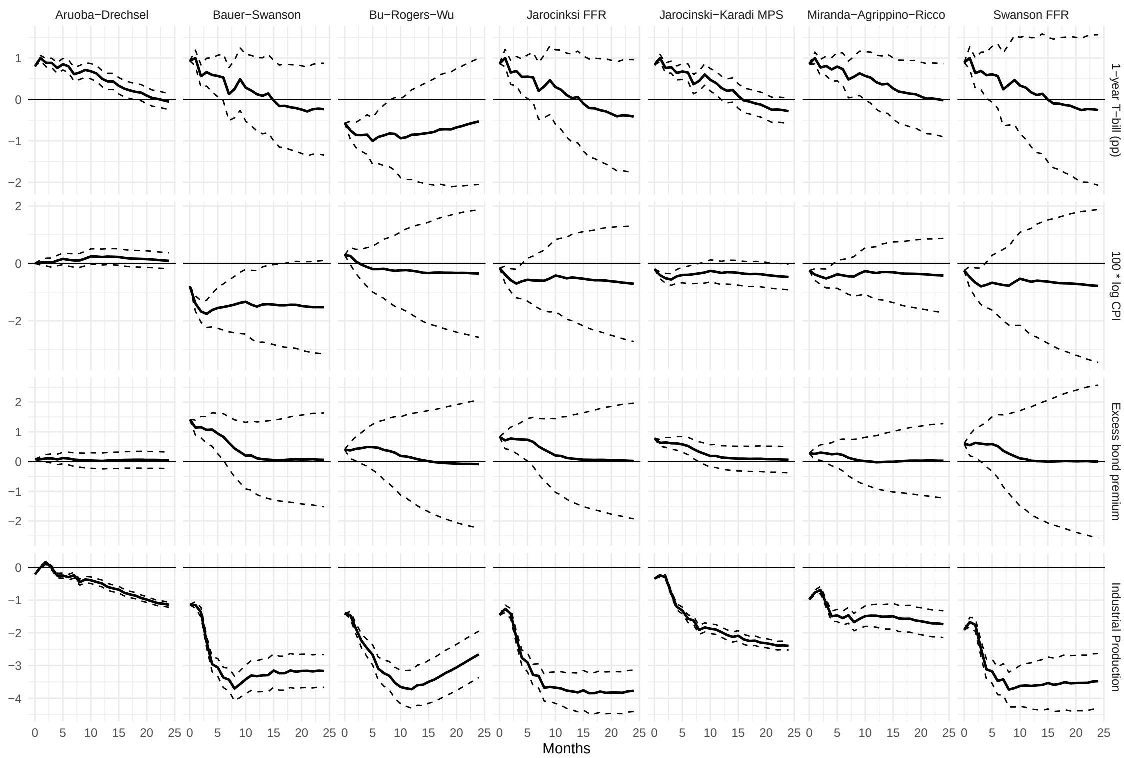
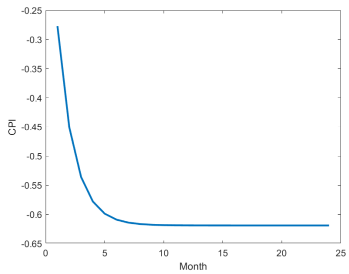
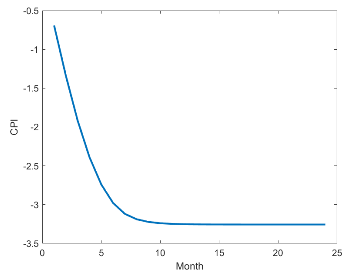


Figure 12: Impulse Responses to Estimated MPS (Expanded Set)

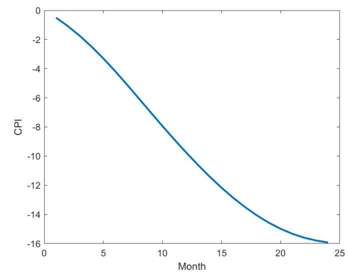
Figure shows impulse responses from a VAR to each of the underlying empirical MPS. Each column shows the response to a different shock. Lag length chosen by AIC.



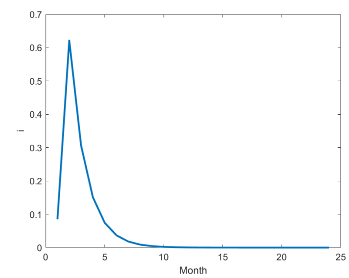
(a) Immediate sMPS: CPI



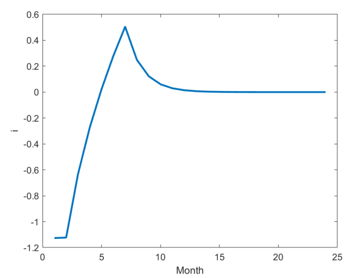
(b) Short-Run sMPS: CPI



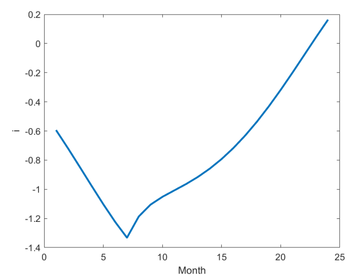
(c) Long-Run sMPS: CPI



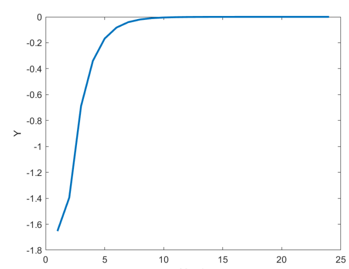
(d) Immediate sMPS: FFR



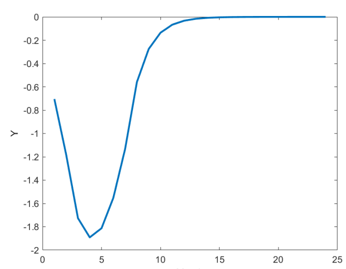
(e) Short-Run sMPS: FFR



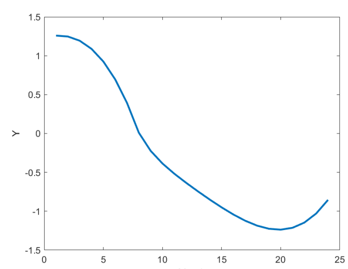
(f) Long-Run sMPS: FFR



(g) Immediate sMPS: GDP



(h) Short-Run sMPS: GDP



(i) Long-Run sMPS: GDP

Figure 13: New Keynesian Responses to News Shocks by Horizon

Each panel plots the IRF for how a synthetic MPS affects a macroeconomic variable over 24 months. The columns correspond to the immediate, short-run, and long-run synthetic shocks. The rows correspond to the price level, interest rate, and output. These effects are calculated from a standard calibration (Galí, 2008) of the textbook New Keynesian model.