The Systematic Origins of Monetary Policy Shocks*

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Abstract

Conventional strategies to identify monetary policy shocks rest on the implicit assumption that systematic monetary policy is constant over time. We formally show that these strategies do not isolate monetary policy shocks in an environment with time-varying systematic monetary policy. Instead, they are contaminated by systematic monetary policy and macroeconomic variables, leading to contamination bias in estimated impulse responses. Empirically, we show that Romer and Romer (2004) monetary policy shocks are indeed predictable by fluctuations in systematic monetary policy. Instead, we propose a new monetary policy shock that is orthogonal to systematic monetary policy. Our shock suggests U.S. monetary policy has shorter lags and stronger effects on inflation and output.

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1 Introduction

Empirical monetary policy shock series form the backbone of a large literature in monetary economics. The estimated responses to these shocks are used to assess the effectiveness of monetary policy, construct policy counterfactuals, study the optimality of monetary policy, estimate structural macroeconomic equations, or estimate DSGE models.[1] These applications require empirical monetary policy shocks that are well identified, meaning they capture exogenous changes in a policy instrument orthogonal to other macroeconomic shocks.

The central point of this paper is that fluctuations in systematic monetary policy pose a challenge to conventional strategies to identify monetary policy shocks. The fundamental problem of conventional identification strategies is the implicit assumption that systematic monetary policy is constant across time. Under the assumption, any time-variation in systematic monetary policy will be contained in the empirical monetary policy shock, consistent with common views about these shocks (see quote below).[2]

> *We do not have many good economic theories for what a structural monetary policy shock should be. Other than "random coin flipping," the most frequently discussed source of monetary policy shocks is shifts in central bank preferences, caused by changing weights on inflation vs unemployment in the loss function or by a change in the political power of individuals on the FOMC.* Ramey (2016, Handbook of Macroeconomics, Vol. 2A, p.89)

This paper makes a theoretical and empirical contribution to the identification of monetary policy shocks. Our theoretical contribution is to formally show that conventional empirical identification strategies do not isolate monetary policy shocks in an environment with time-varying systematic monetary policy. Instead, they are contaminated by systematic monetary policy and other macroeconomic shocks, leading to contamination bias in estimated impulse response functions. The empirical contribution is threefold. First, we show that monetary policy shocks as estimated in the seminal Romer and Romer (2004) are predictable by a time-varying measure of systematic monetary policy. Second, we propose a new monetary policy shock series that is orthogonal to measured fluctuations in systematic monetary policy. Third, we find that inflation and output respond more quickly and strongly relative to the Romer and Romer (2004) shock.

[1]See, e.g., Romer and Romer (1989); Bernanke and Blinder (1992); Bernanke, Gertler, and Watson (1997); Christiano, Eichenbaum, and Evans (1999); Romer and Romer (2004); Christiano, Eichenbaum, and Evans (2005); Gertler and Karadi (2015); Barnichon and Mesters (2020, 2023); McKay and Wolf (2023).

[2]Similarly, in the first Handbook of Macroeconomics, Christiano et al. (1999, p.71-72) argue that an empirical monetary policy shock *[..] reflects exogenous shocks to the preferences of the monetary authority, perhaps due to stochastic shifts in the relative weight given to unemployment and inflation. These shifts could reflect shocks to the preferences of the members of the Federal Open Market Committee (FOMC), or to the weights by which their views are aggregated.*

Our theoretical analysis starts from the assumption that monetary policy follows a general type of Taylor rule. The rule determines a policy instrument as a function of inputs to the rule, e.g., inflation and output, time-varying slope coefficients describing the policy response to macroeconomic conditions, i.e., systematic monetary policy, and a stochastic intercept, i.e., a monetary policy shock.[3] In contrast, many conventional empirical identification strategies implicitly assume a Taylor rule with time-invariant slope coefficients. Empirical monetary policy shocks are estimated as deviations from such rule. Identification strategies following this approach include Taylor rule-type regressions (e.g., Romer and Romer, 2004) and monetary VAR models using exclusion restrictions (e.g., Christiano et al., 1999), sign restrictions (e.g., Uhlig, 2005), narrative restrictions (e.g., Antolín-Díaz and Rubio-Ramírez, 2018), or external instruments (e.g., Gertler and Karadi, 2015).

Against the backdrop of a time-varying Taylor rule, we show that the empirical monetary policy shock contains the (true) monetary policy shock but also time variation in systematic monetary policy interacted with the inputs to the policy rule. To the extent that other macroeconomic shocks affect the inputs to the policy rule, the empirical monetary policy shock is contaminated by these other macroeconomic shocks.

The contaminated shocks lead to biased impulse response estimates. We formally show that they do not identify the causal effects of (true) monetary policy shocks. We analytically characterize three sources of bias reflecting endogeneity and attenuation. The estimated impulse response function remains biased even if time variation in systematic monetary policy is exogenous, i.e., if time variation in the slope coefficients of the Taylor rule is independent of other macroeconomic shocks.

Our theoretical insights similarly apply to empirical monetary shocks identified using high-frequency data (e.g., Gertler and Karadi, 2015). Identification rests on the implicit assumption that systematic monetary policy, as perceived by financial market participants, is constant in a time window around monetary announcements. Otherwise, the shocks are contaminated and lead to biased estimates. Bauer and Swanson (2023a) provide evidence consistent with such high-frequency belief changes. We contribute to this debate by showing analytically that regressing high-frequency monetary surprise on publicly available macroeconomic forecasts (Bauer and Swanson, 2023b) or Greenbook forecasts (Miranda-Agrippino and Ricco, 2021) does not resolve the contamination problem.

While previous work has noted that time-varying systematic monetary policy may complicate the identification of monetary policy shocks (e.g., Coibion, 2012; Bauer and Swanson, 2023a; McMahon and Munday, 2023), our paper is the first to formally characterize (i) how time-

[3]For evidence on fluctuations in the coefficients of the policy rule, see, e.g., Clarida, Gali, and Gertler (2000), Orphanides (2004), Bordo and Istrefi (2023), and Hack, Istrefi, and Meier (2023).

varying systematic monetary policy leads to contamination in the monetary policy shocks obtained from a wide set of conventional empirical identification strategies, and (ii) how contamination leads to biased impulse response estimates. We further go beyond previous work by providing new empirical evidence on shock contamination and a new identification strategy that tackles this problem.

Our empirical analysis starts from the testable prediction of the theory that conventional monetary policy shocks are predictable by time variation in systematic monetary policy interacted with the inputs to the policy rule. We measure time variation in systematic U.S. monetary policy through the historical composition of hawks and doves in the Federal Reserve's Federal Open Market Committee (FOMC). This composition builds on the narrative classification of FOMC members by Istrefi (2019). Hawks are more concerned about inflation. Doves are more concerned about supporting employment and growth.[4] We consider two measures of systematic monetary policy, the Hawk-Dove balance across all voting FOMC members and the balance across the four FOMC members currently with voting rights through the annual rotation. The former is a more comprehensive measure, whereas the latter reflects exogenous variation through the rotation.

We test our prediction using empirical monetary policy shocks as estimated in Romer and Romer (2004), RR in the following.[5] We regress the RR shock on the Taylor rule inputs considered by RR, notably Greenbook forecasts for various macroeconomic variables and horizons, interacted with measured fluctuations in systematic monetary policy. We consider the original RR sample 1969-1996, the extended Wieland and Yang (2020) sample 1969-2007, and the post-Volcker disinflation sample 1983-2007. The regression explains between 10 and 54% of the variance of RR shocks depending on sample and regressors (contemporaneous or lagged). Using the regressors lagged by one FOMC meeting yields the highest R^2, ranging between 0.33 and 0.54. Overall, our evidence strongly suggests that RR shocks are contaminated by fluctuations in systematic monetary policy.[6]

The empirical evidence motivates us to construct a new series of empirical monetary policy shocks that are not predictable by fluctuations in measured systematic monetary policy. We estimate an extension of the Taylor rule regression in RR that includes the interaction of

[4] Istrefi (2019) shows that these preferences match with narratives on monetary policy, preferred interest rates, dissents, and forecasts of FOMC members. Bordo and Istrefi (2023) study the origins of these preferences, linking them to early-life experiences and education. Hack et al. (2023) use the Hawk-Dove classification to study the effects of systematic monetary policy on the propagation of macroeconomic shocks.

[5] The RR identification strategy has been applied to the U.K. (Cloyne and Hürtgen, 2016), Germany (Cloyne, Hürtgen, and Taylor, 2022), Norway (Holm, Paul, and Tischbirek, 2021), Canada (Champagne and Sekkel, 2018) and many other countries (Choi, Willems, and Yoo, 2024).

[6] We show that measured systematic monetary policy also has predictive power for the refined RR shocks in Aruoba and Drechsel (2022), who use textual analysis to create sentiment indicators about the Fed staff's assessment of the economy to better capture the Fed's information set about the state of the economy.

the Hawk-Dove balance with the Taylor rule inputs. The correlation between the original RR shock and our new shock is 0.67. The sign-correlation between the two series is lower, meaning many shocks flip signs. The distribution of new shocks is less dispersed, with a standard deviation of 0.23, compared to 0.34 for the RR shock.

Finally, we compare impulse responses between our new monetary policy shock and the RR shock. We focus on the post-Volcker disinflation sample 1983-2007 because the estimated responses to many conventional monetary policy shock series appear puzzling in this sample (e.g., Ramey, 2016).[7] For comparability, we normalize the size of both shocks to the same impact increase of the FFR. The dynamic FFR response to our new shock is less persistent and smaller at peak. In contrast, the decline in GDP and inflation is substantially larger for the new shock. The trough GDP response is about twice as large for the new shock compared to the RR shock. The differences between the responses to the two shocks are statistically significant at the five percent level for many horizons. Importantly, the RR shock seems to operate with a long lag, not affecting inflation up until two years after the shock. The GDP response is broadly insignificant. In contrast, inflation and GDP respond to our new shock with a lag of one year. Beyond the first year, the responses of inflation and GDP are significantly different from zero at the five percent level.[8] Our findings suggest that the puzzling effects of RR shocks in the 1983-2007 sample may reflect contamination from time-varying systematic monetary policy.

Our paper highlights the importance of accounting for the time-varying nature of systematic monetary policy when identifying monetary policy shocks. An alternative approach addresses time-varying systematic monetary policy by modeling it as latent variable or time-varying coefficients, see, for example, regime-switching models (e.g., Owyang and Ramey, 2004; Sims and Zha, 2006), time-varying coefficient monetary VAR models (e.g., Primiceri, 2005), and Taylor rules with time-varying coefficients (e.g., Boivin, 2006; Coibion, 2012; Bauer, Pflueger, and Sunderam, 2022). Particularly related is Coibion (2012) who uses the latter approach to estimate a monetary policy shock series. The estimated shock is highly correlated with the RR shock and yields similar impulse responses as the RR shock. The difference between this finding and ours might reflect the challenge of time-varying coefficient models to identify genuine time variation in the parameters of interest while avoiding overfitting.

[7] Relatedly, Barakchian and Crowe (2013) show that a variety of conventional monetary policy shock series raise GDP when raising the federal funds rate in a post-1988 sample.

[8] In the 1969-2007 sample, we also find that output and inflation respond more strongly to the new shock, albeit with a sluggish inflation response. We further find that orthogonalizing the Aruoba and Drechsel (2022) shock with respect to systematic monetary policy leads to similar differences in the estimated responses.

2 Identification challenge in theory

In this section, we study the identification of monetary policy shocks in an environment with time-varying systematic monetary policy. We formally show that a wide spectrum of identification strategies to estimate monetary policy shocks yield shocks that are contaminated by other macroeconomic shocks. Using these shocks to estimate impulse response functions generally leads to biased estimates.

2.1 Time-varying systematic monetary policy

Departing from the common assumption that systematic monetary policy is constant across time, we assume monetary policy follows the time-varying Taylor rule

$$i_t = \alpha + (\phi + \tilde{\phi}_t)' x_t + w_t^m, \quad \mathbb{E}[\tilde{\phi}_t] = \mathbb{E}[x_t] = \mathbb{E}[w_t^m] = \mathbb{E}[\phi_t w_t^m] = 0, \tag{2.1}$$

where $i_t \in \mathbb{R}$ is a policy instrument, $x_t \in \mathbb{R}^{n\times 1}$ are the n inputs of the policy rule, e.g., present and lagged (forecasts of) GDP and inflation, $\tilde{\phi}_t \in \mathbb{R}^{n\times 1}$ is a vector of time-varying coefficients describing fluctuations in systematic monetary policy, with $\phi \in \mathbb{R}^{n\times 1}$ the average coefficient vector, and w_t^m denotes a random monetary policy shock. We assume the inputs in x_t are mean zero and set $\alpha = -\mathbb{E}[\tilde{\phi}_t x_t]$, which simplifies some subsequent derivations but is not critical for our results.[9]

Time variations in the coefficients of the rule $\tilde{\phi}_t$ may be driven by changes in the preferences of central bankers that may occur for exogenous reasons, e.g., the FOMC rotation of voting rights (Hack et al., 2023), or for endogenous reasons, e.g., monetary policy may become more responsive to inflation when inflation is high (Davig and Leeper, 2008). Our main results hold irrespective of whether $\tilde{\phi}_t$ fluctuates for exogenous or endogenous reasons. Finally, we assume that ϕ_t does not co-move with monetary policy shocks, $\mathbb{E}\left[\phi_t w_t^m\right] = 0$, which allows for a sharp conceptual distinction between systematic monetary policy and monetary policy shocks, but is otherwise not critical for our results.

2.2 Conventional identification of monetary policy shocks

In this section, we show that time-varying systematic monetary policy implies that conventional identification strategies yield contaminated monetary policy shocks under general

[9] A richer formulation of (2.1) may contain time-varying target variables, e.g., $i_t = \alpha + (\phi + \tilde{\phi}_t)'(x_t - x_t^*) + w_t^m$, where $x_t^* \in \mathbb{R}^{n\times 1}$ is the target, e.g., the inflation target. Shocks to the target generate a third type of monetary policy shock, the effect of which is correlated with fluctuations in systematic monetary policy. In the scope of this paper, we abstract from fluctuations in the target.

conditions. Our result derives from the above monetary policy rule, no further structural assumptions about the macroeconomy are needed.

Many conventional identification strategies estimate monetary policy shocks as residual from a time-invariant Taylor rule-type regression

$$i_t = b' x_t + e_t^m, \tag{2.2}$$

where the estimated regression residual, $\hat{e}_t^m$, is an empirical monetary policy shock. This is a broad description of a wide variety of identification strategies which differ mainly in how the coefficients in equation (2.2), and thus the residual, are estimated. Romer and Romer (2004) propose to directly estimate (2.2) via OLS. A common alternative approach is to use monetary VAR models. Irrespective of identifying assumptions and estimation method, monetary VAR models contain an equation consistent with equation (2.2).[10] This equation is typically identified via internal instruments (Shapiro and Watson, 1988), external instruments, or estimation methods for set-identified models. The estimation method depends on the identifying assumptions, which may be exclusion restrictions (e.g., Christiano et al., 1999), sign restrictions (e.g., Uhlig, 2005), narrative restrictions (e.g., Antolín-Díaz and Rubio-Ramírez, 2018), or external instruments (e.g., Gertler and Karadi, 2015).

Against the backdrop of the time-varying monetary policy rule in (2.1), the time-invariant regression in (2.2) is misspecified. In general, this misspecification leads to contamination in the estimated monetary policy shock. The following proposition formally characterizes the estimated empirical shocks for a given estimate $\hat{b}$.

Proposition 1 (**Monetary policy shock**)**.** *Let monetary policy follow* (2.1)*. Given an estimate $\hat{b}$, let $\hat{e}_t^m$ be the estimated residual from* (2.2)*. The residual satisfies*

$$\hat{e}_t^m = w_t^m + \omega_t^{\hat{b}} + \omega_t^{\tilde{\phi}}$$

where the two wedges are defined by

$$\omega_t^{\hat{b}} = (\phi - \hat{b})' x_t, \quad \textit{and} \quad \omega_t^{\tilde{\phi}} = \tilde{\phi}_t' x_t - \mathbb{E}[\tilde{\phi}_t' x_t].$$

The proof is straightforward when combining (2.1) and (2.2). The proposition characterizes two wedges between the actual monetary policy shock w_t^m and the estimated shock $\hat{e}_t^m$.

[10] A (structural) monetary VAR model is defined by $B(L)Y_t = W_t$, where Y_t is a vector of variables, $B(L)$ a lag polynomial, and W_t a vector of structural shocks. Y_t includes the policy instrument i_t and W_t includes a monetary policy shock, *wlog* the first element of W_t. Then, the first equation of the VAR is a monetary policy rule that is identical with equation (2.2) given a corresponding specification of Y_t.

The first wedge, $\omega_t^{\hat{b}}$, arises whenever the estimate $\hat{b}$ does not equal the average policy coefficient ϕ. This wedge may be present even in the absence of time-variation in systematic monetary policy $\tilde{\phi}_t = 0$. For example, if b is estimated via OLS, a well-known endogeneity bias arises if the monetary policy shock correlates with x_t (Cochrane, 2011; Carvalho, Nechio, and Tristão, 2021). In addition, the presence of time-varying systematic monetary policy generates a second type of endogeneity bias. Formally, the OLS estimate $\hat{b}$ of the regression model (2.2) satisfies $\hat{b} \xrightarrow{p} \phi + \mathbb{E}\left[x_t x_t'\right]^{-1} \mathbb{E}\left[x_t w_t^m\right] + \mathbb{E}\left[x_t x_t'\right]^{-1} \mathbb{E}\left[x_t x_t' \tilde{\phi}_t\right]$.[11] Whatever the method by which (2.2) is estimated, if $\hat{b} \neq \phi$ then the estimated monetary policy shock $\hat{e}_t^m$ correlates with x_t.

The second wedge is novel. It arises because (2.2) is misspecified in the sense that fluctuations in systematic monetary policy are not modeled. Fluctuations in $\tilde{\phi}_t$ interacted with x_t must therefore be captured by the regression residual. The wedge disappears if we assume away fluctuations in systematic monetary policy $\tilde{\phi}_t = 0$. Note that the wedge is present for any estimate $\hat{b}$. Even if $\hat{b} = \phi$, i.e., even if the first wedge is nil, the estimated monetary policy shock is still contaminated by other macroeconomic shocks through $\tilde{\phi}_t' x_t$. In general, x_t reflects all present and past macroeconomic shocks. Thus $\hat{e}_t^m$ is contaminated by other macroeconomic shocks through the two wedges.

The discussion has so far omitted a popular type of conventional identification strategy. High-frequency identification uses interest rate futures (or swaps) to approximate expectations about future interest rates in a narrow time window around a monetary announcement in t. A high-frequency identified monetary policy shock is constructed as $\hat{e}_t^m = \mathbb{E}_{t+\Delta}[i_{t+\tau}] - \mathbb{E}_{t-\Delta}[i_{t+\tau}]$, where $\mathbb{E}_{t+\Delta}[i_{t+\tau}]$ denotes the period $t+\Delta$ expectation of period $t+\tau$ interest rates as measured by the price of an interest rate future contract. If monetary policy follows (2.1), we can rewrite high-frequency monetary policy surprises as

$$\hat{e}_t^m = w_t^m + \mathbb{E}_{t+\Delta}[(\phi + \tilde{\phi}_t)' x_t] - \mathbb{E}_{t-\Delta}[(\phi + \tilde{\phi}_t)' x_t]. \tag{2.3}$$

If systematic monetary policy as perceived by financial market participants varies between $t - \Delta$ and $t + \Delta$, then the monetary policy surprise is contaminated by variation in $\tilde{\phi}_t$ in interaction with x_t. This result has previously been noted by Bauer and Swanson (2023a), who also provide evidence consistent with such contamination. Different from Bauer and Swanson (2023a), we show that the contamination arising from time-varying systematic monetary policy may afflict a wide range of identification strategies.

The contamination result for the high-frequency identified monetary policy shock is closely

[11] In the New Keynesian model with time-varying systematic monetary policy we study in Section 2.4, it generally holds that $\mathbb{E}\left[x_t x_t' \tilde{\phi}_t\right]$ is non-zero.

related to Proposition 1. Different from Proposition 1, however, it is not sufficient for systematic monetary policy to vary at some point(s) in time. Instead, the contamination of high-frequency identified monetary policy shocks requires that perceived systematic monetary policy differs at the end of a narrow window around monetary announcements relative to expectations at the beginning of the time window.[12] Whether (perceived) systematic monetary policy varies outside those narrow windows is irrelevant for high-frequency identification, but not for the other conventional identification strategies.

Importantly, regressing high-frequency identified monetary policy shocks on x_t, whether that is publicly available macroeconomic forecasts (Bauer and Swanson, 2023b) or Greenbook forecasts (Miranda-Agrippino and Ricco, 2021), does not resolve the contamination problem. A simple way to see that is to regress $\tilde{\phi}_t' x_t$ on x_t. The residual will be $\tilde{\phi}_t' x_t - \hat{\gamma} x_t$, with $\hat{\gamma}$ the estimated coefficient. In general, for any $\hat{\gamma}$, the residual still contains variation in $\tilde{\phi}_t' x_t$. Hence, if high-frequency monetary policy shocks are contaminated by time-varying systematic monetary policy, regressing the estimated shock on x_t does not fundamentally heal the problem.

2.3 Impulse response estimate

Empirical monetary policy shocks are often not the object of interest *per se*, but rather the impulse response function (IRF) that is estimated based on these shocks. We analytically show that the contamination of monetary policy shocks generally leads to biased IRF estimates, including relative IRF estimates.

Suppose we are interested in the causal effects of the monetary policy shock w_t^m on some scalar outcome z_{t+h}, h periods after the shock, and where z_t may or may not be contained in the vector x_t. Let z_t follow the Moving Average (MA) process

$$z_t = \gamma_z + \sum_{h=0}^{\infty} \left(\delta_z^h w_{t-h}^m + v_{z,t-h}^h \right), \qquad \mathbb{E}[v_{z,t-h}^h] = \mathbb{E}[w_{t-h}^m v_{z,t-j}^h] = 0 \quad \forall h, j, \tag{2.4}$$

where δ_z^h denotes the causal effect of w_t^m on z_{t+h} and γ_z is a constant. The second term, $v_{z,t+h}^h$, may contain, for example, the linear effects of macroeconomic shocks other than the monetary policy shock, and the effects of all macroeconomic shocks interacted with time-varying systematic monetary policy $\tilde{\phi}_t$ (see Section 2.4 for an example). When the true causal effect of w_t^m on z_{t+h} depends on systematic monetary policy, then δ_z^h can be defined as the best linear prediction and $v_{z,t+h}^h$ contains the residual non-linear effects of w_t^m. The

[12]The high-frequency shocks can also be contaminated if perceived systematic monetary policy remains unchanged around the monetary announcement but expectations over x_t update, the information effect of monetary policy (e.g., Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020).

MA process is general in the sense that we put no restriction on what is contained in $v_{z,t+h}^h$ other than assuming $\mathbb{E}[w_{t-h}^m v_{z,t-j}^h] = 0 \ \ \forall h, j$. It will be convenient to rewrite (2.4) as

$$z_{t+h} = \gamma_z + \delta_z^h w_t^m + \tilde{v}_{z,t+h}^h, \quad \tilde{v}_{z,t+h}^h = \sum_{j=0}^{\infty} v_{z,t+h-j}^h + \sum_{j=0,\ j\neq h}^{\infty} \delta_z^h w_{t+h-j}^m \tag{2.5}$$

and it follows from (2.4) that $\mathbb{E}[w_t^m \tilde{v}_{z,t+h}^h] = 0 \ \ \forall h \geq 0$.[13]

Next, suppose an econometrician aims to estimate the effects of monetary policy via the local projection

$$z_{t+h} = c_z^h + d_z^h \hat{e}_t^m + u_{z,t+h}^h, \tag{2.6}$$

where $\hat{e}_t^m$ denotes the estimated monetary policy shock as described in Proposition 1.[14] If $\hat{e}_t^m = w_t^m$, the econometrician could easily uncover the causal effect via the OLS estimate $\hat{d}_z^h \xrightarrow{p} \delta_z^h$. In general, however, the estimate $\hat{d}^h$ will be biased, as the following proposition shows.

Proposition 2 (**IRF bias**). *Let monetary policy follow* (2.1) *and z_t follow the MA process in* (2.4)*. Consider the local projection in* (2.6) *with $\hat{e}_t^m$ as described in Proposition 1. As $T \to \infty$, the OLS estimate $\hat{d}_z^h$ of the local projection satisfies*

$$\hat{d}_z^h \xrightarrow{p} \delta_z^h + \vartheta_z^{\hat{b}} + \vartheta_z^{\tilde{\phi}} + \vartheta_z^a$$

where the three bias terms are defined by

$$\begin{aligned}
\vartheta_z^{\hat{b}} &= \mathbb{E}\left[(\hat{e}_t^m)^2\right]^{-1} \left(\phi - \hat{b}\right)' \left(\delta_z^h \mathbb{E}\left[x_t w_t^m\right] + \mathbb{E}\left[x_t \tilde{v}_{z,t+h}^h\right]\right), \\
\vartheta_z^{\tilde{\phi}} &= \mathbb{E}\left[(\hat{e}_t^m)^2\right]^{-1} \left(\delta_z^h \mathbb{E}\left[\tilde{\phi}_t' x_t w_t^m\right] + \mathbb{E}\left[\tilde{\phi}_t' x_t \tilde{v}_{z,t+h}^h\right]\right), \\
\vartheta_z^a &= \mathbb{E}\left[(\hat{e}_t^m)^2\right]^{-1} \delta_z^h \left(\mathbb{E}\left[(w_t^m)^2\right] - \mathbb{E}\left[(\hat{e}_t^m)^2\right]\right).
\end{aligned}$$

The proof is straightforward and omitted here. We first discuss the three bias terms in general and then discuss an extension of the local projection.

The first bias $\vartheta_z^{\hat{b}}$ arises from the wedge $\omega_t^{\hat{b}}$ and is zero if $\hat{b} = \phi$ or if $\mathbb{E}\left[x_t w_t^m\right] = \mathbb{E}\left[x_t \tilde{v}_{z,t+h}^h\right] = 0$. For example, a sufficient condition is that the monetary policy shock w_t^m and all other macroeconomic shocks that affect z_{t+h} are uncorrelated with x_t. We argue that strong assumptions are required to satisfy both conditions. For example, in monetary VAR models,

[13] We assume $\tilde{\phi}_t$, x_t, z_t, $\tilde{v}_{z,t+h}^h$ jointly follow a stable and ergodic process with finite fourth moments.

[14] We further consider an extension of the local projection in (2.6) that includes lagged control variables. This leads to broadly similar results, as we discuss further below.

x_t commonly includes endogenous variables such as period t inflation and GDP, where a period is commonly a month or a quarter. Assuming a zero response of these variables to a monetary policy shock in the same period is a strong assumption. In contrast, under the Romer and Romer (2004) strategy, x_t includes forecasts shortly before a monetary policy decision in which w_t realizes. In that case, $\mathbb{E}\left[x_t w_t^m\right] = 0$ seems plausible. However, the second condition still requires a strong assumption. The outcome variable z_{t+h} is commonly a macroeconomic variable observed at a monthly or quarterly frequency. Assuming persistence, the residual $\tilde{v}^h_{z,t+h}$ then contains all period t macroeconomic shocks other than w_t^m. For example, an oil supply shock at the beginning of the period will affect the outcome z_{t+h} but also the forecasts in x_t if the monetary policy meeting was later in the period. Overall, we require strong assumptions to eliminate the first bias $\vartheta_z^{\hat{b}} = 0$.
The second bias $\vartheta_z^{\tilde{\phi}}$ arises from the wedge $\omega_t^{\tilde{\phi}}$, which captures the misspecification of the linear Taylor rule regression. The bias depends on two expectations, $\mathbb{E}\left[\tilde{\phi}_t' x_t w_t^m\right]$ and $\mathbb{E}\left[\tilde{\phi}_t' x_t \tilde{v}^h_{z,t+h}\right]$. Similarly to the first wedge, the first expectation is plausibly zero in the case of a Romer and Romer (2004) identification strategy. The second expectation, however, is generally non-zero. Consider again an oil supply shock at the beginning of the period, before the monetary policy meeting and associated forecast x_t. The shock correlates with x_t, but its effect on z_{t+h} also generally depends on $\tilde{\phi}_t$. Therefore, the second expectation is non-zero. In monetary VAR models, both expectations are generally non-zero, for similar reasons as discussed above. Hence, the second bias is present unless we impose strong assumptions.
The third term, ϑ^a, can be interpreted as a type of attenuation bias. If the estimated monetary policy shock satisfies $\mathbb{E}\left[(\hat{e}_t^m)^2\right] > \mathbb{E}\left[(w_t^m)^2\right]$, the estimate $\hat{d}_z^h$ will be biased toward zero relative to δ_z^h. However, given that w_t^m may correlate with the wedges $\omega_t^{\hat{b}}$ and $\omega_t^{\tilde{\phi}}$, the estimated monetary policy shock is not classical measurement error. If $\mathbb{E}\left[(\hat{e}_t^m)^2\right] < \mathbb{E}\left[(w_t^m)^2\right]$, the estimate $\hat{d}_z^h$ will be biased away from zero. Even if the first two biases are zero, the third bias remains non-zero as long as $\tilde{\phi}_t \neq 0 \forall t$.
The local projection, as specified in (2.6), is highly parsimonious, not including any endogenous control variables. Consider instead the extended local projection $z_{t+h} = c_z^h + d_z^h \hat{e}_t^m + \Gamma(L) Y_t + u^h_{z,t+h}$, where $\Gamma(L) = \sum_{i=0}^{\infty} \Gamma_i L^i$ is a lag polynomial, and Y_t a vector of control variables. The additional control vector means we need to replace $\hat{e}_t^m$ and $\tilde{v}^h_{z,t+h}$ by projections of these variables on $\{Y_{t-1}, Y_{t-2}, ...\}$ in the bias terms in Proposition 2. While the controls may quantitatively change the bias, they do not eliminate the bias. In fact, in the above discussion of the bias terms, we have discussed bias arising from contemporaneous macroeconomic shocks. This bias cannot disappear by regressing on lagged variables.

In many empirical applications, the econometrician aims to identify the relative effect of monetary policy shocks rather than its absolute effect. If δ_{z_1} is the absolute causal effect of w_t^m on z_{1t}, the relative causal effect is $\delta_{z_1}/\delta_{z_2}$, where z_2 denotes another outcome. For example, it is common to study the effects of monetary policy shocks that raise the nominal interest rate by 25 or 100 basis points. This requires dividing the response of some outcome variable of interest by the interest rate response. For many empirical questions, a bias in the estimated absolute effect may be acceptable as long as the bias cancels out in the estimated relative effect. The following proposition provides a condition for the relative estimate to be unbiased.

Proposition 3 (**Relative IRF bias**). *Let monetary policy follow* (2.1) *and* z_{1t} *and* z_{2t} *follow MA processes as in* (2.4). *An econometrician estimates two local projections, as in* (2.6)*, to estimate the effects of* $\hat{e}_t^m$*, the OLS residual based on* (2.2)*, on* z_{1t+h} *and* z_{2t+h}*. The two OLS estimates* $\hat{d}_{z_1}^h$ *and* $\hat{d}_{z_2}^h$ *satisfy*

$$\frac{\hat{d}_{z_1}^h}{\hat{d}_{z_2}^h} \xrightarrow{p} \frac{\delta_{z_1}^h}{\delta_{z_2}^h}$$

if and only if

$$\frac{\left(\phi-\hat{b}\right)'\mathbb{E}\left[x_t\tilde{v}_{z_1,t+h}^h\right]+\mathbb{E}\left[\tilde{\phi}_t' x_t\tilde{v}_{z_1,t+h}^h\right]}{\delta_{z_1}^h}=\frac{\left(\phi-\hat{b}\right)'\mathbb{E}\left[x_t\tilde{v}_{z_2,t+h}^h\right]+\mathbb{E}\left[\tilde{\phi}_t' x_t\tilde{v}_{z_2,t+h}^h\right]}{\delta_{z_2}^h}.$$

The condition under which the relative IRF is not biased is a knife-edge condition, which is generally not satisfied. A sufficient condition is $\hat{b}=\phi$ and $\tilde{\phi}_t=0$, which also yields unbiased absolute IRF estimates.

2.4 A non-linear New Keynesian model

We revisit the results in Proposition 1-3 through the lens of a stylized model. Whereas the propositions provide general conditions for contamination and bias, the model illustrates the bite of the general result and allows us to discuss the bias in special cases of the model.
We consider a dynamic New Keynesian model in which systematic monetary policy may fluctuate for exogenous and endogenous reasons. Monetary policy follows the Taylor rule

$$i_t=\alpha+(\phi+\tilde{\phi}_t)\pi_t+x_t^m, \tag{2.7}$$

where x_t^m follows a stable AR(1) process $x_t^m=\rho_m\log x_{t-1}^m+w_t^m$, where $w_t^m \overset{iid}{\sim} (0,\sigma_m^2)$ denotes a monetary policy shock. As above, we conveniently set $\alpha=-\mathbb{E}[\tilde{\phi}_t\pi_t]$. A second exogenous driving variable is technology, denoted by x_t^a, which also follows a stable AR(1) process $x_t^a=\rho_a\log x_{t-1}^a+w_t^a$, where $w_t^a \overset{iid}{\sim} (0,\sigma_a^2)$ denotes a technology shock. Systematic monetary policy fluctuates according to a stable AR(1) process

$$\tilde{\phi}_t = \rho_\phi \tilde{\phi}_{t-1} + \psi_a w_t^a + q_t, \tag{2.8}$$

which features endogenous movements in response to w_t^a and an exogenous policy shifter $q_t \overset{iid}{\sim} (0, \sigma_q^2)$.
The exogenous drivers of the model are $\{w_t^m, w_t^a, q_t\}$, which we assume to be mutually independent. Absent time-varying systematic monetary policy, the model is a textbook New Keynesian model (Galí, 2015). Based on Hack et al. (2023), the approximate equilibrium dynamics of GDP y_t and inflation π_t follow

$$y_t = a^y + b_m^y x_t^m + b_a^y x_t^a + c_m^y x_t^m \tilde{\phi}_t + c_a^y x_t^a \tilde{\phi}_t + d^y \tilde{\phi}_t, \tag{2.9}$$

$$\pi_t = a^\pi + b_m^\pi x_t^m + b_a^\pi x_t^a + c_m^\pi x_t^m \tilde{\phi}_t + c_a^\pi x_t^a \tilde{\phi}_t + d^\pi \tilde{\phi}_t. \tag{2.10}$$

Given this process, the residual in equation (2.5) for $z = y$ is

$$\begin{aligned}\tilde{v}_{y,t+h}^h =& b_m^y \left(\rho_m^{h+1} x_{t-1}^m + \sum_{i=1}^{h} \rho_m^{h-i} w_{t+i}^m \right) + b_a^y x_{t+h}^a + c_m^y \left(x_{t+h}^m \tilde{\phi}_{t+h} - \mathbb{E}[x_{t+h}^m \tilde{\phi}_{t+h}] \right) \\ &+ c_a^y \left(x_{t+h}^a \tilde{\phi}_{t+h} - \mathbb{E}[x_{t+h}^a \tilde{\phi}_{t+h}] \right) + d^y \tilde{\phi}_{t+h}. \end{aligned} \tag{2.11}$$

We next use the model to revisit Proposition 2. In general, it is straightforward to verify that the estimate $\hat{d}_y^h$ is biased and that all three bias terms are non-zero.
The first bias term, $\vartheta^{\hat{b}}$, and thus both expectations $\mathbb{E}\left[\pi_t w_t^m\right]$ and $\mathbb{E}\left[\pi_t \tilde{v}_{y,t+h}^h\right]$ are zero only under strong assumptions, such as assuming inflation does not respond to monetary policy shocks, or technology shocks, or systematic monetary policy. The second bias term, $\vartheta^{\tilde{\phi}}$, requires similarly extreme assumptions to be zero. For example, if the inflation rate indeed depends on $x_t^m \tilde{\phi}_t$ and $x_t^a \tilde{\phi}_t$, i.e., if $c_m^\pi, c_a^\pi \neq 0$, both expectations $\mathbb{E}\left[\tilde{\phi}_t' \pi_t w_t^m\right]$ and $\mathbb{E}\left[\tilde{\phi}_t' \pi_t \tilde{v}_{y,t+h}^h\right]$ are non-zero. The third bias term, ϑ^a, is even more robust. It is generally non-zero whenever $\tilde{\phi}_t$ varies over time. Note that whether or not fluctuations in $\tilde{\phi}_t$ are fully exogenous, $\psi_a = 0$, or allow for endogenous movements is irrelevant for the question of whether $\hat{d}_y^h$ is biased.
We next consider a special case, an environment without persistence, $\rho_m = \rho_a = \rho_\phi = 0$. For $h = 0$, both expectations in $\vartheta^{\hat{b}}$ and $\vartheta^{\tilde{\phi}}$ remain non-zero, respectively. For $h > 0$, the second expectations equal zero, respectively. However, bias remains through the first expectations in $\vartheta^{\hat{b}}$ and $\vartheta^{\tilde{\phi}}$, respectively, and through the third bias, ϑ^a. For $h > 0$, the causal effect is $\delta_y^h = 0$ and bias means we estimate a non-zero effect.

3 Empirical evidence on the systematic origins of monetary policy shocks

In this section, we provide empirical evidence suggesting that U.S. monetary policy shocks as identified by the Romer and Romer (2004) (henceforth RR) approach are partly explained by fluctuations in the Federal Reserve's systematic monetary policy.

3.1 RR monetary policy shocks

The RR shock is estimated as the residual $\hat{e}_{\tau}^{rr}$ when estimating a Taylor rule-type regression

$$i_{\tau} = a + b' x_{\tau} + e_{\tau}^{rr}, \tag{3.1}$$

via OLS and where τ denotes FOMC meetings. We have reproduced (2.2) here for the convenience of the reader. RR specify i_{τ} as the change in the intended federal funds rate between two FOMC meetings. The right-hand side x_{τ} includes 18 variables: the Greenbook forecast of output growth and inflation, prepared in advance of FOMC meeting τ, respectively for the quarter preceding the FOMC meeting, the current and the two subsequent quarters; the revision of all 8 Greenbook forecasts relative to the same forecasts prepared for the preceding FOMC meeting; the Greenbook forecast of the unemployment rate in the current quarter; and the intended federal funds rate before FOMC meeting τ. We use the estimated monetary policy shocks $\hat{e}_{\tau}^{rr}$ and associated regressors x_{τ} from Wieland and Yang (2020) who extend the RR sample 1969-1996 to 1969-2007.[15]

3.2 Measuring time-varying systematic monetary policy

We describe two time series of systematic monetary policy, the Hawk-Dove balance among all Federal Open Market Committee (FOMC) members and the Hawk-Dove balance among the subset of rotating FOMC members. The subsequent description will be relatively brief, with further details and discussion available in Hack et al. (2023).

The FOMC has authority over U.S. monetary policy and consists of 12 members, among which four members serve one-year terms on a rotating basis. We use the narrative classification of FOMC members as hawks and doves in Istrefi (2019). The hawk-dove classification is a panel that tracks FOMC members over time at FOMC meeting frequency. Hawks are

[15] We end the sample just before the Great Financial Crisis, thus avoiding periods for which policy rules may have changed fundamentally. Likewise, we avoid the period when interest rates reached the effective lower bound. The FFR was kept constant from December 2008 to December 2015 at the zero lower bound.

perceived to be more concerned with inflation, while doves are more concerned with employment and growth.[16] Istrefi (2019) shows that the perceived policy preferences match well with policy tendencies that are unknown in real-time to the public, as expressed by preferred interest rates, with forecasting patterns of individual FOMC members, and with dissents. In addition, Bordo and Istrefi (2023) show that the FOMC members' educational background and early life experience have predictive power for individual policy preferences.

To measure variation in systematic monetary policy over time, we aggregate the individual FOMC member preferences into a Hawk-Dove balance for each meeting (cf. Istrefi, 2019). We do so because the nature of monetary policy-making involves the aggregation of diverse individual policy preferences in a collective decision. We first map the qualitative hawk-dove classification on a numerical scale for FOMC member i at meeting τ ranging from $Hawk_{i\tau}$ =+1 for consistent hawks, +1/2 for hawks who have been doves before, 0 for unclassified member, and -1/2 (-1) for swinging (consistent) doves.[17] We then construct the aggregate Hawk-Dove balance in the FOMC by

$$Hawk_{\tau}^{\mathcal{F}} = \frac{1}{|\mathcal{F}_{\tau}|} \sum_{i \in \mathcal{F}_{\tau}} Hawk_{i\tau} \tag{3.2}$$

where $\mathcal{F}_{\tau}$ denotes the (full) set of FOMC members i at meeting τ.[18]

The Hawk-Dove balance may respond to the state of the economy. For example, the Federal Reserve may become more dovish in response to high unemployment or more hawkish in response to high inflation (cf. Davig and Leeper, 2008). Systematic monetary policy may also change in response to political pressure (e.g., Abrams, 2006; Bianchi, Gómez-Cram, Kind, and Kung, 2023). To address the endogeneity of the Hawk- Dove balance, we construct the Hawk-Dove balance among the set of FOMC members who currently have voting rights through the annual rotation.[19] The mechanical nature of the rotation renders it orthogonal to the state of the economy and political cycles. Formally, the Rotation Hawk-Dove balance is defined by

$$Hawk_{\tau}^{\mathcal{R}} = \frac{1}{|\mathcal{R}_{\tau}|} \sum_{i \in \mathcal{R}_{\tau}} Hawk_{i\tau}, \tag{3.3}$$

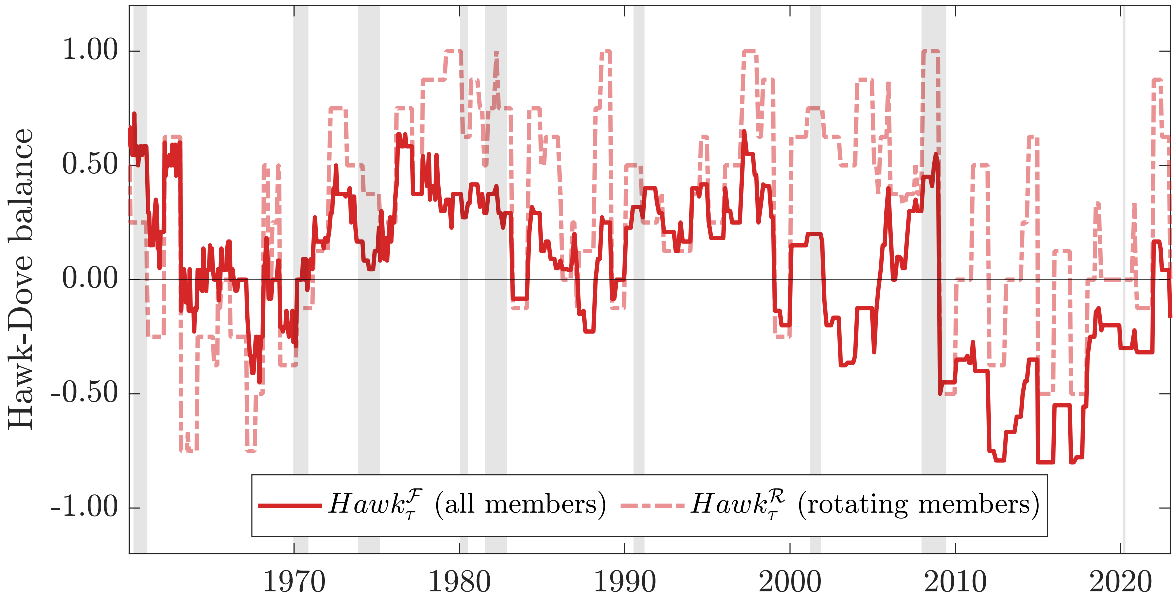
[16]Among the 147 FOMC members between 1960 and 2023, 129 are classified as hawk or dove. The news coverage for the remaining 18 members is insufficient for classification. 95 classified members are consistently hawks or doves, while the others switch camps at least once. The 34 swinging members switch camps at 1.8% of member-meeting pairs.

[17]Hack et al. (2023) show that alternative aggregation schemes lead to similar empirical findings.

[18]Occasionally, $|\mathcal{F}_{\tau}| \leq 12$ because of absent members and vacant positions.

[19]This was originally proposed in Hack et al. (2023) as instrument for systematic monetary policy.

Figure 1: Hawk-Dove balance in the FOMC



Notes: The solid red line shows the aggregate Hawk-Dove balance of the full FOMC $Hawk_\tau^{\mathcal{F}}$ at FOMC meeting frequency from 1960 through 2023. The dashed red line shows the aggregate Hawk-Dove balance of the rotation panel $Hawk_\tau^{\mathcal{R}}$. Grey bars indicate NBER dated recessions.

where $\mathcal{R}_\tau$ denotes the set of rotating FOMC members at FOMC meeting τ.[20] While $Hawk_\tau^{\mathcal{F}}$ is a more comprehensive measure of systematic monetary policy, $Hawk_\tau^{\mathcal{R}}$ has the advantage of reflecting exogenous variation through the rotation.

We present the evolution of $Hawk_\tau^{\mathcal{F}}$ and $Hawk_\tau^{\mathcal{R}}$ from 1960 through 2023 in Figure 1. Both balances vary considerably, featuring hawkish and dovish majorities. The variation reflects the turnover of rotating FOMC members, the turnover of non-rotating FOMC members, and changes in policy preferences of incumbent FOMC members. The correlation between $Hawk_\tau^{\mathcal{F}}$ and $Hawk_\tau^{\mathcal{R}}$ is 0.60, see Table A.1 for further descriptive statistics. Fluctuations in $Hawk_\tau^{\mathcal{R}}$ are relatively more short-lived, reflecting the annual rotation of voting rights.

The Hawk-Dove balance is informative about systematic monetary policy. First, the classification matches well with narratives of monetary policy in the U.S. (Istrefi, 2019). Second, a hawkish FOMC responds to higher inflation by raising the policy rate more aggressively (Bordo and Istrefi, 2023; Hack et al., 2023). Finally, a hawkish FOMC tightens monetary policy more aggressively in response to expansionary government spending shocks, leading to a significantly dampened GDP expansion (Hack et al., 2023).

[20] In our sample, $|\mathcal{R}_\tau| = 4$ for 625 out of 634 FOMC meetings and $|\mathcal{R}_\tau| = 3$ for the remaining meetings.

3.3 Predictability of RR shocks

In this section, we show that RR monetary policy shocks are predictable by fluctuations in measured systematic monetary policy in a way that supports our theoretical results.

If systematic monetary policy is time-varying as in (2.1), the estimated residuals $\hat{e}^{rr}_{\tau}$ based on the regression in (2.2) will include fluctuations in systematic monetary policy multiplied with the inputs of the Taylor rule, the term $\tilde{\phi}_{\tau} x_{\tau}$ in Proposition 1. Hence, a testable prediction of a time-varying Taylor rule is that fluctuations in measured systematic monetary policy multiplied with x_{τ} partly explain conventional RR shocks $\hat{e}^{rr}_{\tau}$. To test this prediction we estimate the following regression

$$\begin{aligned}\hat{e}^{rr}_{\tau} =& \beta_0 + \beta_1' \; x_{\tau-p} Hawk_{\tau-p} + \beta_2' \; x_{\tau-p} \Delta Hawk_{\tau-p} \\ &+ \beta_3' \; Hawk_{\tau-p} + \beta_4' \; \Delta Hawk_{\tau-p} + \beta_5' \; x_{\tau-p} + u_{\tau},\end{aligned} \tag{3.4}$$

where τ denotes an FOMC meeting, $\hat{e}^{rr}_{\tau}$ is the RR shock and x_{τ} the RR regressors, both as defined in Section 3.1, $Hawk_{\tau}$ is either $Hawk^{\mathcal{F}}_{\tau}$ or $Hawk^{\mathcal{R}}_{\tau}$, and $\Delta Hawk_{\tau}$ is the first difference of $Hawk_{\tau}$.[21] We consider contemporaneous regressors ($p = 0$) or lags up to two meetings ($p = 1, 2$). Our motivation to consider lags is to capture that it may take time for FOMC members to affect policy decisions (Hack et al., 2023).[22]

Table 1 presents the R^2 for various specifications of (3.4), as well as the p-values for the null hypothesis that all coefficient estimates are jointly zero, estimated for different sample periods. Across regression specifications, we obtain an R^2 between 0.1 and 0.54. Using a one-meeting lag ($p = 1$) yields the largest R^2 ranging from 0.33 to 0.54. In other words, a sizeable fraction of the variation in RR shocks can be explained by past variables, irrespective of the type of Hawk-Dove balance and the three sample specifications. For $p = 1$, we can reject the null hypothesis that all coefficient estimates are zero at the 1% significance level. Except the post-Volcker sample, the R^2 is lower for $p = 0$, and the R^2 is also lower for $p = 2$. Our finding that lagged regressors raise predictability is consistent with the nature of decision-making in the FOMC.

We next investigate the contribution of the individual regressors for explaining variation in

[21] In Hack et al. (2023), the rotation Hawk-Dove balance is proposed as an instrument to provide causal evidence on the state-dependent effects of macroeconomic shocks with variation in respect to systematic monetary policy. In this paper, we do not use the rotation Hawk-Dove balance explicitly as an instrument because the high number of regressors in our empirical application would render an IV approach unreliable.

[22] For example, former Governor Laurence Meyer remarks: *I came to see policy decisions as often evolving over at least a couple of meetings. The seeds were sown at one meeting and harvested at the next. [...] Similarly, while in my remarks to my colleagues it sounded as if I were addressing today's concerns and today's policy decisions, in reality I was often positioning myself, and my peers, for the next meeting.* Laurence Meyer (2004), A Term at the Fed: An Insiders' View, Harper Business.

Table 1: Explaining RR shocks by systematic monetary policy

	$Hawk_\tau^{\mathcal{F}}$			$Hawk_\tau^{\mathcal{R}}$		
Sample	69-07	69-96	83-07	69-07	69-96	83-07
(a) Contemporaneous FOMC meeting (p=0)						
R^2	0.098	0.133	0.432	0.167	0.216	0.464
p-value	0.248	0.239	0.000	0.003	0.000	0.000
T	354	266	200	354	266	200
(b) One FOMC meeting lag (p=1)						
R^2	0.333	0.430	0.451	0.429	0.541	0.443
p-value	0.002	0.002	0.000	0.000	0.000	0.000
T	350	262	200	350	262	200
(c) Two FOMC meetings lag (p=2)						
R^2	0.236	0.313	0.373	0.279	0.360	0.422
p-value	0.000	0.000	0.000	0.000	0.000	0.000
T	348	260	200	348	260	200

Notes: The table shows results from regressions based on (3.4). The rows of the three subtables show R^2, the p-values for the null hypothesis that all coefficient estimates are jointly zero, and the number of observations T. The three left columns show results for the Hawk-Dove balance across all FOMC members, the three right columns for the Hawk-Dove balance across all rotating FOMC members with voting rights. Columns one to three show differ by the sample period between 1969-2007, 1969-1996, and 1983-2007, and analogously for columns four to six. The three subtables differ by the specification of FOMC meeting lag p.

RR shocks. We focus on the regression specification of (3.4) that yields the largest (total) R^2 in Table 1, i.e., $Hawk_{\tau-p}^{\mathcal{R}}$ and $p = 1$, but we obtain similar results for the other specifications. Table 2 reports the R^2 and p-value when regressing the RR shock $\hat{e}_\tau^{rr}$ separately on subsets of the regressors included in equation (3.4). The first key takeaway is that the interactions between $x_{\tau-1}$ and, respectively, $Hawk_{\tau-1}^{\mathcal{R}}$ and $\Delta Hawk_{\tau-1}^{\mathcal{R}}$ account for the bulk of the total R^2. Both $Hawk_{\tau-1}^{\mathcal{R}}$ and $\Delta Hawk_{\tau-1}^{\mathcal{R}}$ are informative (in interaction with $x_{\tau-1}$), with the latter having more predictive power. The second key takeaway is that the (non-interacted) level of $Hawk_{\tau-1}^{\mathcal{R}}$ and $\Delta Hawk_{\tau-1}^{\mathcal{R}}$ has practically no predictive power for the RR shock. Importantly, this finding further supports the interpretation of the Hawk-Dove balance as capturing variation in systematic monetary policy. If, in contrast, the Hawk-Dove balance also captured significant information about the intercept of the monetary policy rule, we

Table 2: Explaining RR shocks by subsets of regressors

	Interactions			Levels		
Sample	69-07	69-96	83-07	69-07	69-96	83-07
	(a) $Hawk^{\mathcal{R}}_{\tau-1} \times x_{\tau-1}$			(b) $Hawk^{\mathcal{R}}_{\tau-1}$ & $\Delta Hawk^{\mathcal{R}}_{\tau-1}$		
R^2	0.112	0.138	0.117	0.006	0.010	0.002
p-value	0.087	0.058	0.034	0.370	0.330	0.826
	(c) $\Delta Hawk^{\mathcal{R}}_{\tau-1} \times x_{\tau-1}$			(d) $x_{\tau-1}$		
R^2	0.248	0.289	0.065	0.090	0.133	0.255
p-value	0.000	0.000	0.000	0.031	0.005	0.000
	(e) All interactions			(f) All level terms		
R^2	0.341	0.399	0.193	0.096	0.151	0.255
p-value	0.000	0.000	0.000	0.039	0.001	0.000
T	350	262	200	350	262	200

Notes: The table shows results from regressions based on (3.4), considering different subsets of the regressors. The rows of the three subtables show R^2 and the p-values for the null hypothesis that all coefficient estimates are jointly zero, and the number of observations T. The three left columns show results for the interactions between the Hawk-Dove balance and $x_{\tau-1}$, the three right columns show the results for the non-interacted (level) regressors. Columns one to three show differ by the sample period between 1969-2007, 1969-1996, and 1983-2007, and analogously for columns four to six.

could expect the level of the Hawk-Dove balance to have predictive power for the RR shock. Finally, the regressor $x_{\tau-1}$ has some predictive power in explaining RR shocks, in particular for the post-Volcker sample. The results in Table 2 differ by little across the three samples. Overall, our results suggest that a substantial fraction of the conventional RR shocks can be explained by variation in systematic monetary policy. Our evidence thus supports the notion that empirical monetary policy shocks have systematic monetary policy origins.

A potential concern with our results is that the large set of regressors we include might lead to overfitting. We may mechanically absorb variation, although there is no systematic relationship in the data. To address this concern, we use a Lasso estimation, which minimizes the sum of squared residuals (as in OLS) but additionally penalizes the number of estimated parameters to keep the set of included regressors small. We choose the penalization parameter to gradually increment the number of regressors from one to five. We present the results for the sample 1969 - 2007 in Table B.1, in Appendix B. We find that five (scalar) regressors are sufficient to yield an R^2 of 0.15. All five regressors selected by the Lasso estimation involve interactions of elements in $x_{\tau-1}$ with $\Delta Hawk^{\mathcal{R}}_{\tau-1}$. The elements included are one Greenbook forecasts of output growth, two inflation forecasts, and two inflation forecast revisions.

In related work, Aruoba and Drechsel (2022) refine the RR shock by using a large vector x_t with the goal of better capturing the Fed's information set about the state of the economy. They use textual analysis to create sentiment indicators about the Fed staff's assessment of the economy before FOMC meetings. The sentiment indicators are used as additional regressors in Taylor rule-type Ridge regression. We regress their shock on our right-hand side variables in (3.4). We find an R^2 between 0.26 and 0.35 depending on lag order ($p = 0, 1, 2$) and the type of Hawk-Dove balance. We obtain the largest R^2 for $p = 2$ and $Hawk^{\mathcal{R}}_{\tau}$. Thus, even their refined shock is predictable and, hence, may be contaminated by time variation in systematic monetary policy.

4 A new monetary policy shock

The results in Section 3 motivate us to construct a new monetary policy shock that is no longer predictable by measured systematic monetary policy. The shock is the estimated residual when regressing policy rate changes on Greenbook forecasts as well as the interaction between Greenbook forecasts and measured time variation in systematic monetary policy. We find that our new monetary policy shocks affect output and inflation with a substantially shorter delay, more strongly, and at higher statistical significance compared to the RR shock, in particular for a post-Volcker sample.

4.1 Shock identification

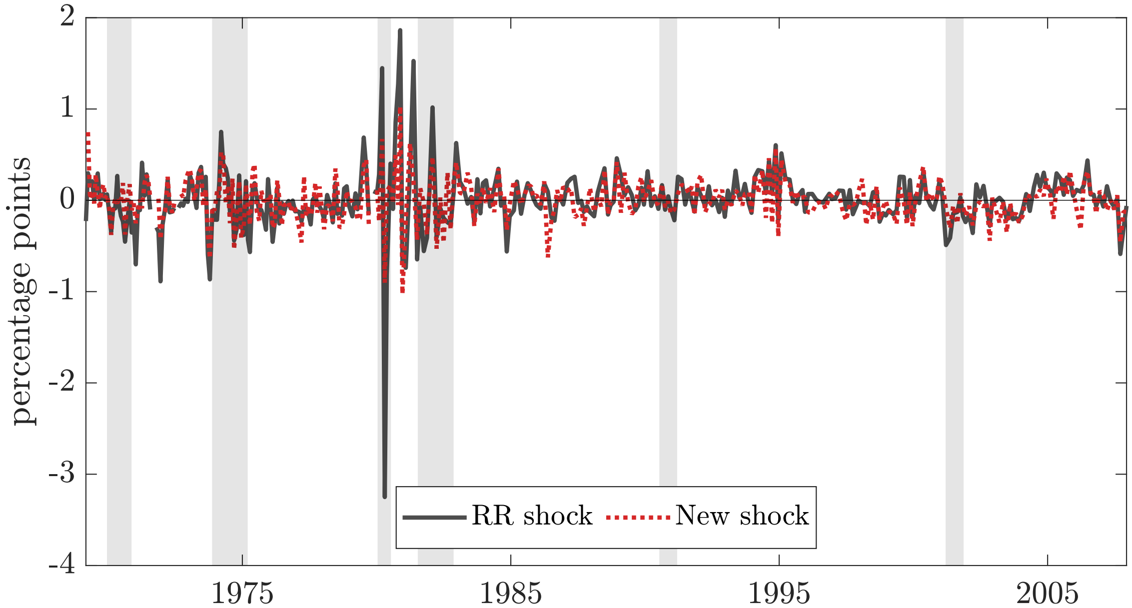
We estimate a new monetary policy shock series via the augmented Taylor rule regression

$$\begin{aligned} i_\tau =& \beta_0 + \beta_1' x_\tau + \beta_2' x_{\tau-1} + \beta_3'\ x_{\tau-1} Hawk_{\tau-1} + \beta_4'\ x_{\tau-1} \Delta Hawk_{\tau-1} \\ &+ \beta_5'\ Hawk_{\tau-1} + \beta_6'\ \Delta Hawk_{\tau-1} + e^{new}_\tau, \end{aligned} \tag{4.1}$$

where the policy instrument i_τ and Greenbook forecast x_τ are specified as in Section 3 and $Hawk_\tau$ is the Rotation Hawk-Dove balance. Our new monetary policy shock is the estimated residual $\hat{e}^{new}_\tau$ when estimating (4.1) via OLS.[23] The specification nests the original Romer and Romer (2004) regression if we restrict $\beta_j = 0\ \forall j > 1$, in which case we denote

[23]While we follow RR in using OLS, this leads to endogeneity bias as discussed in Section 2. However, Carvalho et al. (2021) argue that the endogeneity bias is quantitatively negligible. Finally note that estimating (4.1) via IV is practically challenging because it would require a large number of instruments.

Figure 2: Time series of monetary policy shocks



Notes: The solid black line shows the RR shock $\hat{e}_\tau^{rr}$ based on the regression in (4.1) when restricting $\beta_j = 0 \, \forall j > 1$. The dotted red line shows the new shock $\hat{e}_\tau^{new}$ based on the regression in (4.1). The sample period is 1969 through 2007. Grey bars indicate NBER recession.

the estimated residual by $\hat{e}_\tau^{rr}$. Our baseline sample to identify the shock is the full sample from 1969 through 2007. We discuss the robustness of our results for alternative samples in Section 4.3.

Figure 2 shows the new shock series (red dotted line) in comparison with the original RR shock series (black solid line). The new series is substantially less dispersed than the RR shock with the standard deviation falling from 0.34 to 0.23 (see Table 3). The overall correlation between new and RR shock is 0.67. The correlation between the sign of both shocks is 0.42, meaning new and RR shock frequently have the opposite sign. Both the new shock and the RR shock exhibit practically no serial correlation.[24]

The two shock series most visibly differ during 1979-1982 with our new shock being smaller in magnitude. RR argue that their shocks in this period reflect changes in the Federal Reserve's operating procedures and an increased distaste for inflation. In fact, we do observe a relatively hawkish FOMC, in particular among rotating FOMC members (see Figure 1). Hence, a plausible reason for our new shocks being smaller is that accounting for variation in systematic monetary policy better explains variation in monetary policy during this episode.

[24]For four FOMC meetings, x_τ is missing because not all Greenbook forecasts are available. The regression for the new shock (4.1) includes $x_{\tau-1}$ creating four additional missing observations.

Table 3: Descriptive statistics of monetary policy shocks

	Mean	Median	SD	Autocorr	Corr	Sign-corr	Min	Max	T
RR shock	0.00	-0.01	0.34	0.12	-	-	-3.25	1.86	354
New shock	-0.00	-0.01	0.23	-0.09	0.67	0.42	-1.03	1.03	350

Notes: The table shows descriptive statistics for the new shock ($\hat{e}_\tau^{new}$) and the RR shock ($\hat{e}_\tau^{rr}$) at FOMC meeting frequency from 1969 through 2007. "Autocorr" refers to the meeting-over-meeting autocorrelation. "Corr" refers to the correlation between new and RR shock. "Sign-corr" refers to the correlation of the sign of both shock series.

4.2 Impulse responses

We next compare impulse response estimates for alternative monetary policy shock series.

Econometric framework. We estimate impulse responses using the local projections

$$z_{t+h} - z_{t-1} = \alpha_z^h + \beta_z^h \ \hat{e}_t + \Gamma \ Y_t + v_{t+h}^h, \quad h = 0, \ldots, H, \tag{4.2}$$

where z_t is an outcome variable of interest. The main outcomes of our analysis are the federal funds rate, the inflation rate, and log real GDP. The monetary policy shock $\hat{e}_t$ is either the new shock $\hat{e}_t^{new}$ or the RR shock $\hat{e}_t^{rr}$. The control vector Y_t includes twelve lags of the federal funds rate, the inflation rate, the log of real GDP, and a linear time trend. A period t is a month. This is a common choice in the related literature and limits the need to aggregate the monetary policy shocks.[25] Monthly log real GDP and the monthly GDP deflator inflation rate are obtained by interpolation using the procedure of Chow and Lin (1971).[26] Section 4.3 explores the sensitivity of our results on monthly interpolation and the specification of the control vector. The baseline sample of our analysis is 1983 through 2007, so post-Volcker disinflation and pre-Great Recession. We consider this sample particularly interesting because the estimated responses to many conventional monetary policy shock series appear implausible in such sample (e.g., Ramey, 2016). This sample further avoids potential structural breaks around the Great Inflation episode. Section 4.3 explores the sensitivity of our results regarding the sample.

Responses of main outcomes. Figure 3 presents the estimated responses of our main outcome variables, the federal funds rate, the inflation rate, and log real GDP, to the new

[25] Only 4 months (all between 1969 through 1971) contain more than one FOMC meeting with a monetary policy shock $\hat{e}_\tau$, while a large fraction of quarters across the entire sample contain multiple $\hat{e}_\tau$. In months in which we observe at least one $\hat{e}_\tau$, we construct $\hat{e}_t$ as the sum of $\hat{e}_\tau$ contained in t. Otherwise, we set $\hat{e}_t = 0$.

[26] The related monthly series we use for interpolating GDP and the GDP deflator are CPI, industrial production, one-year treasury yield, and excess bond premium.

shock and the RR monetary policy shock. The key takeaway is that the two shocks differ substantially in the estimated lag of monetary policy transmission, the magnitude of the responses, and statistical significance.

The two panels in the first row of Figure 3 show the estimated response of the federal funds rate (FFR) to the two shocks. While the left-hand side panel shows the 68% and 95% confidence bands for the new shock, the right-hand side panel shows the corresponding confidence bands for the RR shock. The confidence bands are based on heteroskedasticity and autocorrelation consistent estimators. Both shocks are normalized to increase the FFR by 100 basis points on impact. This facilitates comparability of the inflation and GDP responses. The dynamic FFR responses differ markedly in magnitude and persistence. The new shock leads to a peak FFR response of 2.4 percentage points after 6 months and quickly reverts to zero. The RR shock leads to a peak FFR response of 3.7 percentage points after 8 months and remains significantly above zero for 18 months. Figure 4(a) shows that the difference between the FFR responses is statistically significant at the 5% level for some horizons after 15 months, precisely where the RR shock has more persistent effects.[27] Overall, the new monetary policy shock leads to a less strong and more transitory dynamic federal funds rate response than the RR shock. If both shocks are well identified, we might expect a larger demand contraction from the RR shock.

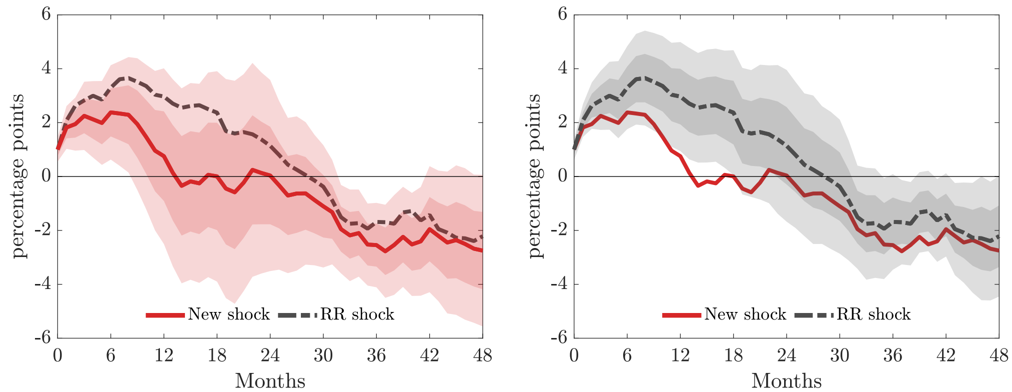
The second row of Figure 3 shows the estimated responses of real GDP. The new shock leads to a contraction of GDP that is mostly significant at the 5% level between 14 months and 37 months after the shock. In contrast, the GDP response to the RR shock is statistically insignificant at the 5% level for all horizons we consider. If we use the (much) lower 32% significance standard, then the new shock leads to a significant GDP contraction starting 8 months after the shock, while it takes 20 months for the RR shock. In addition, the RR shock generates a short-lived significant expansion around 6 months after the shock (an output puzzle). The difference between the two GDP responses is statistically significant for most horizons between 6 and 20 months, see Figure 4(b). The shocks further differ strongly in the magnitude of the GDP response. Despite the larger and more persistent FFR increase for the RR shock, the GDP contraction is substantially larger for the new shock. The trough response is -3.2 percent for the new shock and -1.4 percent for the RR shock.

Finally, the third row shows the estimated responses of inflation. Arguably, the most striking finding of Figure 3 is the difference in the lag of monetary policy affecting inflation. The inflation response becomes 5% significant only after 27 months for the RR shock but after 13 months for the new shock. Our new shock shows that monetary policy shocks affect inflation

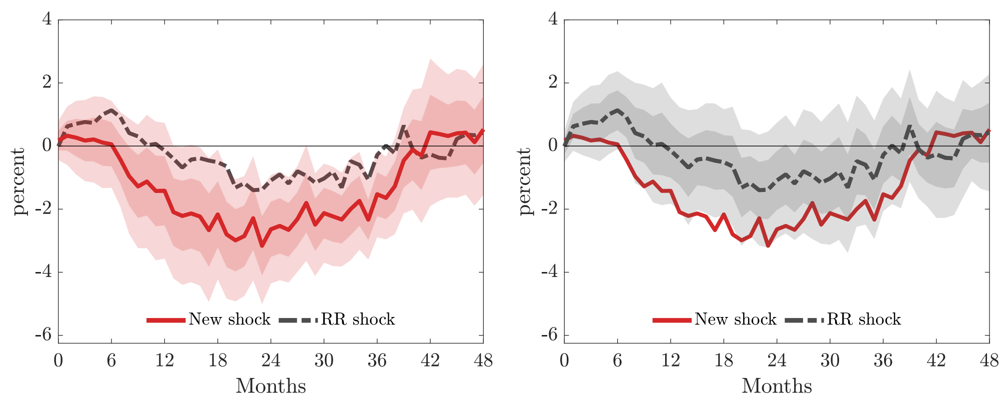
[27] The standard errors for the difference across impulse responses are constructed by estimating both local projections as seemingly unrelated regressions and estimating the joint covariance matrix via Driscoll-Kraay.

Figure 3: Responses of main outcomes to monetary policy shocks

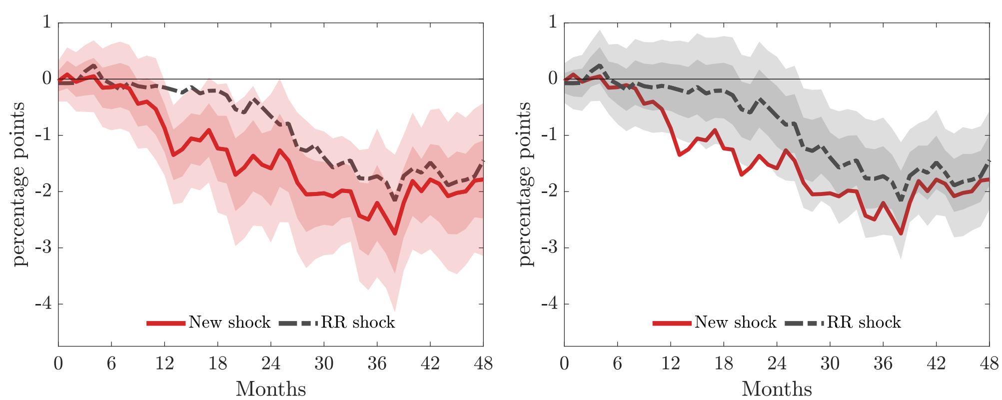
(a) Federal funds rate



(b) Real GDP



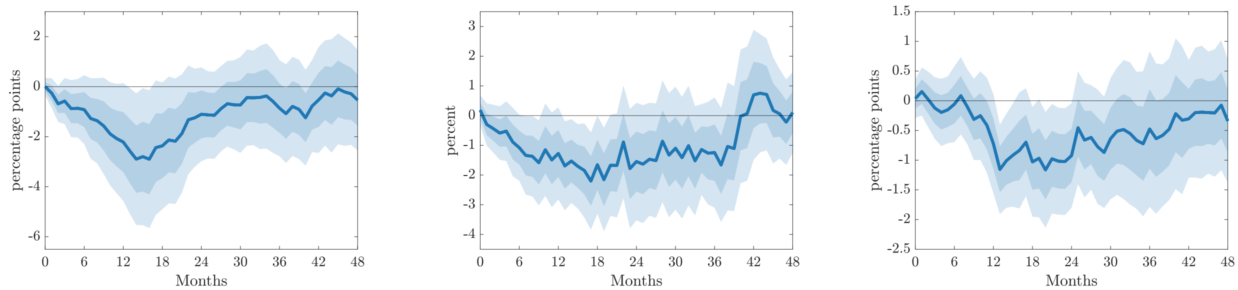
(c) Inflation



Notes: The figure shows responses of the federal funds rate, log real GDP and the inflation rate to a monetary policy shock based on the local projection as specified along with (4.2). The new monetary policy shock is identified as the residual from the Taylor rule regression in (4.1) whereas the conventional monetary policy shock is based on the same regression when $b_j = 0$ for $j > 1$, as in Romer and Romer (2004). The shaded areas indicate 68% and 95% confidence bands using standard errors robust to serial correlation and heteroskedasticity.

Figure 4: Response to new shock "minus" response to RR shock

(a) FFR (b) Real GDP (c) Inflation



Notes: The figure shows the differences across impulse responses for the federal funds rate, log real GDP and the inflation rate to a monetary policy shock based on the local projection as specified along with (4.2). The difference is computed as the response to the new shock minus the response to the old shock for each outcome, respectively. The new monetary policy shock is identified as the residual from the Taylor rule regression in (4.1) whereas the conventional monetary policy shock is based on the same regression when $b_j = 0$ for $j > 1$, as in Romer and Romer (2004). The shaded areas indicate 68% and 95% confidence bands using standard errors robust to serial correlation and heteroskedasticity.

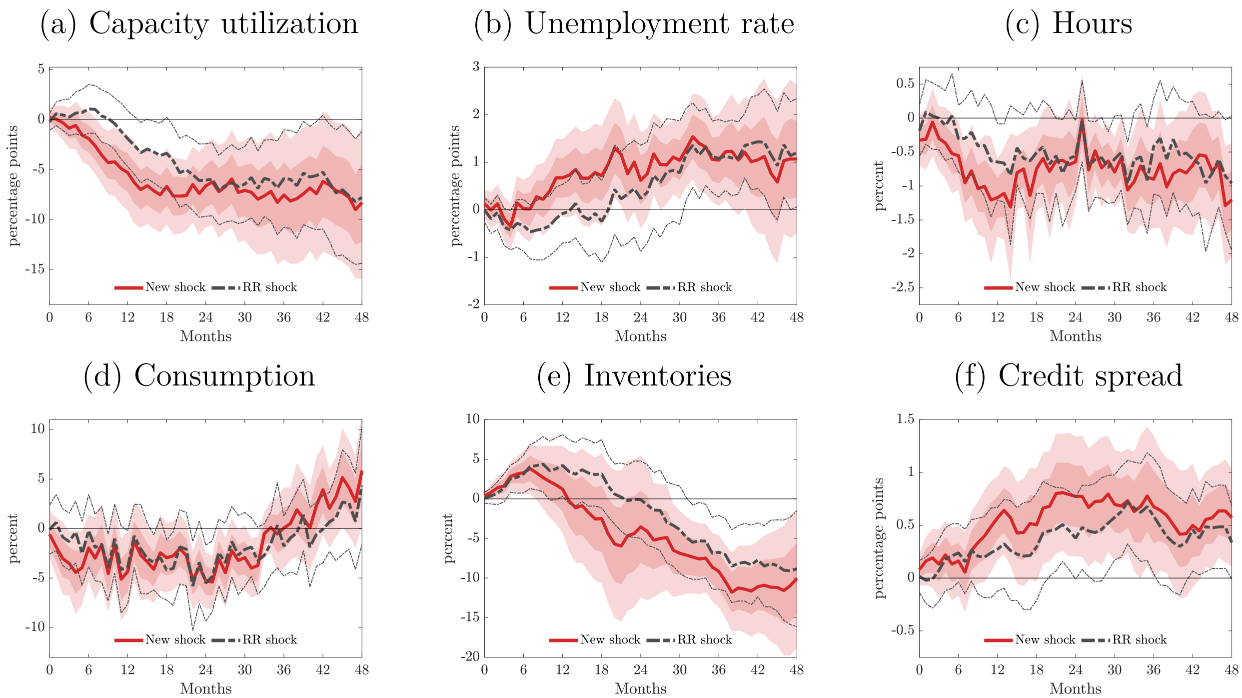
at substantially shorter lags than what the RR shock suggests. The difference between the inflation responses is particularly significant between 12 and 28 months, see Figure 4(c). We further uncover some differences in magnitudes. The trough response is -2.7% for the RR shock and -2.2% for the new shock.

Overall, our results suggest that accounting for time variation in systematic monetary policy is critically important when identifying monetary policy shocks. Disregarding variation in systematic monetary policy may lead to strongly biased impulse response estimates and an inaccurate assessment of the effectiveness of monetary policy. It may further bias analyses using impulse responses estimates to estimate DSGE models, construct policy counterfactuals, or investigate the optimality of monetary policy.

Further outcome variables. In Figure 5, we extend the analysis to further outcome variables, notably capacity utilization, unemployment, hours worked, consumption, inventories, and a credit spread. The variables are informative about the transmission mechanism of monetary policy. In addition, they further show that accounting for systematic monetary policy matters.

In response to the new shock, we find a significant decrease in capacity utilization, increase in the unemployment rate, and decrease in hours worked. All measures suggest an increase of slack in the economy. The responses to the RR shock are broadly similar. However, they suggest (again) a substantially longer lag of monetary policy and the responses are less precisely estimated. We report the differences of responses and confidence bands in Figure C.1 in Appendix C. The response of consumption expenditures to the new shock is much quicker and occurs within the first six months. Beyond the short-run, however,

Figure 5: Response of further outcomes to monetary policy shocks

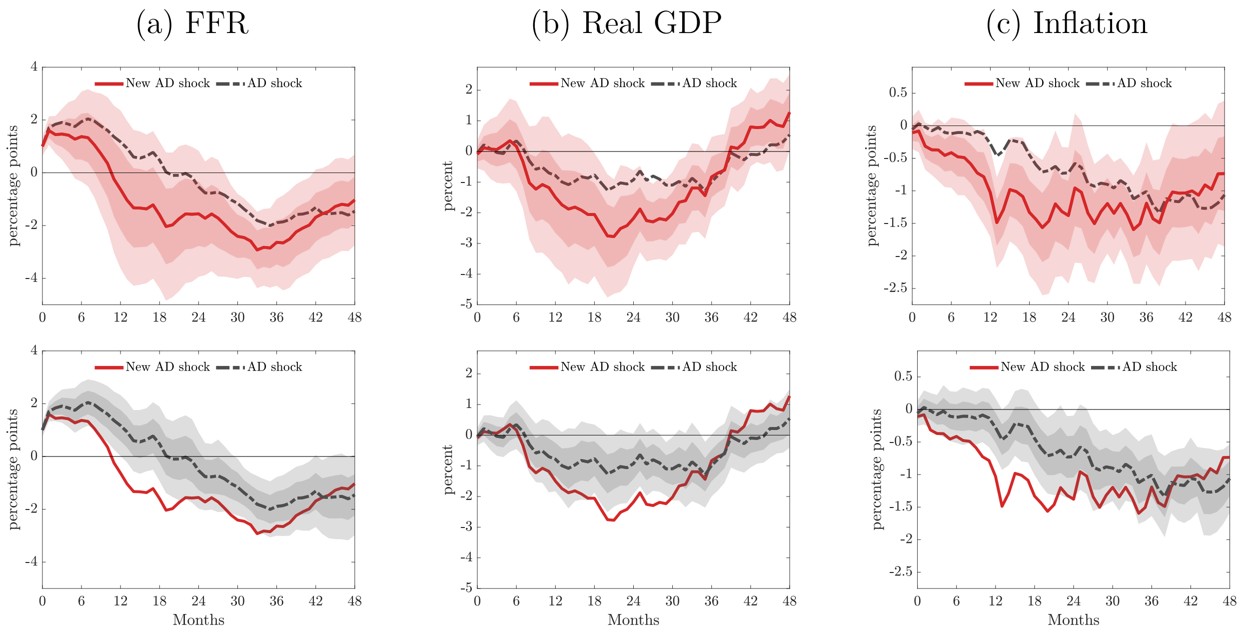


Notes: The figure shows responses of capacity utilization, the unemployment rate, log consumption expenditures, log business inventories, log hours (in manufacturing), and credit spreads (BAA- minus AAA-rated corporate bond yield) to a monetary policy shock based on the local projection as specified along with (4.2). The new monetary policy shock is identified as the residual from the Taylor rule regression in (4.1) whereas the conventional monetary policy shock is based on the same regression when $b_j = 0$ for $j > 1$, as in Romer and Romer (2004). The shaded areas indicate 68% and 95% confidence bands for the new shock, and the dotted lines indicate the 95% confidence band for the conventional shock using standard errors robust to serial correlation and heteroskedasticity for all bands.

the response of consumption is highly similar across the new shock and the RR shock, suggesting that investment, government spending, or net exports respond quite differently to the two shocks. Business inventories initially increase, consistent with a surprise reduction in demand, and then fall. The reduction in inventories is significantly more pronounced for the new shock consistent with the more rapid decline in capacity utilization. Finally, the yield spread between BAA- and AAA-rated corporate bonds responds more strongly and significantly to the new shock. Overall, we find substantial differences in the response of these outcomes, and the effects of the new shock tend to be stronger and more significant.

Aruoba and Drechsel (2022) shock. Section 3 provides evidence suggesting that the shock constructed by Aruoba and Drechsel (2022) (AD shock henceforth) may be contaminated by systematic monetary policy. We next compare the impulse response estimates between the AD shock and a new AD shock, which is the residual AD shock when regressing on the right-hand side variables of (4.1). Figure 6 shows that the new AD shock leads to a more short-lived response of the federal funds rate, a stronger decline of real GDP declines,

Figure 6: Comparison of main responses with Aruoba and Drechsel (2022) shock



Notes: The figure shows responses of the federal funds rate, log real GDP and the inflation rate to a monetary policy shock based on the local projection as specified along with (4.2). The new monetary policy shock is identified as the residual from the Taylor rule regression in (4.1) where we put the Aruoba and Drechsel (2022) shock on the left-hand-side, whereas the conventional monetary policy shock is taken directly from Aruoba and Drechsel (2022). The shaded areas indicate 68% and 95% confidence bands using standard errors robust to serial correlation and heteroskedasticity.

and a substantially shorter lag in the inflation response, when compared to the original AD shock. The differences are sizeable and statistically significant at some horizons, see Figure C.2 in Appendix C.

4.3 Sensitivity analysis

In this section, we provide a sensitivity analysis to assess the robustness of our baseline results. We investigate how our results depend on varying sample periods, the inclusion of additional control variables, and alternative measures of economic activity and prices. We summarize our findings in the following, but delegate all figures to Appendix C.

Alternative sample periods. Our baseline shock measure is estimated on the full sample of Greenbook forecasts from 1969 through 2007, but the impulse responses presented above are estimated on the post-1983 sub-sample. We analyze whether our estimated responses differ if the shock identification regressions (4.1) for both the RR shock and our new shock are estimated on the same post-1983 sub-sample. Figure C.3 shows that the inflation response to the RR shock features a similarly long lag as in the baseline. The GDP response to the RR shock is insignificant but rather expansionary. In contrast, the response of inflation to our new shock remains similar to the baseline, while the GDP response remains contractionary but is less significant than in the baseline. We further estimate impulse responses on the full sample (1969-2007) instead of the post-1983 sample and report the results in Figure C.4. Similar to the baseline, we find that the new shock delivers a significantly stronger contraction in real GDP. Interestingly, the inflation response is similar across both shocks for around two years and features a price puzzle.[28] At longer horizons, however, the new shock leads to a stronger inflation decline. The large difference between estimating the impulse responses on the full-sample vis-à-vis the post-1983 may potentially arise because of the structural breaks around the Great Inflation and subsequent disinflation, which our linear local projection does not model.

Additional control variables. Romer and Romer (2004) and Coibion (2012) impose a recursiveness assumption by including contemporaneous real GDP and inflation as control variables. In effect, these variables cannot contemporaneously respond to the monetary policy shock. Figure C.5 shows that our results are highly similar to the baseline imposing the recursiveness assumption. Parts of the related literature control for lags of the log S&P 500 and the Gilchrist and Zakrajšek (2012) excess bond premium (e.g., Jarociński and Karadi, 2020). Figure C.6 shows that our estimated responses are similar to the baseline when adding twelve lags of the two control variables. Finally, some of the related literature controls for lags of the RR shocks (see, e.g., Ramey, 2016). Figure C.7 shows that our results hardly change when adding twelve lags of the shock under consideration to the baseline set of control variables.

Alternative outcome variables. Our baseline results use interpolated real GDP and the GDP deflator to measure economic activity and prices at monthly frequency as similarly done in Jarociński and Karadi (2020); Aruoba and Drechsel (2022). An alternative is to use industrial production (IP) and CPI inflation, which are readily available at monthly frequency (e.g. Gertler and Karadi, 2015; Bauer and Swanson, 2023b). Figure C.8 shows the responses of IP and CPI. The differences between the new and the RR shock remain similar to the baseline. However, the IP response is not very precisely estimated for the new shock. If we further control for twelve lags of the Gilchrist and Zakrajšek (2012) excess bond premium and the log S&P 500, the IP response is more precisely estimated, see Figure C.9.

[28] Including twelve lags of the log commodity price index (or its growth rate) resolves the price puzzle.

5 Conclusion

This paper revisits conventional empirical strategies to estimate monetary policy shock series. We show theoretically that fluctuations in systematic monetary policy lead to misidentified shocks and bias in the estimated impulse responses. We provide empirical evidence to support the theory. We find that Romer and Romer (2004) monetary policy shocks are predictable by fluctuations in measured systematic monetary policy. We construct a new shock series that is orthogonal to systematic monetary policy and assess its effects on the U.S. economy. Our shock suggests monetary policy has shorter lags and stronger effects on inflation and output relative to comparable evidence for the Romer and Romer (2004) shock.

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Appendix A Data

Table A.1: Descriptive statistics of the Hawk-Dove balances

	Mean	Median	SD	Autocorr	Corr	Min	Max	T
$Hawk_\tau^{\mathcal{F}}$	0.06	0.10	0.34	0.95	-	-0.80	0.73	630
$Hawk_\tau^{\mathcal{R}}$	0.24	0.25	0.47	0.91	0.60	-0.75	1.00	630

Notes: This table shows descriptive statistics for the time series at FOMC meeting frequency from 1960 through 2023. $Hawk_\tau^{\mathcal{F}}$ is the average Hawk-Dove balance of the FOMC. $Hawk_\tau^{\mathcal{R}}$ is the FOMC rotation instrument. "Autocorr" refers to the meeting-over-meeting autocorrelation. "Corr" refers to the correlation between both series.

Appendix B Additional results for Section 3

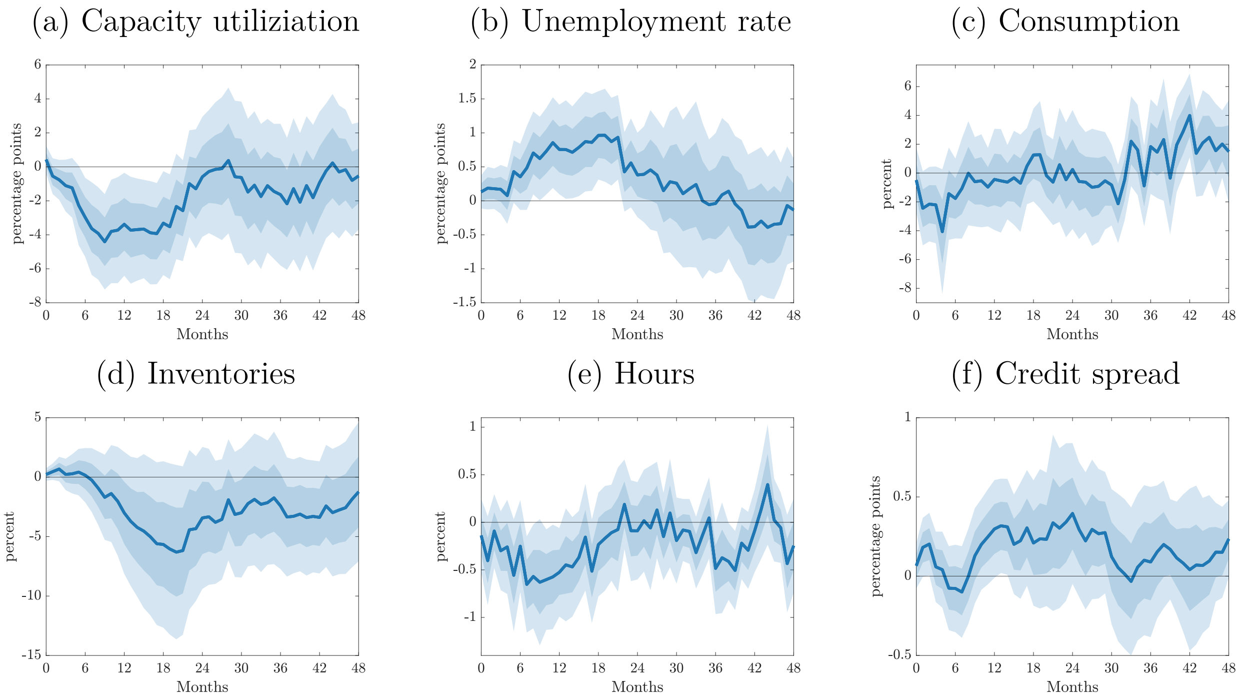
Table B.1: Lasso estimation to explain RR shocks

	(1)	(2)	(3)	(4)	(5)
$\Delta Hawk^{\mathcal{R}}_{\tau-1} \times y_{\tau-1,2}$	-0.195	-0.148	-0.138	-0.107	-0.082
	(0.300)	(0.368)	(0.346)	(0.301)	(0.367)
$\Delta Hawk^{\mathcal{R}}_{\tau-1} \times \Delta\pi_{\tau-1,-1}$		0.149	0.111	0.233	0.224
		(0.137)	(0.244)	(0.047)	(0.054)
$\Delta Hawk^{\mathcal{R}}_{\tau-1} \times \pi_{\tau-1,1}$			0.133	0.076	-0.226
			(0.262)	(0.338)	(0.400)
$\Delta Hawk^{\mathcal{R}}_{\tau-1} \times \Delta\pi_{\tau-1,1}$				0.222	0.273
				(0.032)	(0.026)
$\Delta Hawk^{\mathcal{R}}_{\tau-1} \times \pi_{\tau-1,2}$					0.325
					(0.267)
Constant	0.007	0.002	0.003	0.007	0.006
	(0.713)	(0.917)	(0.864)	(0.678)	(0.715)
T	350	350	350	350	350
R^2	0.046	0.067	0.086	0.145	0.154

Notes: The table shows Lasso regression results based on (3.4). The Lasso shrinkage parameter is chosen to increment the number of regressors from one to five, and the associated results are presented in columns one to five, respectively. The time sample runs from 1969 through 2007, and standard errors robust to serial correlation and heteroskedasticity are in parentheses.

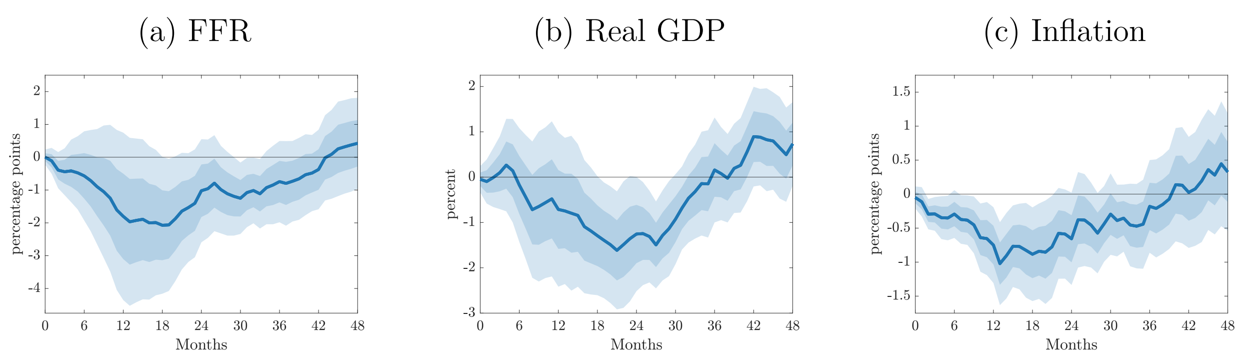
Appendix C Additional results for Section 4

Figure C.1: Response to new shock "minus" response to RR shock



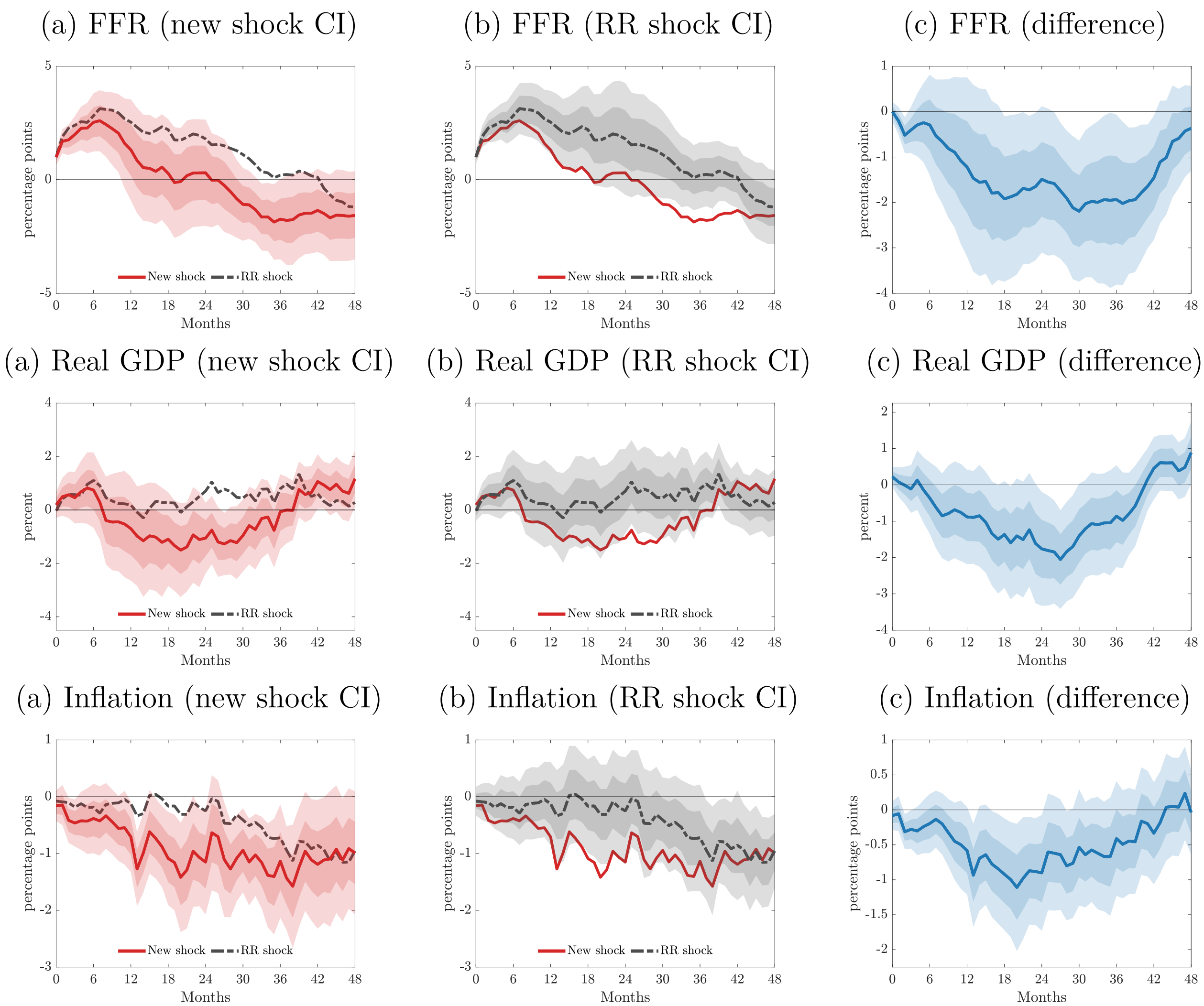
Notes: The figure shows the differences across impulse responses for capacity utilization, the unemployment rate, log consumption expenditures, log business inventories, log hours (in manufacturing), and credit spreads (BAA- minus AAA-rated corporate bond yield) to a monetary policy shock based on the local projection as specified along with (4.2). The difference is computed as the response to the new shock minus the response to the old shock for each outcome, respectively. The new monetary policy shock is identified as the residual from the Taylor rule regression in (4.1) whereas the conventional monetary policy shock is based on the same regression when $b_j = 0$ for $j > 1$, as in Romer and Romer (2004). The shaded areas indicate 68% and 95% confidence bands using standard errors robust to serial correlation and heteroskedasticity.

Figure C.2: Response to new shock “minus”response to Aruoba and Drechsel (2022) shock



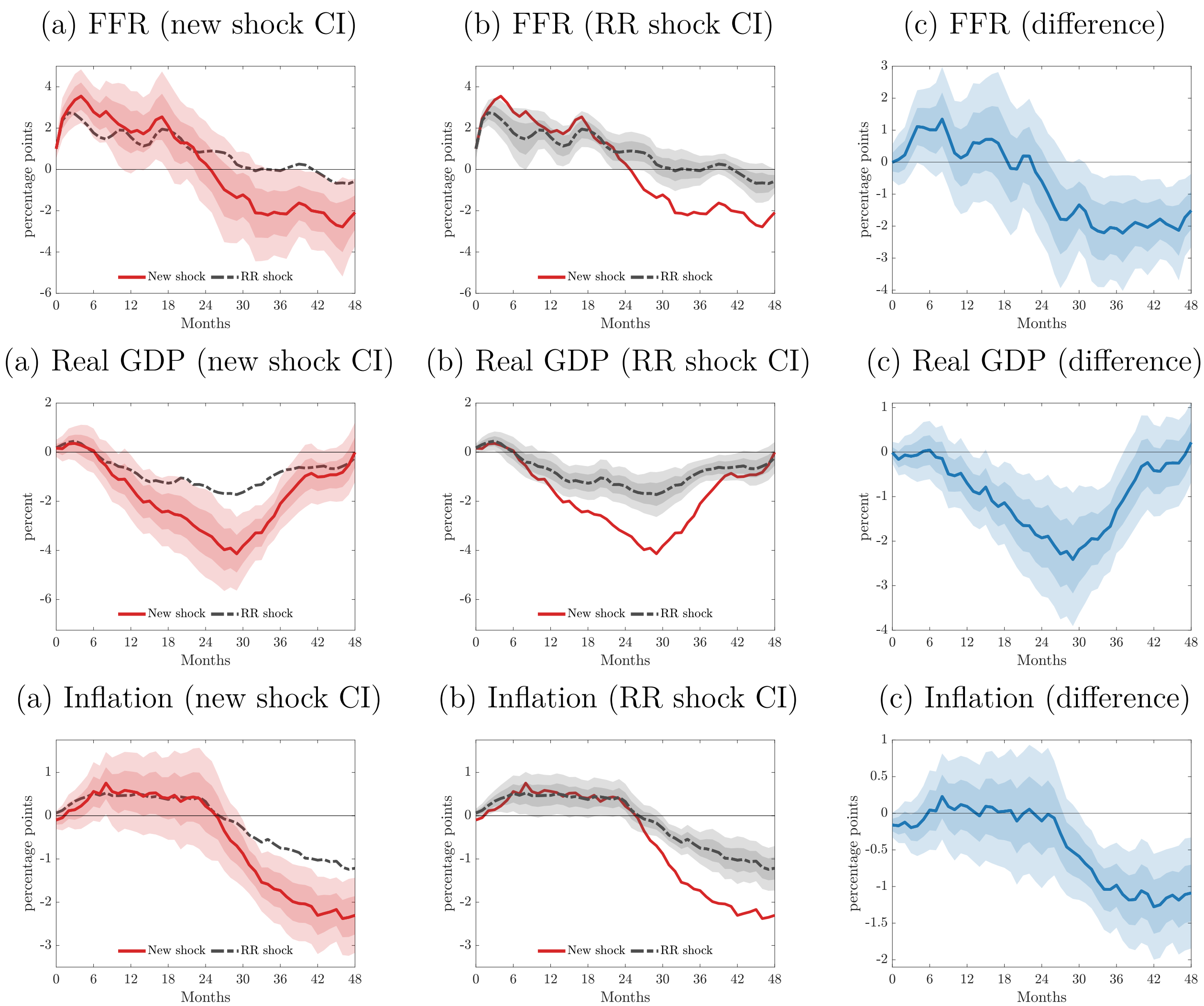
Notes: The figure shows the differences across impulse responses for the federal funds rate, log real GDP and the inflation rate to a monetary policy shock based on the local projection as specified along with (4.2). The difference is computed as the response to the new shock minus the response to the old shock for each outcome, respectively. The new monetary policy shock is identified as the residual from the Taylor rule regression in (4.1) where we put the Aruoba and Drechsel (2022) shock on the left-hand-side, whereas the conventional monetary policy shock is taken directly from Aruoba and Drechsel (2022). The shaded areas indicate 68% and 95% confidence bands using standard errors robust to serial correlation and heteroskedasticity.

Figure C.3: Responses for identification sample 1983-2007



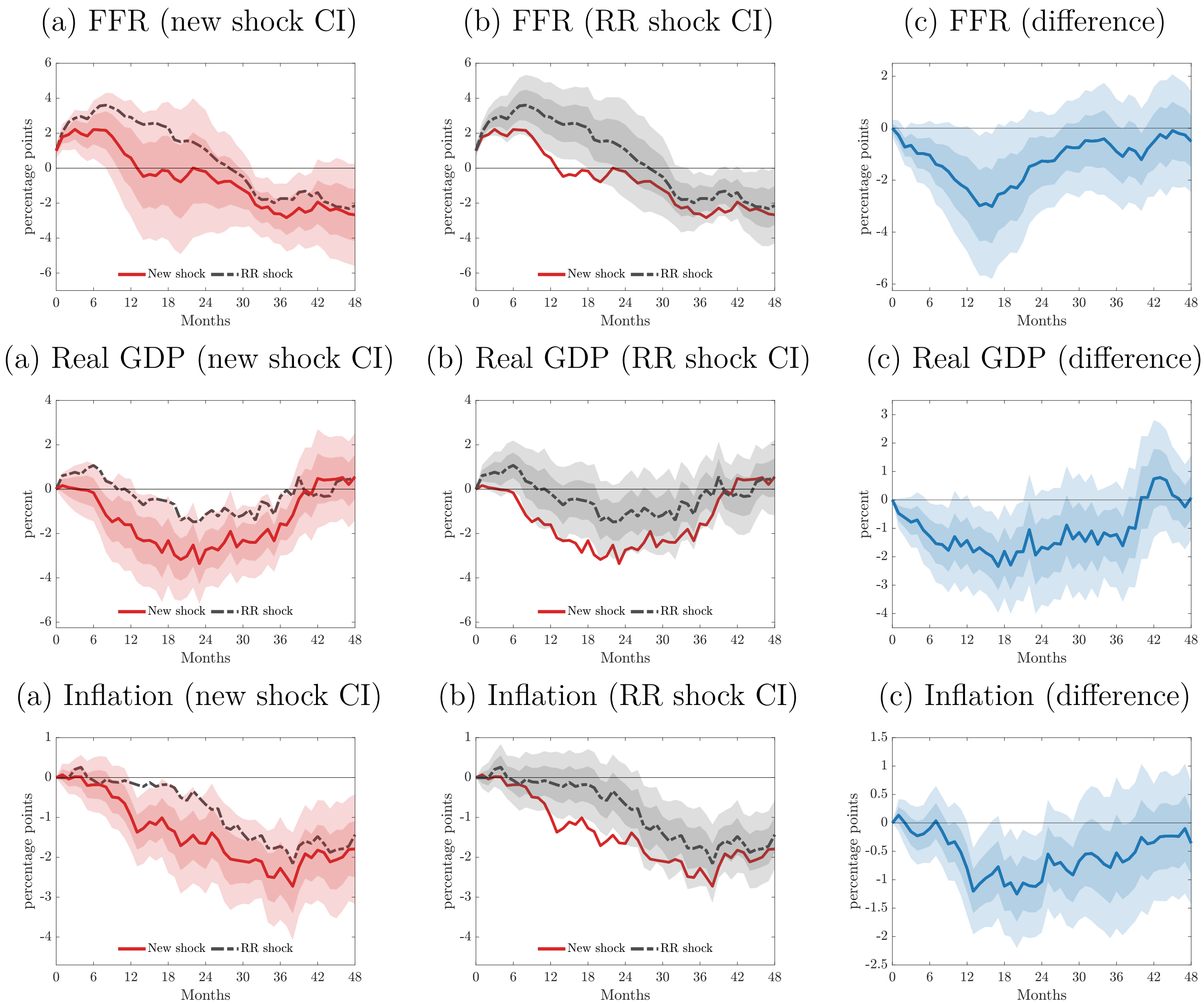
Notes: The figure shows responses of the federal funds rate, log real GDP and the inflation rate to a monetary policy shock based on the local projection as specified along with (4.2). The new monetary policy shock is identified as the residual from the Taylor rule regression in (4.1) whereas the conventional monetary policy shock is based on the same regression when $b_j = 0$ for $j > 1$, as in Romer and Romer (2004). The estimation sample for shock identification coincides with the impulse response estimation sample, running from 1983 until 2007. Columns 1 and 2 display the response to the new shock and conventional shock, respectively. Column 3 display the response to the new shock minus the response to the conventional shock. The shaded areas indicate 68% and 95% confidence bands using standard errors robust to serial correlation and heteroskedasticity.

Figure C.4: Responses for estimation sample 1969-2007



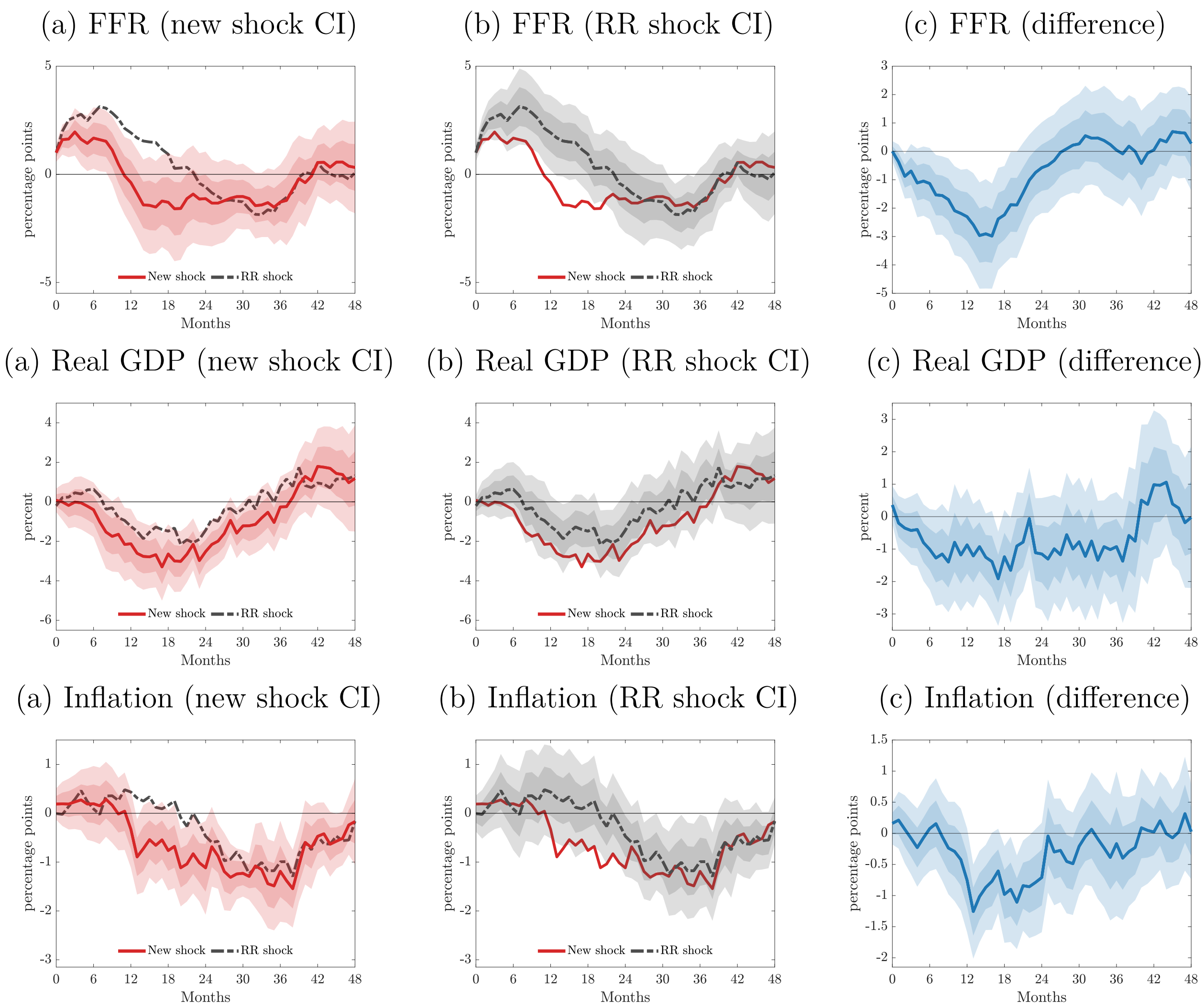
Notes: The figure shows responses of the federal funds rate, log real GDP and the inflation rate to a monetary policy shock based on the local projection as specified along with (4.2). The new monetary policy shock is identified as the residual from the Taylor rule regression in (4.1) whereas the conventional monetary policy shock is based on the same regression when $b_j = 0$ for $j > 1$, as in Romer and Romer (2004). The results correspond to the full sample, running from 1969 until 2007. Columns 1 and 2 display the response to the new shock and conventional shock, respectively. Column 3 display the response to the new shock minus the response to the conventional shock. The shaded areas indicate 68% and 95% confidence bands using standard errors robust to serial correlation and heteroskedasticity.

Figure C.5: Responses when imposing recursiveness assumption



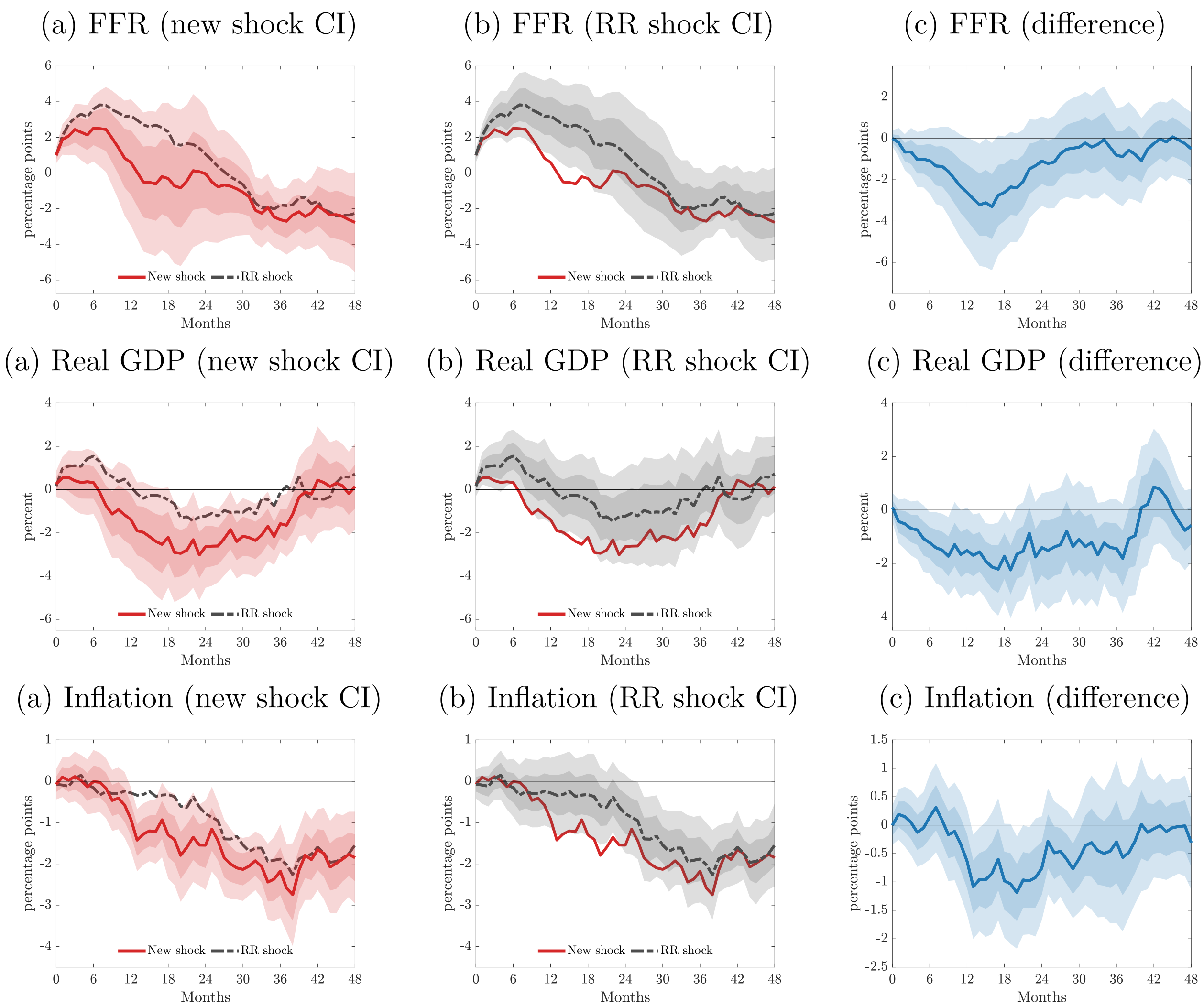
Notes: The figure shows responses of the federal funds rate, log real GDP and the inflation rate to a monetary policy shock based on the local projection as specified along with (4.2). Additionally, we control for contemporaneous log real GDP and inflation imposing the recursiveness assumption that monetary policy shocks affect these variables only with a one-month lag. The new monetary policy shock is identified as the residual from the Taylor rule regression in (4.1) whereas the conventional monetary policy shock is based on the same regression when $b_j = 0$ for $j > 1$, as in Romer and Romer (2004). Columns 1 and 2 display the response to the new shock and conventional shock, respectively. Column 3 display the response to the new shock minus the response to the conventional shock. The shaded areas indicate 68% and 95% confidence bands using standard errors robust to serial correlation and heteroskedasticity.

Figure C.6: Responses when controlling for S&P 500 and EBP



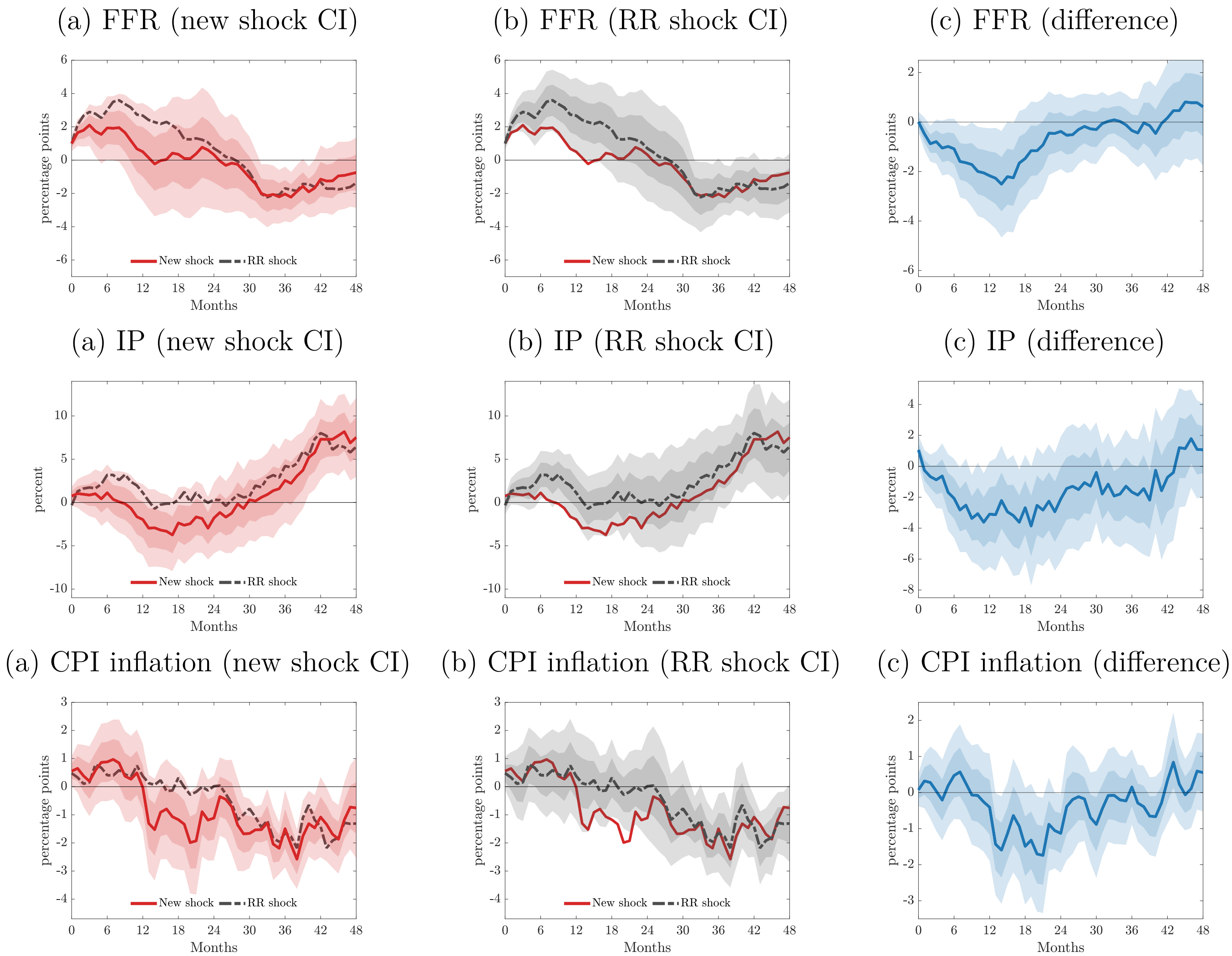
Notes: The figure shows responses of the federal funds rate, log real GDP and the inflation rate to a monetary policy shock based on the local projection as specified along with (4.2). Additionally, we control for 12 lags of both the S&P 500 and the excess bond premium from Gilchrist and Zakrajšek (2012). The new monetary policy shock is identified as the residual from the Taylor rule regression in (4.1) whereas the conventional monetary policy shock is based on the same regression when $b_j = 0$ for $j > 1$, as in Romer and Romer (2004). Columns 1 and 2 display the response to the new shock and conventional shock, respectively. Column 3 display the response to the new shock minus the response to the conventional shock. The shaded areas indicate 68% and 95% confidence bands using standard errors robust to serial correlation and heteroskedasticity.

Figure C.7: Responses when controlling for lagged shocks



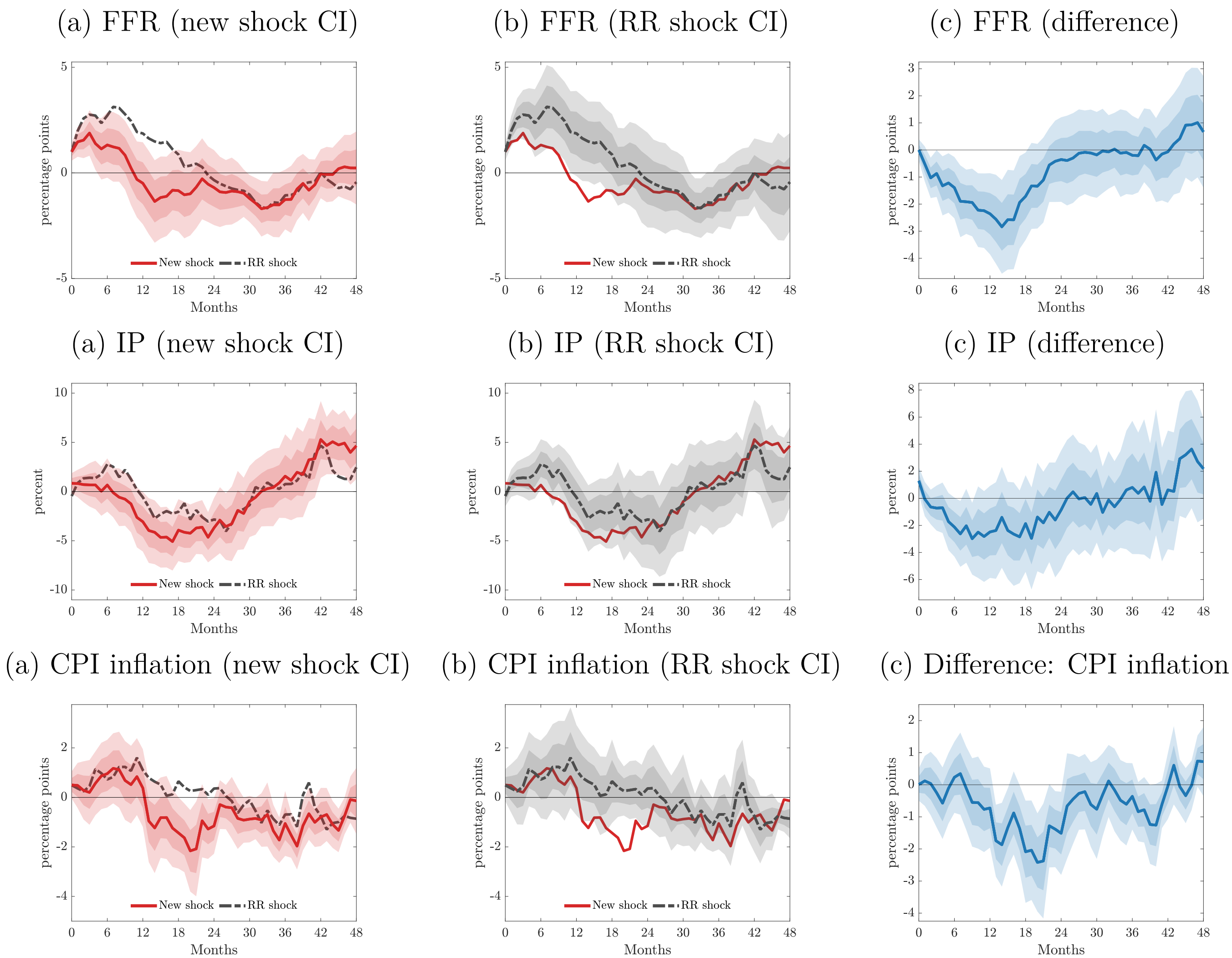
Notes: The figure shows responses of the federal funds rate, log real GDP and the inflation rate to a monetary policy shock based on the local projection as specified along with (4.2). Additionally, we control for 12 lags of monetary policy shock under consideration. The new monetary policy shock is identified as the residual from the Taylor rule regression in (4.1) whereas the conventional monetary policy shock is based on the same regression when $b_j = 0$ for $j > 1$, as in Romer and Romer (2004). Columns 1 and 2 display the response to the new shock and conventional shock, respectively. Column 3 display the response to the new shock minus the response to the conventional shock. The shaded areas indicate 68% and 95% confidence bands using standard errors robust to serial correlation and heteroskedasticity.

Figure C.8: Responses of IP and CPI



Notes: The figure shows responses of the federal funds rate, log industrial product and the CPI inflation rate to a monetary policy shock based on the local projection as specified along with (4.2). We control for 12 lags of both, the log of industrial production and CPI inflation instead of real GDP and inflation based on the GDP deflator. The new monetary policy shock is identified as the residual from the Taylor rule regression in (4.1) whereas the conventional monetary policy shock is based on the same regression when $b_j = 0$ for $j > 1$, as in Romer and Romer (2004). Columns 1 and 2 display the response to the new shock and conventional shock, respectively. Column 3 display the response to the new shock minus the response to the conventional shock. The shaded areas indicate 68% and 95% confidence bands using standard errors robust to serial correlation and heteroskedasticity.

Figure C.9: Responses of IP and CPI when controlling for S&P 500 and EBP



Notes: The figure shows responses of the federal funds rate, log industrial product and the CPI inflation rate to a monetary policy shock based on the local projection as specified along with (4.2). We control for 12 lags of both, the log of industrial production and CPI inflation instead of real GDP and inflation based on the GDP deflator. Additionally, we control for 12 lags of both the S&P 500 and the excess bond premium from Gilchrist and Zakrajšek (2012). The new monetary policy shock is identified as the residual from the Taylor rule regression in (4.1) whereas the conventional monetary policy shock is based on the same regression when $b_j = 0$ for $j > 1$, as in Romer and Romer (2004). Columns 1 and 2 display the response to the new shock and conventional shock, respectively. Column 3 display the response to the new shock minus the response to the conventional shock. The shaded areas indicate 68% and 95% confidence bands using standard errors robust to serial correlation and heteroskedasticity.