# What Are Empirical Monetary Policy Shocks? Estimating the Term Structure of Policy News*

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June 18, 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 EMPS in the literature do not represent textbook policy surprises. Instead, they represent a mix of information about policy at many horizons, and this mix varies depending on how the EMPS is identified. 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 with little effect on prices, while long-term forward guidance is deflationary.

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

*We thank Regis Barnichon, Huixin Bi, Miguel Faria-e-Castro, Thomas Drechsel, Andy Glover, Christian Matthes, and Felipe Saffie, seminar participants at the IMF, 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 Eric Swanson who shared early versions of his series with us. This paper previously circulated as "The Term Structure of Monetary Policy News". 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 well-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 empirical monetary policy shocks (EMPS).

But what are these EMPS? The premise of this paper is that 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. That is, EMPS do not represent the textbook monetary policy shock, which is typically implemented immediately and without warning (i.e. a monetary policy surprise). Instead, each EMPS embodies a different combination of both policy surprises *and* news about future policies (i.e. forward guidance shocks).[1]

Taking this idea seriously poses a challenge when trying to confront theory with data. If models imply that shocks with news at different horizons should have different effects, but EMPS are some combination of shocks at different horizons, then how should we interpret estimated responses to EMPS? 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 empirical shock? Without a way to put some discipline on how a given EMPS combines shocks at different horizons, it is impossible to say.

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 surprises and news shocks for every future horizon. Our method 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 often emphasize that EMPS are not pure monetary 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 [large scale asset purchases] is difficult, because many of the FOMC's announcements provide information about both types of policies simultaneously". More generally, McKay and Wolf (2023) formalize how news about policy at many different horizons constitutes many different fundamental shocks to an economy, and show that isolating the effects of each news shock can be used to conduct counterfactual policy analysis.

[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

Next, the monetary policy residual is calculated from the estimated rule, and then stripped of correlation with lagged residuals 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.

Our second contribution is to estimate the term structure of sixteen well-known EMPS. We find that EMPS are definitely not policy surprises. Instead, the majority of their policy information is about forward guidance. However, there is substantial heterogeneity, with each EMPS uniquely blending information at different horizons. Our term structure decomposition quantifies the extent of this blending. For example, although narrative-based EMPS such as that of Aruoba and Drechsel (2024) are relatively close to a policy surprise, they still contain significant information at horizons up to six months. Methods that thoughtfully decompose monetary events into several dimensions are qualitatively effective: Swanson (2024) and Jarociński (2024) distinguish forward guidance shocks from target rate shocks at high frequencies. In both cases, the forward guidance shocks are driven principally by news about future policy at horizons longer than six months, while the target rate shocks are the closest to true policy surprises.

Our third contribution is to show how to connect EMPS back to theory. We develop a method to construct *synthetic monetary policy shocks* with any desired term structure from a linear combination of extant EMPS. As a result, it is possible to construct a synthetic shock that closely approximates a true policy surprise, news about a particular horizon, or any other pattern of forward guidance. We demonstrate by estimating the effects of a synthetic surprise constructed from a linear combination of five recent EMPS and find that, as is usually expected, an interest rate surprise raises rates and causes a contraction in real activity. However prices have near zero response. In contrast, longer-run forward guidance shocks feature a small output contraction but a large deflationary effect. We thus conclude that the observed deflationary effects of many of the component EMPS are thus mainly due to the contributions of long-run forward guidance. Decomposing EMPS into their term structures in this way reveals otherwise hidden features of the underlying mechanisms.

Aside from the central contributions of our paper, we make two additional technical advances. 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 deriv-

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.

ing 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 to 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 $\pi_t$ is inflation, $y_t$ is the output gap, and $i_t$ is the nominal interest rate. $\nu_t$ is exogenous and white noise. However, we introduce news to this model: $\nu_t$ 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.

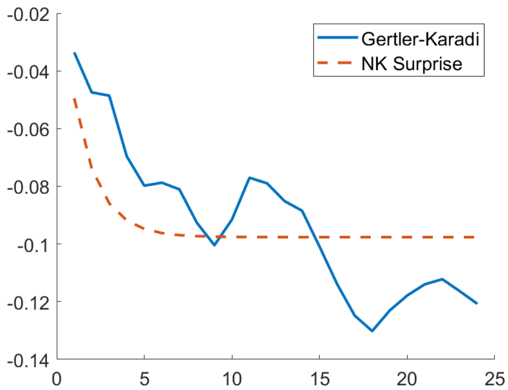
Figure 1a compares the price level IRFs from the New Keynesian model to that of a well-known high frequency EMPS, that of Gertler and Karadi (2015) . The shock causes a gradual deflation over 18 months. In contrast, the standard New Keynesian monetary policy surprise $\nu_{0,t}$ (dashed red line) causes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

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.

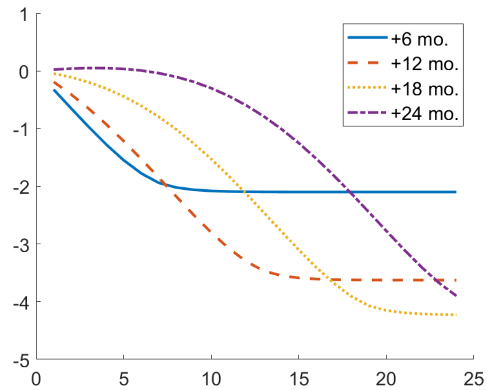
The IRF of the Gertler-Karadi shock is perfectly consistent with the New Keynesian model for *some* term structure. In other words, there is some linear combination of surprise and news that exactly replicates the empirical IRF. Panel 1c demonstrates, by approximating the Gertler-Karadi IRF as linear 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.[3]

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*.

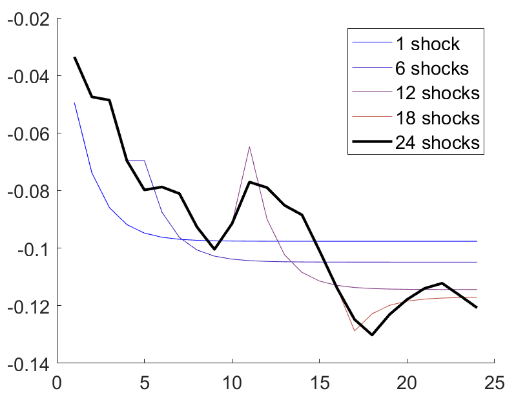
[3]It is not smooth of course, as all news shocks have smooth IRFs in the NK model, so jagged linear weights are required to recover the jagged Gertler-Karadi IRF. This also prompts the question: how close can a smooth term structure come to matching the empirical IRF? Is there a tradeoff between smoothness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



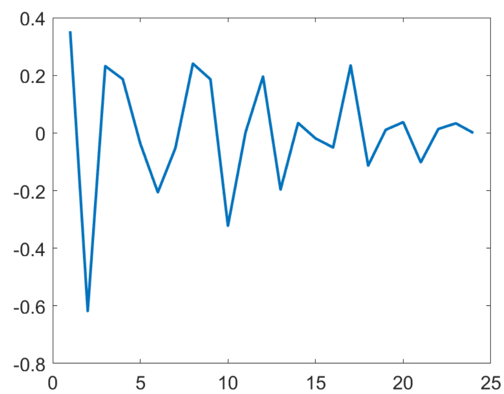

(a) EMPS vs. NK Surprise Shock




(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.

# 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, $x_t$ is a row vector of endogenous inputs to the policy rule, and $\phi$ is a vector of coefficients.

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

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

Together, equations (1) and (2) nest a very broad set of Taylor rule specifications. In principle, these two equations could be combined into one by including sufficient lags of observable variables in $x_t$ itself. But splitting them out maintains the familiarity and parsimony of a Taylor-type rule in equation (1), while allowing for a general autocorrelation structure of the residual with equation (2).

The monetary policy innovation $\nu_t$ is white noise, but not necessarily unforecastable. We write the residual $\nu_t$ as a sum of news shocks at $H_\nu$ 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 $\nu_{h,t} \sim N(0, \sigma_h^2)$.[4]

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

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

information about potentially many future residuals, as well as Gaussian error $\xi_t$:

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

where $\xi_t$ is orthogonal to the monetary policy innovation $\nu_{t+h}$ for all $h$. $\xi_t$ 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 $\nu_t$ 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 $\nu_t$:

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

where $u_t$ is a residual. The $\beta_h^j$ coefficients from equation (4) and $\gamma_h^j$ 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 $\nu_t$ are not. The next section describes how to estimate the term structure using instrumental variables.

### 3.2 Estimation Strategy

Estimating the $\gamma_h^j$ coefficients from equation (5) faces several challenges: $\nu_t$ is unobserved, it is unknown how it relates to the monetary policy residual $r_t$, and $r_t$ itself 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 $x_t$:[5]

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

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

The 4-stage approach for estimating the $\gamma_h^j$ 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 $\mathbf{x}_t \equiv \begin{pmatrix} y_{t-1} & x_{t-1} & \dots & y_{t-L} & x_{t-L} \end{pmatrix}$ 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 $\mathbf{w}_t \equiv \begin{pmatrix} w_t^j & w_{t-1}^j & \dots & w_{t-H_w}^j \end{pmatrix}$ 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*

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

[5] 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.

**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 $\beta_h^j$ coefficients can be calculated from the $\gamma_h^j$ 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.

What must be true for this estimation strategy to work? First, we need to correctly specify the policy rule. The rule represents the systematic, average way that policy decisions depend on the state of the economy, while the residual represents a transient deviation by monetary policymakers. Whether or not the rule is perfectly specified, our method needs to accurately isolate the innovations to these residuals. Thus, evaluating the variables we include in equation (1) and the lag length in equation (8) will constitute important robustness checks. Second, we require valid instruments to use in the IV step, which we discuss next. Our Monte Carlo simulation exercise, in Appendix E, also touch on this issue, since it present a specific cases where the estimation starategy does work.

### 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 $\Omega$ is needed as usual. Because Proposition 1 ensures that $\gamma$ 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 $\lambda$ 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 $\lambda$ 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.

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

| 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 (2024) | 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

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 (2024) 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. (2025) | 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. (2025).

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 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 produces 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 estimation 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 detrended private non-farm employment. These correspond directly to the two legs of the Fed's mandate: employment and price stability.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 $L = 6$.[6] Because instruments can have persistent effects, we include six lags of the IVs. Table 3 also includes many alternative measures of real activity. As expected, the estimated coefficient on real activity is affected by whether we use Christiano-Fitzgerald filtered real GDP,[7] GDP growth, an alternative detrending method, industrial production, or unemployment affects. However, the inflation coefficients are largely unchanged, and generally satisfy the Taylor

[6]We vary these choices in the robustness checks found in Section 6.

[7]We use monthly GDP estimated from a Kalman Smoother which matches the quarterly NIPA data and monthly consumption series (Barrett, 2025).

principle, that $\phi_\pi > 1$. We also include some specifications where we introduce additional variables. Including the excess bond premium has little effect. In contrast, the introduction of inflation expectations (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.

#### 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 $h = 0$. In other words, even the best 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

| | Baseline | CF-filtered GDP | GDP growth | HP-filtered GDP | IP | Unemployment | Add EBP | Add $\pi_1^e$, Clev. | Add $\pi_1^e$, Mich. |
|---|---|---|---|---|---|---|---|---|---|
| 12-month PCE Inflation, demeaned | 1.517*** | 1.536*** | 1.541*** | 1.528*** | 1.512*** | 1.187*** | 1.512*** | -0.249*** | 2.294*** |
| | (0.035) | (0.035) | (0.034) | (0.034) | (0.037) | (0.033) | (0.033) | (0.057) | (0.106) |
| GDP, CF-low-pass | | 0.697*** | | | | | | | |
| | | (0.076) | | | | | | | |
| GDP, HP-filtered | | | | 0.273*** | | | | | |
| | | | | (0.068) | | | | | |
| Cleveland Fed inflation expectations, 1 year, demeaned | | | | | | | | 2.180*** | |
| | | | | | | | | (0.052) | |
| Excess bond premium, demeaned | | | | | | | 0.440*** | | |
| | | | | | | | (0.090) | | |
| GDP growth, annualized, demeaned | | | 0.031*** | | | | | | |
| | | | (0.010) | | | | | | |
| Industrial Production, CF low-pass filter | | | | | 0.058** | | | | |
| | | | | | (0.026) | | | | |
| Michigan inflation expectations, 1 year, demeaned | | | | | | | | | -1.170*** |
| | | | | | | | | | (0.141) |
| Private nonfarm payroll employment, departures from quadratic log trend, demeaned | 0.370*** | | | | | | 0.377*** | -0.033** | 0.408*** |
| | (0.010) | | | | | | (0.010) | (0.014) | (0.013) |
| Unemployment rate | | | | | | 0.265*** | | | |
| | | | | | | (0.005) | | | |
| Residual autocorrelation | 0.95 | 0.95 | 0.95 | 0.96 | 0.96 | 0.96 | 0.96 | 0.89 | 0.92 |
| $R^2$ | 0.58 | 0.38 | 0.46 | 0.45 | 0.47 | 0.49 | 0.59 | 0.79 | 0.56 |
| Observations | 569 | 569 | 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 | CPI, 1m |
|---|---|---|---|---|---|---|---|---|
| 12-month PCE Inflation, demeaned | 1.517*** | 1.525*** | | | | | | |
| | (0.035) | (0.037) | | | | | | |
| 1-month Core PCE Inflation, demeaned | | | | | | 1.511*** | | |
| | | | | | | (0.109) | | |
| 1-month PCE Inflation, demeaned | | | 0.598*** | 0.627*** | | | | |
| | | | (0.076) | (0.077) | | | | |
| 12-month Core PCE Inflation, demeaned | | | | | 2.031*** | | | |
| | | | | | (0.037) | | | |
| 12-month CPI inflation, demeaned | | | | | | | 1.125*** | |
| | | | | | | | (0.029) | |
| CPI inflation, demeaned | | | | | | | | 0.372*** |
| | | | | | | | | (0.047) |
| Private nonfarm payroll employment, departures from quadratic log trend, demeaned | 0.370*** | | 0.344*** | | 0.423*** | 0.371*** | 0.343*** | 0.340*** |
| | (0.010) | | (0.025) | | (0.007) | (0.034) | (0.010) | (0.022) |
| Residual autocorrelation | 0.95 | 0.96 | 0.89 | 0.88 | 0.95 | 0.61 | 0.96 | 0.93 |
| $R^2$ | 0.58 | 0.46 | 0.34 | 0.20 | 0.64 | 0.42 | 0.54 | 0.29 |
| Observations | 569 | 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.

information, or because the high frequency variables used to inform the magnitude of the shock are inherently forward-looking.

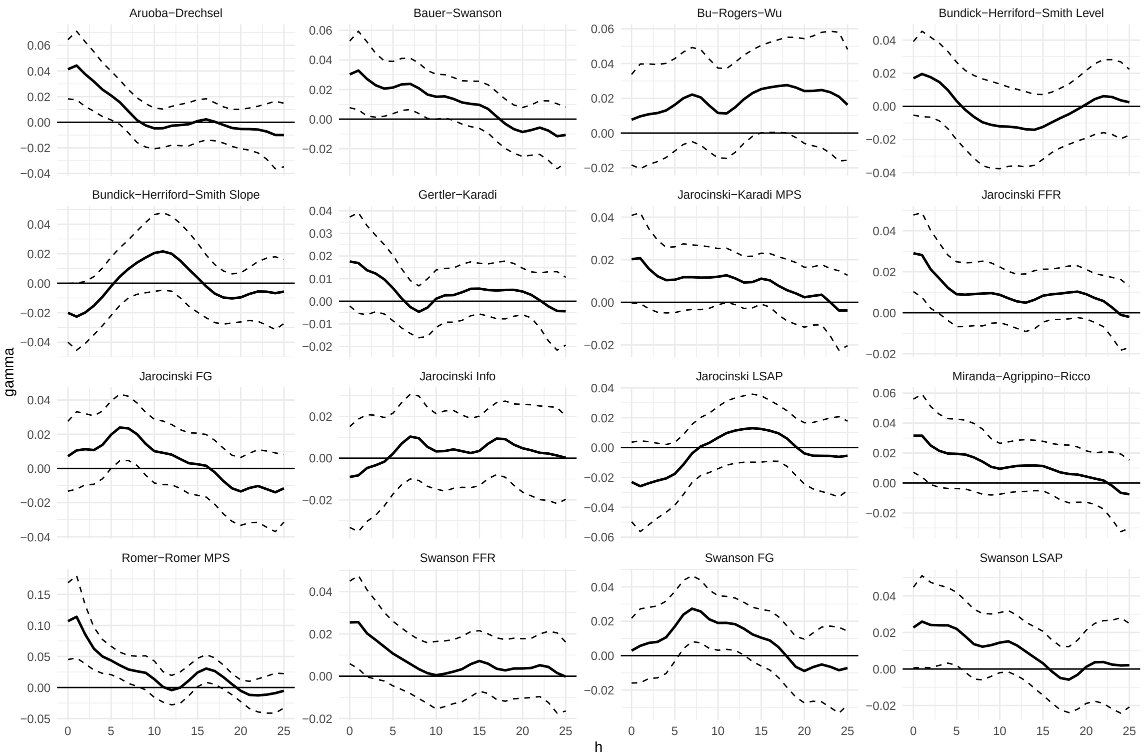



Figure 2: Estimated Term Structures

Figure shows the estimated $\gamma_h^j$ coefficients, i.e. the impact of each identified monetary policy shock $h$ periods later on the monetary policy innovation $\hat{\nu}_{t+h}$. Dashed lines show 95 percent confidence intervals.

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 $\nu_t$ 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.[8] The first column is $R^2_{0:1}$, which—since monetary policy announcements can happen on any day during a month—we interpret as the share of the EMPS that is due to an "immediate" change in the monetary policy innovation. Table 5 illustrates several of our key findings. The most obvious is that the shocks which explicitly aim to to identify surprises have a large share of their term structure variation at short horizons. Specifically, the EMPS that are most driven by the immediate horizons are the Swanson (2024) and Jarociński (2024) FFR shocks (both of which are "target level" shocks, identified by methods which split separate shocks to the future path of policy), the Aruoba and Drechsel (2024) and Romer and Romer (2004) narrative shocks, and the Gertler and Karadi (2015) shock. It is intuitive that the FFR shocks should appear here near the bottom of the table: these shocks are constructed by considering how many asset prices respond to Fed events, and isolating the only component that affects short term rates. However, no shock perfectly isolates true policy surprises. Even these well-constructed shocks which explicitly target interest rate surprises have much information at longer horizons. In some cases, this information dies out after around six months. But in other cases, the tail of the term structure is longer.

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 news*, which is realized in the remaining half year after the immediate horizons. Column 3 reports *medium-run news*, which sums the $R^2_k$ statistic for next half year (months $7 - 12$), and the final column reports *long-run news*, which occurs over the following year.

Reassuringly, two of the shocks that are the most driven by forward guidance are the aptly-named Forward Guidance shocks estimated by Swanson and Jarociński. These shocks contain almost no information about policy surprises in the short-run. This of course does not have to be true; the shocks are constructed to have no information about policy surprises at very high frequencies, but could have a large $R^2_{0:1}$ statistic by containing extremely short-run news in the immediate or following month. But they do not. In Swanson's case, the news is concentrated in the medium-run, while for Jarociński the news is more spread out over the two-year window. Joining these low-surprise examples is the Bu-Rogers-Wu

[8] 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 $\lambda$ 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 $\lambda$ 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 $\lambda$ in our baseline results, which is close to the average of the EMPS-specific optimal values. We consider alternate values of $\lambda$ in the robustness checks found in Section 6.

| Shock | $R^2_{0:1}$ | $R^2_{2:6}$ | $R^2_{7:12}$ | $R^2_{13:24}$ |
|---|---|---|---|---|
| Swanson FG | 0.01 | 0.22 | 0.59 | 0.18 |
| Bu-Rogers-Wu | 0.02 | 0.11 | 0.16 | 0.71 |
| Jarocinski FG | 0.04 | 0.35 | 0.36 | 0.25 |
| Jarocinski Info | 0.18 | 0.11 | 0.32 | 0.40 |
| Bundick-Herriford-Smith Slope | 0.21 | 0.17 | 0.43 | 0.19 |
| Swanson LSAP | 0.23 | 0.50 | 0.22 | 0.05 |
| Bundick-Herriford-Smith Level | 0.24 | 0.22 | 0.25 | 0.29 |
| Bauer-Swanson | 0.27 | 0.36 | 0.26 | 0.11 |
| Jarocinski LSAP | 0.28 | 0.45 | 0.07 | 0.20 |
| Jarocinski-Karadi MPS | 0.28 | 0.25 | 0.28 | 0.19 |
| Miranda-Agrippino-Ricco | 0.34 | 0.38 | 0.16 | 0.12 |
| Jarocinski FFR | 0.43 | 0.27 | 0.11 | 0.18 |
| Gertler-Karadi | 0.44 | 0.35 | 0.04 | 0.17 |
| Aruoba-Drechsel | 0.47 | 0.48 | 0.02 | 0.04 |
| Swanson FFR | 0.49 | 0.40 | 0.02 | 0.09 |
| Romer-Romer MPS | 0.52 | 0.36 | 0.05 | 0.07 |

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. Shocks are ordered by $R^2_{0:1}$

shock, which is rare in that it is constructed to capture a high frequency identification strategy without using proprietary high frequency data. Their method produces a shock that overwhelmingly contains news about long-run policy; no other shock has more than 50% of its term structure appear more than a year in the future.

### 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 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 applying OLS to the simulated data 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 complement 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 is to think of the different methods as picking different points on the trade-off between bias and maximizing informative variation. Lagged variable GMM following Clarida et al. (2000) reduces endogeneity bias under certain assumptions 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 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 consider 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

In the next section, we study the impulse responses to some synthetic shocks defined by specific term structures. This is just one application. Many others are possible. For example, synthetic news shocks could be useful in applying the method of McKay and Wolf (2023) to generate counterfactual policy responses robust to the Lucas critique. Another possibility is to create synthetic shocks which match the term structure of a target EMPS. This would allow the construction of a comparable shock series over periods where the target series is unavailable, e.g. extending to more recent data. Moreover, the broader principle is not limited just to monetary shocks. In general, one could apply our methods of to other sources of macro fluctuations with partially anticipated components, such as fiscal or technological shocks.

## 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 five 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, Miranda-Agrippino and Ricco, and the Swanson FFR, FG, and LSAP 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.

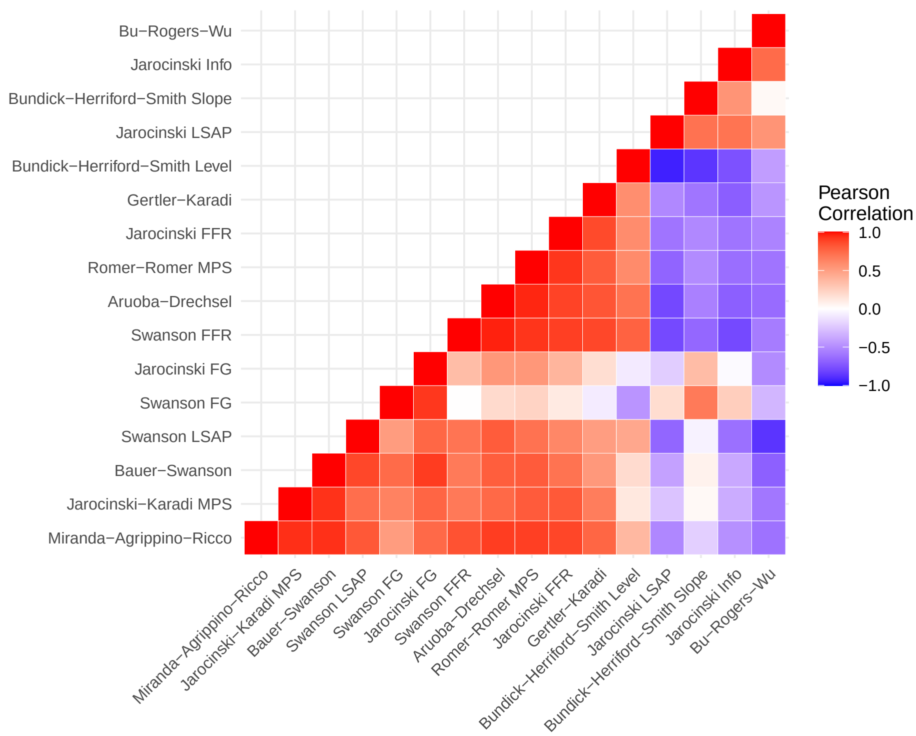



Figure 3: Term Structure Correlations

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

Using the five 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 the 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.

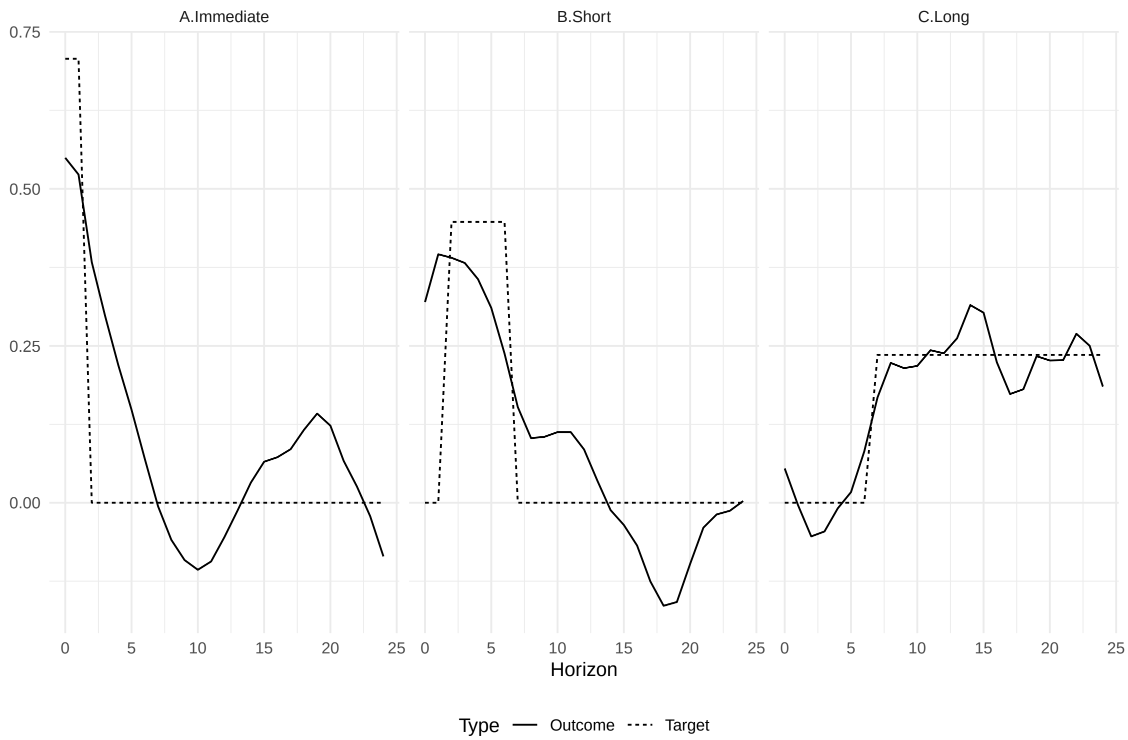



Figure 4: Target and Matched Synthetic MPS Term Structures

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 five empirical shocks, we cannot match these targets exactly. But five shocks gets us surprisingly 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.[9] In Appendix D we use additional shocks to get closer to the targets structures; doing so does not substantially change the estimated IRFs.

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 Treasury yields, log CPI, log industrial production, and the excess bond

[9]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.

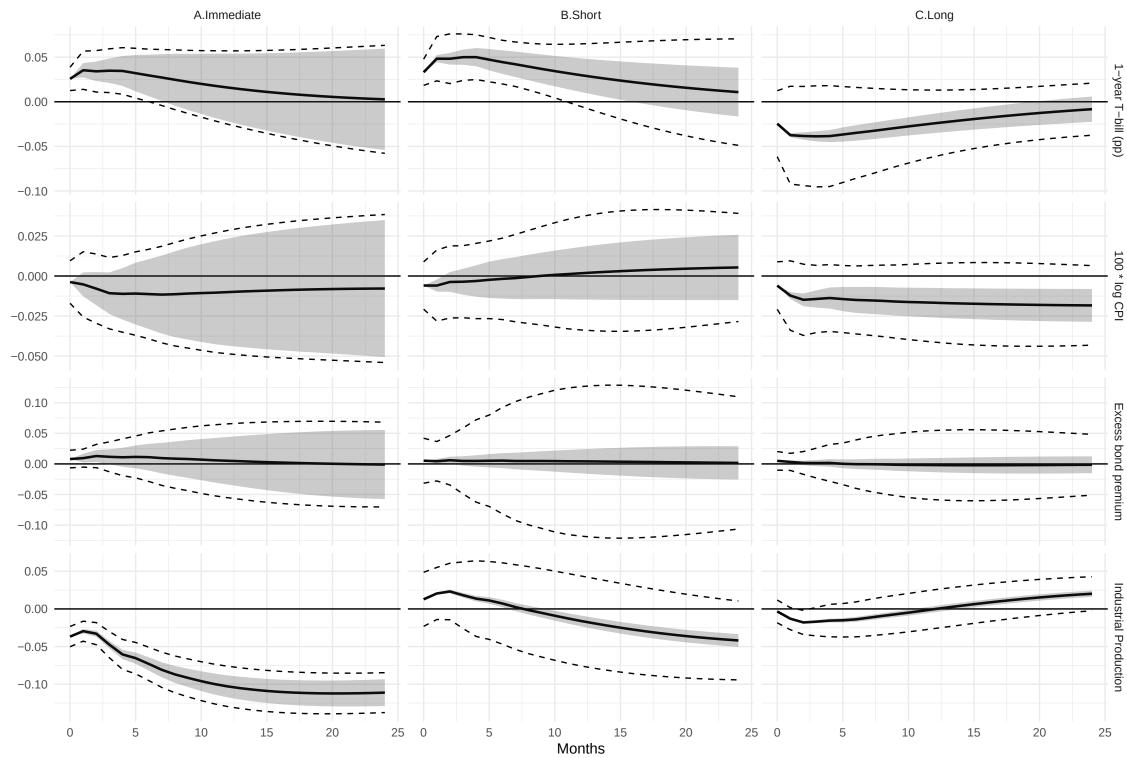



Figure 5: Impulse Responses to Synthetic Shocks

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.

premium (EBP). We pick these variables so that our VAR is a close as possible to the "standard" framework in the literature. One cost of this is that we cannot include the exact variables that are used in our Taylor rule estimation. We then construct the responses to synthetic shocks by projecting each synthetic 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. The immediate shock is a clear monetary policy tightening: interest rates rise immediately and cause a contraction. There is perhaps a deflationary effect, but the

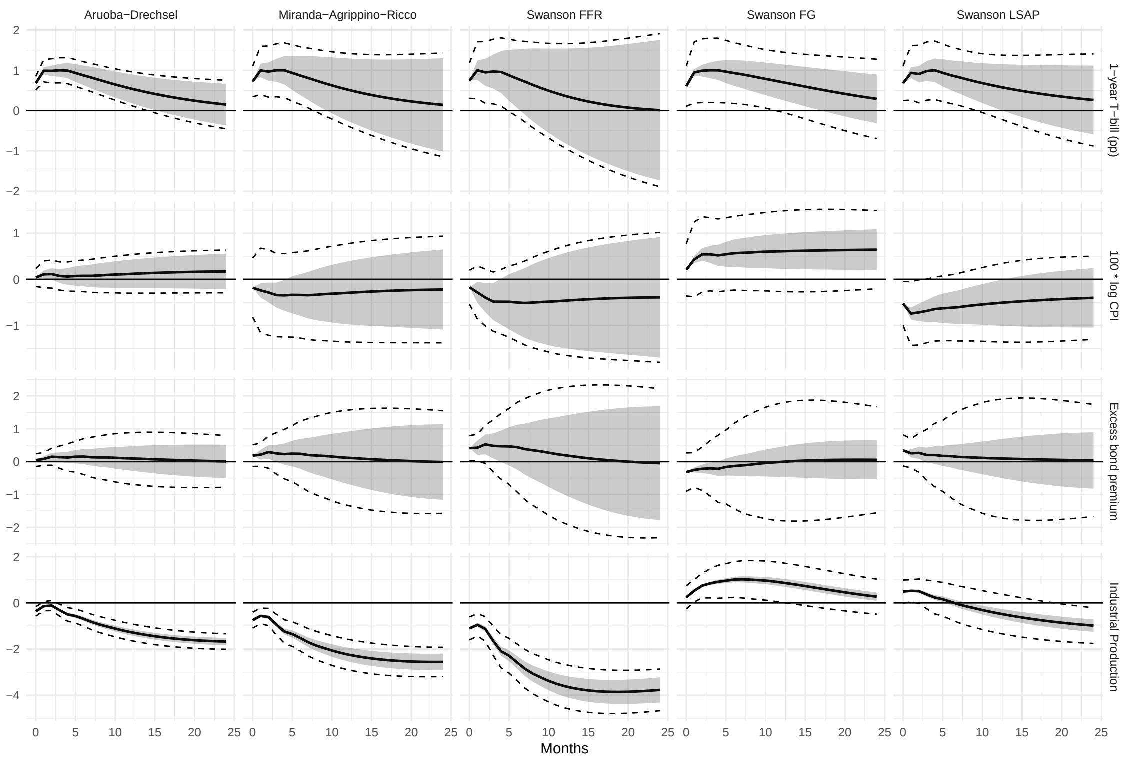



Figure 6: Impulse Responses to Estimated MPS

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.

price level response is not statistically different from zero. These effects are consistent with the two most important components of the synthetic surprise: the Swanson FFR and Aruoba-Drechsel shocks are the closest EMPS to true policy surprises, and both cause large declines in real activity and near-zero price effects.

The short-run news shock also increases rates, but this shock is expansionary in the initial half year. Indeed, the expansionary effect is what allows rates can rise without a short-run monetary policy residual; real activity increases so the increase in rates in the short run is the endogenous policy responses. In the longer run, this shock is contractionary, and there is no large effect on prices at any horizon. In contrast, the long-run news shock is the only deflationary one, matching the textbook New Keynesian prediction. Counterintuitively it decreases rates in the short run, but this is also qualitatively consistent with the textbook model: the long-run forward guidance shock is contractionary, so short-term monetary policy responds endogenously 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 relatively homogeneous: they all predict higher rates, reduced real activity, and zero or modest deflation, with the exception of the Swanson Forward Guidance shock. So how can the synthetic shock IRFs look so different from the component IRFs? The key is that even though the component IRFs look relatively similar they are linearly independent, so they span a wide variety of potential outcomes. Thus different linear combinations of EMPS can produce IRFs that are strikingly different form those plotted in Figure 6 .

We learn that the relatively homogeneous empirical MPS are mixing heterogeneous effects of different news horizons. The standard rate increases are driven by *immediate* and *short-run news*. The standard deflation is driven almost entirely by *long-run news*. And the rapid contractions are not a property of forward guidance, but instead due to *immediate news*. How are we able to uncover these lessons? Because even though they are qualitatively similar, quantitative variation in the EMPS impulse responses 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 standard that a surprise policy tightening is contractive, and it is typical that future monetary policy contractions can cause rates to decline in anticipation. However, the short-run expansionary effect of a short-run news shock is hard to explain with the textbook model, given that this shock also raises rates. 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 short-run synthetic shock. Moreover, when we repeat our exercise using alternative smaller and larger sets of component shocks (Appendix D), the results still resemble our baseline.

More substantially, it is hard to reconcile the sharp contraction of the immediate policy shock with a New Keynesian explanation when there is effectively zero effect on prices. This tension is well known (Ramey, 2016), but many shocks from the recent generation either suffered from the historical "price puzzles" (as in Aruoba and Drechsel (2024)) or caused at most a small price decline (as in Miranda-Agrippino and Ricco (2021)). Our analysis does not resolve this tension, but it does offer a richer characterization of it. Surprises do not cause large deflation; rather, the largest deflationary effects of EMPS are driven by the long-run forward guidance components.

# 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 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, so too are the Romer & Romer narrative shocks, as well as the Swanson and Jarociński HFI Fed Funds shocks. In contrast, the Bu-Rogers-Wu shock is mostly long horizon news for all specifications, as are the Swanson and the Jarociński Forward Guidance shock.

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.

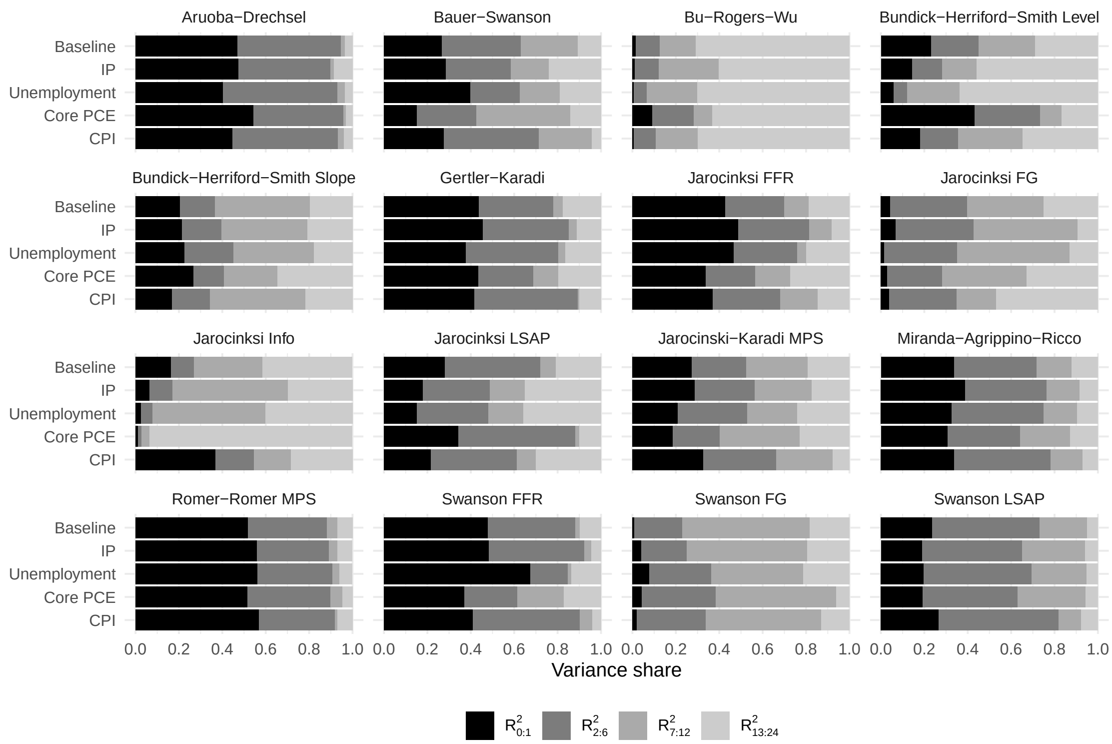



Figure 7: Term Structure Variance Decomposition: Robustness to Taylor rule variables.

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 vertical 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 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. 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.

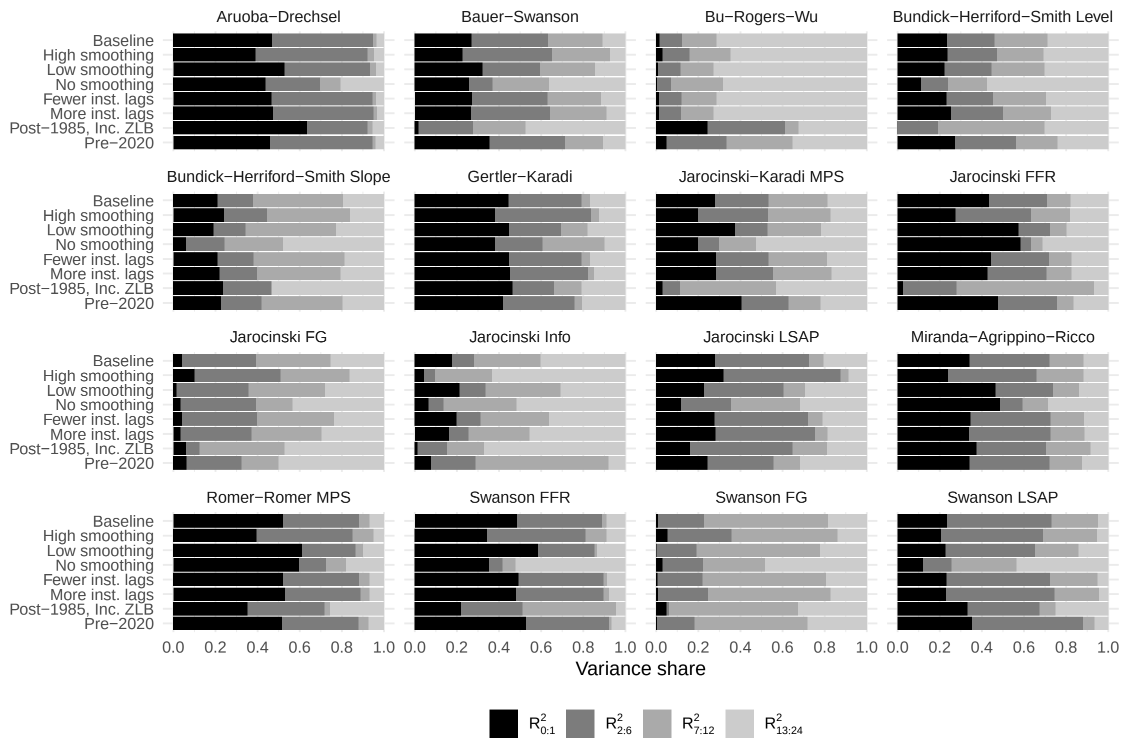



Figure 8: Term Structure Variance Decomposition: Robustness to sample and estimation method

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.

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. Our synthetic shock approach also offers opportunities for many further potential applications. And our specific findings 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 measured effect of news shocks at multiple horizons set an empirical benchmark for future models to reflect.

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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:

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

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

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

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

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

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

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 $\nu_t$ 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

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

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

Combining these two equations gives the ratio

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

■

# 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 $\gamma_h$ 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 $\alpha_k$ 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 $\alpha_k$ 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 $\alpha$ is the $K+1$-dimensional vector of coefficients, and $\epsilon$ 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 $\lambda$ is a positive shrinkage parameter, and $\mathbf{P}$ is the penalty matrix. $\lambda$ 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 $r$th 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 $\sigma^2$ 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 $\alpha_k^j$ 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 immediate shock is contractionary whit little effect on prices, the short-run shock is expansionary at some horizons, and the long-run shock is deflationary and reduces rates on impact.

In our first alternative, we employ a smaller set of EMPS, restricted to a few shocks that are thought to represent traditional monetary policy tools. In this implementation, we drop the Swanson LSAP shock from the baseline, which may capture non-traditional tools used by the Fed beyond classic interest rate policy. Figure 9 plots the estimated IRFs to the synthetic shocks estimated from this smaller set. They closely resemble the baseline approach, although now the short-run news shock does not feature a temporary production expansion.

In our second alternative, we employ an expanded set of EMPS in order to more accurately approximate the target synthetic shock structure (Figure 2). To the baseline we add the Jarociński and Karadi (2020) shock, which controls for central bank information in a different way than Miranda-Agrippino and Ricco (2021). And even though they have

| | Baseline | Fewer inst. lags | More inst. lags | $L = 1$ | $L = 12$ | $L = 24$ | $n_{H_\nu}$=12 |
|---|---|---|---|---|---|---|---|
| 12-month PCE Inflation, demeaned | 1.517*** | 1.578*** | 1.358*** | 1.517*** | 1.517*** | 1.517*** | 1.518*** |
| | (0.035) | (0.045) | (0.032) | (0.040) | (0.032) | (0.028) | (0.035) |
| Private nonfarm payroll employment, departures from quadratic log trend, demeaned | 0.370*** | 0.318*** | 0.359*** | 0.370*** | 0.370*** | 0.370*** | 0.367*** |
| | (0.010) | (0.023) | (0.007) | (0.010) | (0.009) | (0.007) | (0.009) |
| Residual autocorrelation | 0.95 | 0.95 | 0.96 | 0.95 | 0.95 | 0.95 | 0.95 |
| $R^2$ | 0.58 | 0.57 | 0.61 | 0.58 | 0.58 | 0.58 | 0.59 |
| Observations | 569 | 565 | 575 | 569 | 569 | 569 | 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 | Post-1985, Inc. ZLB | Pre-2020 |
|---|---|---|---|---|---|
| 12-month PCE Inflation, demeaned | 1.517*** | 1.138*** | 0.454*** | 0.091*** | 1.501*** |
| | (0.035) | (0.031) | (0.015) | (0.018) | (0.031) |
| Private nonfarm payroll employment, departures from quadratic log trend, demeaned | 0.370*** | 0.186*** | 0.237*** | 0.373*** | 0.372*** |
| | (0.010) | (0.017) | (0.004) | (0.018) | (0.009) |
| Residual autocorrelation | 0.95 | 0.97 | 0.98 | 0.99 | 0.96 |
| $R^2$ | 0.58 | 0.59 | 0.58 | 0.61 | 0.68 |
| Observations | 569 | 569 | 449 | 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 | 1.517*** | 1.517*** | 1.517*** | 1.652*** | 1.111*** | 1.652*** |
| | (0.035) | (0.035) | (0.035) | (0.042) | (0.037) | (0.042) |
| Private nonfarm payroll employment, departures from quadratic log trend, demeaned | 0.370*** | 0.370*** | 0.370*** | 0.118*** | 0.514*** | 0.118*** |
| | (0.010) | (0.010) | (0.010) | (0.014) | (0.009) | (0.014) |
| Residual autocorrelation | 0.95 | 0.95 | 0.95 | 0.96 | 0.97 | 0.96 |
| $R^2$ | 0.58 | 0.58 | 0.58 | 0.50 | 0.57 | 0.50 |
| 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 | 1.517*** | 0.038 | 0.282 | 0.038 | 0.282 | 0.038 | 0.282 |
| | (0.035) | (0.089) | (0.487) | (0.089) | (0.487) | (0.089) | (0.487) |
| Private nonfarm payroll employment, departures from quadratic log trend, demeaned | 0.370*** | 0.488*** | -0.004 | 0.488*** | -0.004 | 0.488*** | -0.004 |
| | (0.010) | (0.160) | (0.934) | (0.160) | (0.934) | (0.160) | (0.934) |
| Residual autocorrelation | 0.95 | -0.01 | 0.95 | -0.01 | 0.95 | -0.01 | 0.95 |
| $R^2$ | 0.58 | 0.96 | 0.65 | 0.96 | 0.65 | 0.96 | 0.65 |
| 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.

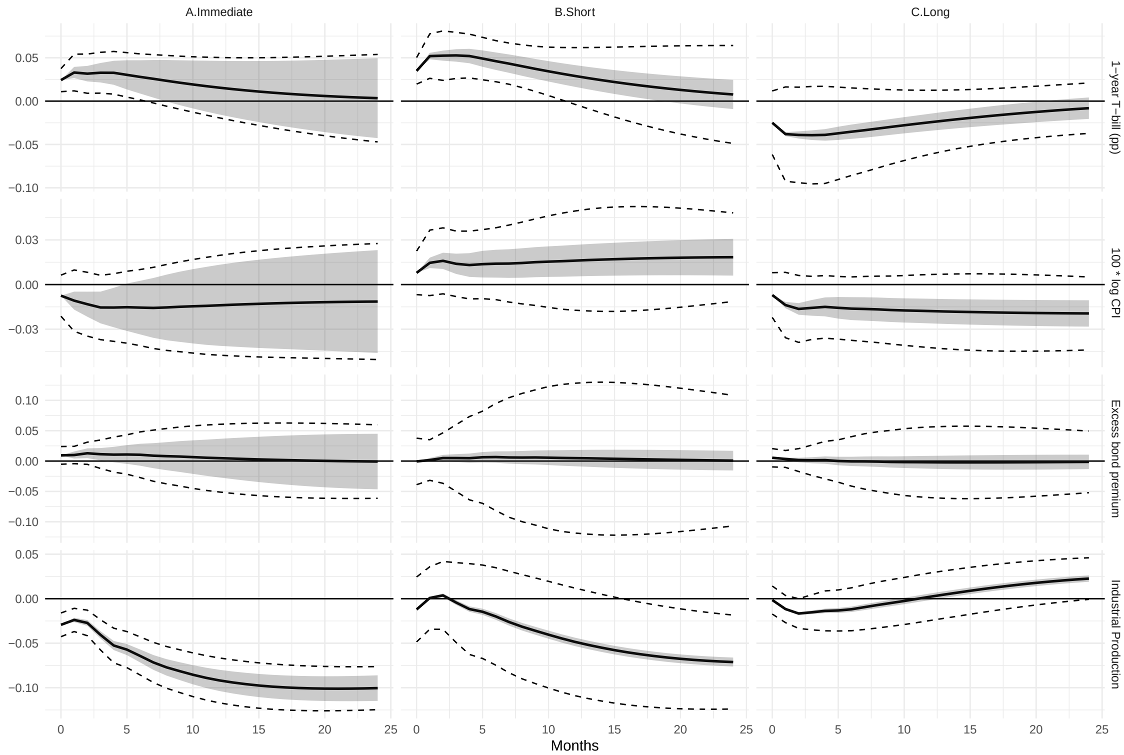


Figure 9: Impulse Responses to Synthetic Shocks (Smaller Set)

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 due to the proxy VAR. The VAR lag length is 11 and is chosen by AIC.

relatively similar term strucutres, the shocks are not perfectly correlated and cover different samples improving our statistical power. Figure 10 plots the IRFs. The main difference relative to the baseline is that the IRFs are more precisely estimated. Beyond this, the short-run news shock has a more moderate effect on rates, its contraction is now delayed, and the instantaneous price effect of the immediate shock has disappeared entirely.

Our final alternative adds the Bundick and Smith (2020) term structure uncertainty level shock, which is constructed from high frequency data to capture yet another channel of monetary policy. Altogether, we use seven different EMPS to construct this series of synthetic shocks. The IRFs of the synthetic shocks are plotted in Figure 11, and the IRFs of each component are plotted in Figure 11. Again, the main differences between these results and the baseline specification are in the effects of short-run news. The interest rate effect is small, prices no longer increase, and real activity falls for several months before a

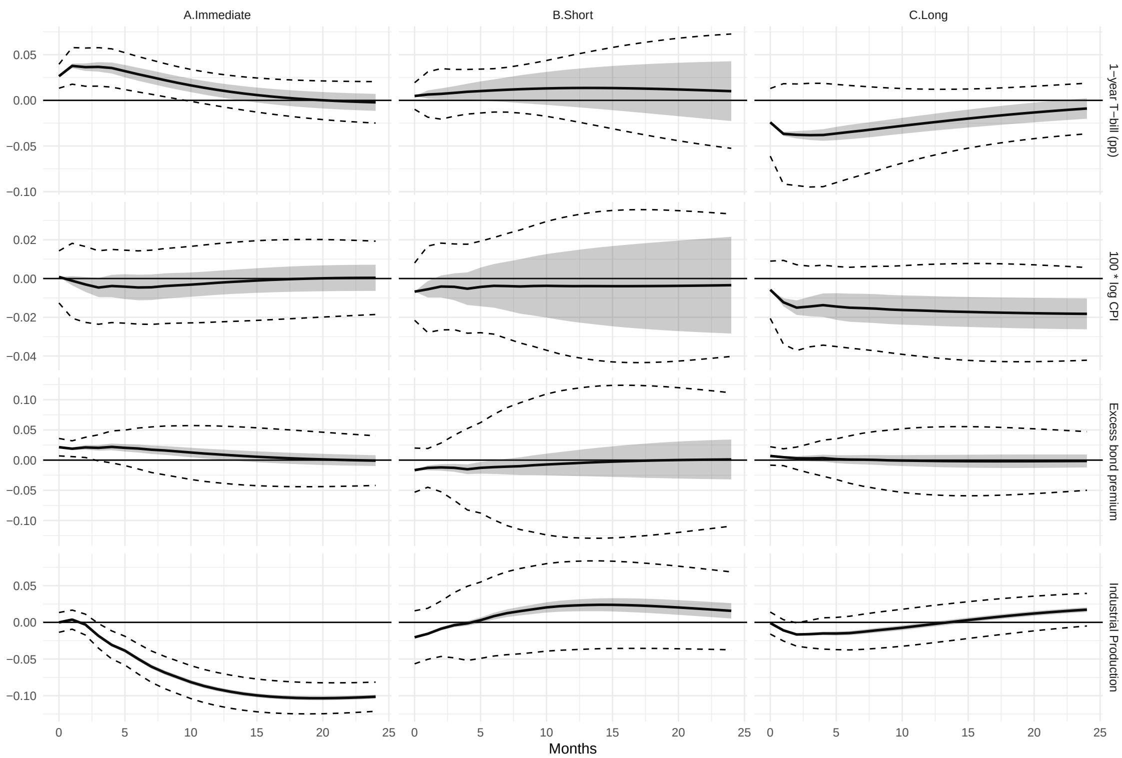


Figure 10: Impulse Responses to Synthetic Shocks (Larger Set)

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 due to the proxy VAR. The VAR lag length is 11 and is chosen by AIC.

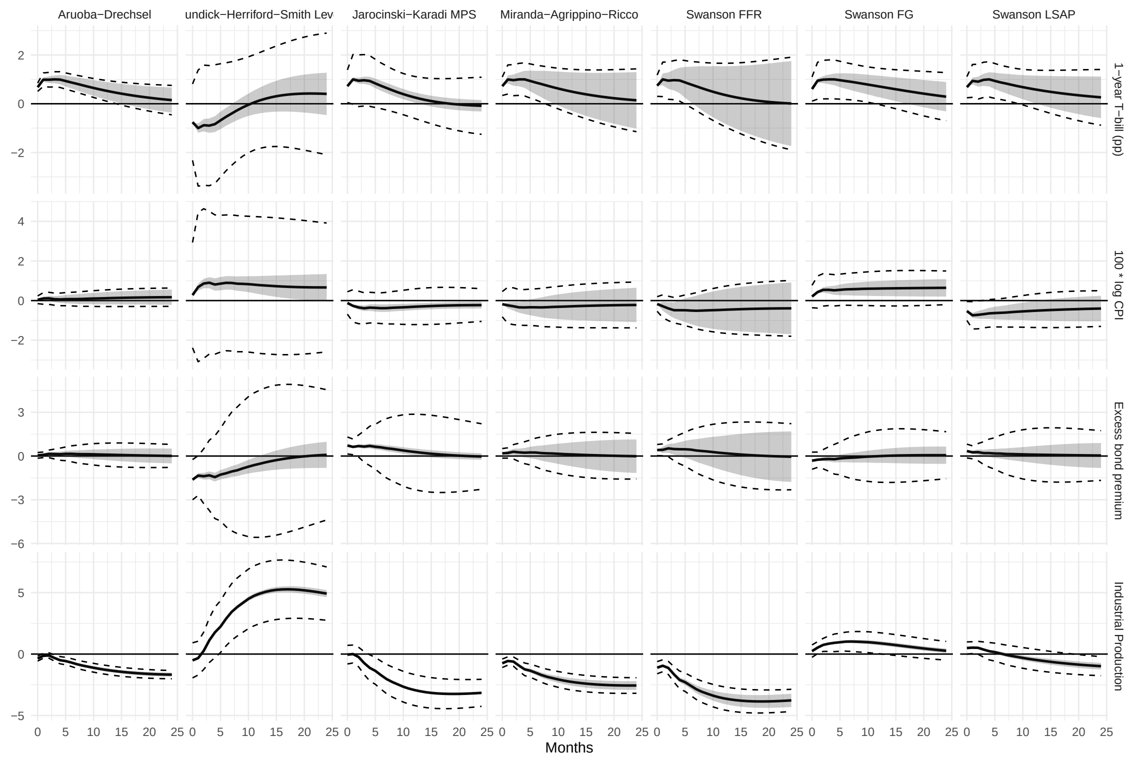


Figure 11: Impulse Responses to Synthetic Shocks (Largest Set)

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.

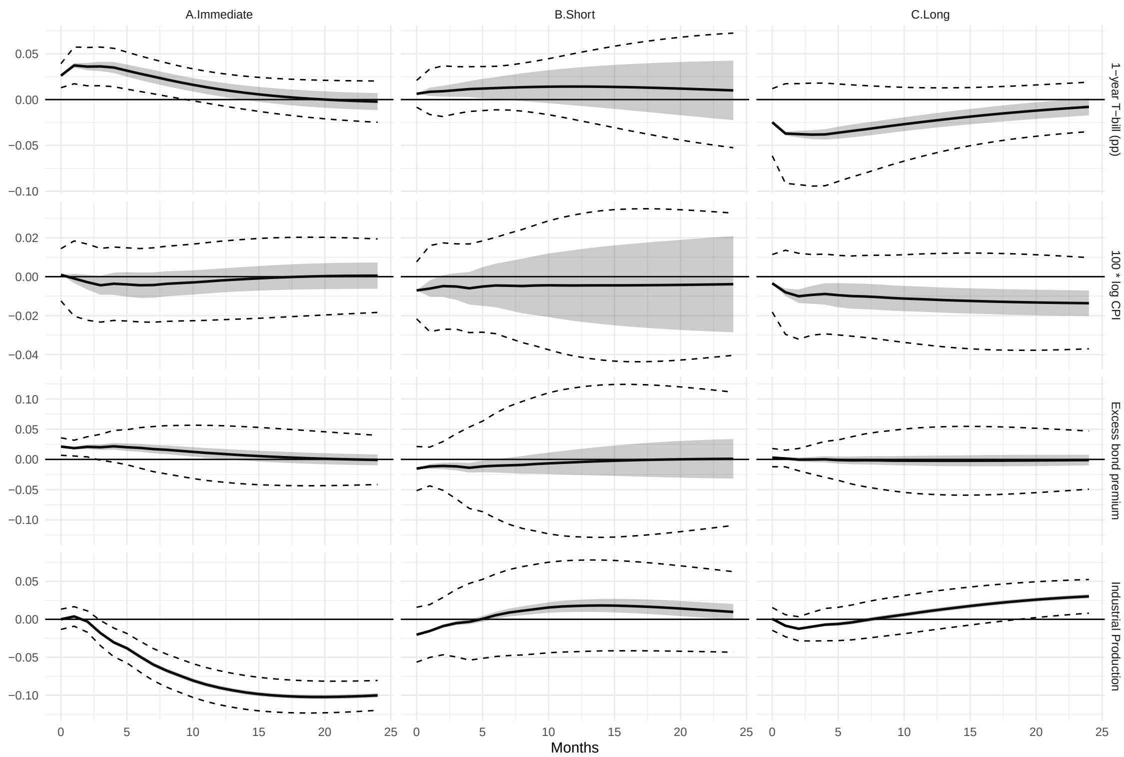


Figure 12: Impulse Responses to Synthetic Shocks (Largest Set)

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.

mild expansion. And, as in the previous case, the immediate shock has no price effect.

# 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 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 | $\beta$ | Utility discount factor | 0.997 |
| $\rho_a$ | Technology shock persistence | 0.98 | $\rho_r$ | Interest rate smoothing in Taylor rule | 0.49 |
| $\rho_z$ | Demand shock persistence | 0.56 | $\rho_{zpc}$ | Supply shock persistence | 0.49 |
| $\sigma$ | Risk aversion | 1.0 | $\varphi$ | Labor supply elasticity | 1.0 |
| $\phi_\pi$ | Taylor rule inflation coefficient | 1.5 | $\phi_\pi$ | Taylor rule output gap coefficient | 0.125 |
| $\theta$ | 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, $\gamma_i$, 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.[10] 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 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* | $\phi_\pi$ | 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) |
| | $\phi_y$ | 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* | $\gamma_0$ | 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) |
| | $\gamma_1$ | 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) |
| | $\gamma_2$ | 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) |
| | $\gamma_3$ | 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, $\pi_t$ | | | 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

[10] 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.

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 $\gamma_0$, 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.[11] The confidently incorrect Taylor rule estimates from OLS are heavily penalized by this convexity and so are projected 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 $\gamma_0$. In contrast, confidence intervals based on OLS cannot be trusted for any parameters for small sample sizes or for $\phi_\pi, \phi_y$, or $\gamma_0$ at any sample size.

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

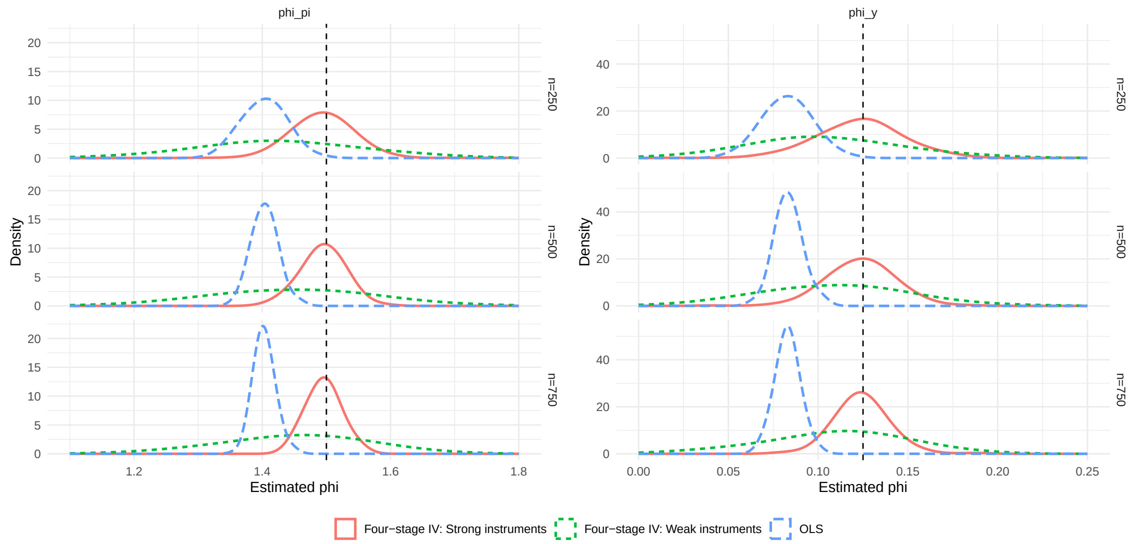


Figure 13: Short sample simulation: Distribution of estimated Taylor Rule coefficients

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.

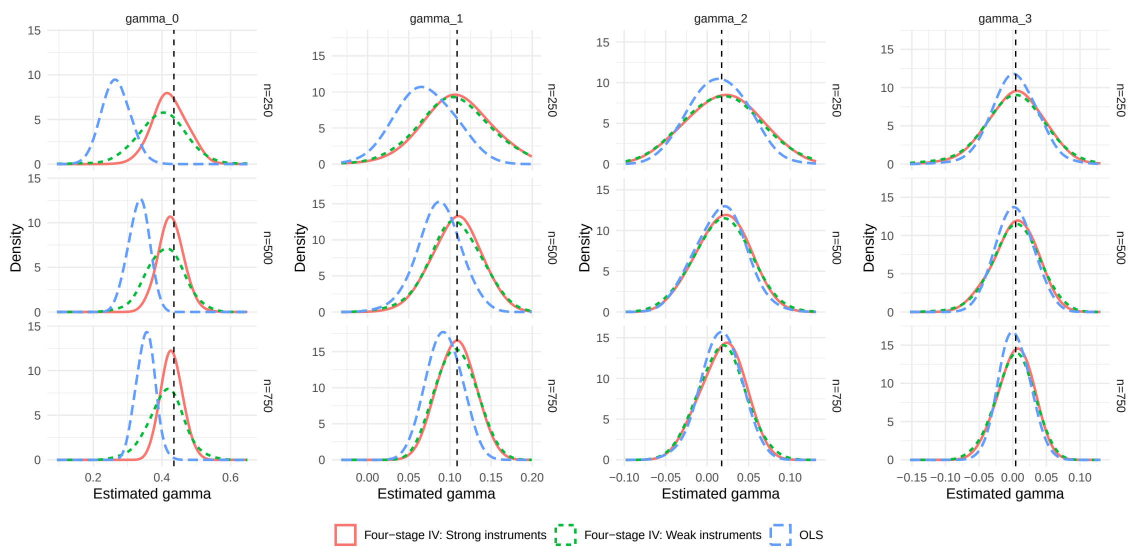


Figure 14: Short sample simulation: Distribution of estimated term structure of monetary policy.

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.

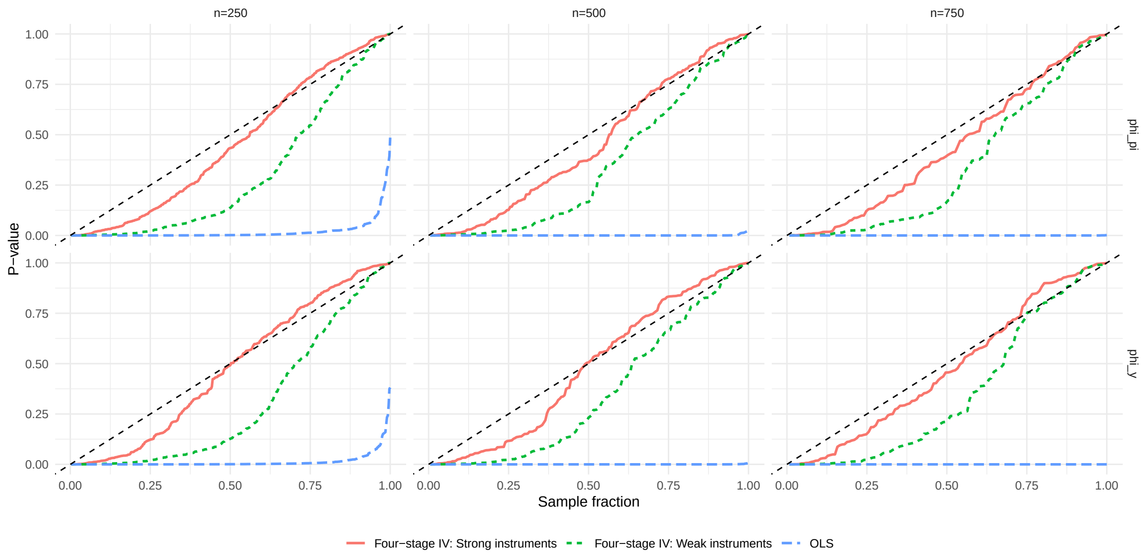


Figure 15: Short sample simulation: Distribution of p-values for Taylor Rule coefficients

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.

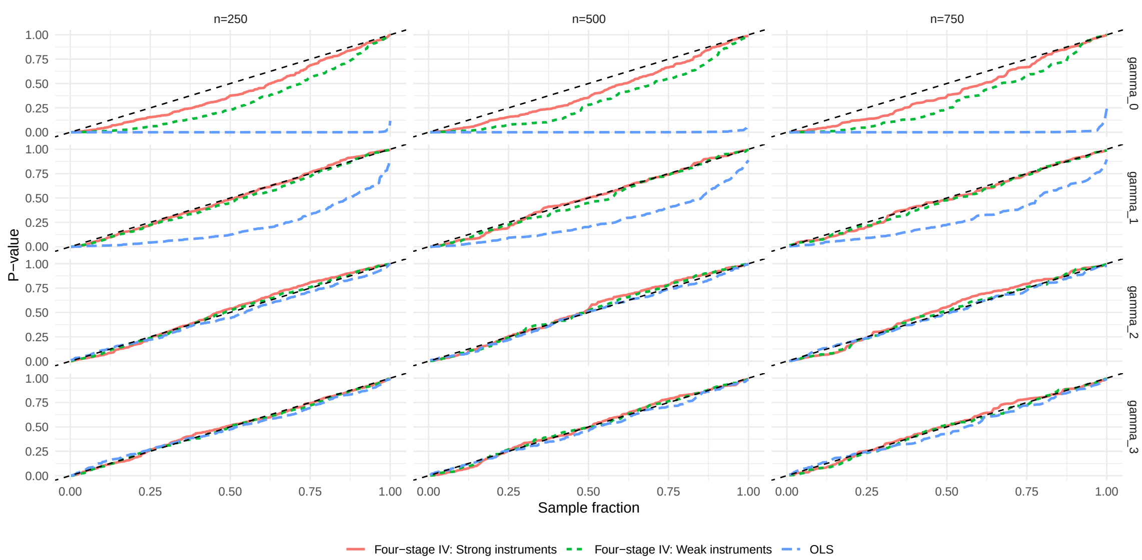


Figure 16: Short sample simulation: Distribution of p-values for term structure of monetary policy.

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.