Identifying News Shocks from Forecasts

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Abstract

We propose a method to identify the anticipated components of macroeconomic shocks in a structural VAR. We include empirical forecasts about each time series in the VAR. This introduces enough linear restrictions to identify every structural shock and to further decompose each one into "news" and "surprise" shocks. We estimate a VAR on U.S. time series using forecast data from the SPF, CBO, Federal Reserve, and asset prices. Unanticipated fiscal stimulus and monetary policy shocks have typical effects that match existing evidence. In our news-surprise decomposition, we find that news drives around one quarter of U.S. business cycle volatility. News explains a larger share of the variance due to fiscal shocks than for monetary policy shocks. Finally, we use the news structure of the shocks to estimate counterfactual policy rules, and compare the ability of fiscal and monetary policy to moderate output and inflation. We find that coordinated fiscal and monetary policy are substantially more effective than either individually.

JEL-Codes: C32, E32, E52, E62

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1 Introduction

Anticipated and unanticipated changes to macroeconomic forces can have different effects. Current methods focus on understanding these differences for a subset of macroeconomic shocks – typically, one shock at a time. In this paper we extend this line of thinking, considering an environment where *all* shocks have anticipated and unanticipated components, and introduce a general method to identify them.

Our strategy is to include data on forecasts about the macroeconomic time series in a vector autoregression (VAR). Forecasts are valuable because they reveal information about the future that is not otherwise revealed by the macroeconomic time series alone. We modify a standard structural VAR driven by a series of structural shocks, by assuming that each shock has an anticipated component – the "news" – and an unanticipated component – the "surprise". This data generating process is consistent with a large class of standard macroeconomic models. We identify shocks from cross-equation restrictions which impose consistency of the forecasts with the VAR's predictions. We prove that under relatively weak conditions, adding a forecast about each time series in the VAR identifies the news and surprise components of *every* structural shock.

Our method is not only useful for isolating news from surprise: it is a method to identify structural shocks themselves. Structural VARs typically assume that shocks are mutually orthogonal in order to identify them from reduced form innovations in the observed time series. Indeed, this orthogonality is what defines structural shocks. If we treat news and surprise components similarly, i.e. as mutually orthogonal, then our method identifies the *entire set* of structural shocks, including their news and surprise components. Thus our method is an alternative to the large variety of other strategies for identifying the full set of structural shocks in VARs.[1]

We apply our method by estimating a VAR on U.S. time series. We take data on forecasts from the Survey of Professional Forecasters (SPF), the Federal Reserve's Greenbook forecasts, and also construct some expectations from asset prices. In our VAR, we estimate a variety of structural shocks that resemble well-understood objects, including shocks to fiscal and monetary policy. Our estimated shocks have realistic unanticipated effects, including

[1] A classic approach is to make assumptions about the causal ordering of shocks within a period, and apply a Cholesky decomposition to the variance matrix (Sims, 1980). Other linear restrictions can identify the structural shocks by making assumptions about long-run effects (Shapiro and Watson, 1988), restrictions on the signs of shocks (Uhlig, 2005) or outside evidence on the magnitude of short-run effects (Blanchard and Perotti, 2002). Recently, attention has been focused on identifying the set of structural shocks using higher order moments and heteroskedasticity. Examples with dynamic heteroskedasticity include Sentana and Fiorentini (2001), Rigobon (2003), Lanne et al. (2010), and Lewis (2021). Lütkepohl and Netšunajev (2017) reviews this literature further. Other papers lean on non-Gaussianity more generally including Hyvärinen et al. (2010) and Gouriéroux et al. (2017).

fiscal multipliers that match other estimates in the literature, quantitatively realistic effects of monetary policy shocks that resemble those implied by high-frequency-identified instruments. Crucially, we can decompose each shock into the news and surprise components. For example, we find that the effects of fiscal shocks on output are relatively anticipated, and the news component implies a larger government spending multiplier than the surprise component, echoing the findings in Ramey (2011). In contrast, the effects of monetary policy shocks are mostly surprises.

By identifying the news and surprise components of all shocks, we can compute a variance decomposition which allows us to make general statements about the role of anticipated and unanticipated shocks in macroeconomic fluctuations. We find a modest role for news in explaining business cycles: one quarter of output volatility is due to news shocks. This echoes the findings of a large literature studying the relevance of news shocks for the macroeconomy. Many of these papers focus on news about technology[2] but we join a sizeable group studying news about policy shocks, discussed below. This is more challenging, because policies are endogenous, preventing the application of standard VAR methods developed by Barsky and Sims (2011), Kurmann and Sims (2021) or Chahrour and Jurado (2022) to identify news about exogenous processes. Indeed, many papers follow a conceptually similar approach to ours by including a forecast in their VAR to isolate surprises or news about the forecasted variable.[3] However, including a single forecast identifies a specific news shock only if there is a single structural shock that is anticipated. Otherwise, what might appear to be news about a shock such as fiscal policy also includes news about shocks to supply, demand, and so forth.[4] This is the main advantage of our approach relative to existing VAR studies of news: by including forecasts about every time series, we can distinguish the effects of news to different structural shocks in a single framework. And we find that conflation of news about multiple shocks is a nontrivial concern, as the news component of nearly all shocks is

[2]Examples include Beaudry and Portier (2006), Barsky and Sims (2012), Schmitt-Grohé and Uribe (2012), Blanchard et al. (2013), Ben Zeev and Khan (2015), Chahrour and Jurado (2022), and Kilian et al. (2024). The most closely related papers are those that utilize forecast data to identify news about technology: Miyamoto and Nguyen (2020) and Hirose and Kurozumi (2021) include forecast data in New Keynesian DSGE models to identify news shocks and estimate that technology news drives a large share of business cycle volatility; Cascaldi-Garcia (2022) uses forecast revisions of economic growth to instrument for technology news shocks, which drive $11\% - 26\%$ of output volatility depending on the horizon.

[3]Papers including forecasts to identify fiscal surprises include Ramey (2011), Auerbach and Gorodnichenko (2012), and Born et al. (2013). VAR methods using forecasts and additional structural assumptions to identify fiscal news include Caggiano et al. (2015), Ricco (2015), Ricco et al. (2016) and Forni and Gambetti (2016).

[4]For example, Acosta (2023) uses textual analysis to show that monetary policy "shocks" include news about future interest rates as well as news about future demand and supply factors. Milani and Rajbhandari (2020) study a DSGE model with news shocks to all exogenous states; they find that the news shocks are not well identified from one another when using realizations alone, but including forecasts tightens the Bayesian posteriors on the model parameters, particularly those related to the news processes.

relevant for at least one time series.

A valuable benefit of decomposing shocks into news and surprise is the ability to estimate the effects of counterfactual policies. McKay and Wolf (2023) demonstrate that, under some assumptions, impulse response functions to news about shocks at different horizons are sufficient to construct counterfactual impulse response functions under alternative policy rules. We implement their approach using our identification of impulse responses to news and surprise shocks and conduct several counterfactual experiments.

Crucially, our method's ability to recover news about multiple shocks allows us to study counterfactual fiscal and monetary policy in a single exercise. This allows us to estimate how monetary and fiscal policy can coordinate to achieve policy objectives. We find that fiscal policy can be effective at stabilizing output over the business cycle, but the effectiveness varies depending on the cause of output fluctuations. And current fiscal policy is already somewhat stabilizing; when we consider a counterfactual with fixed government spending, real activity and inflation are both more volatile. We come to similar conclusions as Wolf and McKay when considering counterfactual monetary policy, including that interest rate pegs do not lead to more volatile inflation but cause output to be more elastic to shocks in the short run. The best counterfactual monetary policy rules that we can construct are less able to stabilize output than fiscal stimulus, but more able to stabilize inflation. Fortunately, the shocks that fiscal policy is not effective at moderating, are precisely the shocks that monetary policy is more effective at responding to, suggesting a role for fiscal and monetary coordination. Working together, fiscal and monetary policy can almost entirely eliminate output volatility.

Other related literature: We contribute to a large literature studying the effects of news about policy. Antolín-Díaz et al. (2021) include SPF interest rate forecasts in an SVAR and use narrative sign restrictions to separately identify monetary policy news shocks from surprise shocks. Doh and Smith (2022) use Bayesian priors to enforce consistency between survey and VAR forecasts, which improves estimation of structural VARs; they apply sign restrictions to identify forward guidance shocks. In Adams and Barrett (2025), we use a macro IV method to decompose empirical monetary policy shocks from the literature into their surprise and news components across many horizons.

With regard to fiscal policy, Ramey (2011) uses narrative methods to identify changes in current and future government spending driven by military events, and argues the many fiscal shocks identified by structural VARs are actually anticipated. Fisher and Peters (2010) use financial returns to defense contractors to identify shocks that include news about future defense spending. Ben Zeev and Pappa (2017) apply the Barsky and Sims (2012) methodology to identify the shock dimension that contains the most news about government defense spending over a 5-year horizon. [5] A common theme in these papers is that the fiscal multiplier due to news about government spending is large.

The revenue side of fiscal policy has received a similar treatment. Leeper et al. (2009) argue VAR-based estimates of shocks will be misleading when tax changes are anticipated. Romer and Romer (2010) use a narrative approach to construct a series of anticipated tax changes, and estimate that legislation of relatively exogenous tax increases have large contractionary effects. Mertens and Ravn (2012) decompose the Romer-Romer series into anticipated and unanticipated components, and show that they have opposite effects on output in the short run. House and Shapiro (2006) come to a similar conclusion studying tax reforms in the early 2000s. Ramey (2019) surveys additional evidence.

2 A Simple Example: Monetary Policy News

We introduce our identification strategy in a simple example, before exploring the general case. The example allows for news about monetary policy, shows how the presence of news confounds the estimation of monetary policy shocks in a standard VAR, and how including forecasts in the VAR correctly identifies the shocks and their effects.

2.1 The New Keynesian Model with Monetary Policy News

Consider the following three-equation New Keynesian model:

$$\begin{aligned}
&\text{New Keynesian Phillips curve:} && \pi_t = \beta\mathbb{E}_t[\pi_{t+1}] + \kappa y_t + x_t \\
&\text{Euler equation:} && 0 = \mathbb{E}_t[z_t + \gamma(y_t - y_{t+1}) + i_t - \pi_{t+1}] \\
&\text{Taylor rule:} && i_t = \phi_\pi \pi_t + h_t
\end{aligned}$$

where π_t, y_t, and i_t are inflation, the output gap, and the nominal interest rate respective, x_t is an i.i.d. cost-push shock, z_t is an i.i.d. demand shock. The crucial part of this example is the introduction of a shock with separate news and surprise components. The persistent policy residual h_t, is given by

$$h_t = \rho h_{t-1} + u_t + v_{t-1}$$

where the policy innovation $u_t + v_{t-1}$ has two components. One is an i.i.d. surprise, u_t, wholly unanticipated at time t. The other is i.i.d. news shock, v_{t-1}, known in period $t-1$.

[5] In addition, a number of papers use some measure of forecast updates from professional forecasters to derive measures of fiscal news, including Ricco (2015), Ricco et al. (2016), Cimadomo et al. (2016), and End and Hong (2022).

These different components capture the fact that monetary policy changes are often signalled in advance. For example, if a monetary policymaker communicated in period $t-1$ that in period t they would depart from their usual policy rule by increasing interest rates by 25 basis points, then $v_{t-1} = 0.25$. If in period t they then actually departed from their usual policy rule by 50 basis points, then $u_t = 0.25$ as well, for a total policy shock of $u_t + v_{t-1} = 0.5$. Because the news shock v_{t-1} is in the $t-1$ information set, this framework allows for an anticipation effect at time $t-1$ for pre-announced policy decisions.

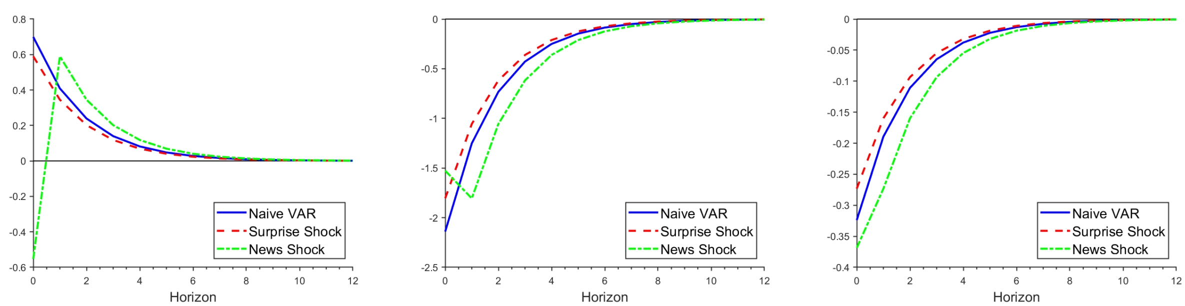
The solution to this model can be written in the following form:

$$\pi_t = b_h^\pi h_t + b_v^\pi v_t + b_x^\pi x_t + b_z^\pi z_t$$

$$y_t = b_h^y h_t + b_v^y v_t + b_x^y x_t + b_z^y z_t$$

$$i_t = b_h^i h_t + b_v^i v_t + b_x^i x_t + b_z^i z_t$$

The corresponding impulse responses to news and surprise shocks to the policy rule are shown in Figure 1 for a standard calibration. Qualitatively, they have very different effects on impact. News of an interest rate rise tomorrow means that agents anticipate a recession in the next period. Because of consumption smoothing, they reduce spending today, lowering output and prices. The central bank responds to this through their Taylor rule, cutting interest rates to mitigate the downturn.



(a) Interest Rate IRFs (b) Output IRFs (c) Inflation IRFs

Figure 1: Impulse Response Functions in the Simple Example

Figure 1 shows impulse responses to news and surprise shocks to monetary policy in the simple New Keynesian model, as well as the IRFs from a VAR estimated without forecasts ("Naive VAR"). Model parameters are set to standard values for a monthly calibration, largely adapting the quarterly calibration from Galí (2008): $\beta = 0.997$, $\kappa = 0.2$, $\gamma = 1$, and $\phi_\pi = 1.5$. However, we choose a lower persistence $\rho = 0.6$ than Gali, and set all shock variances to one.

2.2 Identifying Shocks in the Simple Example

As we have seen, the impact of news and surprise shocks are quite different. Can an econometrician identify them from data on (π_t, y_t, i_t)?

In general, no: there are four structural shocks (u_t, v_t, x_t, z_t) but only three time series. Since the effects of the four shocks are linearly independent, this is not enough information, even if the structural coefficients are known exactly. Model agents, however, do have enough information; they know all the shocks in the model. Of course, it is not reasonable to assume that the econometrician can interrogate agents directly about the shocks – that assumes away the problem entirely. A more realistic assumption is that agents make public forecasts about the endogenous variables.

By including agents' forecasts in the VAR we can identify all of the structural shocks, given that we know the model that generated the time series. In this simple example, including a single forecast is sufficient, so consider the inflation forecast $f_t^\pi \equiv \mathbb{E}_t[\pi_{t+1}]$:

$$f_t^\pi = b_h^\pi(\rho h_t + v_t)$$

Now, the four time series $(f_t^\pi, \pi_t, y_t, i_t)$ can identify the structural shocks. h_t is found by

$$h_t = i_t - \phi\pi_t$$

Using the forecast, the policy news shock v_t is identified by

$$v_t = \frac{f_t^\pi}{b_h^\pi} - \rho h_t$$

which identifies the policy surprise shock u_t by

$$u_t = h_t - \rho h_{t-1} - v_{t-1}$$

The remaining shocks can be identified by

$$\begin{pmatrix} x_t \\ z_t \end{pmatrix} = \begin{pmatrix} b_x^\pi x_t & b_z^\pi z_t \\ b_x^y & b_z^y \end{pmatrix}^{-1} \begin{pmatrix} \pi_t - b_h^\pi h_t - b_v^\pi v_t \\ y_t - b_h^y h_t - b_v^y v_t \end{pmatrix}$$

except in non-invertible edge cases where demand and cost-push shocks have colinear effects on output and inflation.

What if the econometrician in our simple example did not properly account for news and surprises separately? The "Naive VAR" (solid blue curves) plot the IRFs implied by a SVAR without forecasts; the curves are responses to forecast errors in the policy residual h_t, which can be calculated by the appropriate causal ordering (Sims, 1980). This would consistently identify the effects of a monetary policy surprise u_t in the absence of any news. But when news shocks v_{t-1} affect monetary policy, this method fails. The Naive VAR identifies neither, returning instead a linear combination of current and past shocks.

In this simple structural example, one need include only forecasted inflation to allow for news and surprises to be separately identified. But identification is more complicated in a general VAR, for which it is not known ex ante how to map forecast errors back into structural shocks, and where there may be more than one news shock. Nevertheless, the lessons from the simple example generalize: including rational forecasts is enough for identification without any additional structure.[6]

3 Identification

This section outlines the general structural VAR, provides a constructive proof of identification, describes how rational forecasts are cleaned from empirical forecasts, and derives the implied impulse response functions.

3.1 The Basic Statistical Model

As is common, we consider an $n-$dimensional time series of macroeconomic data x_t is generated by n causal, economically-meaningful "structural" shocks, denoted ϵ_t. We depart from standard time series methods in allowing the structural shocks to be partially anticipated in ways not directly observable to the econometrician. The shock ϵ_t has a surprise component u_t and a news component v_{t-1} that is anticipated one period in advance:

$$\epsilon_t = u_t + v_{t-1}$$

We assume the components are orthogonal so that news does not predict surprises: $u_t \perp v_{t-1}$. Thus v_{t-1} is the one-period ahead conditional expectation of ϵ_t, $\mathbb{E}_{t-1}\epsilon_t = v_{t-1}$.

[6]This intuition is similar to that underpinning Leeper et al. (2013), who show that a fiscal model with news shocks about future taxes generates observable data which does not identify the true shocks. This is closely related to the issue we discuss here. Indeed, Leeper et al.'s Figure 1 is the direct analogue of our Figure 1, showing how even in a simple model a naive econometric approach will confound news and surprises. Leeper et al. also emphasize that the crux of this identification problem is that agents have an information set different from the econometrician. And, much as in our case, the resolution to this problem is to extend the information set of the econometrician so that is spans that of model agents. Our contribution is to show that forecasts are enough to do this under some assumptions.

Analogous to the standard SVAR assumption that each entry in the shock vector is mutually orthogonal, we further assume that the entries in the surprise and news components are mutually orthogonal. That is, $Var(u_t) = D_u^2$ and $Var(v_{t-1}) = D_v^2$ where D_u and D_v are diagonal matrices.[7]

We assume a dynamic functional form for the data generating process which maps information about the structural shocks into x_t:

$$x_t = \sum_{j=1}^{m} B_j x_{t-j} + A\epsilon_t + Cv_t \tag{1}$$

Where the B_j, A and C are $n \times n$ matrices. Without loss of generality we can normalize the structural shocks to unit variance:

$$Var(\epsilon_t) = D_u^2 + D_v^2 = I \tag{2}$$

Equation (1) is the data generating process we study in this paper. Without news it would be a standard SVAR, which we have modified so that observables may be affected by news v_t about future shocks. The matrices A and C measure respectively the contemporaneous response of x_t to unanticipated and anticipated shocks. In general, one cannot recover the macroeconomic shocks from the time series of x_t alone, because there are $2n$ shocks but only n observables in every period.[8] In Section 3.3, we show that extending the data to include forecasts not only resolves this problem but introduces additional linear restrictions which are sufficient to recover the shocks. Before that, we show in the next Section that equation (1) is a relevant model, in that it describes the equilibrium time series in a large class of standard macroeconomic models with news.

3.2 Theoretical Motivation for the Statistical Model

When should we expect time series governed by a dynamic economic model to obey the structure that we assume in equation (1)? The model must satisfy a key condition: the model must have an *inclusive form*. Here, we explain what this means.

[7]Alternatively, this property is implied by assuming that the structural shocks are not just uncorrelated, but independent.

[8]Thus the time series x_t is neither invertible (in the language of Hansen and Sargent (1980) or Fernández-Villaverde et al. (2007)) nor fundamental (as defined in Lippi and Reichlin (1993)).

Consider a general linear model of the following form:[9]

$$0 = \mathbb{E}_t\left[\Psi_{x,1}x_{t+1}\right] + \sum_{j=0}^{k}\Psi_{x,-j}x_{t-j} + \Psi_{y,0}y_t + \mathbb{E}_t\left[\Psi_{y,1}y_{t+1}\right] \tag{3}$$

where x_t is a vector of endogenous variables and y_t is a vector of stochastic exogenous variables. The time subscript denotes the time that the variables in the vector x_t are chosen, in order to avoid treating state and control variables separately.[10] We assume y_t is a VAR(1) following

$$y_t = R_y y_{t-1} + K_y \epsilon_t$$

with all eigenvalues of R_y inside the unit circle, and ϵ_t a vector of i.i.d. standard normal random variables. The shock ϵ_t has an anticipated news component, so that entry i satisfies

$$\epsilon_t^i = u_t^i + v_{t-1}^i$$

with $u_t^i \sim N(0, \sigma_{i,u}^2)$, $v_{t-1}^i \sim N(0, \sigma_{i,v}^2)$, $u_t^i \perp v_{t-1}^i$, and $\sigma_{i,u}^2 + \sigma_{i,v}^2 = 1$.

We say that a model can be written in *inclusive form* if it has a representation satisfying equation (3) with $R_y = 0$. This form implies that any exogenous state variables driving the exogenous process y_t either appear directly in x_t, or can be expressed as a linear combination of entries in x_t and its lags.[11] This recasting of exogenous state variables as endogenous state variables is standard, and a large class of standard macroeconomic models satisfy inclusivity. However, there are some models which do not satisfy this requirement. Perhaps most obviously, models with latent states or other cases where not all of x_t is observed by the econometrician.

We assume that the Blanchard and Kahn (1980) conditions hold so that the model has a unique solution, and can be rewritten in the following way:

$$0 = \mathbb{E}_t\left[\Phi_0\left(I - \Xi L^{-1}\right)\left(I - \sum_{j=1}^{k}\Phi_j L^j\right)x_t + \Psi_{y,0}y_t + \Psi_{y,1}y_{t+1}\right] \tag{4}$$

such that Φ_0 is invertible, and the Ξ and Φ_j matrices have all eigenvalues inside the unit

[9]Uhlig (1995) studies this general form in detail. This form nests a large class of popular macroeconomic models.

[10]The same convention is followed when current-period capital stock is written k_{t-1}.

[11]For example, in the model studied in Section 2, interest rates follow a Taylor Rule $i_t = \phi\pi_t + h_t$ where h_t is an AR(1) exogenous state variable; but h_t is linear in observables, so including the lags π_{t-1} and i_{t-1} in x_t allows the model to be written in inclusive form without including h_{t-1} directly. Likewise, in the canonical RBC model (Kydland and Prescott, 1982) productivity is an exogenous state variable, but can written as a linear combination of output and inputs.

circle.[12] With these assumptions, we prove the following Theorem:

Theorem 1 *If the model can be written in inclusive form, then the implied time series x_t follows the form* (1)

Proof: Appendix A

Theorem 1 implies that many models have equilibrium time series satisfying our assumed structure. The crucial condition is that the model can be written in inclusive form. When this is not satisfied, estimation is more challenging and our main identification result, Theorem 2, does not apply. Still, identification may be possible; Appendix K describes how.

3.3 A VAR with Forecasts

Assume that in addition to x_t, we also observe f_t, a vector of *rational expectations* for the corresponding time series:

$$f_t = E\left[x_{t+1}|\{x_{t-j}\}_{j=0}^{m-1}, \epsilon_t, v_t\right] \tag{5}$$

The expectation is conditional on current news v_t, so the vector f_t contains time-t information that is known to forecasters, but may not be directly observable to the econometrician.

Because f_t is the rational expectation, there exist restrictions on the relationship between f_t and x_t that are sufficient to identify all of the structural shocks. Equation (1) implies that f_t follows

$$f_t = E\left[\sum_{j=1}^{m} B_j x_{t+1-j} + A\epsilon_{t+1} + Cv_{t+1}|\{x_{t-j}\}_{j=0}^{m-1}, \epsilon_t, v_t\right]$$

$$f_t = \sum_{j=1}^{m} B_j x_{t+1-j} + Av_t \tag{6}$$

because $E\left[\epsilon_{t+1}|\{x_{t-j}\}_{j=0}^{m-1}, \epsilon_t, v_t\right] = v_t$ and $E\left[v_{t+1}|\{x_{t-j}\}_{j=0}^{m-1}, \epsilon_t, v_t\right] = 0$.

The time series x_t can be written recursively in terms of current surprises u_t and current news v_t using the dynamic structure (1) and the rational expectation (6):

$$x_t = \sum_{j=1}^{m} B_j x_{t-j} + A(u_t + v_{t-1}) + Cv_t$$

$$= \sum_{j=1}^{m} B_j x_{t-j} + (f_{t-1} - \sum_{j=1}^{m} B_j x_{t-j}) + Au_t + Cv_t$$

$$= f_{t-1} + Au_t + Cv_t$$

[12] In this form, the eigenvalues of Ξ are either zeros or the inverses of the standard "explosive" eigenvalues in the Blanchard and Kahn (1980) condition.

The expectations f_t can similarly be written

$$f_t = B_1 x_t + \sum_{j=2}^{m} B_j x_{t+1-j} + A v_t$$

$$= B_1 (f_{t-1} + A u_t + C v_t) + \sum_{j=2}^{m} B_j x_{t+1-j} + A v_t$$

Stack the expectations and time series into a single VAR($m-1$):

$$\begin{pmatrix} f_t \\ x_t \end{pmatrix} = \sum_{j=1}^{m-1} \mathbf{B}_j \begin{pmatrix} f_{t-j} \\ x_{t-j} \end{pmatrix} + \mathbf{A} \begin{pmatrix} v_t \\ u_t \end{pmatrix} \tag{7}$$

where

$$\mathbf{B}_j \equiv \begin{cases} \begin{pmatrix} B_1 & B_2 \\ I & 0 \end{pmatrix} & j = 1 \\ \begin{pmatrix} 0 & B_{j+1} \\ 0 & 0 \end{pmatrix} & j > 1 \end{cases}$$

and

$$\mathbf{A} \equiv \begin{pmatrix} B_1 C + A & B_1 A \\ C & A \end{pmatrix}$$

Estimating the VAR (7) recovers the coefficients $\{B_j\}_{j=1}^{m}$ and the variance matrix of forecast errors Σ, which satisfies

$$\Sigma = \mathbf{A} \begin{pmatrix} D_v^2 & 0 \\ 0 & D_u^2 \end{pmatrix} \mathbf{A}'$$

The symmetric matrix Σ has $2n^2 + n$ unique entries. B_1 is identified from the VAR, while A and C each have n^2 unknown parameters. D_u^2 and D_v^2 each have n unknowns, but equation (2) implies n additional restrictions, enough to exactly identify the unknown parameters.

3.4 Deriving the Estimator

In this section, we introduce and prove the main identification theorem. The proof is constructive, describing how to estimate the unknown matrices given estimates from the reduced form VAR of the first coefficient matrix B_1 and the residual covariance matrix Σ.

The model must satisfy three key assumptions. First, A must be invertible: this implies that the shocks in ϵ_t have linearly independent effects on the time series. Second, D_v^2 must be invertible: each shock must have a nontrivial news component. However, we do not require that D_u^2 is invertible, i.e. some shocks can be fully anticipated.[13] Third, D_v^2 must have distinct diagonal entries, while A must have distinct singular values. This assumption rules out edge cases where applications of the singular value decomposition are not sufficiently unique.

Theorem 2 *If A and D_v^2 are full rank, and neither A nor D_v^2 have repeated singular values, then C, D_u^2 and D_v^2 are determined (up to sign and column order) by Σ and B_1.*

Proof. Subdivide the matrix $\Sigma = \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix}$ into $n \times n$ blocks. The off-diagonal submatrices satisfy $\Sigma_{12} = \Sigma_{21}'$, so the three remaining submatrices are given by

$$\begin{pmatrix} \Sigma_{11} & \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix} = \begin{pmatrix} (B_1C + A)D_v^2(B_1C + A)' + B_1AD_u^2A'B_1' & \\ CD_v^2(B_1C + A)' + AD_u^2A'B_1' & CD_v^2C' + AD_u^2A' \end{pmatrix}$$

Define the $n \times n$ matrices Θ and Γ by

$$\Theta \equiv \Sigma_{11} - B_1\Sigma_{21} - \Sigma_{21}'B_1' + B_1\Sigma_{22}B_1'$$

$$= AD_v^2A'$$

$$\Gamma \equiv \Sigma_{22} - (\Sigma_{21} - \Sigma_{22}B_1')\Theta^{-1}(\Sigma_{21} - \Sigma_{22}B_1')'$$

$$= CD_v^2C' + AD_u^2A' - CD_v^2A'(AD_v^2A')^{-1}AD_v^2C'$$

$$= AD_u^2A'$$

Equation (2) implies

$$\Theta + \Gamma = AA'$$

The singular value decomposition (SVD) of $\Theta + \Gamma$ gives unitary matrix U and diagonal matrix Λ^2 such that

$$\Theta + \Gamma = U\Lambda^2U'$$

and

$$A = U\Lambda V'$$

[13] If this assumption fails to hold because D_v has zeros on the diagonal, then an alternative assumption can be used. Identification is still possible if D_u has an entirely non-zero diagonal, i.e. if all shocks have surprise components but perhaps zero news component. Under this assumption, a different estimation method must be used: apply the Appendix B method, with $H = 1$.

for some unitary V. A has no repeated nor zero singular values, so U is uniquely determined up to column sign and order from the SVD of $\Theta + \Gamma$.

The SVD of $\Lambda^{-1}U'\Theta U\Lambda^{-1}$ gives the matrices V and D_v^2 from

$$\Lambda^{-1}U'\Theta U\Lambda^{-1} = V'D_v^2 V$$

D_v^2 has no repeated nor zero singular values, so V is found uniquely up to column sign and order from this SVD. This gives the matrices $A = U\Lambda V'$ and $D_u^2 = I - D_v^2$. Then the final matrix C is found from

$$C = (\Sigma_{21} - \Sigma_{22}B_1')(D_v^2 A')^{-1}$$

■

The application of the singular value decomposition makes it clear that the shocks are only identified up to sign and column order; the distinctness assumptions only ensure that the SVD is unique up to reordering of the singular values, and resigning the columns of their coefficient matrices. Choosing an order for the singular values implies an ordering of the shocks in ϵ_t. Moreover, our method only determines the variances of the shocks D_u^2 and D_v^2, so the shock signs are also indeterminate.

3.5 Forecast Cleaning

In practice, empirical forecasts $\tilde{f}_t$ may not correspond to the rational expectation (6). For example, there is extensive evidence that surveyed expectations feature predictable biases, which can arise if agents have behavioral expectations or incomplete information.[14] Therefore it is necessary to "clean" any empirical forecasts in order to transform them into rational expectations.[15] For this, the cleaned forecast's errors must be orthogonal to m lags of the time series x_t, of the empirical forecasts $\tilde{f}_t$, and any other data z_t in the information set.

To construct the rational expectation f_t, we run the VAR(k) with $k \geq m$:

$$\begin{pmatrix} \tilde{f}_t \\ z_t \\ x_t \end{pmatrix} = \sum_{j=1}^{k} \mathbf{G}_j \begin{pmatrix} \tilde{f}_{t-j} \\ z_{t-j} \\ x_{t-j} \end{pmatrix} + \omega_t$$

where ω_t is a reduced form error. This estimation can be done by OLS or, as we do in our

[14]Notable examples include Souleles (2004), Greenwood and Shleifer (2014) Coibion and Gorodnichenko (2015), and Bordalo et al. (2020), among many others.

[15]This cleaning process removes the variation exploited in Adams and Barrett (2024), where we also include forecasts in a VAR but use innovations in the component that deviates from rational expectations to identify shocks to belief distortions.

Section 4 application, by machine learning in order to avoid overfitting.

Let $\mathbf{G}_{x,j}$ denote the final n rows of $\mathbf{G}_j$. The cleaned rational forecast f_t is given by

$$f_t = \sum_{j=1}^{k} \mathbf{G}_{x,j} \begin{pmatrix} \tilde{f}_{t+1-j} \\ z_{t+1-j} \\ x_{t+1-j} \end{pmatrix} \tag{8}$$

which is the best linear forecast of x_{t+1} conditional on the information set spanned by lags of measured forecasts $\tilde{f}_t$, the time series x_t, and other regressors z_t.

Under some assumptions, this cleaning procedure recovers the true rational expectation. We model empirical forecasts $\tilde{f}_t$ as linear deviations from the rational forecast f_t. The deviations may depend on lags of the rational forecast f_t, the time series x_t, observable confounders z_t, fundamental surprises u_t, or fundamental news v_t:

$$\tilde{f}_t = \sum_{j=0}^{k} \left(H_j^f f_{t-j} + H_j^x x_{t-j} + H_j^z z_{t-j} + H_j^u u_{t-j} + H_j^v v_{t-j} \right)$$

or in terms of lag operator polynomials

$$\tilde{f}_t = H^f(L) f_t + H^x(L) x_t + H^z(L) z_t + H^u(L) u_t + H^v(L) v_t \tag{9}$$

Theorem 3 *If $H^f(L)$ is causally invertible, then the rational forecast f_t is given by equation* (8).

Proof: Appendix C.1

This approach makes two strong assumptions: the additional confounding terms z_t are all observable, and $H^f(L)$ is invertible. In particular, if aggregate forecasts reflect publicly available information, the observability assumption is a reasonable one. But – as with any regression – it will be essential to include all of the relevant controls in the forecast cleaning.

What if the assumptions are broken, so that forecasts are affected by some unobserved confounders beyond z_t? In these cases we can still clean the forecast and identify shocks under looser assumptions. But the interpretation of a news shock changes. Appendix C.2 considers this case.

3.6 Impulse Response Functions in the Presence of News

This section describes the impulse response functions implied by the structural VAR.

The horizon h impulse response $\phi_u(h)$ to a surprise u_t is standard:

$$\phi_u(h) = \begin{cases} A & h = 0 \\ \sum_{j=1}^{\min(m,h)} B^h \phi_u(h-j) & h > 0 \end{cases}$$

$\phi_u(h)$ is a matrix, so that the entry in row i and column j captures the horizon h response of time series i to shock j.

The impulse responses to news have an additional term, because the news shock v_{t-1} first affects the period $t-1$ time series through the news channel, and then again in period t when the full shock is realized. The corresponding impulse response matrix is:

$$\phi_v(h) = \begin{cases} C & h = 0 \\ B_1 C + A & h = 1 \\ \sum_{j=1}^{\min(m,h)} B^h \phi_v(h-j) & h > 1 \end{cases}$$

The impulse response functions are related to conditional expectations by:

$$\mathbb{E}[x_{t+h}|u_t] = \phi_u(h)u_t \qquad \mathbb{E}[x_{t+h}|v_t] = \phi_v(h)v_t$$

3.7 Generalizations and Alternatives

Our main approach applies to a broad class of dynamic models. But it still includes some restrictions that can be further relaxed.

3.7.1 Multiple News Horizons

Thus far, we have assumed that news occurs one period in advance, but news might realistically have longer horizons. For example, Mertens and Ravn (2012) estimate the effects of tax changes with announcements measured up to 16 quarters in advance of the policy change. Just as identifying one-period-ahead news shocks requires a set of one-period-ahead forecasts, it is possible to identify many-periods-ahead news shocks by incorporating many-periods-ahead forecasts. We generalize our method to allow for multiple news horizons in Appendix B.

But there is no free lunch: allowing for additional forecasts necessitates additional data, and estimating additional parameters. Appendix A shows that each additional news horizon adds an $n \times n$ matrix to be estimated. Therefore, in our application we restrict our application to the one-period-ahead case. The main reason is principally data availability. Identifying news shocks occurs at H different horizons requires forecasts at each additional horizon. For many macroeconomic variables, long time series of forecasts at multiple horizons beyond a year in advance do not typically exist, although for some variables (e.g. interest rates and inflation) it is possible.

3.7.2 Other Extensions

Practitioners might also be concerned that forecasts reported in survey data include measurement error. Appendix J details a procedure that accounts for the presence of measurement error in the forecasts and still allows news and surprise shocks to be identified. The necessary assumptions are that the measurement error is classical and that absent the measurement error, forecasters would report their rational expectation. This latter assumption is crucial, because the cost of this procedure is that we cannot simultaneously correct for measurement error and apply our forecast cleaning approach. Thus the practitioner must decide whether measurement error or non-rationality is a greater concern for their forecast data. In our application, we chose the latter.

This tradeoff between accounting for measurement error and non-rationality is related to the problem tackled by Doh and Smith (2022), who use a Bayesian prior to penalize departures of empirical forecasts from VAR-implied rational forecasts. This allows empirical forecasts to be non-rational, but not by too much, and the allowable error is controlled by a penalty parameter. When the penalty parameter is very large, it imposes that restriction that empirical forecasts must be the rational expectation, which corresponds to our "literal forecasts" robustness check in Appendix E.1.[16] Their Bayesian approach is a nice method to pair with sign restrictions, which they use to explore forward guidance shocks. In contrast, our forecast cleaning step derives a rational forecast that is necessarily consistent with the VAR forecast; this is a useful way to handle the problem that empirical forecasts are inconsistent with a VAR, because it implies restrictions that allow us to identify a large vector of structural shocks.

We have also assumed thus far that the econometrician has data on all relevant state variables in the economy. That is, they observe the entire vector x_t and the associated forecasts in the structural equation (1). But what if a critical time series is missing from the data? Appendix K derives the appropriate SVAR restrictions when some state variables are unobserved. News and noise shocks may still be identified, but the problem is computationally more intensive; we do not have an analytical solution for the implied decomposition of

[16] Doh and Smith (2022) provide also suggestive evidence that imposing forecast consistency is not a bad approximation to reality; in their application they show that the optimal weight on survey forecasts is much closer to strict consistency than to a diffuse prior.

the variance matrix Σ.

4 Application to U.S. Data

We apply our structural VAR method to data on U.S. time series. We identify clear fiscal shocks and monetary policy shocks, estimate the implied multipliers, and study the general effects of news versus surprises.

4.1 Data

Our main source of forecast data is the Survey of Professional Forecasters (SPF), which is currently run by the Federal Reserve Bank of Philadelphia. The survey is administered quarterly to roughly 40 anonymous forecasters since 1968. We take the median reported values as our measure of forecasts.

Some variables are not available in the SPF for the entire sample, so we turn to other sources. In particular, the SPF only collects estimates on real government consumption and investment since 1981:III, so before this period we draw from the Federal Reserve's official forecasts reported in the Greenbook for every FOMC meeting. These values are not collected in publicly available datasets for all periods, so when necessary, we transcribe them from the original Greenbooks. For each quarter, we take the most recent estimate. We also use the Greenbook forecasts for federal budget receipts and surpluses. For these variables, we use the dataset collected by Croushore and van Norden (2018), which we extend to 2016:IV by transcribing from the most recently released Greenbooks.

For interest rates, we measure forecasts directly from the yield curve. We use this measure because the SPF only provides forecasts for a limited number of interest rate horizons, and only since 1981:III. Where r_t^h denotes the return from time t to $t+h$, we calculate the forecast $\mathbb{E}[r_{t+1}^h]$ by

$$\mathbb{E}[r_{t+1}^h] = r_t^{h+1} - r_t^1$$

This is known to be a biased forecast, as the yield curve incorporates liquidity and risk premia as well as expectations. As with the SPF forecasts of other variables, we scrub these measures of bias during the "forecast cleaning" stage of our estimation.[17]

Finally, we use 3-month-ahead futures contracts to measure forecasts for oil prices and exchange rates. Covered interest rate parity predicts that the implied forecasted growth rates

[17] While the yield curve-implied forecasts do not exactly match the SPF forecasts, they track each other very closely; for 3-month T-bills, the correlation coefficient is 0.996. Moreover, the market-based forecasts are at least as accurate as those provided by the SPF. For periods in which both forecasts are available, the root mean squared error for market-based forecasts is 0.53%, but 0.57% for the SPF.

should track 3-month interest rates closely, but not exactly; deviations depend on expected costs of holding oil or interest rate differences across countries, respectively.

Table 1 reports the time series that we use. We transform the variables in three different ways. For NIPA variables and federal budget variables, we follow Ramey (2016) and divide by an estimated quadratic time trend in real GDP. This transformation allows fiscal multipliers to be read directly from the impulse response functions. For the price level as measured by the GDP deflator, we take log differences and annualize to calculate the inflation rate. For other variables that grow regularly (e.g. housing starts), we take logs, but we leave in levels those variables that are not clearly nonstationary (unemployment, interest and exchange rates). Finally, we remove a quadratic trend and linear seasonal factors from all variables.

Variable	Date range	Source for Empirical Forecast, $\tilde{f}_t$
Baseline Specification		
Real GDP	1968:IV - 2022:II	SPF
Federal tax receipts	1968:IV - 2016:IV	Fed Greenbooks
Real government spending	1968:IV - 2022:II	Fed Greenbooks for 1968:IV - 1981:II SPF for 1981:III - 2022:II
GDP deflator	1968:IV - 2022:II	SPF
3-month Treasury rate	1968:IV - 2022:II	Yield curve
Housing starts	1968:IV - 2022:II	SPF
Additional Variables		
Unemployment Rate	1968:IV - 2022:II	SPF
Industrial production	1968:IV - 2022:II	SPF
Federal budget surpluses	1968:IV - 2016:IV	Fed Greenbooks
USD/CAD exchange rate	1968:IV - 2022:II	Futures contracts
Real oil price	1983:I - 2022:II	Futures contracts
1, 2, 3, 4, and 5-year Treasury rates	1968:IV - 2022:II	Yield curve

Table 1: List of Variables

Our baseline specification appears above the break in Table 1. We include output, government spending, taxes, short term interest rates, and inflation so that we might identify shocks that reflect fiscal and monetary policy, which have well-understood effects on these variables. We also include housing starts as a second measure of real activity; housing starts have SPF forecasts that cover our entire sample, and aggregate forward-looking decisions that may be informative about news. The additional variables are used in the forecast cleaning step, as well as in the alternative VAR specifications that we consider in the Robustness Appendix E.

The data sources in Table 1 give us the empirical forecasts $\tilde{f}_t$, which we "clean" to give the rational forecast f_t. In constructing the forecast series f_t we aim to satisfy three objectives. The first objective is plausibility: that our forecasts plausibly reflect all information about outcomes x_{t+1} at time t. The second objective is that we do not overfit to the data. The third is the forecasts must satisfy the identifying assumption: that forecasts contain all the information already available to the VAR structure, formalized in equation (5).

To meet these objectives we proceed in in two steps, based on the methodology in Section 3.5. We start by constructing a vector of variables z_t which aims to include as much as possible of the information available at time t about relevant future outcomes. To do this without overfitting, we a construct three machine learning models separately for each of the six variables in the baseline VAR: an elastic net, a regression tree, and a simple linear projection. Each model predicts one-period-ahead outcomes using up to eight lags of both data and outcomes for all 16 variables in Table 1, some 256 possible predictors. We use rolling cross-validation to select tuning parameters and then pick the model with the lowest out-of-sample average RMSE individually for each of the six variables. The fitted predictions thus embody plausible forecasts of x_t robust to overfitting. These, we label z_t. And so the N entries of z_t are the machine learning predictions for each of the elements of x_{t+1}. We then include these z_t in the cleaning process described in 3.5.

The advantage of this approach is that if there is a variable not in the VAR specification that contains reliable information about future outcomes, this will be included in the constructed forecast f_t. For example, if lagged oil prices – a variable not in our baseline VAR – happen to be a robust predictor of inflation, then the machine learning models will include them. And so the relevant entry of z_t will contain the component of inflation that can be explained by oil prices. If this information is supplementary to the information in the lags of the data and the empirical forecasts, $(x_t, \ldots, x_{t-m}, \tilde{f}_t, \ldots, \tilde{f}_{t-m})$, then the cleaned forecast f_t will put weight on it. Likewise, if the empirical forecasts $\tilde{f}_t$ happen to embody all the information available about future outcomes, this method would allow f_t to fully reflect that.[18]

One disadvantage of this method is that there remains some risk of overfitting. This arises because we clean the forecasts after cross-validating, and so there may be spurious reliance on the variables in the VAR. However, this is mitigated by the relatively short lag length and limited specification of the baseline VAR. Moreover, this reflects a deeper issue, that the well-known bias-variance tradeoff in forecasting means that our objective of not overfitting is not always compatible with the identifying assumption in equation (5). Yet our approach aims to limit the extent of this problem by using the machine learning forecasts as a bottleneck, limiting information about future outcomes to the same dimension as the

[18]In robustness checks we also consider a case where we use the empirical forecasts without cleaning them.

data itself. Appendix F plots the cleaned forecasts and their associated time series.

4.2 Estimation

In principle, implementing our method is straightforward: one needs only estimate a VAR and then decompose the shocks in line with the method outlined in Section 3.4. In practice though, things are rather more difficult, with two interacting issues making accurate estimation more challenging.

The first issue is that although ordinary least squares estimates for vector autoregressions are consistent, they are biased in small samples. This is well-known (see Shaman and Stine (1988) for an early discussion in the univariate context).To address this, we apply a bias-correction approach based on the bootstrap proposed by Kilian (1998). A full description of the algorithm is provided in Appendix D.1 but the basic idea is to approximate the bias at the point estimate with the average bias in bootstrapped samples generated by the point estimate. One can then adjust the point estimate to offset this bias. This gives reduced-form coefficients $B_1^{(j)}, \ldots, B_m^{(j)}, \Sigma^{(j)}$ for simulations $j = 1, \ldots, N$. The variation in these reflects sampling uncertainty under the null hypothesis that the point estimates are consistent.

This approach serves a double purpose since the bootstrap provides a large number of simulated reduced-form coefficients. To compute confidence intervals for various statistics, including structural impulse responses and a variance decomposition, we apply the identification process to each of the simulated reduced form estimates, using algorithm outlined in Theorem 2. For each $j = 1, \ldots, N$ this gives estimates for the structural parameters $A^{(j)}, C^{(j)}, D_u^{(j)}, D_v^{(j)}$.

The second issue is that the simulated structural matrices are only unique up to sign and re-ordering of the shocks. For example, if shock number 1 in the point estimate A happens to be a demand shock, there is no guarantee that the same shock is in column 1 of the simulated estimate $A^{(j)}$. Depending on the ordering of components of the singular value decomposition, a completely different shock may be ordered first. Moreover, because the identification relies on a second-order statistic – the variance-covariance matrix – the identification is not unique up to sign. Multiplying the same column in the A and C matrices by -1 gives the same time series properties, just with the interpretation of what constitutes positive and negative shocks reversed.

Thus for each simulation, we search over all possible combinations of re-orderings and sign flips to find that which minimizes the square difference to the point estimates for the structural impulse responses. With $N = 6$ variables, this is potentially very large, with 2^N possible sign flips and $N!$ possible re-orderings, giving $2^N \times N! = 46,080$ possible combinations in total. In Appendix D.2 we show how this can be reduced to a modified version of the Quadratic Assignment Problem – a central problem in combinatorial optimization for which there are well-understood and relatively swift solutions. This ordering procedure minimizes a continuous loss function, satisfying the requirements for Lewis (2021) Theorem 4: our labeling method does not affect the asymptotic distribution of the structural matrices (and so neither the implied impulse response functions). We can thus use the sample of structural parameters so created to calculate the distributions of model statistics as required.

The two issues outlined above also interact in potentially pernicious ways. Without carefully bias-correcting the reduced form estimates, an incorrect ordering of the simulated structural decompositions becomes more likely, causing much wider error bands.

The resulting distribution of estimates reflects a broad range of sources of uncertainty, not always included in other approaches. Because we re-estimate the shock variance matrices $D_u^{(j)}, D_v^{(j)}$ for each simulation, our impulse responses show not just the uncertainty over how a given shock propagates, but also that due to the uncertainty over the size of each shock. This is particularly important when computing error bands for the decomposing the variance of the time series data into that attributable to news versus surprises. Moreover, sampling variation means that the reordering and re-signing of the shocks is imperfect – variation due to one shock may be mistakenly attributed to another. By using estimated residuals in the bootstrap, we also allow for non-normality of our estimates. And because we apply the exact identification method to each reduced form simulation, we capture the full extent of nonlinearity in the identification procedure (versus, for example, applying a linear approximation such as the delta method). Finally, because our bootstrap technique matches the observed sample length, we include variation appropriate to a small sample, and do not rely on large-sample approximations.

We choose lag length via the Akaike Information Criterion. This selects fairly conclusively a one-lag specification (see Figure 11 in Appendix E.2 for details). Although this might seem a little short, this is not unexpected in the current setting. That is because the stacked VAR that we estimate in equation (7) *already* includes rational forecasts of the next-period outcome. These incorporate a large amount of information lagged outcomes relevant for future outcomes. In addition, the data generating process here is VARMA, not a VAR. Given that the MA component has an infinite autoregressive interpretation, this further shortens the lag length, since the MA part can account for a considerable part of the persistence that one might otherwise need several lags to capture. We consider alternative lag structures in robustness checks.

4.3 Impact of Surprises and Shock Labels

Our method recovers the structural shocks, but it does not tell us what they are. As usual in the structural VAR literature, we devise a labeling scheme for the shocks, giving each shock a name to help with interpretation. Our aim here is to be uncontroversial, giving names to each of the shocks, aligned with commonly understood impacts of each shock's effects on multiple variables. As such, we base this on the signs of the impulse responses to surprises, rather than news or a combination of the two. We do this because we think that responses to unanticipated surprises are the most commonly studied and so arguably those for which which readers are likely to have the strongest priors. Thus, by using the surprise impulse responses as a means for attributing shock labels we hope to match generally-held views on standard responses to structural shocks. In the interest of presenting the results swiftly, our arguments for the shock labels are somewhat heuristic. In the next section we check that the quantitative responses match those estimated elsewhere for the monetary and fiscal policy shocks.

The responses to unanticipated surprises are shown in Figure 2, which we calculate as described in Section 3.6. For all variables, the response is measured as the percentage deviation from trend associated with a unit standard deviation structural shock.[19] Dashed lines show 10th and 90th percentiles of the bootstrapped distribution of outcomes.

The first shock we label "fiscal stimulus". The shock features an immediate and statistically significant contraction in government tax revenues and a prolonged and statistically significant increase in government spending, albeit somewhat delayed. At the same time, output and real activity (as measured by housing starts) increase with a lag. This we label as a fiscal stimulus shock. In Section 4.4.1 we verify that the magnitude of the output response is consistent with tax and spending multipliers in the literature. One slightly surprising response is that the fiscal expansion induces a decline in inflation; Patel and Peralta-Alva (2023) find the same pattern in a structural VAR identified with sign restrictions.

The second shock we label "monetary policy", which features a clear, statistically significant, and immediate increase in short term interest rates. This is followed by a decline in output over the next year or so and then a subsequent reduction in inflation, although not always strongly statistically significant.[20] In Section 4.4.2 we again verify this shock, by comparing to estimated monetary policy shocks in the literature.

[19]That is, impulse responses are scaled by the appropriate element of D_u.

[20]These effects are characteristic of monetary policy shocks that have been purged of information effects (Miranda-Agrippino and Ricco, 2021). Without accounting for information, contractionary monetary policy shocks can be estimated to cause output or prices to rise (Ramey, 2016). Jarociński and Karadi (2020) show that this is because central bank information shocks raise rates while also causing economic expansion and inflation.

The third and fourth shocks we label as demand and supply respectively. In the case of the former, the output response is immediate and statistically significant, with a more long-lasting increase in inflation and a delayed interest rate response. In contrast to the fiscal shock, spending goes down and taxes go up, consistent with a aggregate expansion not driven by the public sector. In the case of the latter, we base our labeling on the markedly opposing responses of inflation and output on impact.

We leave the final two shocks unlabeled. This is not to say that one could not make a case for a structural interpretation of either. In particular, the second unlabeled shock appears much like our monetary policy shock, except it also causes a large and immediate fiscal expansion. However, these shocks both fail some of the quantitative validation tests below. And so we remain silent on the interpretation of these.

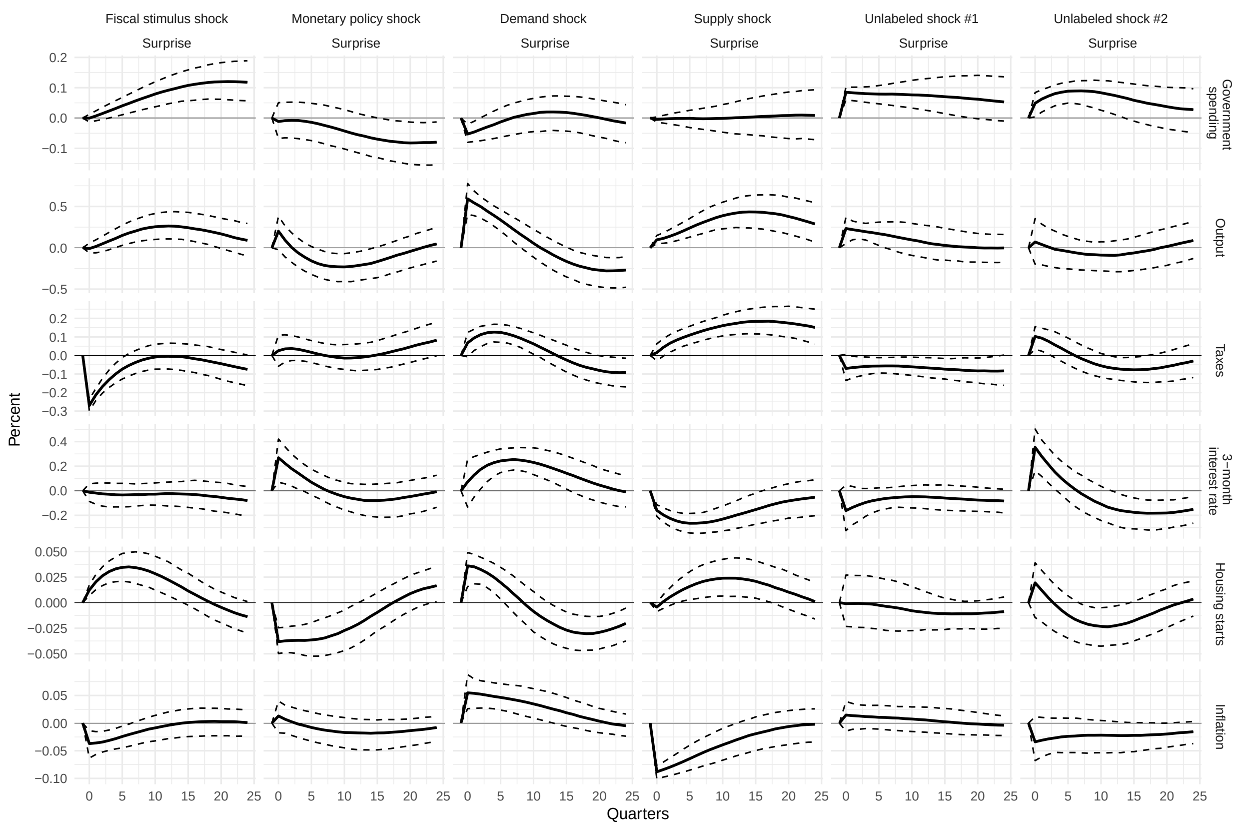


Figure 2: Impulse Responses to Structural Shocks: Surprises

Impulse responses for a one standard deviation shock to the unanticipated surprise for each shock, as calculated in Section 3.6. The solid line and dashed lines show respectively the $50^{th}, 10^{th}$, and 90^{th} percentiles from a bootstrap simulation with $N^{sim} = 1000$ replications. For government consumption, output, and taxes, units are percentage points relative to trend lagged output. For inflation, interest rates, and housing starts, units are annualized percentage points relative to trend. Surprise and news shocks all occur at $t = 0$.

4.4 Validating the Shock Interpretations

In the preceding section, we assigned labels to the identified shocks based on the signs of their effects. Can we be confident that what we label as "fiscal" and "monetary" actually capture these kinds of shocks? In this section we show that the impulse responses match quantitatively those estimated elsewhere.

4.4.1 The Fiscal Policy Shock

To corroborate our interpretation of the first shock as fiscal policy, we show that the responses are consistent with tax and spending multipliers estimated the literature.

Typically, the $h-$period fiscal multiplier in response to a fiscal policy shock is defined as the ratio of the cumulative change in output relative to the cumulative change in the relevant fiscal variable (either taxes or spending).[21] That is, the multipliers are:

$$\mu_G^h = \frac{\sum_{s=0}^h \mathbb{E}_t \Delta Y_{t+s}}{\sum_{s=0}^h \mathbb{E}_t \Delta G_{t+s}} \qquad \mu_T^h = \frac{\sum_{s=0}^h \mathbb{E}_t \Delta Y_{t+s}}{\sum_{s=0}^h \mathbb{E}_t \Delta T_{t+s}}$$

where Y_t and G_t are output and government spending relative to trend GDP. An increase in government spending over h periods totaling 1 percent of trend GDP thus leads to an increase in cumulative output over the same period equivalent to μ_G^h percent of trend GDP.

As we estimate a more general fiscal shock, which includes both tax and spending changes, we cannot compute these multipliers individually. However, we can do this exercise in reverse. That is, taking as given estimates of multipliers from the literature, we can compute the output response that would be implied by the tax and spending profiles. So for fixed values of μ_T^h, μ_G^h we can compute:

$$\mu_Y^h = \mu_G^h \sum_{s=0}^{h} \mathbb{E}_t \Delta G_{t+s} + \mu_T^h \sum_{s=0}^{h} \mathbb{E}_t \Delta T_{t+s} \tag{10}$$

If we have identified a fiscal shock, and the multipliers estimated in the literature are correct, then this quantity should be close to our cumulative estimated output response, $\sum_{s=0}^h \mathbb{E}_t \Delta Y_{t+s}$. This fact allows us to construct a test of whether of our fiscal shock labeling is consistent with the estimates in the literature. We substitute values from several papers for the tax and spending multipliers into equation (10) and replace the conditional expec-

[21] Notable papers using this definition include Mountford and Uhlig (2009), Farhi and Werning (2016), Hagedorn et al. (2019), and others mentioned in the main text. See Batini et al. (2014) or Ramey (2016) for an overview. Other definitions of multipliers are sometimes used; for example, Blanchard and Perotti (2002) measure the multiplier using the peak output response, while Leeper et al. (2017) use real interest rates to discount future quantities.

tations for changes in tax and spending with out estimated impulse responses to compute μ_Y^h at various horizons.[22] Of course, satisfying this condition is not a sufficient criterion for concluding that a shock is consistent with previously estimated fiscal multipliers. But it is a necessary one – failing it rules out any reasonable interpretation of the shock as fiscal.

To begin our comparison, the most similar exercise is Lewis (2021), who also identifies the entire set of structural shocks and must label fiscal shocks based on estimated IRFs. To this we add results from three classic papers: Blanchard and Perotti (2002), Ramey (2016), and Romer and Romer (2010).[23] As the latter two estimate only spending and tax multipliers separately, we combine them. To these, we add the well-known estimates of Caldara and Kamps (2017) who use two approaches to estimate dynamic tax and spending multipliers. We also consider two recent estimates of the spending multiplier – Ricco (2015) and Ben Zeev and Pappa (2017) – again supplementing them with tax multipliers from Romer and Romer (2010).

The individual points in Figure 3 the show the corresponding literature-consistent output responses, μ_Y^h, for each of these estimates. This is compared to our estimated cumulative output response, for the bootstrapped median (solid line) and confidence intervals (dashed and dotted). The agreement with the Lewis (2021) estimates is remarkably close. Ex ante, there is nothing which necessarily says that these should line up – the lines are our cumulative output response, and the points are linear combinations of the tax and spending responses. This close agreement suggests that is shock very similar to the fiscal shock identified by Lewis (2021). The remaining estimates are generally a little larger than our estimates. The most notable difference is compared to that using the Blanchard and Perotti (2002) multipliers, for which the output response is substantially larger. This reflects the fact that they simply find multipliers which are much larger than those measured in more recent work.

To some extent, differences with other estimates may reflect the different combinations of news and surprise shocks. For us, a surprise is a shock that begins contemporaneous with its announcement, and news is a shock that start one period after. Other estimates take a slightly different approach. For example, in Ramey (2011) fiscal "news" about defense spending could result in changes in expenditure at any number of different horizons.

Although this test cannot guarantee that our "Fiscal Stimulus" shock is fiscal, it at least can rule out those which are not consistent with standard multipliers. Of course, it

[22] This is a benefit of scaling these variables relative to trend GDP prior to estimating our VARs (see Section 4.1). It means that the impulse responses are already in the appropriate units.

[23] Blanchard and Perotti (2002) and Romer and Romer (2010) do not report their estimates as cumulative multipliers, so in order to compare with the other studies, we use the values re-estimated by Lewis (2021) using Blanchard and Perotti's method, and the multipliers re-estimated by Favero and Giavazzi (2012) using Romer and Romer's method.

could be that this is a particularly weak criterion – perhaps most or all shocks show a similar consistency with estimated fiscal multipliers. To address this concern, Figure 12 in Appendix E.3.1 repeats this exercise with all the other shocks. For three of the others – the supply and demand shocks, and the second unlabeled shock – we can definitively reject a fiscal interpretation based on extant multipliers. The monetary policy shock shows some similarities to the estimated multipliers, although the fact that both government spending and taxes respond statistically insignificantly at almost all horizons surely undermines any possible fiscal interpretation. The cumulative output response for the first unlabeled shock, however, is not wildly different from what would be consistent with standard multipliers, suggesting that it may have some fiscal aspect. This is a point we return to in the variance decomposition below.

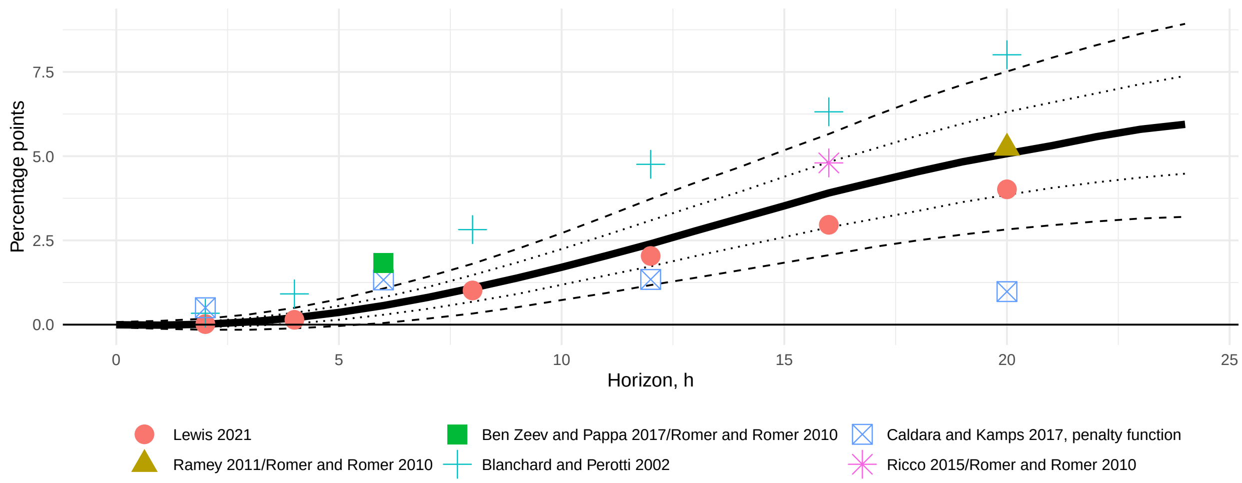


Figure 3: Cumulative Output Response, Fiscal Stimulus Shock

The solid line is the median cumulative output response for an unanticipated epsilon fiscal expansion shock from a bootstrap simulation with $N^{sim} = 1000$ replications. The dashed and dotted lines respectively are the $10^{th} - 90^{th}$ and $25^{th} - 75^{th}$ percentile ranges. The points show the cumulative output responses, μ_Y^h, implied by our estimated tax and spending responses if the multipliers were those in the literature, summarized in Appendix E.3.1.

4.4.2 The Monetary Policy Shock

Here we validate our claim that the second shock in Figure 2 can reasonably be interpreted as a monetary policy shock. Our overall objective is to show that the shocks that we recover are similar to those estimated elsewhere in the literature.

To assess whether estimated shocks have similar effects on macroeconomic variables as ours, we use shocks from a set of classic papers as exogenous variables in a multi-variate dynamic model (either a vector autoregression or a local projection) and compute the impact on the same endogenous variables in our model. If these look qualitatively and quantitatively similar to our impulse responses, then we can reasonably conclude that we have identified a monetary shock (or at worst, something observationally equivalent).

Specifically, we assemble the monetary shocks from five empirical papers which estimate monetary policy shocks. All use some sort of high frequency identification approach, isolating shocks to monetary policy from changes in measures of monetary policy around policy events, such as FOMC meetings, policymakers speeches, and the like. The first, labelled "Bauer-Swanson" is taken from Bauer and Swanson (2022) and is simply the change in Eurodollar futures rates around both FOMC announcements and speeches by the Fed chair. This can be thought of as a stand-in for a fairly large class of papers which use a similar approach, of which perhaps the most well-known is Gertler and Karadi (2015). We supplement this with an orthogonalized version of this shock, which purges predictable changes in the shock reflected in asset prices. In addition to these, we use two papers by Romer & Romer. One, Romer and Romer (2023) updates their classic 1988 paper on the narrative method of identifying shocks, computed by close reading of official transcripts of FOMC meetings. The other, Romer and Romer (2004) uses changes in Federal forecasts to remove predictable changes in future outcomes.[24] Finally, we also include Jarociński and Karadi (2020) who use differential interest rate and stock price movements to separate the monetary surprise from information about future outcomes. We aggregate the shocks at quarterly frequency. Table 2 summarizes the coverage of the various monetary shocks.

Shock	Orig. Freq.	Start	End	N
Bauer-Swanson	M	1988-03-01	2019-12-01	128
Bauer-Swanson (orthogonalized)	M	1988-03-01	2019-12-01	128
Jarocinski-Karadi, HFI from Fed Funds	M	1990-03-01	2016-12-01	108
Romer-Romer 2023	Q	1969-03-01	2019-12-01	204
Romer-Romer 2004 (up to 2007)	Q	1969-03-01	2007-12-01	156

Table 2: Monetary Policy Shocks in the Literature

The reported impact of monetary policy shocks may differ for many reasons other than fundamental differences in what is measured. One such reason is differences in specification of the dynamic model used. And so to compare like with like we estimate the effects of these shocks in a common framework. Our headline results use a one-lag VAR – the most directly comparable to our specification – but in Appendix E.3.2 we also report results from a longer-lagged VAR and from local projections.[25]

[24]We use the re-estimated version of this shock, extended to 2007 by Wieland and Yang (2020).

[25]For each monetary shock identified in the literature, we compute a vector autoregression using our baseline data and the monetary shock. We then perform a Cholesky decomposition with the monetary shock

Another reason that impulses may differ across studies is that they capture shocks of different magnitudes. As pointed out by Coibion (2012), the much larger response of macro variables to monetary shocks when measured by narrative methods can, to a considerable extent, be explained by the magnitude of the shock. That is, narrative methods simply capture a subset of particularly large monetary shocks. To address this we rescale the impulse responses to have equivalently-sized interest rate responses. We consider two such rescalings: one with an initial 100 basis point increase in interest rates, and one with a cumulative 100 basis point increase in interest rates. The latter is our preferred measure as it not only accounts for differences in both the size and duration of the monetary impulse, but is also robust to slight differences in the very short-run dynamics of interest rates.

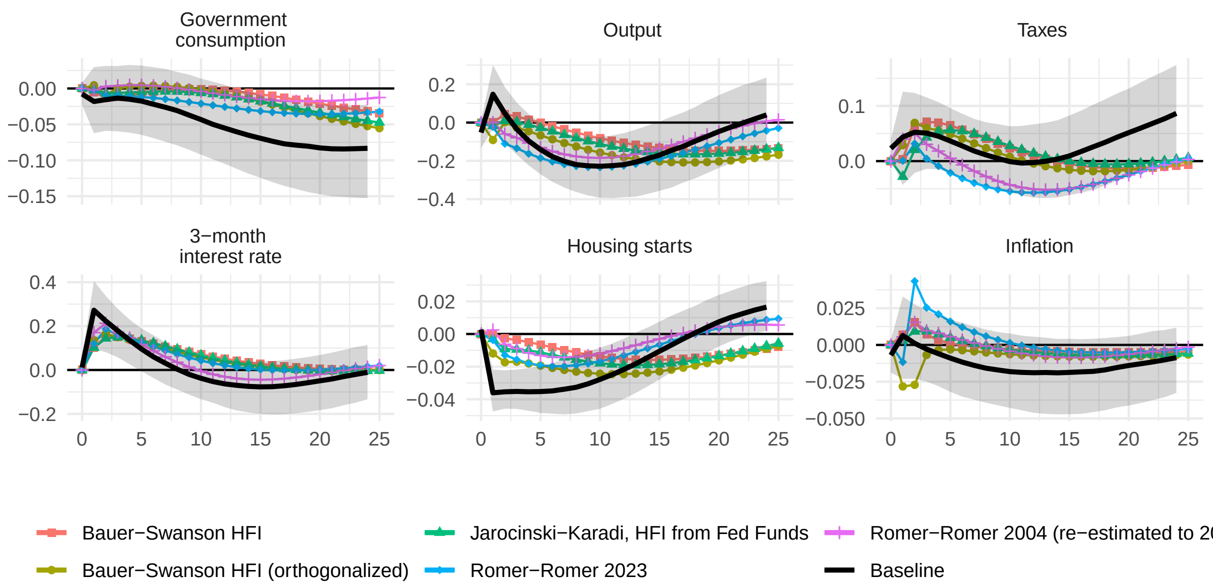


Figure 4: Estimated IRFs to Monetary Shocks, comparison to the literature

Figure shows estimated impulse responses to a monetary policy shock from our baseline compared to those computed from various sources in the literature. To match samples and specification, each line reports the results from estimating a one-lag VAR with the same variables and coverage as our baseline model, extended to including the shocks from the relevant source and where the impulse responses are computed from a Cholesky decomposition with the monetary shock ordered first. The solid line labeled "Baseline" and shaded area show respectively the median and $10^{th} - 90^{th}$ percentile ranges from a bootstrap simulation with $N^{sim} = 1000$ replications. To account for differences in the magnitude of estimated shocks, all impulses are scaled such that the cumulative two-year interest rate impulse is 100 basis points.

Thus in Figure 4, we report the impulse responses to the five other sources as well as our monetary shock response with two adjustments to guarantee comparability: a common VAR framework and data (coverage aside); and rescaling to match the cumulative interest

ordered first. This recovers the causal impact of the shock, using the VAR dynamics for propagation.

rate response in the first 8 quarters. Overall, the results are both qualitatively and quantitatively similar to ours. Given the interest rate shock which raises interest rates by about 20 basis points, output declines around 0.2 percent both for our shock and for those identified elsewhere in the literature. The timing of the output response is a little different, with generally longer lags on the shocks from previously-estimated shocks. However, this is not entirely surprising given their slightly more backward-loaded impulse. For inflation, almost all methods show a small positive liquidity effect in the short run and a decline at longer horizons. And although our estimated effect on inflation is generally a little larger, most other estimates are within the confidence interval and agree on a peak impact on inflation at two to three years. The remaining variables, government consumption, taxes, and housing starts broadly agree, although with some differences in dynamics. Variants on this, reported in Appendix E.3.2, confirm that this finding is robust to changes in specification, estimation method, and the normalization of the size of the shock.

Overall, the validation exercise for the monetary shock shows a notable consistency between our estimated monetary impulses and those considered standard in the literature. This need not have been the case. Had it been wrongly labelled, our claimed monetary could have been quantitatively very different to the responses computed using externally-identified shocks. That it is not seems like reasonable validation of our interpretation.

4.5 The Impact of News

Having labeled and verified the labeling of our shocks, we can now compare news to surprise shocks. We start in Figure 5 with the two policy shocks. For comparability across the news and surprise impulses, we scale the news impulses by the standard deviation of the *surprise*. This gives the plotted impulses a natural interpretation: that in period 1, it is revealed that there will be a one standard deviation surprise shock in period 2. The news impulse therefore combines both the anticipation of the policy change in period 2 and its realized impact. The advantage of this rescaling is that it separates out the impact and anticipation effect of a shock (the matrices A and C respectively) distinct from relative importance of news and surprise shocks (captured by D_u and D_v).

The overall impression from Figure 5 is that, as one might expect, an anticipated shock has much the same effect as an unanticipated one in the long run – the impulses after more than 10 or 12 quarters are much the same. However, in the short run some notable differences arise. For the fiscal shock, taxes systematically jump up prior to an announced expansion, implying that governments make an immediate grab for revenue in order to offset some of their future largess. Interest rates fall persistently, consistent with a tighter fiscal position.

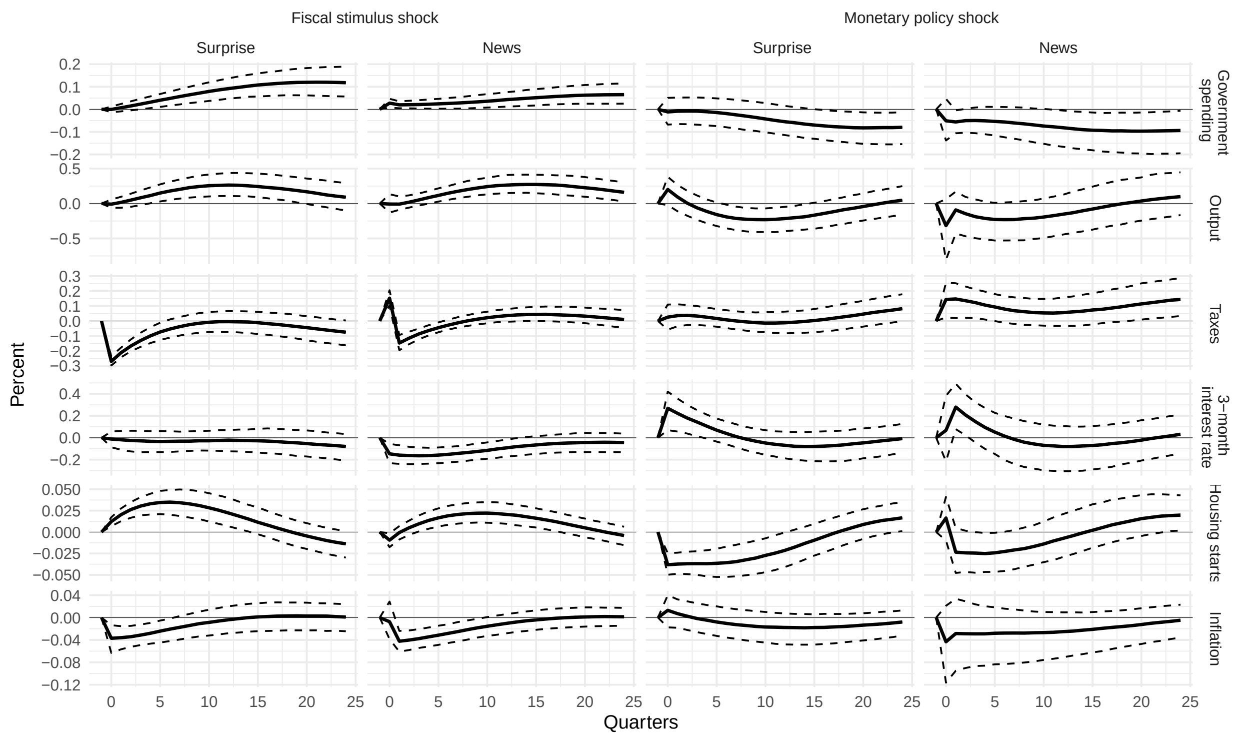


Figure 5: Impulse Responses to Policy Shocks: News vs. Surprises

Impulse responses for unanticipated surprise and news for each shock, as calculated in Section 3.6. For comparability, both shocks are scaled by the standard deviation of the surprise shock. The solid line and dashed lines show respectively the $50^{th}, 10^{th}$, and 90^{th} percentiles from a bootstrap simulation with $N^{sim} = 1000$ replications. For government consumption, output, and taxes, units are percentage points relative to trend lagged output. For inflation, interest rates, and housing starts, units are annualized percentage points relative to trend. Surprise and news shocks all occur at $t = 0$.

Despite stronger tax revenues, the output response to the news shock is similar, implying slightly larger multipliers for pre-announced fiscal expansions than for surprise ones. And although the anticipation effect for output is minimal, real activity as measured by housing starts shows an immediate decline before rebounding, perhaps reflecting the possibility that house builders hold off until the fiscal stimulus kicks in.

For the monetary policy shock, anticipation effects seem a little larger, although the news shock is not as well estimated. An anticipated monetary tightening causes a small contemporaneous increase in interest rates, along with a temporary expansion in housing starts – perhaps as interest-sensitive home builders engage in intertemporal substitution of production. Inflation and output also drop much sooner than for an unanticipated shock, although the confidence intervals around these estimates are large. However, the well known "liquidity effect" – whereby activity and inflation increase temporarily on impact of a monetary policy tightening – appears to be a feature only of surprises and not of news shocks.

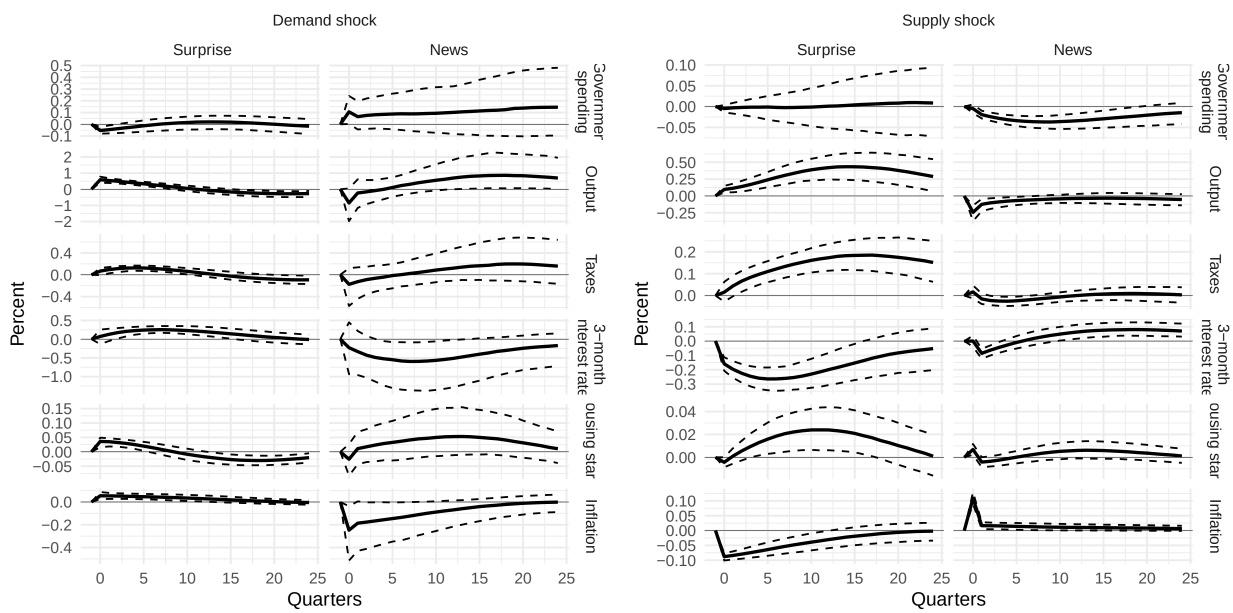


Figure 6: Impulse Responses to Economic Shocks: News vs. Surprises

Impulse responses for unanticipated surprise and news for each shock, as calculated in Section 3.6. For comparability, both shocks are scaled by the standard deviation of the surprise shock. The solid line and dashed lines show respectively the $50^{th}, 10^{th}$, and 90^{th} percentiles from a bootstrap simulation with $N^{sim} =$ 1000 replications. For government consumption, output, and taxes, units are percentage points relative to trend lagged output. For inflation, interest rates, and housing starts, units are annualized percentage points relative to trend. Surprise and news shocks all occur at $t = 0$.

In Figure 6 we plot the same impulse responses for the supply and demand shocks. Generally, the news component of the demand shock is very poorly estimated. This reflects the fact that the news component is estimated to be very small (see further discussion of the relative importance of news and surprises in the next section). As a result, we do not offer a strong defense of the news impulse responses for the demand shock. For the supply shock, however, we see a large and often countervailing anticipation effect. When expected future supply increases, inflation spikes today, as one would expect if agents expect higher future incomes without an immediate expansion in supply. As a result, the gains in output and housing starts and the decline in interest rates are all much mitigated.

4.6 The Importance of News Versus Surprises in Macroeconomic Fluctuations

In the preceding section, we compared the relative *shapes* of the news and surprise impulses, rescaling them to abstract from differences in their *size*. Here, we reintroduce the magnitude of the two different shock types, using this to investigate the relative contributions of news and surprise shocks to aggregate macroeconomic fluctuations.[26]

To investigate this issue, we construct an explicit variance decomposition for all the variables and shocks in our model. It is relatively straightforward to show that the $h-$step ahead forecast error variance can be written as the sum of contributions from the news and surprise components of each of the structural shocks. In Appendix I, we work out this decomposition for the general case. But when $M = 1$, this becomes:

$$\begin{aligned} MSE_t x_{t+h} = & \sum_{j=1}^{N} \left(\sum_{s=1}^{h} B^{h-s} (A_j A_j') (B')^{h-s} \right) \sigma_{u,j}^2 \\ & + \sum_{j=1}^{N} \left(\sum_{s=1}^{h} 1_{h>1} B^{h-s-1} \left(A_j A_j' + B(C_j A_j') + (A_j C_j') B' \right. \right. \\ & \left. \left. + B(C_j C_j') B' \right) (B')^{h-s-1} + (C_j C_j') \right) \sigma_{v,j}^2 \end{aligned} \tag{11}$$

where A_j and C_j are the jth columns of matrices A and C respectively and $1_{h>1}$ is an indicator function that is 1 if $h > 1$ and 0 otherwise. Note that because this is linear in the variances of each of the news and surprise shocks (the $\sigma_{u,j}^2$ and $\sigma_{v,j}^2$), this can be interpreted as an additive decomposition of the total variance with each term representing the contribution from each shock.

Table 3 reports this variance decomposition for $h = 24$, a reasonable proxy for the

[26] To complement the quantitative results in this section, Appendix G describes the impulse responses to structural shocks composed of the average combination of news and surprise.

long-run decomposition. Overall, this comports with the results in Figure 16.[27] For most variables, both news and surprises play an important role. In general, news seems to account for a smaller share of variance, although not a trivial one. For all but one variable, the news shocks account for between one quarter and one fifth of the variance. This substantial role of news is consistent with broad themes in the literature. Empirical studies of news following Beaudry and Portier (2006) and Barsky and Sims (2011) broadly find large roles for news to explain business cycles. These types of papers associate news with forecast errors about technology; with our identification strategy, we can go further and find news associated with the entire set of structural shocks.

One variable where news matters relatively more is inflation, where it accounts for almost two fifths of fluctuations 6 years ahead. This is principally driven by news about supply – consistent with the idea that inflation is driven by forward-looking agents responding to changes in the balance between aggregate supply and demand.

The relative importance of news is not symmetric across shocks. The unweighted average across variables gives a crude measure of the "newsiness" of each shock, and is shown in the last three lines of Table 3.[28] In general, fiscal shocks are the ones where news matters most relative to surprises, likely reflecting the long lags in implementing fiscal policies.

Some variable-shock-specific points are also worth highlighting here. For example, monetary policy shocks only drive a small amount of the variance in interest rates. Although this might seem counter-intuitive at first, this is exactly what would occur if monetary policymakers generally adhere to a policy rule which responds to other shocks. This says that monetary policy is not injecting noise into interest rates. The same is not true for fiscal variables, which are predominantly driven by policy changes and, in the case of taxes, supply and demand. Housing starts, a particularly forward-looking measure of real activity, are most affected by monetary policy, demand and fiscal shocks, as one might expect.

[27] Some notes on interpreting this table: first, Jensen's inequality implies that, the variance decomposition of the mean of the distribution of estimates (i.e. the point estimate) is quite different from the mean of the distribution of the variance decomposition. And so, the variance decomposition of the point estimate is not a consistent estimator for the variance shares. We thus report an average over the bootstrap simulation. Second, the relative news and surprise shares should correspond to the contributions to the average impulse responses in Figure 16. However, the quantitative relationship between Figure 16 and Table 3 is not straightforward. The former shows the contemporaneous response per unit of shock standard deviation. The latter shows the cumulative variance. For example, news is clearly much less important than surprises for demand shocks in Figure 16, but quantitatively accounts for almost one sixth of the unweighted average variance ($2.9/18 \simeq 1/6$). Nevertheless, the *ordinal* importance should almost always be preserved – if news shocks appear more important in a given panel in Figure 16 they should generally have the greater share in Table 3.

[28] This is not a perfect summary measure, since different variables have different variances. However, it is at least transparent.

Variable	Type	Fiscal stimulus	Mon. policy	Demand	Supply	Unlabeled #1	Unlabeled #2	Total
Gov. spending	News	4.5	3.6	1.6	5.6	2.2	1.1	24.3
	Surprise	20.4	10.0	3.8	2.3	14.8	12.3	75.7
	Total	25.6	15.8	6.4	9.7	18.5	14.5	100.0
Output	News	7.0	2.2	3.7	4.3	2.1	2.3	26.3
	Surprise	8.0	6.7	19.5	23.9	4.6	4.3	73.7
	Total	15.9	9.9	24.4	28.3	8.3	7.7	100.0
Taxes	News	4.9	3.3	1.9	1.7	1.8	2.3	19.4
	Surprise	12.5	4.7	11.6	30.3	7.6	7.4	80.6
	Total	18.2	8.6	14.5	32.1	10.1	10.9	100.0
3-month interest rate	News	5.6	2.2	3.7	5.8	2.1	2.3	25.9
	Surprise	2.8	8.0	16.9	18.1	4.9	17.4	74.1
	Total	9.2	11.2	22.5	24.8	8.1	20.0	100.0
Housing starts	News	5.1	2.4	2.2	2.0	1.8	1.8	19.0
	Surprise	13.8	18.4	17.7	8.3	6.0	9.6	81.0
	Total	19.3	21.7	20.8	11.4	8.3	12.2	100.0
Inflation	News	4.1	1.9	4.3	17.0	1.5	2.9	37.8
	Surprise	5.2	4.0	12.6	21.9	2.4	7.0	62.2
	Total	10.0	7.4	19.6	40.4	4.8	11.8	100.0
Unweighted average	News	5.2	2.6	2.9	6.1	1.9	2.1	25.5
	Surprise	10.5	8.6	13.7	17.5	6.7	9.7	74.5
	Total	16.4	12.4	18.0	24.5	9.7	12.8	100.0

Table 3: Forecast error variance decomposition, 24 quarters ahead

The forecast error decomposition shows for each variable in percent the fraction of the overall forecast error variance attributable to each shock, split into the news and surprise components. Totals are shown in the right hand column. The news and surprise components sum to 100 for each variable. Table reports the average from a bootstrap with $N^{sim} = 1000$ replications. The "Unweighted average" entries are a simple average of the contributions across each variable, and thus give an approximate measure of the relative contributions of news and surprises to macroeconomic fluctuations for each shock.

4.7 Robustness

Appendix E presents results from a number of different specifications, including with different lag structures, different variables, and different sample lengths. We also consider a version where forecasts are taken literally, without processing them via machine learning. Although the resulting shocks are not always directly comparable across specifications, the role of news and surprises remains very similar to our baseline (see variance decomposition in Figure 10).

5 Counterfactual Policy

This section applies the McKay and Wolf (2023) method to study counterfactual policy rules. The method requires estimates of the effects of policy news shocks. Because our method identifies the entire set of news shocks, it is useful for comparing counterfactual monetary and fiscal policy in a consistent setting. Moreover, this allows for the estimation of counterfactuals where monetary and fiscal policy can coordinate.

5.1 Method

One of the key observations in McKay and Wolf (2023) is that in a world where news shocks matter, policymakers are able to pursue their goals not just through their current actions but also through news about their future actions. They exploit this insight to address a long-standing critique of the usefulness of VARs for computing purely empirical policy counterfactuals: that they are subject to the Lucas critique (Lucas, 1976).

For intuition, imagine that one were to able to perfectly identify the impact of a monetary policy shock using a VAR and wanted to understand what would have happened if policy had followed a different rule, one that perfectly stabilized inflation. One possibility, pioneered by Sims and Zha (2006), would be to use the estimated impulse responses for inflation from the monetary shock to compute the sequence of policy innovations which would have stabilized inflation period-by-period. The challenge to this approach is that the policy realized ex post is inconsistent with agents' expectations. Thus, the estimated counterfactual impulse response is wrong – if it were implemented as in such a way, rational agents' expectations would respond, changing the data generating process.

McKay and Wolf (2023) show that identification of news shocks is sufficient to overcome this challenge in a relatively large class of commonly used macro models.[29] The intuition is that policymakers can implement a different rule not just through a surprise today but by also communicating their future actions as news shocks. As a result, agents' ex ante beliefs are then consistent with the ex post policy rule. This in turn means that policy counterfactuals can be estimated in three steps: 1) identifying news and surprise shocks, 2) compute the linear combination of news and surprises which would implement the counterfactual policy, 3) use the estimated impulse responses to calculate the responses of the macroeconomy under that rule.[30] So far, this paper has been about the first of these steps. We now turn to the remaining ones.

To apply this approach to our setting, we start by classifying our estimated shocks as either policy shocks (the fiscal stimulus and monetary policy shocks) or as others (demand, supply, and the unlabeled shocks). We then consider one-at-a-time the problem of the policymakers in control of each policy shock, assuming that they wish to minimize some loss function.

[29] Barnichon and Mesters (2023) come to a similar Lucas critique-robust conclusion, but use the responses to news shocks to solve the time-t decision problem of a policymaker in contrast to constructing a complete counterfactual.

[30] Strictly speaking, the Wolf & McKay result requires estimates of news shocks at all forecast horizons. The exact number of news shocks depends on the lag structure of the true data generating process. But in general, to perfectly implement an alternate policy rule, the econometrician may need to know the news shocks at all horizons. However, a key finding of McKay and Wolf (2023) is that using a single news shock can be a good approximation to the true counterfactual.

Specifically, assume that the policymaker controls both the surprise and the news for shock g, denoted u_t^g and v_t^g. We denote the vectors of non-policy shocks by u_t^{-g} and v_t^{-g}. We consider linear policy counterfactuals which can be written as:

$$\begin{bmatrix} u_t^g \\ v_t^g \end{bmatrix} = \alpha \begin{bmatrix} u_t^{-g} \\ v_t^{-g} \end{bmatrix} \tag{12}$$

where α is a $2 \times 2(n-1)$ matrix recording how the policymaker responds to the other structural shocks.

Let the impulse responses to surprise and news under this rule be denoted by $\psi_u(h)$ and $\psi_v(h)$. Then:

$$\begin{bmatrix} \psi_u(h) & \psi_v(h) \end{bmatrix} = \begin{bmatrix} \phi_u^{-g}(h) & \phi_v^{-g}(h) \end{bmatrix} + \begin{bmatrix} \phi_u^{g}(h) & \phi_v^{g}(h) \end{bmatrix} \alpha$$

We then assume that the policymaker aims to minimize a period loss function which depends on a linear combination of the macroeconomic variables, x_t:

$$\min ||Fx_t||$$

for some matrix F. This loss function could be a direct loss due to macroeconomic fluctuations (e.g. departures from an inflation target) or it could be deviations from a specific policy rule (e.g. a Taylor rule). In either case, we follow McKay and Wolf (2023) by computing α to minimize this loss. A sufficient condition for this is to minimize the loss function on the impulse responses, as these are just the building blocks of the linear model. We thus rewrite the problem as:

$$\min \left|\left| F \begin{bmatrix} \psi_u(h) & \psi_v(h) \end{bmatrix} \right|\right| = \min \left|\left| F \begin{bmatrix} \phi_u^{-g}(h) & \phi_v^{-g}(h) \end{bmatrix} + F \begin{bmatrix} \phi_u^{g}(h) & \phi_v^{g}(h) \end{bmatrix} \alpha \right|\right|$$

When the metric $|| \cdot ||$ is a sum of squares, this can be solved by estimating α from the regression:

$$F \begin{bmatrix} \phi_u^{-g}(h) & \phi_v^{-g}(h) \end{bmatrix} = -F \begin{bmatrix} \phi_u^{g}(h) & \phi_v^{g}(h) \end{bmatrix} \alpha + \epsilon_h \tag{13}$$

5.2 Counterfactual Exercises

In this section, we compare and contrast how fiscal and monetary policy can be used for business cycles stabilization.[31] For each policy instrument, we select the linear combination

[31] Appendix H.2 presents additional counterfactual policies where the objective is passivity, e.g. acyclical government spending and interest rate pegs.

of news and surprise shocks that minimize the variance in one of three objectives: (1) output, (2) inflation, and (3) a "dual mandate" weighted average. For each objective, this implies a different policy response for each of the remaining 10 shocks (for each policy instrument there are 5 remaining structural shocks, each with a news and noise component.) All of these shocks affect the summary numbers that we report later in Table 4, but for readability our plots only contain the counterfactual impulse responses to the non-policy "supply" and "demand" structural shocks.

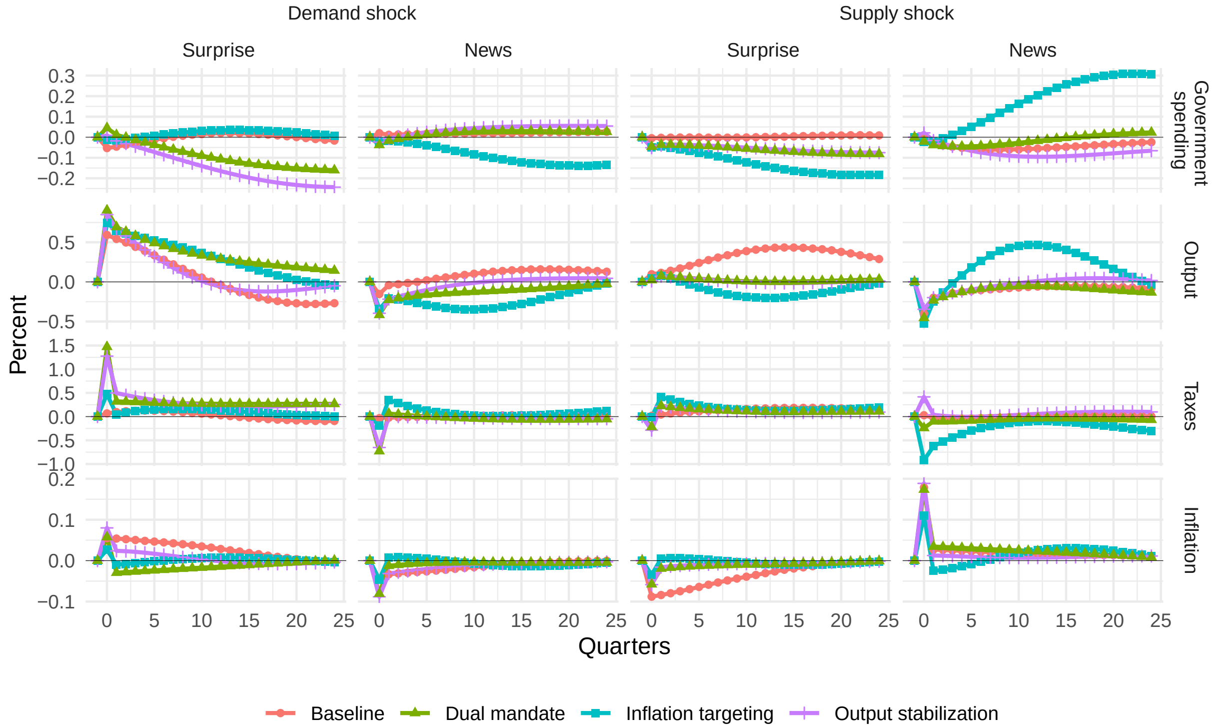


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Figure 7: Counterfactual Business Cycle Stabilization Using Fiscal Policy

Time series impulse responses to news and surprise components of the two identified non-policy structural shocks under four policy regimes computed following equation (13): the prevailing baseline rule, and then the best feasible approximations to inflation stabilization, output stabilization, and a dual mandate which weights inflation and output in inverse proportion to their standard deviations in the data.

Figure 7 plots the impulse response functions to demand and supply shocks when fiscal policy is used to moderate business cycles.[32] The red line (diamond markers) are the baseline IRFs without any counterfactual policies. The purple line (cross markers) plots the IRFs when fiscal policy is used to minimize detrended output variance. Fiscal policy is more

[32]For readability, this figure only plots point estimates; we discuss and report confidence intervals in Appendix H.1.

effective at moderating some shocks than others. For example, output expands after a surprise supply shock in the baseline. When fiscal policy is used, nearly the entire output response is eliminated. This is achieved by lower government spending and raising taxes after the shock. Fiscal policy similarly effective at moderating the output response to demand news, but is less effective at moderating demand surprises or supply news. This is because these shocks have large, quickly decaying responses, while the baseline effects of fiscal shocks on output are highly persistent (Figure 2). After these latter shocks, output responses are mostly moderating in the medium-run, but only barely in the short-run.

The teal line (square markers) plots the IRFs when fiscal policy is used to minimize inflation variance. In general, the slow passthrough of fiscal policies and the transitory response of inflation to most shocks mean that inflation stabilization is achieved by centering inflation fluctuations around zero, rather than successfully damping the short-term fluctuations. Moreover, this comes at the cost of typically much larger swings in taxes and spending. Overall, fiscal policy has to work very hard to offset inflation fluctuations and is not terribly effective at doing so. This accords with the commonly-held belief that fiscal policy is not an appropriate took to to offset inflation fluctuations. The "dual mandate" is the teal line (triangle markers), which minimizes a weighted average of output and inflation objectives. This produces policies and outcomes approximately halfway between the inflation targeting and output stabilization cases.

Figure 8 plots the impulse response functions to demand and supply shocks when monetary policy is used to moderate business cycles. Monetary policy is effective at stabilizing the output response to two shocks: after a demand surprise, interest rates are immediately raised to reduce the demand-induced output boom, at the cost of creating deflation; supply news features a similar response with opposite sign. But other shocks are not moderated well with monetary policy. In the baseline, supply surprises only create an output boom with a long delay, so monetary policy is only effective at reducing medium-run output variance with an immediate interest rate hike.

Monetary policy is more consistently effective at moderating inflation, where the sole objective is to minimize the inflation variance. For example, demand surprises create immediate inflation in the baseline, so the inflation-targeting policymaker responds by suddenly hiking interest rates, pushing the inflation IRF nearly to zero. However, monetary policy is not perfect for all shocks; supply news creates a short-term burst of inflation, which cannot be easily moderated because monetary policy affects inflation smoothly and persistently. The inflation targeting policymaker chooses to reduce the short-term burst only somewhat, while tolerating some medium-run deflation.

Table 4 extends this exercise, reporting the unconditional variances of the various time

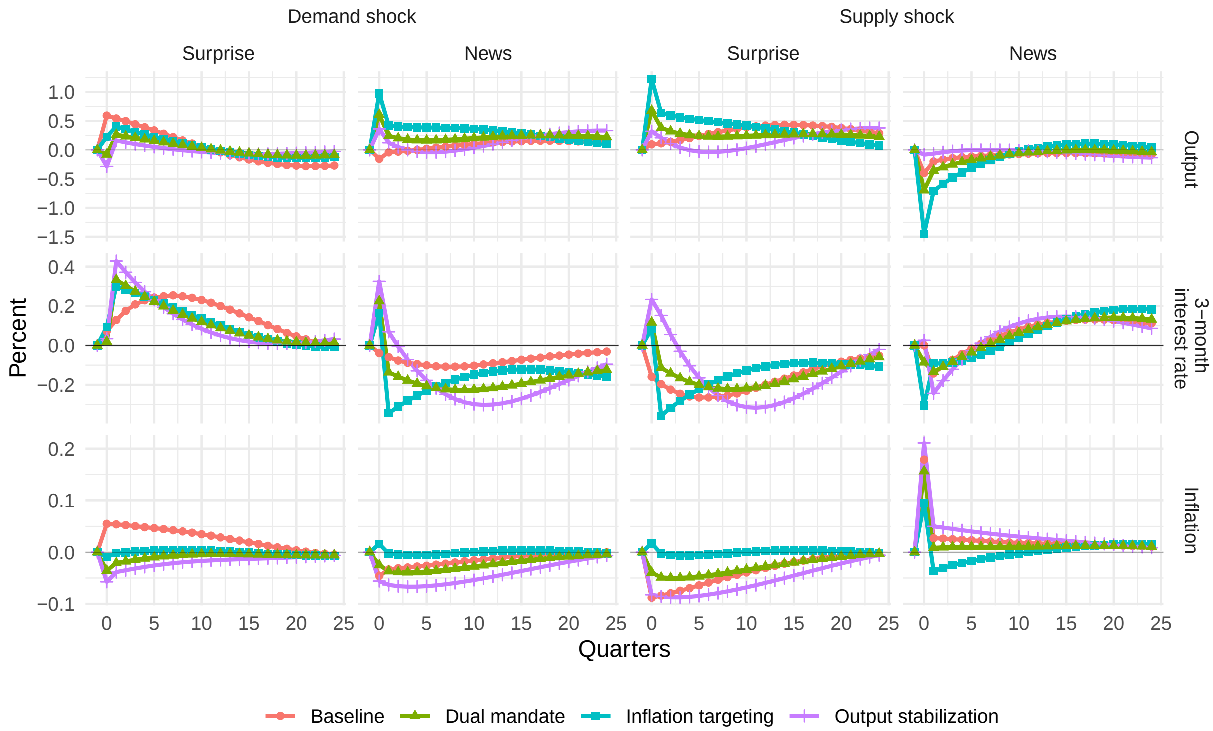

Figure 8: Counterfactual Business Cycle Stabilization Using Monetary Policy

Time series impulse responses to news and surprise components of the two identified non-policy structural shocks under four policy regimes computed following equation (13): the prevailing baseline rule, and then the best feasible approximations to inflation stabilization, output stabilization, and a dual mandate which weights inflation and output in inverse proportion to their standard deviations in the data.

series for each policy instrument and objective function, relative to baseline (i.e. the data). It shows that fiscal and monetary policies are more effective when cooperating than either one is individually. When output stabilization is the goal, fiscal or monetary policy alone can reduce the output variance by about two thirds. But when both fiscal and monetary policy are used, the output variance can be reduced to nearly zero. In some sense, this is not surprising since joint policy allows for four degrees of freedom in stabilizing just one target. Inflation is a similar story. Monetary policy is more effective than fiscal policy at moderating inflation, but together they can nearly eliminate inflation volatility.

Table 4 also reveals some further insight into variance trade-offs. Almost every counterfactual policy increases the volatility of government spending and taxes. When used alone, fiscal policy tends to increase interest rate volatility as well. When monetary policy aims to moderate output, interest rate volatility rises, but when the goal is moderating inflation, less interest rate volatility is needed. As such, the dual mandate exercise is perhaps a more

Target:	Inflation			Output			Dual Mandate		
Policy used	*Fisc.*	*Mon.*	*Joint*	*Fisc.*	*Mon.*	*Joint*	*Fisc.*	*Mon.*	*Joint*
Inflation	**0.19**	**0.09**	**0.00**	0.46	1.41	0.80	**0.43**	**0.44**	**0.34**
Output	1.03	1.45	1.56	**0.30**	**0.33**	**0.01**	**0.56**	**0.58**	**0.37**
Government spending	3.28	2.73	1.24	2.77	1.08	2.47	2.49	1.22	1.32
Taxes	4.56	2.22	3.06	5.15	2.09	3.91	6.02	1.43	1.72
3-month interest rate	1.22	0.84	2.02	1.06	1.15	2.12	1.69	0.82	0.43
Housing starts	1.85	1.09	1.09	0.92	1.06	0.89	0.80	0.68	0.25

Table 4: Counterfactual Variances Relative to Baseline

Table 4 shows the relative variance compared to the baseline of each of the model variables in nine counterfactual simulations, as measured by the norm of the impulse response function. The counterfactual simulations all seek to minimize the variance of some objective – either inflation, output, or a weighted average of both (the "Dual Mandate" column, which weights inflation and output by their relative standard deviations). They also vary by the policy instrument used – using either the fiscal shock, the monetary shock, or a combination of both.

challenging and realistic test. Here, the benefits of coordination are less extreme, but still more effective than either policy instrument is individually. The incremental reduction in variance of joint policy is in the order of around an extra 50 percent for output and 20 percent for inflation.[33]

6 Conclusion

In this paper, we study a general structural VAR describing economies where agents have news about the economy's structural shocks. The effects of surprises and news shocks are not easily disentangled with traditional methods. So we derived a new approach that incorporates measures of forecasts into the VAR, which identifies the entire vector of structural surprises and news.

Our method is useful in any setting where there might be news about multiple shocks in the economy. One such example is the case where agents have news about both fiscal and monetary policy. We separately identify the effects of these shocks, which allows us to study how counterfactual fiscal and monetary coordination can coordinate to moderate business cycles.

[33]For example, the improvement in output variance reduction for output relative to monetary policy alone $= (1 - 0.58)/(1 - 0.37) = 1.5$

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A Additional Proofs Regarding the Structural Model

To solve the general macro model 3, we prove an intermediate result: Lemma 1. This lemma applies to a more general form of the structural model in which the structural shock vector ϵ_t can have $H \geq 1$ news horizons:

$$\epsilon_t = \nu_{t|t} + \nu_{t|t-1} + \nu_{t|t-2} + ... + \nu_{t|t-H}$$

where $\nu_{t|t-j}$ is the vector of news shocks received j periods in advance. When $j = 0$, $\nu_{t|t}$ is the surprise shock.

Then, we prove Theorem 1 by considering the special case of $H = 1$.

Lemma 1 *The solution to the general model* (3) *is*

$$x_t = \sum_{j=1}^{k+1} \beta_j x_{t-j} + \sum_{j=1}^{H} \eta_j \left(\mathbb{E}_t \left[\epsilon_{t+j}\right] - \rho \mathbb{E}_{t-1} \left[\epsilon_{t-1+j}\right]\right) + \eta_0 \epsilon_t \tag{14}$$

with h-period-ahead forecast

$$f_t^h = \sum_{j=1}^{k+1} \beta_j \mathbb{E}_t[x_{t+h-j}] + \sum_{j=1}^{H-h} \eta_j \left(\mathbb{E}_t \left[\epsilon_{t+h+j} - \rho \epsilon_{t+h-1+j}\right]\right) + \eta_0 \mathbb{E}_t[\epsilon_{t+h}]$$

where $\alpha \equiv -\sum_{j=0}^{\infty} \Xi^j (H_{z,0} + H_{z,1} R_y) R_y^j$, $\rho \equiv \alpha R_y \alpha^{-1}$, *and*

$$\eta_j = \begin{cases} \alpha K_y & j = 0 \\ \Xi^{j-1} \left(\Xi \alpha - H_{z,1}\right) K_y & j > 0 \end{cases}$$

$$\beta_j = \begin{cases} \Phi_1 - \rho & j = 1 \\ \Phi_j - \rho \Phi_{j-1} & 1 < j \leq k \\ -\rho \Phi_k & j = k+1 \end{cases}$$

Proof of Lemma 1. Rewrite the model as

$$0 = \mathbb{E}_t \left[\left(I - \Xi L^{-1}\right) z_t + H_{z,0} y_t + H_{z,1} y_{t+1}\right] \tag{15}$$

where $z_t \equiv \left(I - \sum_{j=1}^{k} \Phi_j L^j\right) x_t$, $H_{z,0} \equiv \Phi_0^{-1} \Psi_{y,0}$, and $H_{z,1} \equiv \Phi_0^{-1} \Psi_{y,1}$. This implies

$$z_t = -H_{z,0} y_t - H_{z,1} \mathbb{E}_t \left[y_{t+1}\right] + \Xi \mathbb{E}_t \left[z_{t+1}\right]$$

and $\mathbb{E}_t \left[y_{t+1}\right] = R_y y_t + K_y \mathbb{E}_t \left[\epsilon_{t+1}\right]$ implies

$$z_t = -(H_{z,0} + H_{z,1} R_y) y_t - H_{z,1} K_y \mathbb{E}_t \left[\epsilon_{t+1}\right] + \Xi \mathbb{E}_t \left[z_{t+1}\right]$$

$$= -H_{z,1}K_y\mathbb{E}_t\left[\epsilon_{t+1}\right] - (H_{z,0} + H_{z,1}R_y)y_t$$

$$- \mathbb{E}_t\left[\sum_{j=1}^{\infty}\Xi^j H_{z,1}K_y\epsilon_{t+1+j}\right] - \mathbb{E}_t\left[\sum_{j=1}^{\infty}\Xi^j (H_{z,0} + H_{z,1}R_y)y_{t+j}\right]$$

$$= -\mathbb{E}_t\left[\sum_{j=0}^{\infty}\Xi^j H_{z,1}K_y\epsilon_{t+1+j}\right] - \mathbb{E}_t\left[\sum_{j=0}^{\infty}\Xi^j (H_{z,0} + H_{z,1}R_y)y_{t+j}\right]$$

use $y_{t+j} = R_y^j y_t + \sum_{i=1}^{j} R_y^{j-i}K_y\epsilon_{t+i}$:

$$= -\mathbb{E}_t\left[\sum_{j=0}^{\infty}\Xi^j H_{z,1}K_y\epsilon_{t+1+j}\right] - \mathbb{E}_t\left[\sum_{j=1}^{\infty}\Xi^j (H_{z,0} + H_{z,1}R_y)\sum_{i=1}^{j} R_y^{j-i}K_y\epsilon_{t+i}\right] - \sum_{j=0}^{\infty}\Xi^j (H_{z,0} + H_{z,1}R_y)R_y^j y_t$$

to collect terms, use $\alpha = -\sum_{j=0}^{\infty}\Xi^j(H_{z,0} + H_{z,1}R_y)R_y^j$:

$$= -\mathbb{E}_t\left[\sum_{j=0}^{\infty}\Xi^j H_{z,1}K_y\epsilon_{t+1+j}\right] + \mathbb{E}_t\left[\sum_{j=1}^{\infty}\Xi^j \alpha K_y\epsilon_{t+j}\right] + \alpha y_t$$

$$= \mathbb{E}_t\left[\sum_{j=1}^{\infty}\Xi^{j-1}\left(\Xi\alpha K_y - H_{z,1}K_y\right)\epsilon_{t+j}\right] + \alpha y_t$$

The η_j definition gives

$$= \mathbb{E}_t\left[\sum_{j=1}^{\infty}\eta_j\epsilon_{t+j}\right] + \alpha y_t$$

Then substituting for y_t implies

$$z_t = \mathbb{E}_t\left[\sum_{j=1}^{\infty}\eta_j\epsilon_{t+j}\right] + \alpha(I - R_yL)^{-1}K_y\epsilon_t$$

Inverting $\alpha(I - R_yL)^{-1}$ gives

$$(I - R_yL)\alpha^{-1}z_t = (I - R_yL)\alpha^{-1}\mathbb{E}_t\left[\sum_{j=1}^{\infty}\eta_j\epsilon_{t+j}\right] + K_y\epsilon_t$$

Use $\rho = \alpha R_y\alpha^{-1}$:

$$(I - \rho L)z_t = (I - \rho L)\mathbb{E}_t\left[\sum_{j=1}^{\infty}\eta_j\epsilon_{t+j}\right] + \alpha K_y\epsilon_t$$

$$z_t = \rho L z_t + (I - \rho L)\mathbb{E}_t\left[\sum_{j=1}^{\infty}\eta_j\epsilon_{t+j}\right] + \alpha K_y\epsilon_t$$

Substitute back in with the definition of z_t:

$$\left(I - \sum_{j=1}^{k} \Phi_j L^j\right) x_t = \rho \left(I - \sum_{j=1}^{k} \Phi_j L^j\right) L x_t + (I - \rho L)\mathbb{E}_t \left[\sum_{j=1}^{\infty} \eta_j \epsilon_{t+j}\right] + \alpha K_y \epsilon_t$$

Adding $\sum_{j=1}^{k} \Phi_j L^j x_t$ to both sides gives the model solution:

$$x_t = \sum_{j=1}^{k+1} \beta_j x_{t-j} + \sum_{j=1}^{H} \eta_j \left(\mathbb{E}_t \left[\epsilon_{t+j}\right] - \rho \mathbb{E}_{t-1} \left[\epsilon_{t-1+j}\right]\right) + \eta_0 \epsilon_t$$

using $\eta_0 = \alpha K_y$, and recognizing that shocks are unforecastable beyond horizon H.

The h-period-ahead forecast f_t^h is given by the time t expectation:

$$\mathbb{E}_t[x_{t+h}] = \sum_{j=1}^{k+1} \beta_j \mathbb{E}_t[x_{t+h-j}] + \sum_{j=1}^{H-h} \eta_j \left(\mathbb{E}_t \left[\epsilon_{t+h+j} - \rho \epsilon_{t+h-1+j}\right]\right) + \eta_0 \mathbb{E}_t[\epsilon_{t+h}]$$

■

Proof of Theorem 1. Written in inclusive form, $R_y = 0$, so $\rho = 0$. Lemma 1 implies that the solution simplifies to

$$x_t = \sum_{j=1}^{k+1} \beta_j x_{t-j} + \sum_{j=0}^{H} \eta_j \mathbb{E}_t \left[\epsilon_{t+j}\right]$$

and $\epsilon_t = u_t + v_{t-1}$ implies

$$x_t = \sum_{j=1}^{k+1} \beta_j x_{t-j} + \eta_0 \epsilon_t + \eta_1 v_t$$

which matches the equation (1) form for $\beta_j = B_j$, $\eta_0 = A$, $\eta_1 = C$, and $m = k + 1$. ■

B Additional News Horizons

Our baseline method considers 1-period-ahead news. But sometimes shocks are anticipated even further in advance. In this appendix, we describe how to generalize our method to account for news at multiple horizons by including additional forecasts in the VAR. Then we demonstrate the method with the New Keynesian model.

B.1 Structure and Notation with Multiple News Horizons

We define some new notation decomposing structural shocks into their anticipated components over many horizons, similar to McKay and Wolf (2023):

$$\epsilon_t = \nu_{t|t} + \nu_{t|t-1} + \nu_{t|t-2} + ... + \nu_{t|t-H} \tag{16}$$

The shock vector ϵ_t depends on news shocks $\nu_{t|t-j}$ received at each horizon j in the past, up to H total horizons. Mapping to our original one-period-ahead notation, the first two horizons of news were written as $\nu_{t|t} = u_t$ and $\nu_{t|t-1} = v_{t-1}$. As before, we normalize the structural shocks ϵ_t to have unit variance: $Var(\epsilon_t) = I$. Each structural shock is independent, so the news components are orthogonal: $Var(\nu_{t|t-h}) = D_h^2$, where D_h is diagonal. Orthogonality over time implies

$$\sum_h^H D_h^2 = I \tag{17}$$

We return to the general macroeconomic model to derive the implied restrictions for news at multiple horizons. The model (4) is

$$0 = \mathbb{E}_t \left[\Phi_0 \left(I - \Xi L^{-1} \right) \left(I - \sum_{j=1}^{k} \Phi_j L^j \right) x_t + \Psi_{y,0} y_t + \Psi_{y,1} y_{t+1} \right]$$

$$y_t = R_y y_{t-1} + \epsilon_t$$

We assume that the model is written in inclusive form so that $R_y = 0$. In this case, Lemma 1 implies that x_t is given by a dynamic equation:

$$x_t = \sum_{j=1}^{m} B_j x_{t-j} + \sum_{h=0}^{H} A_h \mathbb{E}_t \epsilon_{t+h} \tag{18}$$

which is a generalization of the baseline statistical model (1) for H news horizons.[34] To allow for identification, we assume that the columns of A_h exclusively associated with zero-variance shocks are also zero.

B.2 Identification with Multiple News Horizons

In our baseline method, we rewrote the model as a VAR, and proceeded to identify the model matrices from the VAR estimates. However, with multiple news horizons, the VAR representation becomes unwieldy, in particular the error variance matrix. So instead, we describe a method estimated by running several independent equations. This is also helpful for determining what works and what fails when the horizon length is incorrectly specified.

In the baseline setting, one-period-ahead forecasts were needed to identify the one-period-ahead news shocks. Now with H horizons, forecasts 1 through H-periods-ahead are needed. Theorem 4 formalizes this result, and shows how to identify each unknown matrix recursively.

We first introduce some new notation. $f_t^h = \mathbb{E}_t[x_{t+h}]$ denotes the h-period-ahead forecast. $\mathbf{f}_t^h$ denotes the forecast update $f_t^h - f_{t-1}^{h+1}$.

Theorem 4 *If A_0 and D_0^2 are full rank, and neither A_0 nor D_0^2 have repeated singular values, then the time series $\{\tilde{\mathbf{f}}_t^h\}_{h=0}^H$ identifies $\{\beta_j\}_{j=0}^M$, and $\{A_h, D_h\}_{h=0}^H$ up to sign and column order.*

[34]Mapping to the original notation, $A_1 = C$ and $A_0 = A$.

Proof. The h-period ahead forecast of time series x_t following (18) is given by Lemma 1:

$$f_t^h = \sum_{j=1}^{m} \beta_j f_t^{h-j} + \sum_{j=0}^{H-h} A_j \mathbb{E}_t \left[\epsilon_{t+h+j}\right] \tag{19}$$

where implicitly f_t^{h-j} is taken to denote the jth lag of x_t when $j \geq h$.

When $h = H$, equation (19) becomes

$$f_t^H = \sum_{j=1}^{m} \beta_j f_t^{h-j} + A_0 \nu_{t+H|t}$$

using $\nu_{t+H|t} = \mathbb{E}_t \left[\epsilon_{t+H}\right]$. Substitute for each right-hand side forecast using the forecast update $\mathbf{f}_t^h \equiv f_t^h - f_{t-1}^{h+1}$:

$$f_t^H = \sum_{j=1}^{m} \beta_j f_{t-1}^{h+1-j} + \sum_{j=1}^{m} \beta_j \mathbf{f}_t^{h-j} + A_0 \nu_{t+H|t} \tag{20}$$

Equation (20) implies that a regression of f_t^H on $t-1$ forecasts identifies the β_j coefficients, because $\nu_{t+H|t}$ and time t forecast updates are all orthogonal to time $t-1$ information.

Following equation (19), we can write any current forecast update $\mathbf{f}_t^h$ as

$$\mathbf{f}_t^h = \sum_{j=1}^{m} \beta_j \left(f_t^{h-j} - f_{t-1}^{h+1-j} \right) + \sum_{j=0}^{H-h} A_j \left(\mathbb{E}_t \left[\epsilon_{t+h+j}\right] - \mathbb{E}_{t-1} \left[\epsilon_{t+h+j}\right] \right)$$

Because the news shock $\nu_{t+h+j|t}$ is the forecast update for ϵ_{t+h+j}, the equation becomes

$$\mathbf{f}_t^h = \sum_{j=1}^{m} \beta_j \mathbf{f}_t^{h-j} + \sum_{j=0}^{H-h} A_j \nu_{t+h+j|t} \tag{21}$$

Forecast updates are observed and β_j coefficients are known from equation (20). And let the H-horizon forecast update be constructed using the implied $\mathbf{f}_t^{H+1} = \sum_{j=1}^{m} \beta_j \mathbf{f}_t^{H-j}$. Define the unknown residual in equation (21) as

$$R_t^h \equiv \mathbf{f}_t^h - \sum_{j=1}^{m} \beta_j \mathbf{f}_t^{h-j} = \sum_{j=0}^{H-h} A_j \nu_{t+h+j|t}$$

Then orthogonalize the R_t^h residual with respect to all R_t^k for $k > h$, and denote this orthogonalized residual by $\mathbf{R}_t^h$. At the final horizon, $\mathbf{R}_t^H = R_t^H = A_0 \nu_{t+H|t}$. At the penultimate horizon, $R_t^{H-1} = A_0 \nu_{t+H-1|t} + A_1 \nu_{t+H|t}$, so the associated orthogonalized residual is $\mathbf{R}_t^{H-1} = A_0 \nu_{t+H-1|t}$. In general, the orthogonalized residuals are

$$\mathbf{R}_t^h = A_0 \nu_{t+h|t}$$

The variance of the orthogonalized residual is

$$Var(\mathbf{R}_t^h) = A_0 D_h^2 A_0' \tag{22}$$

so equation (17) implies

$$\sum_{h=0}^{H} Var\left(\mathbf{R}_t^h\right) = A_0 A_0' \tag{23}$$

Let $U_h \Lambda_h V_h'$ denote the SVD of A_h. Equation (23) identifies $U_0 \Lambda_0^2 U_0'$. Apply these matrices thusly:

$$\Lambda_0^{-1} U_0' Var\left(\mathbf{R}_t^0\right) U_0 \Lambda_0^{-1} = \Lambda_0^{-1} U_0' A_0 D_0^2 A_0' U_0 \Lambda_0^{-1} = V_0' D_0^2 V_0$$

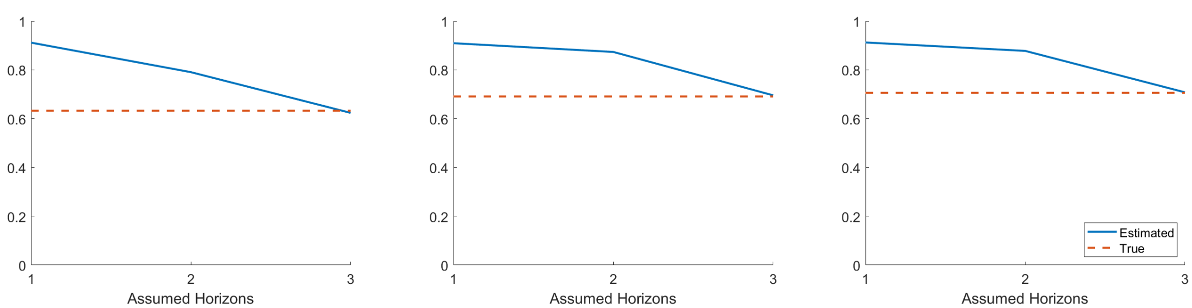
and an SVD of this matrix identifies V_0 and D_0 up to sign and order (under the assumption that D_0 is non-zero on the diagonal.) With A_0 known, equation (22) then gives D_h for all h, up to sign.

To find the remaining matrices, compute the covariance between residuals R_t^{h-k} and $\mathbf{R}_t^h$ for any $k \leq h$:

$$Cov\left(R_t^{h-k}, \mathbf{R}_t^h\right) = A_k D_h^2 A_0'$$

Inverting A_0 gives a sequence $\{A_k D_h^2\}_{h=k}^{H}$. D_h^2 are diagonal, but possibly with zeros and not invertible. Thus the sequence identifies the columns of A_k associated with news shocks that have non-zero variance at any horizon (e.g. if D_h is invertible, then A_h is recovered immediately from $A_h D_h^2 A_0'$). If there is some dimension i such that the ith entry of D_h is zero for all $h \geq k$, then the ith column of A_k is never associated with a non-zero shock, so the column is itself zero per the model assumption. ■

B.3 Monte Carlo Simulation with Multiple News Horizons



(a) Output (b) Inflation (c) Interest rates

Figure 9: Estimated Surprise Share of Forecast Error Variance with Multiple News Horizons

Each panel corresponds to a different variable in the simulated New Keynesian model. In all cases, the y-axis measures the share of the forecast error variance that is attributed to surprise shocks. The model is simulated with 3 horizons of news, and the dashed red lines denote the true surprise shares. The blue line denotes the estimated surprise shares, which vary depending on the assumed news horizon (x-axis).

To demonstrate the estimation method with multiple news horizons, we return to the New Keynesian model with forward guidance shocks described in Section 2. As before, the

Taylor rule residual h_t is given by

$$h_t = \rho h_{t-1} + \varepsilon_t$$

where the structural shock ε_t is partially anticipated. However, we now allow for H different horizons of news shocks driving ε_t, as in equation (16). We simulate the model for many periods, and apply the multiple horizon identification procedure under different assumptions. The true model is generated with $H = 3$ news horizons. However, we apply our method to the simulation in 3 cases: correctly assuming that $H = 3$, but also incorrectly assuming $H = 1$ or $H = 2$. To summarize the efficacy of our method in each case, we calculate the estimated share of the forecast error variance for each observable variable (y_t, π_t, i_t) that is due to surprise shocks. Figure 9 reports these shares for each case.

When H is chosen correctly, our decomposition correctly identifies the news and surprise shocks. This implication of Theorem 4 is confirmed in the Monte Carlo. The blue lines in Figure 9 denote the estimated surprise share for output, inflation, and interest rates. When $H = 3$, the lines match up exactly with the dashed red lines, which denote the true surprise shares in the model.

However, when H is chosen incorrectly, we misattribute some effects of news shocks to surprises. This is unavoidable; $H = 3$ so there are 6 structural shocks in the model, but incorrectly choosing $H = 1$ or $H = 2$ assumes that there only 4 or 5 shocks respectively. This is clear in Figure 9: when we estimate assuming $H = 1$ or $H = 2$, the estimated surprise share is higher than the true surprise share.

C Forecast Cleaning Properties

C.1 Proof of Theorem 3

Proof. Equation (9) and the causal invertibility assumption imply that we can write the rational expectation as

$$f_t = H^f(L)^{-1}\tilde{f}_t - H^f(L)^{-1}H^x(L)x_t - H^f(L)^{-1}H^z(L)z_t - H^f(L)^{-1}H^u(L)u_t - H^f(L)^{-1}H^v(L)v_t$$

Lags of u_t and v_t can be written in terms of current and past rational forecasts and observables, per equation (7). Denote these representations with the invertible lag operator polynomials $u_t = M^u_x(L)x_t + M^u_f(L)f_t$ and $v_t = M^v_x(L)x_t + M^v_f(L)f_t$. The rational expectation becomes:

$$f_t = H^f(L)^{-1}\tilde{f}_t - H^f(L)^{-1}H^x(L)x_t - H^f(L)^{-1}H^z(L)z_t - M^u_x(L)x_t - M^u_f(L)f_t - M^v_x(L)x_t - M^v_f(L)f_t$$

$$= (I + M^u_f(L) + M^v_f(L))^{-1}\left(H^f(L)^{-1}\tilde{f}_t - (H^f(L)^{-1}H^x(L) + M^u_x(L) + M^v_x(L))x_t - H^f(L)^{-1}H^z(L)z_t\right)$$

which we simplify by defining the causal lag operator polynomials $\psi^{\tilde{f}}$, ψ^x, and ψ^z to collect coefficients, allowing us to write the rational expectation as

$$f_t = \psi^{\tilde{f}}(L)\tilde{f}_t + \psi^x(L)x_t + \psi^z(L)z_t \tag{24}$$

Consider the relationship between x_{t+1} and the lagged observables:

$$x_{t+1} = f_t + Au_{t+1} + Cv_{t+1}$$

$$= \psi^{\tilde{f}}(L)\tilde{f}_t + \psi^x(L)x_t + \psi^z(L)z_t + Au_{t+1} + Cv_{t+1}$$

u_{t+1} and v_{t+1} are orthogonal to current and past observables, so forecasting x_{t+1} by regressing on lags of $\tilde{f}_t$, x_t, and z_t recovers the rational expectation:

$$E[x_{t+1}|\{\tilde{f}_{t-j}, x_{t-j}, z_{t-j}\}_{j=0}^{\infty}] = E[f_t + Au_{t+1} + Cv_{t+1}|\{\tilde{f}_{t-j}, x_{t-j}, z_{t-j}\}_{j=0}^{\infty}]$$

$$= E[f_t|\{\tilde{f}_{t-j}, x_{t-j}, z_{t-j}\}_{j=0}^{\infty}]$$

which is given by equation (8). ■

C.2 Noisy Forecast Cleaning

When the conditions of Theorem 3 are not satisfied, the interpretation of our forecast cleaning becomes weaker, but still useful.

Instead of an ideal rational expectation conditional on all information in available to forecasters, our cleaned forecasts are the best unbiased forecasts given the observable time series and reported forecasts. The interpretation of news must change as well. Instead of the component of structural shocks that is anticipated by forecasters, news is now the component that can be forecasted by the VAR.

First, we modify equation (1) so that the structural VAR depends on expectations of future shocks $E_t[\epsilon_{t+1}]$ in general rather than the news component v_t explicitly. This expectation may include noise shocks or other confounders in addition to the structural v_t:

$$x_t = \sum_{j=1}^{m} B_j x_{t-j} + A\epsilon_t + CE_t[\epsilon_{t+1}]$$

Next modify equation (9) so that forecasts are now given by

$$\tilde{f}_t = H^x(L)x_t + H^z(L)z_t + H^u(L)u_t + H^v(L)v_t + H^\zeta(L)\zeta_t$$

Now the empirical forecasts $\tilde{f}_t$ are not deviations from some ideal rational expectation. Rather, they are just some linear combination of observables, structural shocks, and the noise shocks ζ_t.

The component of forecasts excluding the observable terms is

$$\xi_t \equiv H^u(L)u_t + H^v(L)v_t + H^\zeta(L)\zeta_t$$

Let $H^\xi(L)w_t^\xi$ denote the Wold decomposition of ξ_t, with w_t^ξ white noise. Forecasting x_{t+1} gives the cleaned forecast:

$$f_t = E[x_{t+1}|\Omega] = \sum_{j=1}^{m} B_j x_{t+1-j} + AE[\epsilon_{t+1}|\Omega]$$

$$= \sum_{j=1}^{m} B_j x_{t+1-j} + AE[\epsilon_{t+1}|\{\xi_{t-j}\}_{j=0}^{\infty}] = \sum_{j=1}^{m} B_j x_{t+1-j} + AE[\epsilon_{t+1}|w_t^{\xi}]$$

so we define our reduced form news $\tilde{v}_t$ as

$$\tilde{v}_t \equiv E[\epsilon_{t+1}|w_t^{\xi}]$$

$$= D_v H_0^{v\prime} \Sigma_{w^{\xi}}^{-1} w_t^{\xi}$$

where H_0^v is the contemporaneous coefficient matrix in the $H^v(L)$ polynomial.

$\tilde{v}_t$ enters the structural VAR in the same way as the true news shock v_t. So when can we identify it using the method derived in Section 3? When the dimensions of $\tilde{v}_t$ are orthogonal, i.e. when $H_0^{v\prime}\Sigma_{w^{\xi}}^{-1}$ is diagonal. What does this mean? The fundamental shock ϵ_{t+1}^i to dimension i is associated one-for-one with a noise shock ζ_t^i to that dimension. Noise shocks to different dimensions cannot co-vary.

Does this imply agents cannot receive signals about different fundamentals with correlated noise? No. For example, GDP can still be a noisy signal about both productivity and labor supply. Rather, the condition requires that the noise shocks can be separated into orthogonal noise for each fundamental shock. News-noise equivalence (Chahrour and Jurado, 2018) implies that this condition is equivalent to the structural assumption that news shocks are mutually orthogonal.

Online Appendix

D Computational details

D.1 Computing Impulse Responses

Denote the data by $[FX]$, where $F = (f_1, f_2, \ldots, f_T)'$ is the set of forecasts and $X = (x_1, x_2, \ldots, x_T)'$ the non-forecast data. To compute the impulse responses we conduct the following steps.

1. Calculate and initial reduced-form point estimate $\tilde{\mathbf{B}}_{pt}, \tilde{\Sigma}_{pt}$ from a restricted VAR using the specification in equation (7), and where Σ_{pt} is the variance-covariance matrix of residuals.

2. Simulate N_{sim} samples of the data using estimates $\tilde{\mathbf{B}}, \tilde{\Sigma}$. Call these $\{[\tilde{F}_n, \tilde{X}_n]\}_{n=1}^{N_{sim}}$. Note that the simulated forecasts reflect the noise in the data from all sources, including due to imperfect estimation of conditional expectations.

3. Apply the same estimation process as in step 1 to each of the data sets simulated in step 2. Call the resulting estimates $\{\tilde{\mathbf{B}}_{sim,n}, \tilde{\Sigma}_{sim,n}\}_{n=1}^{N_s im}$

4. Define the mean simulated coefficient as:

$$\tilde{\mathbf{B}}_{sim,avg.} = \frac{1}{N_{sim}} \sum_{n=1}^{N_{sim}} \tilde{\mathbf{B}}_{sim,n}$$

   Approximate the mean bias in the reduced-form estimates of $\mathbf{B}$ via:

$$\Phi = \tilde{\mathbf{B}}_{pt} - \tilde{\mathbf{B}}_{sim,avg.}$$

5. Following Kilian (1998), we can define the bias-corrected reduced form point estimate as:

$$\hat{\mathbf{B}}_{pt} = \tilde{\mathbf{B}}_{pt} + \Phi$$

6. The corresponding reduced-form errors for the point estimate are then the residuals given by:

$$\hat{E} = [FX]_{-1} - [FX]_{-T}\hat{\mathbf{B}}_{pt}$$

   Where M_{-k} means removing the k^{th} row from matrix M. Then we can compute the point estimate of the reduced form variance-covariance matrix from

$$\hat{\Sigma}_{pt} = \frac{1}{T}\hat{E}'\hat{E}$$

7. Use the bias-corrected reduced form point estimate to construct N_{sim} samples of the

data using estimates $\hat{\mathbf{B}}_{pt}, \hat{\Sigma}_{pt}$. Call these $\{[\hat{F}_n, \hat{X}_n]\}_{n=1}^{N_{sim}}$. This is a bias-corrected bootstrap of the true data generating process.

8. Compute a bias-corrected bootstrap of the reduced-form coefficients in two steps.

   i. Apply same estimation process as in step 1 to each of the data sets $\{[\hat{F}_n, \hat{X}_n]\}_{n=1}^{N_{sim}}$. Denote these estimates $\{\bar{\mathbf{B}}_{sim,n}\}_{n=1}^{N_{sim}}$

   ii. Bias-correct *these* estimates to get the final bootstrapped estimates

$$\hat{\mathbf{B}}_{sim,n} = \bar{\mathbf{B}}_{sim,n} + \Phi \qquad \forall\, n$$

9. Compute the set of bootstrapped variance-covariance estimators $\{\hat{\Sigma}_{sim,n}\}_{n=1}^{N_{sim}}$ using the residuals computed from the simulated data $\{[\hat{F}_n, \hat{X}_n]\}_{n=1}^{N_{sim}}$ via the method in step 6.

10. To get a point estimate and distribution of structural parameters, simply apply the algorithm in Theorem 2 to $\hat{\mathbf{B}}, \hat{\Sigma}$ and each element of $\{(\hat{\mathbf{B}}_{sim,n}, \hat{\Sigma}_{sim,n})\}_{n=1}^{N_{sim}}$.

11. To compute confidence intervals for a given impulse response, compute the structural impulse separately for each element of the bootstrap (see next section for elaboration og this step). To form confidence intervals, take percentiles.

D.2 Labelling Shocks in the Bootstrap

Computing the bootstrapped impulse responses (final step in the preceding section) is not trivial. To see why, let $\phi_x^{pt}(h)$ denote a structural impulse response at horizon h for type x (either news or surprise) computed using the point estimate. This is an $N \times N$ matrix, where the columns correspond to the structural shocks and the rows correspond to the different series in the data. Let $\phi_x^n(h)$ be the equivalent object for the n^{th} bootstrapped simulation.

Identification is unique only up to sign and ordering of the shocks. This means that, without further restrictions, we cannot distinguish between $\phi_x^n(h)$ and

$$\tilde{\phi}_x^n(h) = DP\phi_x^n(h)$$

where P is a $N \times N$ permutation matrix and D is a $N \times N$ diagonal matrix D with entries 1 and -1.

To address this issue, for each n re-order and re-sign the shocks by computing D^*, P^* to minimize the sum of squares of the deviation of the bootstrapped impulse response from the point estimate:

$$(D^*, P^*) = \arg \min_{D\in\mathbb{D}, P\in\mathbb{P}} \sum_{h=1}^{H} \|\phi_x^{pt}(h) - DP\phi_x^n(h)\|_2$$

Where $\mathbb{D}$ and $\mathbb{P}$ are the sets of all possible D and P, and $\|\cdot\|_2$ is the entry-wise sum of squares. This ordering procedure minimizes a continuous function of the underlying structural parameters, and so satisfies the requirements for Lewis (2021) Theorem 4.

On the face of it, this is not a straightforward problem. There are 2^N possible D matrices, and $N!$ possible P matrices. However, a related problem is has a well-understood solution: the quadratic assignment problem. There, one seeks to minimize the assign N objects to N locations, where the cost of assigning object i to location j is $phi(i,j)$. Given a re-signing of the shocks, D, the problem at hand can be cast in this form. Because the metric we use is additively separable, one simply needs to compute the loss from assigning shock j to position i for all i and j. This is only N^2 calculations, rather than $N!$, greatly saving time over a brute force method. Of course, one still needs to solve the assignment problem given the cost matrix, but efficient algorithms are readily available.

Of course, we still have the D matrix to worry about. One possibility is to solve the quadratic assignment problem for all possible D. But this still requires 2^N applications of the solution algorithm. Much more efficient is to include this step in the calculation of the cost matrix.

For any $i \in 1, \ldots, N$, and any $j \in 1, \ldots, N$, and any $d \in \{0, 1\}$ we define a the function:

$$\psi(i,j,d) = \sum_{h=1}^{H} \|\phi^n_{x(i)}(h) - (-1)^d \phi^n_{x(j)}(h)\|_2$$

That is, this is the component of the objective function above coming from assigning shock j to position i given a resigning of shock j. Additive separability again means we can just consider the re-signing of for each combination individually.

$$\psi(i,j) = \min(\psi(i,j,0), \psi(i,j,1))$$

Thus, we need only make $2N^2$ calculations to compute a cost matrix which is then passed to a solver for the quadratic assignment problem.

E Robustness

This section reports the results from several robustness checks: alternatives to the baseline specification (Section E.1), a discussion of lag length selection (Section E.2), and additional shock validation exercises (Section E.3).

E.1 Alternative Specifications

We consider six alternative specifications, spanning a wide range of possible ways that our model might be mis-specified. These are listed in detail below. Two consider alternate lag structures, with either 2 or 4 lags respectively. One checks the extent to which our creation of proxy expectations series might be driving our results. Another re-runs our method using a data sample from the post-Volcker disinflationary era. And the remaining two substitute alternative measures of public spending and a secondary real activity measure.

Alternate specifications:

1. *Baseline.* The baseline specification in the text

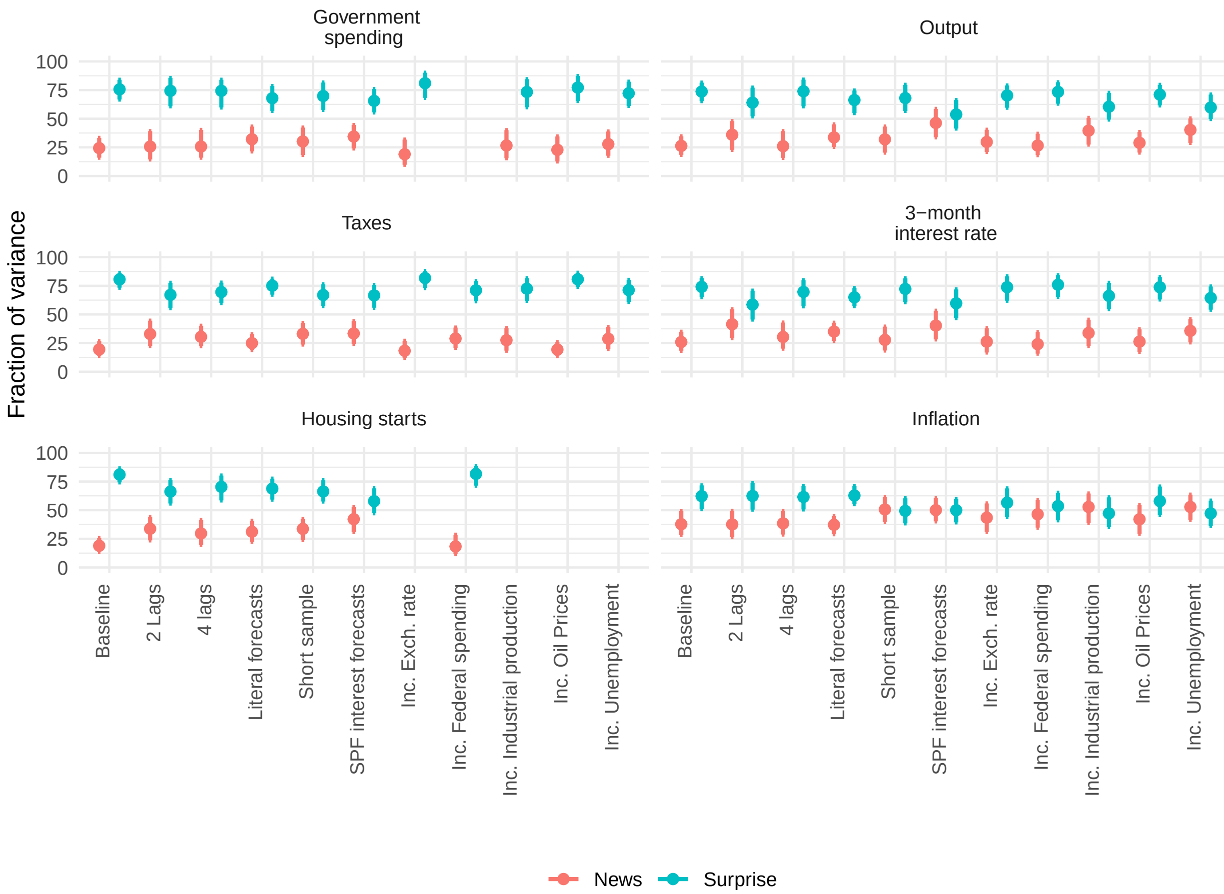


Figure 10: Variance decomposition: Comparison across specifications

Figure shows the 24-quarter horizon variance decomposition for the baseline and six different specifications. Points show 50th percentile and error bars the 10th to 90th percentile range from a bootstrap simulation of 1000 draws. Only common variables are shown, so specifications which replace one variable with another will be missing from one panel.

2. *2 Lags.* Baseline but with 2 lags in the VAR.
3. *4 Lags.* Baseline but with 4 lags in the VAR.
4. *Literal forecasts.* Uses the collected forecasts without any machine learning or other processing.
5. *SPF Interest Forecasts.* Uses SPF forecasts for the interest rate (only available starting 1981Q1).
6. *Short Sample.* Data starts in March 1988
7. *Inc. Federal Spending.* Replaces government spending with Federal Government Spending,
8. *Inc. Unemployment.* Replaces housing starts with unemployment.

9. *Inc. Industrial Production.* Replaces housing starts with industrial production.

10. *Inc. Oil prices.* Replaces housing starts with oil prices.

Given the difficulty in comparing impulse responses across specifications, as our main summary measure we take the variance in each variable attributable to news and surprise. For the baseline specification this is the rightmost column shown in Table 3 and gives an overall sense of how our method attributes fluctuations in variables to news and surprise shocks. Figure 10 presents this measure for each of the variables in our core dataset and for each of the specifications considered. Although there is some variation, the general impression clearly shows that the split between news and surprise shocks in driving outcomes is very stable across specifications. For almost all variables, a single value fits within the confidence interval for all news shocks (likewise for surprises). Qualitatively, the picture described in the main text is consistently produced here. Surprise shocks account for around three quarters of the variance for most variables except inflation, where news plays a more important role (and in some specifications, the dominant role).

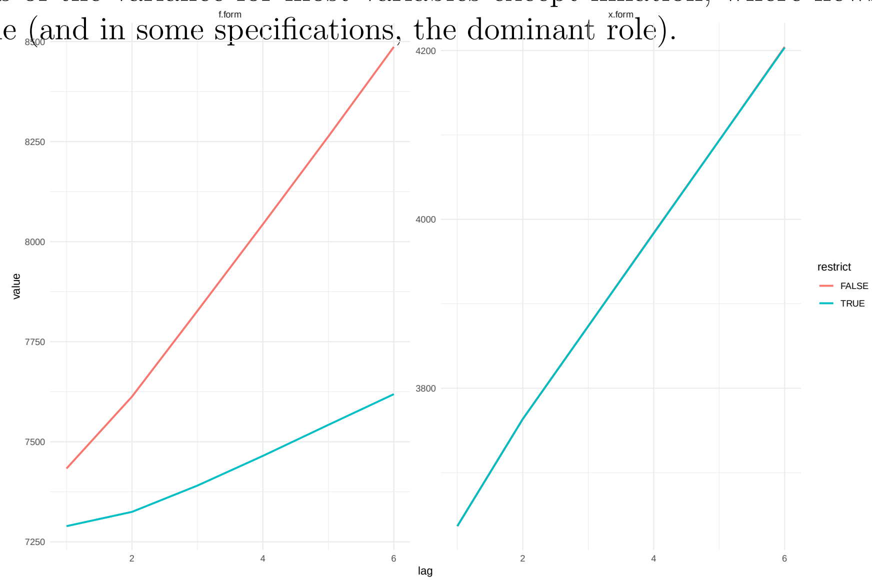


Figure 11: Akaike Information Criterion

Figure shows four different ways of computing the Akaike information. See text for details

E.2 Lag Selection

Figure 11 presents four ways to calculate the Akaike Information Criterion. They vary in the set of residuals used to compute the likelihood and in the restrictions on the estimation process. The "F-form" uses a likelihood for the stacked VAR in equation (7). The "X-form" uses just the residuals from the errors on the non-forecast variables. For each form, the likelihood is computed for two ways of estimating the reduced form coefficients. In the "restricted" case, the zero restrictions on the B_j matrices are imposed. In the "unrestricted" case, they are not. These lines are equivalent for the X-form AIC because the restrictions do not bind on the lower half of the stacked coefficient matrices – the estimation always puts weight one on the forecasts. In all cases, the one-lag specification is strongly preferred.

E.3 Shock Validation Exercises

This section provides extra validation checks for our shock labelling.

E.3.1 Fiscal Shock

Table 5 lists the values of the multipliers we use and their sources.

Source	h	2	4	6	8	12	16	20
Lewis 2021	μ_G^h	0.56	0.57		0.57	0.64	0.76	0.87
	μ_T^h	0.03	-0.09		-0.71	-1.33	-1.77	-2.06
Ramey 2011/Romer and Romer 2010	μ_G^h							1.20
	μ_T^h							-2.60
Ben Zeev and Pappa 2017/Romer and Romer 2010	μ_G^h			2.40				
	μ_T^h			-1.25				
Blanchard and Perotti 2002	μ_G^h	0.61	0.60		0.56	0.60	0.70	0.80
	μ_T^h	-0.64	-1.01		-2.28	-3.63	-4.69	-5.41
Caldara and Kamps 2017, penalty function	μ_G^h	0.05		0.35		0.55		0.25
	μ_T^h	-1.05		-1.20		-0.80		-0.45
Ricco 2015/Romer and Romer 2010	μ_G^h						1.50	
	μ_T^h						-2.60	

Table 5: Tax and Spending Multipliers from the Literature

Table 5 shows the values of the tax and spending multipliers used to calculate μ_Y^h, the implied cumulative output response from the tax and spending responses for the fiscal shock. Where a pair of papers is cited, the former is used to calculate the spending multiplier, μ_G^h, and the latter the tax multiplier, μ_T^h. The cumulative Blanchard and Perotti (2002) multipliers are those reported by Lewis (2021), and the cumulative Romer and Romer (2010) multipliers are those reported by Favero and Giavazzi (2012).

Figure 12 reproduces the validation exercise in Figure 3 for the other shocks. In general, the responses to the other shocks do not have implicit multipliers similar to those measured in the literature. The only shock where this might appear to be the case is for the monetary shock, although this is based on tax and spending responses which are statistically indistinguishable from zero.

E.3.2 Monetary Shock

This section reports alternate version of the monetary shock validation in Section 4.4.2. The following results are analogous to Figure 4: we estimate the impulse responses of our baseline time series to a set of monetary policy shocks estimated in the literature, and compare the estimates to our method's monetary policy shock. Figure 13a re-scales the shocks to increase the 3-month interest rate by 100 basis points (rather than the 2-year interest rate). Figure 13b adds additional lags to the VAR. In all cases, the effects of our monetary policy shock are broadly consistent with the shocks estimated elsewhere.

In addition to comparing the IRFs of our monetary policy shock to those from the literature, we also calculate simple correlation coefficients. The correlations are necessarily small: empirical monetary policy shocks, particularly those identified with high-frequency methods, have little explanatory power for aggregate time series. Their main appeal is

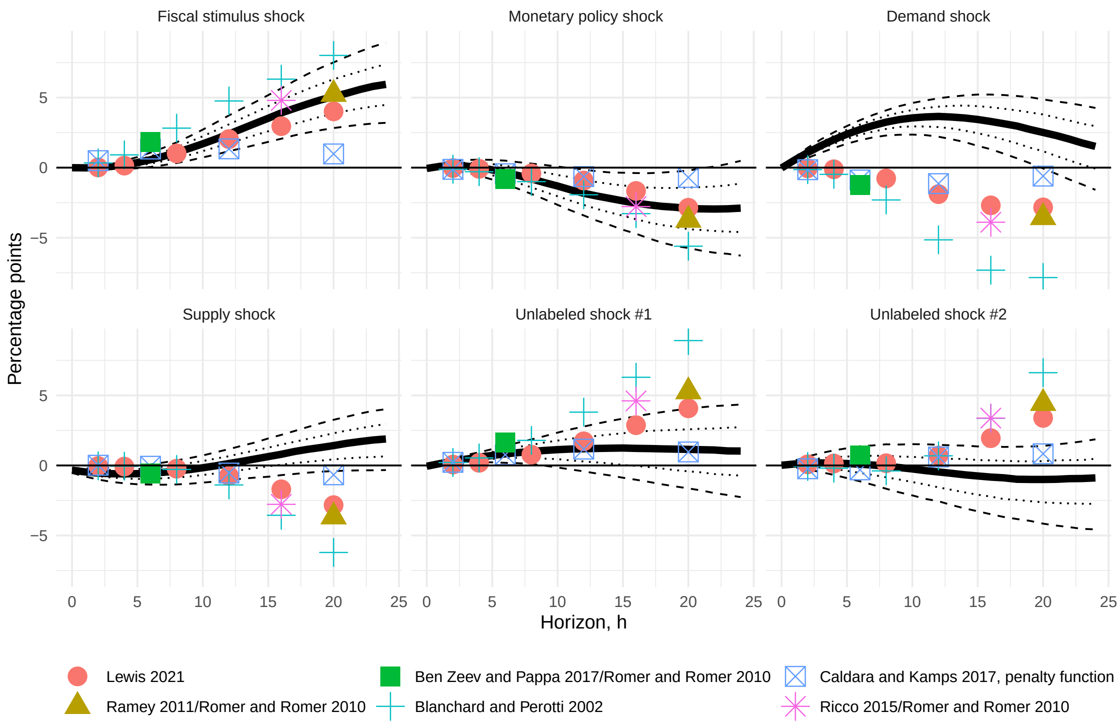


Figure 12: Cumulative Output Response: All Shocks

The solid line is the median cumulative output response for an unanticipated surprise fiscal expansion shock from a bootstrap simulation with $N^{sim} = 1000$ replications. The dashed and dotted lines respectively are the $10^{th} - 90^{th}$ and $25^{th} - 75^{th}$ percentile ranges. The points show the cumulative output responses, μ^h_Y, implied by our estimated tax and spending responses if the multipliers were those in the literature, summarized in Appendix E.3.1.

instead that they are cleanly identified. In contrast, our estimated series are derived from SVAR innovations; they explain a much larger share of aggregate volatility but require stronger assumptions. As a result, one should not expect high correlations even if our method is perfect.

	MPS Surp.	MPS News	R-R	A-D	B-S	G-K	J-K	M-A-R
MPS Surp.	1							
MPS News	0	1						
Romer-Romer	0.20	0.17	1					
Aruoba-Drechsel	0.10	0.14	0.26	1				
Bauer-Swanson	0.15	0.03	0.04	0.20	1			
Gertler-Karadi	0.12	0.10	0.08	0.25	0.43	1		
Jarocinski-Karadi	0.15	0.03	0.09	0.23	0.64	0.67	1	
Miranda-Agrippino-Ricco	0.09	0.13	0.08	0.25	0.48	0.66	0.58	1
Observations	296							

Table 6: Correlations with Monetary Policy Shocks in the Literature

Table reports correlation coefficients between the baseline estimated monetary shocks and monetary policy shocks from the literature. Column title abbreviations correspond to the row titles.

We report correlations with monetary policy shocks from the literature in Table 6. Beyond those already discussed in Section 4.4.2, we also include monetary policy shocks calculated by Jarociński and Karadi (2020), Miranda-Agrippino and Ricco (2021), and Aruoba and Drechsel (2024). In Adams and Barrett (2025) we argue that all of these shocks in the literature contain both surprise and news components, so we compare them with both of our estimated monetary shocks in the table. As expected, the correlations are small, but they are also all positive. This is further evidence that our method is capturing a monetary policy shock.

F Time Series Plots of Data and Shocks

Figure 14 plots the detrended and deseasonalized time series in the baseline specification and their associated forecasts.

Figure 15 presents the time series of the estimated shocks. In line with the variance decomposition, the variance of the news shock is relatively larger for the fiscal stimulus and supply shocks. The time series profile also admits an interpretation of specific episodes. One such example is the Global Financial crisis of 2008-2009. This is one of the few episodes where the news and surprise components of the monetary policy shock are of similar magnitudes (the standard deviation of the news component is around half that of the surprise for monetary policy). This is consistent with the idea that the Federal Reserve started using more explicit guidance about future interest rates as a tool of monetary policy.

G Effects of Average Structural Shocks

In general, structural shocks are combinations of news and surprises. The extent to which a given structural shock is more driven by news versus surprise varies across shocks, depending not only on the relative variances of news and noise (as captured by the differences in D_u and D_v) but also their differing causal impacts (the A and C matrices). One way to portray these differences is by constructing "average" impulse responses. Shown in Figure 16, these capture the dynamic response of macroeconomic variables to an average structural shock without regard for the news-surprise split.[35] For example, if one were able to identify monetary policy shocks without separating the news and surprise components, the result would be the relevant response in Figure 16.

The fundamental shock $\epsilon_t = u_t + v_{t-1}$ is the sum of the surprise and news components. We calculate the IRF to a unit ϵ_t shock as the response to an *average* ϵ_t realization:

$$\phi_\epsilon(h) = \mathbb{E}[x_{t+h}|\epsilon_t = 1]$$

$$\begin{aligned} &= \mathbb{E}\left[\mathbb{E}[x_{t+h}|u_t] + \mathbb{E}[x_{t+h}|v_{t-1}]|\epsilon_t = 1\right] \\ &= \mathbb{E}\left[\phi_u(h)u_t + \phi_v(h+1)v_{t-1}|\epsilon_t = 1\right] \\ &= \phi_u(h)\mathbb{E}\left[u_t|\epsilon_t = 1\right] + \phi_v(h+1)\mathbb{E}\left[v_{t-1}|\epsilon_t = 1\right] \\ &= \phi_u(h)D_u^2 + \phi_v(h+1)D_v^2 \end{aligned}$$

where D_u^2 and D_v^2 are the diagonal matrices of shock variances.

Accordingly, for each shock i, a unit impulse to ϵ_t^i is the sum of a $Var(u_t^i)$ impulse to u_t^i and a $Var(v_{t-1}^i)$ impulse to v_{t-1}^i. Because of the news timing, the impulse response to ϵ_t is non-causal: it can affect time series in period $t-1$. Correctly accounting for the timing, the impulse response matrix is:

$$\phi_\epsilon(h) = \phi_u(h)D_u^2 + \phi_v(h+1)D_v^2$$

$$= \begin{cases} CD_v^2 & h = -1 \\ B^{h+1}CD_v^2 + B^h A(D_u^2 + D_v^2) & h \geq 0 \end{cases}$$

Figure 16 clearly shows that overall news shocks seem perhaps less important than surprises in driving macroeconomic fluctuations, although this varies considerably across different shocks. For instance, supply and demand shocks are driven more by news and surprises respectively. This accords with the common view of demand shocks as relatively fast-moving and harder to predict and supply shocks as slower-moving. Likewise, fiscal policy appears on average a larger surprise component than monetary policy, for which surprises seem generally to be more important.

The relative importance of news and surprise shocks also varies across variables and horizons, albeit to a lesser extent. In particular, news is generally a more important driven of inflation especially at short horizons. In contrast, taxes seem to in general be more

[35] More formally, they are an average of the news and surprise impulses, weighted by their respective standard deviations (see formal discussion in Section 3.6).

dependent on surprise shocks.

H Additional Counterfactual Policy Results

H.1 Confidence Intervals

Our main results in Section 5 reported the point estimates for the IRFs under counterfactual policies. It is also possible to construct confidence intervals. McKay and Wolf (2023) do so in the process of estimating their Bayesian VARs. Our VAR is not Bayesian, so we take a different approach

To give a sense of the statistical importance of our counterfactual estimates, Figure 17 plots percentiles from the distribution of counterfactual impulse responses for one example, where fiscal policy is used to stabilize output. Here, the bootstrapped counterfactual impulses are computed by applying the counterfactual policy for the median structural estimate to the bootstrapped impulse responses. The interpretation of this is that it captures the uncertainty a policymaker has if they choose to implement a single optimal policy program when they have uncertainty about the true economy given by the confidence intervals in Figure 6.[36] In almost all periods, counterfactual output remains inside the estimated confidence interval. This is a measure of the extent to which the optimal policy regime successfully hits its target. The confidence intervals also have an economic value. For example, they say at short horizons one should be relatively more confident in the immediate tax raises needed to stabilize output than of cuts to government spending. At longer horizons, this is reversed.

H.2 Passive Policies

In addition to the objective-maximizing policies, we can also study other alternative policy rules. In this section, we consider counterfactuals where the policy instruments are as fixed as possible. Figure 18 plots these impulse responses.

When government spending is as passive as possible (green line with triangle markers) output is substantially more volatile, with larger IRFs to demand and supply shocks in Figure 18. This suggests that the current government spending behavior is already playing a role to moderate business cycles. Taxes are predictably similar: when tax revenues are as acyclical as possible (teal line with square markers), output IRFs are also amplified.

When attempting to approximate passive interest rates, we come to a similar conclusion as McKay and Wolf (2023): it is difficult to construct a policy counterfactual where interest rates are passive. The interest rate volatility-minimizing counterfactual (purple line, cross markers) only modestly reduces interest rate responses to shocks, although it also amplifies output responses suggesting that current monetary policy is effectively reducing some output volatility. This inability to achieve a passive interest rate counterfactual may be due to

[36]The alternative – re-estimating the optimal policy for each simulation in the bootstrap – has no similarly clean interpretation. It corresponds to a thought experiment in which a policymaker is subject to uncertainty over the economy's data generating process but simultaneously somehow sees through it to reset their optimal policy for any given the draw from the estimated distribution of parameters.

the news/surprise structure of our time series, or it may be reflecting more fundamental properties of the macroeconomy.

I Variance Decomposition Derivation

Restating equation (1)

$$
\begin{aligned}
x_t &= \sum_{j=1}^{m} B_j x_{t-j} + A\epsilon_t + Cv_t \\
&= \sum_{j=1}^{m} B_j x_{t-j} + Au_t + Av_{t-1} + Cv_t
\end{aligned}
$$

Letting X_t be the appropriately stacked vector of m lags of x_t. Then:

$$X_t = \hat{B}X_{t-1} + \hat{A}u_t + \hat{A}v_{t-1} + \hat{C}v_t$$

Where $\hat{B}$ concatenates the B_j and adds the lag matrix at the bottom, and $\hat{A}$ and $\hat{C}$ add a bunch of zeros in the extra rows.

Then the $h-$period forecast error is:

$$X_{t+h} - \mathbb{E}_t X_{t+h} = \begin{cases} \hat{A}u_{t+1} + \hat{C}v_{t+1} & h = 1 \\ \sum_{s=1}^{h} \hat{B}^{h-s}\hat{A}u_{t+s} + \sum_{s=1}^{h-1} \hat{B}^{h-s-1}\left(\hat{A} + \hat{B}\hat{C}\right) v_{t+h} + \hat{C}v_{t+h} & h > 1 \end{cases}$$

And the corresponding error variance for the forecast is:

$$MSE_t X_{t+h} = \begin{cases} \hat{A}D_u(\hat{A})' + \hat{C}D_v(\hat{C})' & h = 1 \\ \sum_{s=1}^{h} \hat{B}^{h-s}\hat{A}D_u^2\hat{A}'(\hat{B}')^{h-s} & \\ \qquad + \sum_{s=1}^{h-1} \hat{B}^{h-s-1}\left(\hat{A} + \hat{B}\hat{C}\right) D_v^2 \left(\hat{A} + \hat{B}\hat{C}\right)' (\hat{B}')^{h-s} + \hat{C}D_v^2\hat{C}' & h > 1 \end{cases}$$

And the h-period-ahead variance due to the jth shock has contemporaneous and news components given by:

$$\text{Surprise} = \sigma_{u,j}^2 \sum_{s=1}^{h} \hat{B}^{h-s}(\hat{A}_j\hat{A}_j')(\hat{B}')^{h-s}$$

$$\text{News} = \begin{cases} \sigma_{v,j}^2(\hat{C}_j\hat{C}_j')' & h = 1 \\ \sigma_{v,j}^2(\hat{C}_j\hat{C}_j') & \\ \quad + \sum_{s=1}^{h} \hat{B}^{h-s-1}\left(\hat{A}_j\hat{A}_j' + \hat{B}(\hat{C}_j\hat{A}_j') + (\hat{A}_j\hat{C}_j')\hat{B}' + \hat{B}(\hat{C}_j\hat{C}_j')\hat{B}'\right)(\hat{B}')^{h-s-1} & h > 1 \end{cases}$$

Where $\hat{A}_j$ etc. are the jth column of the corresponding matrix

J Measurement Error

A concern with using survey data on forecasts is that they may be contaminated with measurement error. In this section, we describe how to adapt our method to account for the possibility of measurement error.

The empirical forecast vector $\tilde{f}_t$ is given by

$$\tilde{f}_t = f_t + w_t$$

where f_t is the rational expectation and w_t is classical measurement error (orthogonal to the other time series x_t and f_t) with variance matrix W_0. w_t may be serially correlated, with autocovariance matrix W_1.

The presence of measurement error changes how to write the time series x_t in terms of past forecast data and shocks:

$$\begin{aligned} & x_t = f_{t-1} + Au_t + Cv_t \\ \implies & x_t = \tilde{f}_{t-1} + Au_t + Cv_t - w_{t-1} \end{aligned} \tag{25}$$

The expectations f_t can similarly be rewritten

$$f_t = \sum_{j=1}^{m} B_j x_{t+1-j} + Av_t$$

$$\implies \tilde{f}_t = \sum_{j=1}^{m} B_j x_{t+1-j} + Av_t + w_t \tag{26}$$

We cannot stack these equations into a VAR in $\begin{pmatrix} \tilde{f}_t \\ x_t \end{pmatrix}$ as we did in equation (7), because w_{t-1} will show up in the error term. w_{t-1} is correlated with $\tilde{f}_{t-1}$, so a stacked VAR will not consistently estimate the B_j matrices. Fortunately, we can still do so using equation (26) alone.

Collect the residuals from equations (26) and (25) into a vector:

$$\begin{pmatrix} Av_t + w_t \\ Au_t + Cv_t - w_{t-1} \end{pmatrix} = \tilde{\mathbf{A}} \begin{pmatrix} v_t \\ u_t \\ w_t \\ w_{t-1} \end{pmatrix} \tag{27}$$

where

$$\tilde{\mathbf{A}} \equiv \begin{pmatrix} A & 0 & I & 0 \\ C & A & 0 & -I \end{pmatrix}$$

The covariance matrix $\tilde{\Sigma}$ of the residual vector $\begin{pmatrix} Av_t + w_t \\ Au_t + Cv_t - w_{t-1} \end{pmatrix}$ is

$$\tilde{\Sigma} = \begin{pmatrix} AD_v^2 A' + W_0 & AD_v^2 C' + W_1' \\ CD_v^2 A' + W_1 & CD_v^2 C' + AD_u^2 A' + W_0 \end{pmatrix}$$

The appearance of the measurement error variance matrices W_0 and W_1 means that our baseline method cannot be applied directly.

But there is a fix. W_0 can be estimated by:

$$-\mathbb{E}\left[(x_t - \tilde{f}_{t-1})\tilde{f}'_{t-1}\right] = -\mathbb{E}\left[(Au_t + Cv_t - w_{t-1})(f_{t-1} + w_{t-1})'\right]$$

per equation (25). The orthogonality of w_{t-1} implies

$$= -\mathbb{E}\left[(-w_{t-1})(w_{t-1})'\right] = W_0$$

Similarly, W_1 can be estimated by

$$-\mathbb{E}\left[(x_t - \tilde{f}_{t-1})\tilde{f}'_{t-2}\right] = -\mathbb{E}\left[(Au_t + Cv_t - w_{t-1})(f_{t-2} + w_{t-2})'\right]$$

$$= -\mathbb{E}\left[(-w_{t-1})(w_{t-2})'\right] = W_1$$

With W identified, subtracting from the variance matrix $\tilde{\Sigma}$ gives

$$\tilde{\Sigma} - \begin{pmatrix} W_0 & W_1' \\ W_1 & W_0 \end{pmatrix} = \begin{pmatrix} AD_v^2A' & AD_v^2C' \\ CD_v^2A' & CD_v^2C' + AD_u^2A' \end{pmatrix}$$

With this matrix, Theorem 2 can be applied (setting $B_1 = 0$) to identify the matrices A, C, D_v, and D_u.

The crucial assumptions for this method were that the measurement error is classical, and that absent the measurement error, forecasters would report the rational expectation. This would be a poor assumption when applied to household forecasts – such as those reported in the Michigan Survey – which display clear and persistent biases. However, the assumptions might be appropriate when applied to professional forecasters, who have strong financial incentives for accuracy. Eva and Winkler (2023) find little evidence that professional forecasters depart from rational expectations when appropriately testing their out-of-sample forecasts.

K Hidden States

Our identification method requires that the structural model in equation (1) is the true data generating process. But what if there are hidden states in the economy that do not appear in the data? In this section, we generalize the method to allow for this possibility.

Again suppose that the state vector x_t follows equation (1), but has some dimensions that are not directly observed. Instead, the data vector y_t is determined by the observation equation

$$y_t = x_t + Gu_t + Gv_{t-1} + Hv_t \tag{28}$$

Without loss of generality, we can normalize the hidden states to obey equations (1) and (28).

Observations are related to forecasts by

$$y_t = f_{t-1} + (A+G)u_t + (C+H)v_t$$

while the forecasts $f_t = \mathbb{E}_t[y_{t+1}]$ are now given by

$$f_t = \mathbb{E}_t[x_{t+1}] + Gv_t = \sum_{j=1}^{m} B_j x_{t+1-j} + (A+G)v_t$$

$$= \sum_{j=1}^{m} B_j(y_{t+1-j} - Gu_{t+1-j} - Gv_{t-j} - Hv_{t+1-j}) + (A+G)v_t$$

$$= B_1(y_t - Gu_t - Gv_{t-1} - Hv_t) + \sum_{j=2}^{m} B_j(y_{t+1-j} - Gu_{t+1-j} - Gv_{t-j} - Hv_{t+1-j}) + (A+G)v_t$$

$$= B_1(f_{t-1} + Au_t - Gv_{t-1} + Cv_t) + \sum_{j=2}^{m} B_j(y_{t+1-j} - Gu_{t+1-j} - Gv_{t-j} - Hv_{t+1-j}) + (A+G)v_t$$

Stack the expectations and time series into a single VARMA($m-1$,m):

$$\begin{pmatrix} f_t \\ y_t \end{pmatrix} = \sum_{j=1}^{m-1} \mathbf{B}_j \begin{pmatrix} f_{t-j} \\ y_{t-j} \end{pmatrix} + \sum_{j=0}^{m} \mathbf{A}_j \begin{pmatrix} v_{t-j} \\ u_{t-j} \end{pmatrix} \tag{29}$$

where (as before)

$$\mathbf{B}_j \equiv \begin{cases} \begin{pmatrix} B_1 & B_2 \\ I & 0 \end{pmatrix} & j = 1 \\ \begin{pmatrix} 0 & B_{j+1} \\ 0 & 0 \end{pmatrix} & j > 1 \end{cases}$$

and

$$\mathbf{A}_j \equiv \begin{cases} \begin{pmatrix} B_1C + A + G & B_1A \\ C + H & A + G \end{pmatrix} & j = 0 \\ \begin{pmatrix} -B_jG - B_{j+1}H & -B_{j+1}G \\ 0 & 0 \end{pmatrix} & m > j > 0 \\ \begin{pmatrix} -B_mG & 0 \\ 0 & 0 \end{pmatrix} & j = m \end{cases}$$

As in the simple VAR case, the autoregressive terms identify the B_j matrices. But now $\mathbf{A}_0$ has two additional matrices that thwart identification: G and H. Fortunately, the hidden state structure introduces additional MA terms, which allow for possible identification of G and H. We emphasize that with the structure, we only have sufficient conditions for identification – at least as many linearly independent equations as unknowns – but not a constructive proof analogous to Theorem 2. This is because our baseline method admits an analytical solution to the decomposition of the variance matrix Σ, but we have found no such analytical solution in this generalization, so estimation must use a numerical decomposition.

We use $\mathbf{A}_1$ to demonstrate identification, although these matrices are now potentially *overidentified*, so we can use even more lags to improve the statistical power when estimating G and H. The variance matrix of forecast errors is now

$$\Sigma_0 = \mathbf{A}_0 \begin{pmatrix} D_v^2 & 0 \\ 0 & D_u^2 \end{pmatrix} \mathbf{A}_0'$$

but with the MA structure, it is possible to identify the covariance matrix of any two MA components, i.e.:

$$\Sigma_{ij} = \mathbf{A}_i \begin{pmatrix} D_v^2 & 0 \\ 0 & D_u^2 \end{pmatrix} \mathbf{A}_j'$$

To calculate the $\mathbf{A}_i$ matrices, subdivide the matrix $\Sigma_{jj} \equiv \begin{pmatrix} \Sigma_{j,11} & \Sigma_{j,12} \\ \Sigma_{j,21} & \Sigma_{j,22} \end{pmatrix}$ into $n \times n$ blocks. The off-diagonal submatrices satisfy $\Sigma_{j,12} = \Sigma_{j,21}'$, so the remaining submatrices are given by

$$\begin{aligned} \Sigma_{0,11} &= (B_1C + A + G)D_v^2(B_1C + A + G)' + B_1AD_u^2A'B_1' \\ \Sigma_{0,21} &= (C + H)D_v^2(B_1C + A + G)' + (A + G)D_u^2A'B_1' \\ \Sigma_{0,22} &= (C + H)D_v^2(C + H)' + (A + G)D_u^2(A + G)' \end{aligned}$$

which correspond to the three block matrix equations that we used to identify the original VAR (Theorem 2). With two additional matrices to identify, use the covariance between MA terms:

$$\Sigma_{01} = \begin{pmatrix} -(B_1C + A + G)D_v^2(B_1G + B_2H)' - B_1AD_u^2G'B_2' & 0 \\ -(C + H)D_v^2(B_1G + B_2H)' - (A + G)D_u^2G'B_2' & 0 \end{pmatrix}$$

Which, in addition to

$$D_u^2 + D_v^2 = I$$

is as many linear restrictions as unknowns.

L Monte Carlo Simulation with One News Horizon

L.1 Set up

We extend the New Keynesian model of Section 2 to allow for persistent shocks with news and surprise components on all the equations. That is:

New Keynesian Phillips curve:	$\pi_t = \beta\mathbb{E}_t[\pi_{t+1}] + \kappa y_t + x_t$
Euler equation:	$0 = \mathbb{E}_t[z_t + \gamma(y_t - y_{t+1}) + i_t - \pi_{t+1}]$
Taylor rule:	$i_t = \phi_\pi \pi_t + h_t$

Where:

$$\begin{aligned}
x_t &= \rho_x x_{t-1} + u_t^x + v_{t-1}^x \\
z_t &= \rho_z z_{t-1} + u_t^z + v_{t-1}^z \\
h_t &= \rho_h h_{t-1} + u_t^h + v_{t-1}^h
\end{aligned}$$

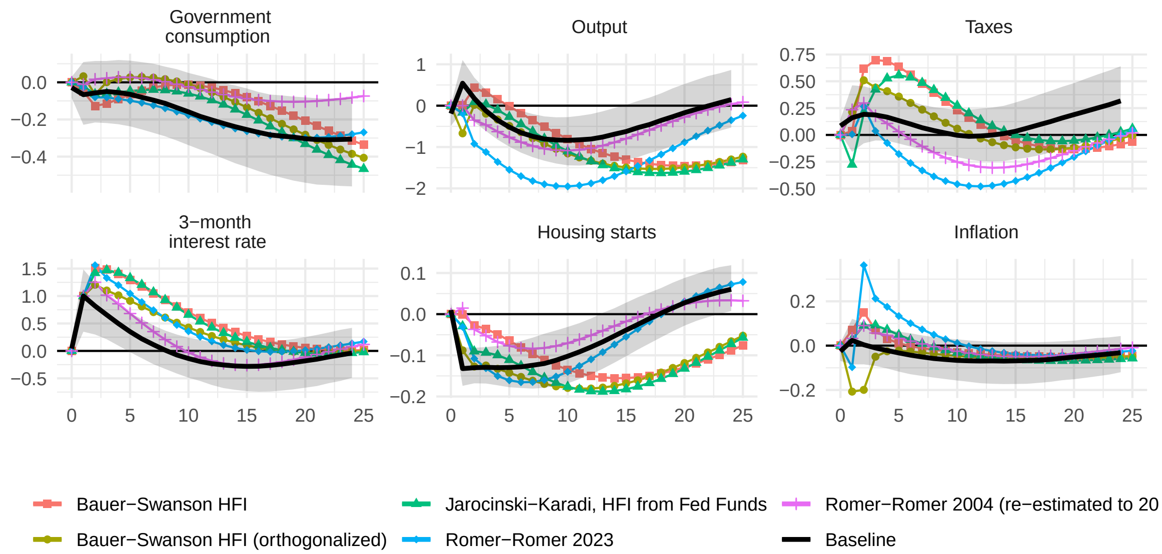
L.2 Letting the Variance of News Shocks Limit to Zero

A key identifying assumption of our model is that all shocks have at least some news component. Here we investigate weak failures of this identification criterion by applying our method to simulated data where the news component of a given shock is very close to zero.

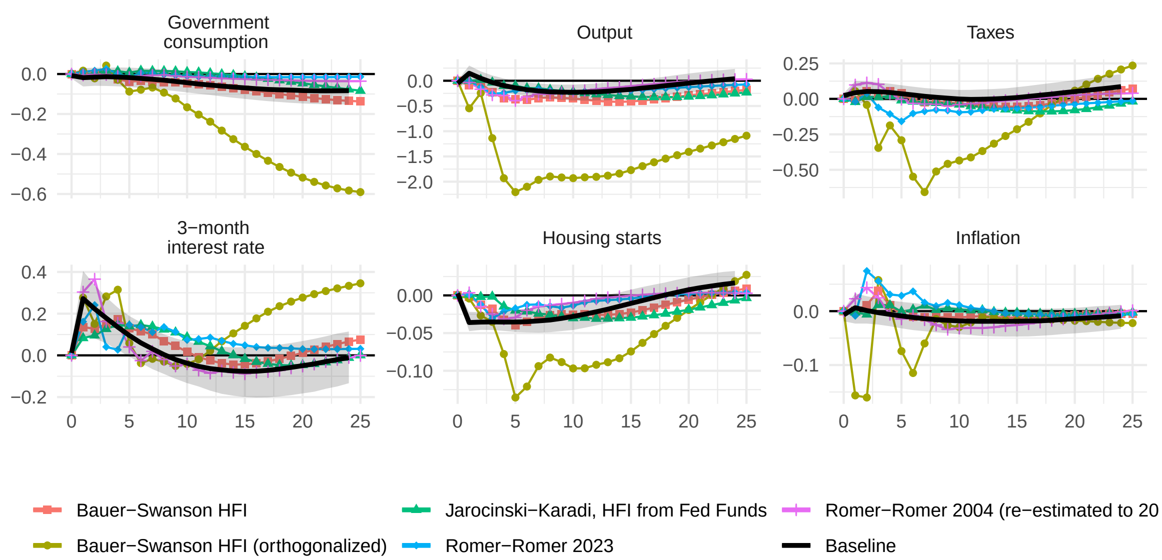
To abstract from small-sample issues, we simulate the model for one million periods and run our method on the resulting data. We compare the resulting variance decomposition (the direct analogue of Table 3) to the exact variance decomposition from the model solution. In the baseline, the monetary news and surprise shock variances are equal; each is 0.5. But in alternate simulations we consider the case where this share is 0.95, 0.99, and 1.

Figure 19 reports the results of this exercise. Panels 19a through 19c show almost exact agreement between the exact variance decomposition from the model and the results of applying our method to the simulated data. Of course, in Panel 19d this breaks down. There, the identifying assumption fails and the method does not correctly attribute macroeconomic fluctuations to news and surprise shocks.

There are two takeaways from this exercise. First, that our method works well even in cases where a shock has a very small news component. Near-failures of this identifying assumption do not cause our method to perform poorly. Second, that this agreement is not somehow predetermined; when we confront our method with the knife-edge case where it should fail (i.e. when the news share of variance is zero) it does fail.



(a) Initial 100 BPS Shock



(b) Additional Lags

Figure 13: Estimated IRFs to Monetary Shocks: Additional VAR Specifications

Figure shows estimated impulse responses to a monetary policy shock from our baseline compared to those computed from various sources in the literature. To match samples and specification, each line reports the results from estimating a VAR with the same variables and coverage as our baseline model, extended to including the shocks from the relevant source and where the impulse responses are computed from a Cholesky decomposition with the monetary shock ordered first. The solid line labeled "Baseline" and shaded area show respectively the median and $10^{th} - 90^{th}$ percentile ranges from a bootstrap simulation with $N^{sim} = 1000$ replications. To account for differences in the magnitude of estimated shocks, all impulses are scaled such that the initial interest rate impulse is 100 basis points. In panel (a), this scaling is applied to the 3-month rate rather than the 2-year rate as in other plots. In panel (b), the VAR is extended to include 4 lags.

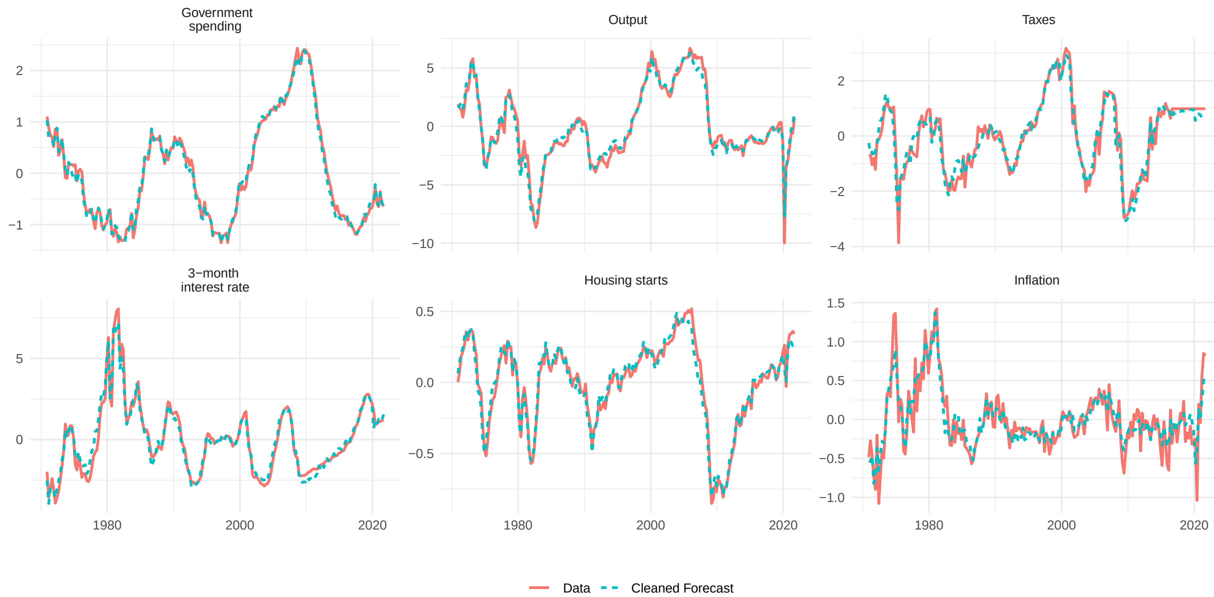


Figure 14: Baseline Time Series and Forecasts

The solid red line plots our baseline time series. Government spending, output, and federal taxes are real, deflated by the GDP deflator, and expressed relative to a quadratic real GDP trend. Housing starts are the natural log, and all data series are deseasonalized and detrended. The source of forecast data is the SPF for all baseline series, except the Federal Reserve's Greenbook is used for government spending before 1981:III, and for taxes, while the Treasury forecast is derived from the yield curve. Forecasts are cleaned to be rational in sample.

Figure 15: Time Series of Estimated Shocks

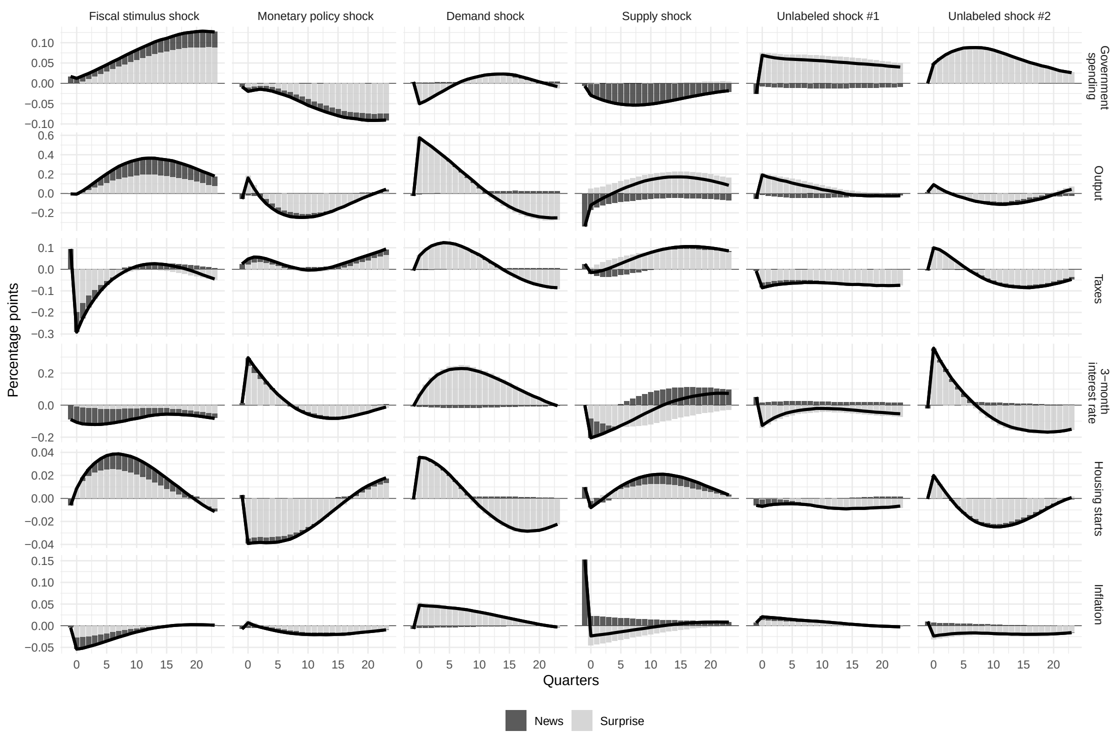


Figure 16: Impulse Responses to Structural Shocks: Average of News and Surprise Components

The impulse response functions are plotted to an average unit structural shock, calculated as in Section 3.6. The dark and light gray bars capture the relative contribution of news and surprises respectively. For government consumption, output, and taxes, units are percentage points relative to trend lagged output. For inflation, interest rates, and housing starts, units are annualized percentage points relative to own-variable trend.

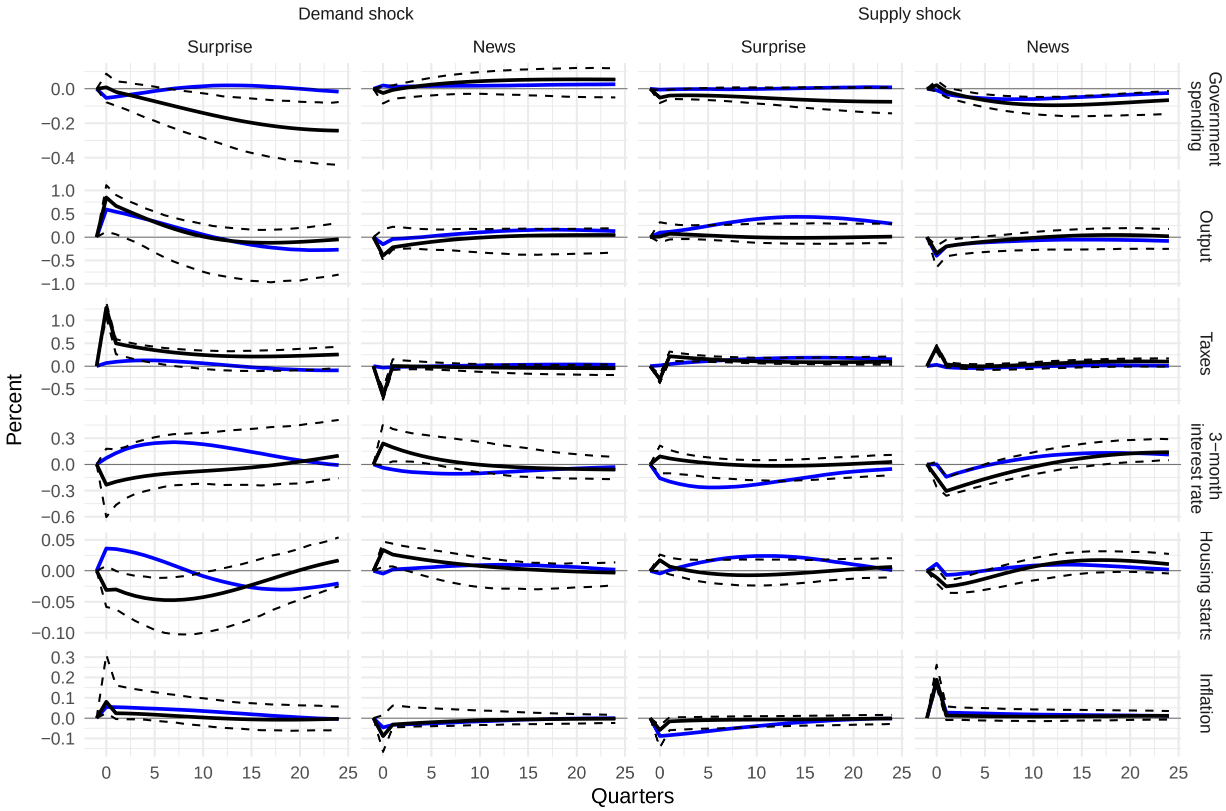


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Figure 17: Counterfactual Business Cycle Stabilization Using Fiscal Policy: Output Stabilization

Time series impulse responses to news and surprise components of the two identified non-policy structural shocks under a dual mandate which weights inflation and output in inverse proportion to their standard deviations in the data. The blue line shows the baseline responses. Solid and dashed black lines show the 50^{th}, 10^{th}, and 90^{th} percentiles respectively from a bootstrap simulation with $N^{sim} = 1000$ replications

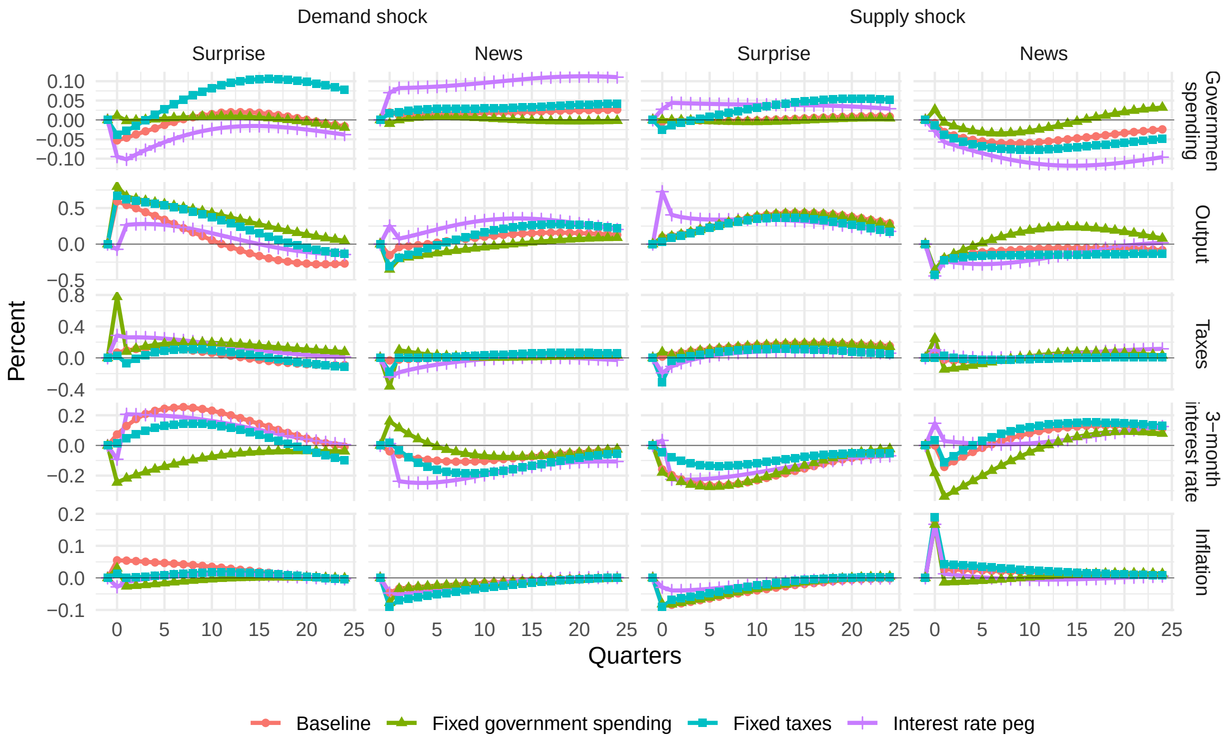

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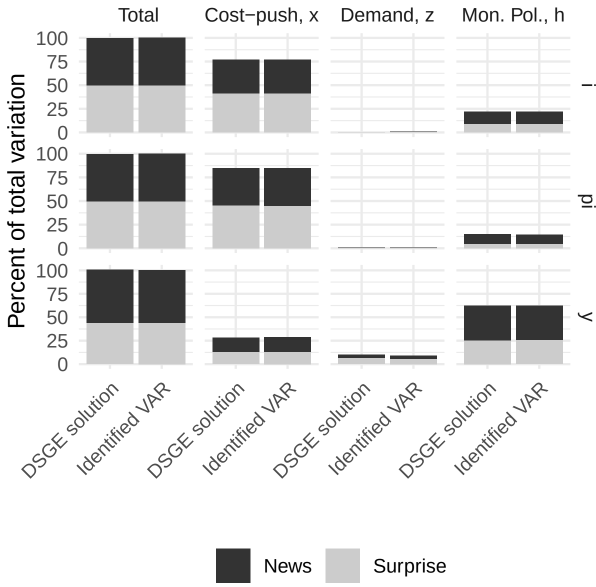
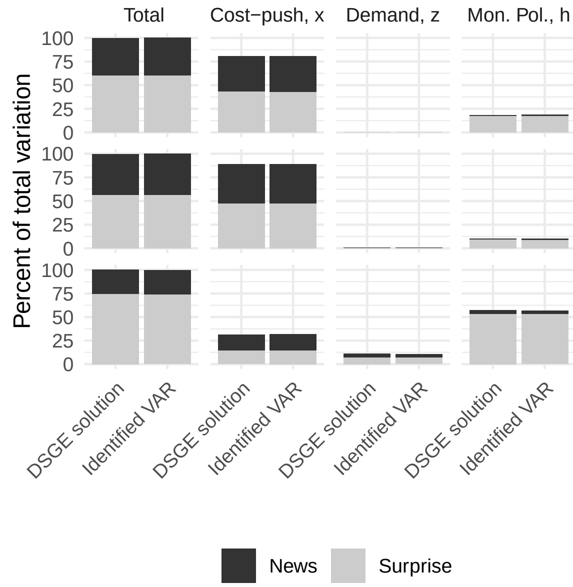
Figure 18: Passive government policies

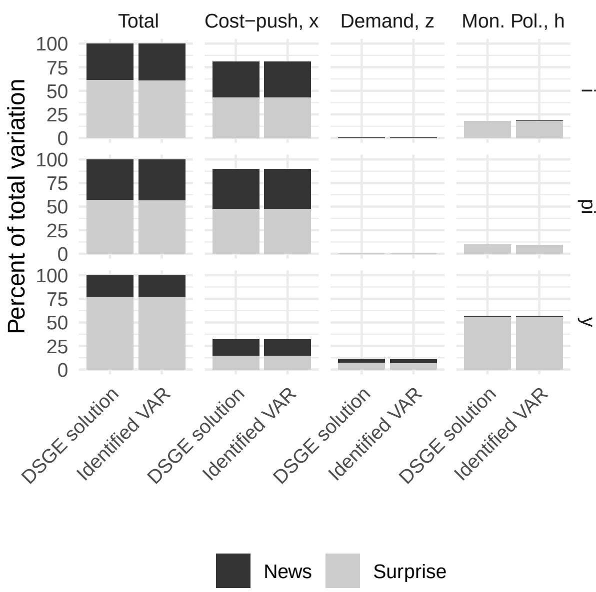
Time series impulse responses to news and surprise components of the two identified non-policy structural shocks under four policy regimes computed following equation (13): the prevailing baseline rule, and then the best feasible approximations to an interest rate per, fixed taxes, and fixed government spending.



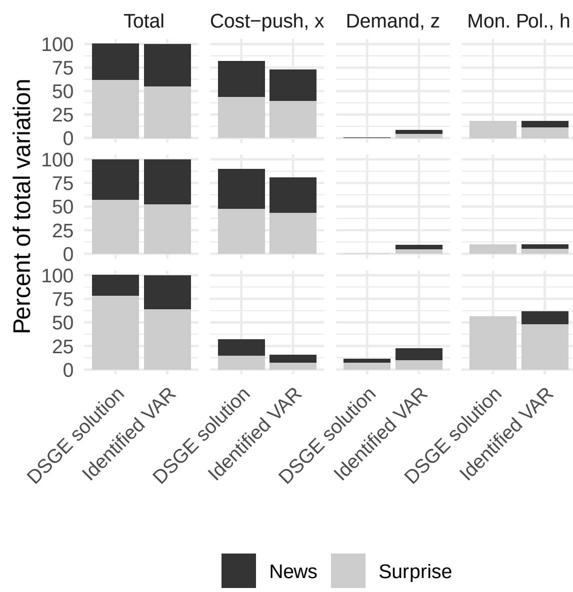
(a) Baseline, $D_v^2(m) = 0.5$



(b) $D_v^2(m) = 0.95$



(c) $D_v^2(m) = 0.99$



(d) $D_v^2(m) = 1$

Figure 19: Variance Decomposition for Simulated Data: Estimated and Exact Values

Figure 19 shows the variance decomposition for the New Keynesian model with one-period-ahead news. Each panel compares the exact results, labeled "DSGE solution", to those obtained from applying our method, labeled "Identified VAR". Panels vary by the relative variance of news versus surprise for the monetary shock, with $D_v^2(m)$ denoting the monetary shock entry in the diagonal of D_v^2. For each panel, the share of monetary shock variance due to surprises is thus $D_u^2(m) = 1 - D_v^2(m)$.