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THE FEDERAL RESERVE'S IMPLICIT INFLATION TARGET AND MACROECONOMIC DYNAMICS: AN SVAR ANALYSIS*

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This article identifies shocks to the Federal Reserve's inflation target as vector autoregression innovations that make the largest contribution to future movements in long-horizon inflation expectations. The effectiveness of this scheme is documented via Monte-Carlo experiments. The estimated impulse responses indicate that a positive shock to the target is associated with a large increase in inflation and long-term interest rates in the United States. Target shocks are estimated to be a vital factor behind the increase in inflation during the pre-1980 period and are an important driver of the decline in long-term interest rates over the last two decades.

1. INTRODUCTION

This article proposes a structural vector autoregression (SVAR) that can be used to identify shocks to the implicit inflation target of the Federal Reserve (Fed). The identification scheme exploits the idea that innovations to the inflation target are the main driver of *long-horizon* inflation expectations in the medium to the long run. Whereas policy, aggregate demand, and technology shocks can affect inflation expectations, their influence diminishes in the medium and long run if the monetary authority is perceived to be credible. Thus, deviations of predicted long-horizon inflation expectations from their realized values are largely driven by innovations to the inflation target. We use the methodology of Uhlig (2004a), and identify the inflation target shock as the VAR innovation that makes the largest contribution to the forecast error variance (FEV) of a measure of long-horizon inflation expectations.

Estimates of this SVAR using U.S. data indicate that an inflation target shock that raises long-horizon inflation expectations by 1% has a large impact on the U.S. economy. This shock is associated with a contemporaneous impact on annual Consumer Price Index (CPI) inflation of about 1.5–3%, and a peak increase in short- and long-term interest rates of a similar magnitude. Real Gross Domestic product (GDP) growth is estimated to increase by about 0.6–1.2% on impact in response to this shock. The contribution of this shock to the FEV of GDP growth and inflation, in our benchmark model, is 10% and 70%, respectively, at the five-year horizon. The shock is especially important for long-term interest rates with a long-run contribution to the FEV of around 60–70%.

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Most of therecent analysis of inflation target shocks has been based on state-space models (e.g., Kozicki and Tinsley, 2005) or dynamic stochastic general equilibrium (DSGE) models (Ireland, 2007; De Graeve et al., 2009). These approaches require strong assumptions regarding the process governing the inflation target, the structure of the economy being modelled,or the equations of the state-space system. In contrast, our procedure is largely agnostic regarding the dynamic relationship among the endogenous variables, placing only minimal restrictions.

We use an extensive Monte-Carlo experiment to show that the proposed identification scheme can be used in a number of settings. The model considered in this study is a typical New Keynesian model (á la Smets and Wouters (2007) and Justiniano et al. (2010)) augmented with liquidity frictions that allow the government's long-term maturity debt to be used by households as an additional instrument to smooth their consumption allocation across time (De Graeve and Theodoridis, 2016). [1] The nominal (prices and wages) rigidities allow the central bank to influence economic activity by adjusting the policy rate based on a reaction function that features a time-varying inflation target. The introduction of the long-term asset (and its prices) is motivated by the strong interaction between monetary policy announcements and financial market participants, especially those that hold government debt. Using an estimated version of this model as the data-generating process (DGP), we show that the strategy can successfully recover the inflation target shock and its impact on macroeconomic and financial variables. Importantly, this identification scheme continues to perform well even if the DGP is characterized by regime switches in policy activism or if agents in the model have imperfect information regarding the target. This shows that the VAR-based identification scheme is consistent with a range of structural models and can be used as a benchmark.

The success of the identification scheme relies on the fundamental building block of the New Keynesian economic theory, which requires the monetary authority to act as the nominal anchor. A credible central bank would always adjust its policy instrument to keep the inflation close to its target, ensuring in this way that agents' long-term inflation expectations and the target coincide. In other words, long-term inflation expectations could decouple from the inflation target only if monetary policymakers allow it. The adverse supply (price/wage markup or/and energy) shocks that lead a negative output gap are natural examples of the central bank's determination to deliver the inflation target even at the cost of higher unemployment (e.g., Volcker's disinflation).[2] As explained by Del Negro et al. (2015), the behaviour of inflation during the Great Recession is another illustration of the central bank's ability to keep long-term inflation expectations well anchored despite the collapse of the economic activity. Under this narrative, the long-term inflation expectations series can be viewed as a strong instrument to proxy the inflation target shocks.The identification scheme extracts the slow-moving component of the series that captures the anticipated policy actions by the Fed to deviate persistently from its objective function. We refer to these deviations as inflation target shocks.

The article is organized as follows: Section 2 describes the SVAR employed in thisstudy, and the shock identification scheme. The empirical results are presented in Section 3, while Section 4 describes the Monte-Carlo experiments used to test the method's performance and Section 5 concludes.

2. IDENTIFYING SHOCKS TO THE INFLATION TARGET

Our empirical strategy is based on the following simple idea. From a theoretical point of view, long-horizon inflation expectations π^{LH} are driven by shocks to the central bank's in-

[1] The model collapses to a standard New Keynesian model by setting liquidity friction equal to zero.

[2] We illustrate these points through a number of simulation exercises in Section 4.

flation target ($\varepsilon_t^{\pi^*}$) and range of additional disturbances ($\tilde{\varepsilon}_t$) which include technology shocks and policy and nonpolicy aggregate demand shocks:

$$\pi^{LH} = f\left(\varepsilon_t^{\pi^*}, \tilde{\varepsilon}_t\right). \tag{1}$$

However, over the medium- to long-run horizons, the role of $\varepsilon_t^{\pi^*}$ dominates in relative terms. Whereas $\tilde{\varepsilon}_t$ can affect long-horizon inflation expectations, fluctuations in π^{LH} in the medium- to long run are largely driven by shocks to the inflation target. In other words, if, on average, across the sample, the monetary authority reacts systematically to changes in inflation and is, at least, perceived to be credible in the long run, then long-horizon inflation expectations would coincide with the inflation target. As a consequence, any further changes in long-horizon inflation expectations reflect shocks to the inflation target.

We use a VAR model to approximate these economic disturbances. In particular, we estimate:

$$Y_t = \alpha + \sum_{j=1}^{P} \beta_{t-j} Y_{t-j} + A_0 \varepsilon_t, \tag{2}$$

where the endogenous variables Y_t include a measure of long-horizon inflation expectations $\hat{\pi}^{LH}$ and a set of macroeconomic and financial variables X_t, and we order $\hat{\pi}^{LH}$ first for simplicity. The orthogonal shocks are denoted by ε_t and A_0 represents the contemporaneous impact matrix such that $A_0 A_0' = \Sigma$. It is well known that A_0 is not unique, but the space spanned by these matrices can be written as $\tilde{A}_0 Q$ where Q is an orthonormal rotation matrix such that $Q'Q = I$.

The shock to the inflation target is then identified by imposing the restriction that this shock makes the largest contribution to the FEV of $\hat{\pi}^{LH}$. Consider the VAR in structural moving-average form:

$$Y_t = B(L) A_0 \varepsilon_t.$$

The k-period–ahead forecast error of the ith variable is given by

$$Y_{it+k} - \hat{Y}_{it+k} = e_1 \left[\sum_{j=0}^{k-1} B_j \tilde{A}_0 Q \varepsilon_{t+k-j} \right],$$

where e_1 is a selection vector that picks out $\hat{\pi}^{LH}$ in the set of variables. Following Uhlig (2004a), the proposed identification scheme thus amounts to finding the column of Q that solves the following maximization problem:

$$\arg\max_{Q_1} e_1' \left[\sum_{k=0}^{K} \sum_{j=0}^{k-1} B_j \tilde{A}_0 Q_1 Q_1' \tilde{A}_0' B_j' \right] e_1$$

such that $Q_1' Q_1 = 1$. Here, Q_1 is the column of Q that corresponds to the shock that explains the largest proportion of the FEV of the first variable in the VAR, $\hat{\pi}^{LH}$. As shown by Uhlig (2004b), the maximization can be rewritten as an eigenvalue eigenvector problem, and a solution can be readily obtained.[3]

[3] Denoting $B_j \tilde{A}_0$ by R_j, the objective function is $\arg\max_{Q_1} e_1' [\sum_{k=0}^{K} \sum_{j=0}^{k-1} R_j Q_1 Q_1' R_j'] e_1 \text{st } Q_1' Q_1 = 1$. The objective function can be rewritten as $\arg\max_{Q_1} e_1' [\sum_{k=0}^{K} \sum_{j=0}^{k-1} R_j Q_1 Q_1' R_j'] e_1 = \sum_{k=0}^{K} \sum_{j=0}^{k} trace[Q_1' R_j' (e_1 e_1') R_j Q_1] = Q_1' [\sum_{k=0}^{K} \sum_{j=0}^{k} R_j' (e_1 e_1') R_j] Q_1 = Q_1' S Q_1$, where $S = [\sum_{k=0}^{K} \sum_{j=0}^{k} R_j' (e_1 e_1') R_j]$. The Lagrangian for this maximization problem is $L = Q_1' S Q_1 - \lambda (Q_1' Q_1 - 1)$ with first-order condition $S Q_1 = \lambda Q_1$. Note that the first-order condition is the definition of an eigenvalue decomposition.

The proposed identification differs from the method used in Michelis and Iacoviello (2016) to identify target shocks. These authors impose exact long-run restrictions on the behaviour of inflation and interest rates. In contrast, our approach is more agnostic and focuses on the medium-run dynamics of variables instead of their behaviour in the infinite future which may be hard to pin down with a limited sample (see Erceg et al., 2005). In a recent contribution, Arias et al. (2016) uses a mix of sign and zero restrictions to identify the systematic component of monetary policy as embodied in the contemporaneous coefficients in a policy rule. In related work, Uribe (2017) uses a mix of long-run and sign restrictions to distinguish between permanent and transitory monetary policy shocks and provides evidence in favour of the Neo-Fisher effect. In contrast, our approach focuses on the implicit inflation target and imposes no explicit restrictions on the interest rate equation in the SVAR model.

3. EMPIRICAL ANALYSIS

3.1. *Data and Model Specification.* Implementation of the SVAR model described above requires a series of long-horizon inflation expectations. The existing literature typically uses either survey-based measures or those derived from financial market prices. For our purpose, an important concern relates to the span of the data available. In other words, it may be the case that shocks to the inflation target are not observed regularly, and therefore, the proposed identification strategy is more effective in a reasonably long sample. With this in mind, our benchmark proxy for π^{LH} is a spliced survey-based measure of long-horizon Personal Consumption Expenditures (PCE) inflation expectations used in the Federal Reserve board model. This measure (with mnemonic PTR) is available on a quarterly basis from 1968Q1 to 2016Q3. In the earlier part of the sample, PTR uses estimates of inflation expectations from Kozicki and Tinsley (2001). Data for the 1980s are obtained from the discontinued Decision Makers poll (DMP). Published by Richard Hoey, this survey aimed to capture the 5- to 10-year-ahead expectations of participants in the financial markets. From 1991Q4 onward, the series is based on 1- to 10-year-ahead inflation expectations taken from the Survey of Professional Forecasters.

We check the robustness of the results by using an alternative measure based on blue chip economic indicators and the Livingstone survey. Ten-year-ahead expectations regarding CPI inflation are available from the latter survey since 1991 and are published in June and December of each year. This survey represents the views of academic and nonacademic economists. Prior to 1991, this series is based on lomg-horizon forecasts of CPI inflation included in blue chip economic indicators. These forecasts are published in March and October and are available from October 1979.[4] As these data are biannual, we use a mixed frequency version of the VAR model (see Schorfheide and Song, 2015) described below. As this series is available at a lower frequency and for a smaller period, PTR remains our preferred proxy for π^{LH}.

The two inflation expectations series are shown in Figure 1. The figure shows that over the sample period where both measures are available, their movements are similar, with an estimated correlation of 0.96. Both series reach their peak at the end of 1980 and then decline sharply. Long-horizon inflation expectations have been fairly stable in the post-2000 period.

The benchmark VAR model is given by

$$Y_t = \alpha + \sum_{j=1}^{P} \beta_{t-j} Y_{t-j} + v_t, \tag{3}$$

where α is a vector of intercepts, Y_t includes $\hat{\pi}^{LH}$, real GDP growth (y_t), annual CPI inflation (π_t^a), the 10-year government bond yield (I_t), and the three-month treasury bill rate (R_t). We also estimate an extended version of this model that includes real personal consumption

[4] From 1979 to 1983, the blue chip forecasts are for the Gross National Product (GNP) deflator. A combined series is made available by the Federal Reserve Bank of Philadelphia.

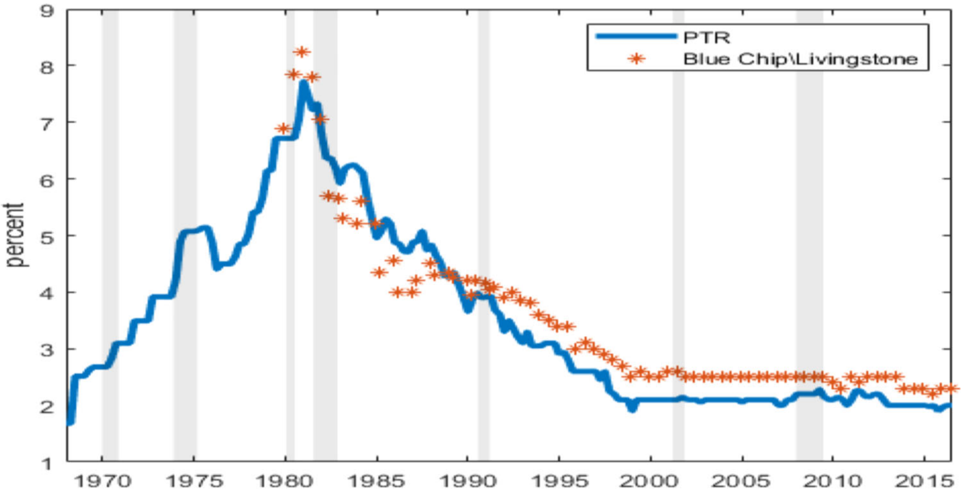


FIGURE 1

MEASURES OF 10-YEAR INFLATION EXPECTATIONS

expenditure (C_t) and real private fixed nonresidential investment (inv_t). The data for the 10-year yield are obtained from Global Financial data. All remaining variables are taken from the Federal Reserve Bank of St. Louis FRED database. The Appendix describes the data sources in detail. When the blue chip and Livingstone series are used for $\hat{\pi}^{LH}$, the model is augmented by an observation equation that implements the assumption that the observed expectations data are an average of missing observations in the previous and current quarter. These missing observations are treated as latent variables with the transition equation given by (3) in companion form.

The lag length P is set to 4 in the benchmark model. We adopt a Bayesian approach to model estimation and use a Gibbs sampling algorithm to approximate the posterior distribution of the parameters. As described in the technical appendix, we use a natural conjugate prior with tightness set to values commonly used in the literature for U.S. data. As discussed below, the results are not sensitive to the tightness of the prior. The Appendix provides details of the conditional posterior distributions and the steps of the Gibbs sampler. We also provide a description of the extended algorithm used to estimate the mixed frequency VAR model when the inflation expectations based on the blue chip and Livingstone surveys are employed in the estimation.

As discussed above, the shock to the implicit inflation target is identified via the restriction that this shock makes the largest contribution to the FEV of $\hat{\pi}^{LH}$ at horizon K. The benchmark model uses $K = 40$, but the results are robust to using a longer horizon.

3.2. *Empirical Results.* Figure 2 presents the inflation target implied by the historical decomposition from the benchmark SVAR model that uses PTR as the measure of long-horizon inflation expectations. This is calculated as the portion of inflation driven by the identified inflation target shocks, with the remaining innovations set to zero. The estimates of the target level show a number of similarities to estimates of this object presented in Kozicki and Tinsley (2005), Coibion and Gorodnichenko (2011), and Ireland (2007). In particular, the mid- and the late-1970s saw the target rise substantially with peaks of about 10%. The rise in the estimated target in these periods lagged the increase in actual inflation, suggesting that the Fed was accommodating the impact of inflationary shocks (see Kozicki and Tinsley, 2005). After the appointment of Paul Volcker to the chairmanship of the Fed in 1979Q4, both target and actual inflation declined. After the mid-1980s, the target level has hovered close to the 2% mark.

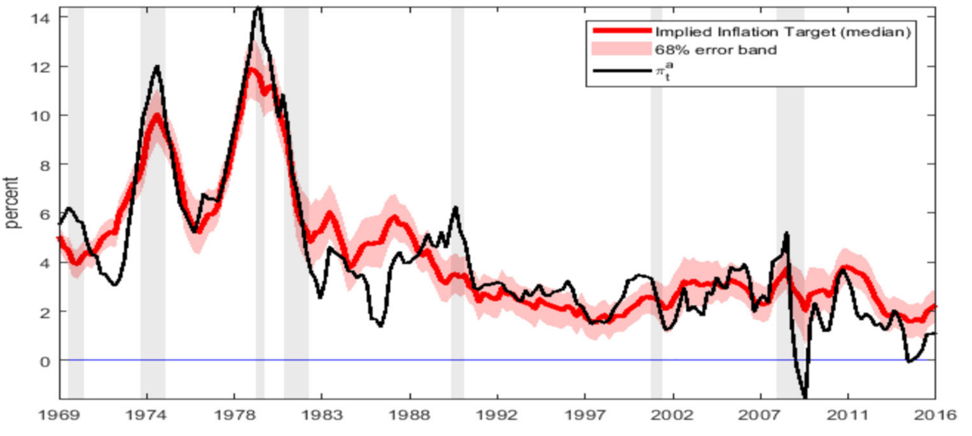
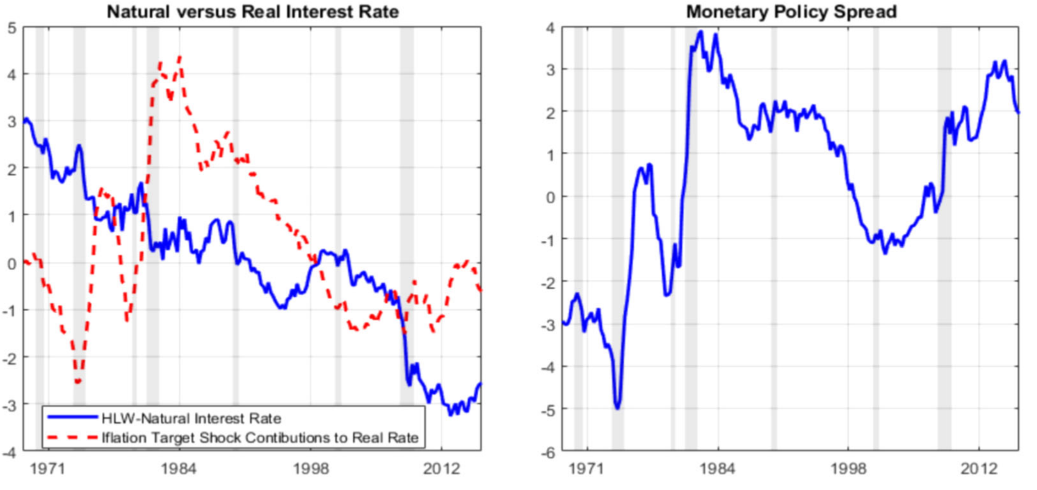


FIGURE 2

THE FEDERAL RESERVE'S INFLATION TARGET AND ACTUAL INFLATION



NOTES: The left-hand-side figure plots the Holston et al. (2017) natural interest rate estimate (blue solid line) against the contribution of the inflation target shock to the real rate (red dashed line). The right-hand-side figure plots the difference between the two lines.

FIGURE 3

MONETARY POLICY STANCE

The left-hand side of Figure 3 plots the Holston et al. (2017) natural interest rate estimate (solid blue line) against the inflation target contribution to the real interest rate (red dashed line) estimated using the VAR model. Similar to Bianchi et al. (2022), we also display the monetary policy spread (right-hand side), defined by the authors as the difference between the real and natural interest rate indicating the monetary policy stance. However, in our case, the real interest rate measure captures only the contributions of the inflation target shock, and consequently, the policy stance displayed on the right-hand side of Figure 3 accounts only for the inflation target instrument. Negative values of the monetary policy spread imply accommodative policy, whereas positive values suggest that monetary policy had been restrictive during these periods. The inspection of Figures 2 and 3 indicates that the high inflation seen until 1980 is associated with accommodative monetary policy. The policy spread turned positive between 1980 and 2000, coinciding with the protracted inflation rate decline and its stabilization. Policy turned looser in 2000 in the aftermath of the dot-com bubble collapse and the subsequent crisis. Finally, policy (again accounting only for the inflation target shock) appears to be tight during the zero lower bound period.

3.2.1. *Impulse responses.* Figure 4 presents the impulse responses to an inflation target shock. The figure presents the response to a shock that raises $\hat{\pi}^{LH}$ by 1% on impact. The impact effect on GDP growth is estimated to be large (1.2%) but dissipates quickly. In terms of the cumulated level of GDP ($\tilde{y}_t$), this implies an increase of about 1% that is statistically different from zero for three quarters. The initial increase in inflation is large and the response displays persistence—the impact at the 10-year horizon estimated to be about 1%. The last panel in the figure shows that the increase in π_t^a is larger compared to the rise in the short rate over the first three years of the horizon. As a consequence, the ex-post real interest rate declines substantially before increasing by about 1.5% over the second half of the horizon. Whereas the response of the long rate I_t is more sluggish than that of the short rate, the magnitude of the two responses is very similar at long horizons.

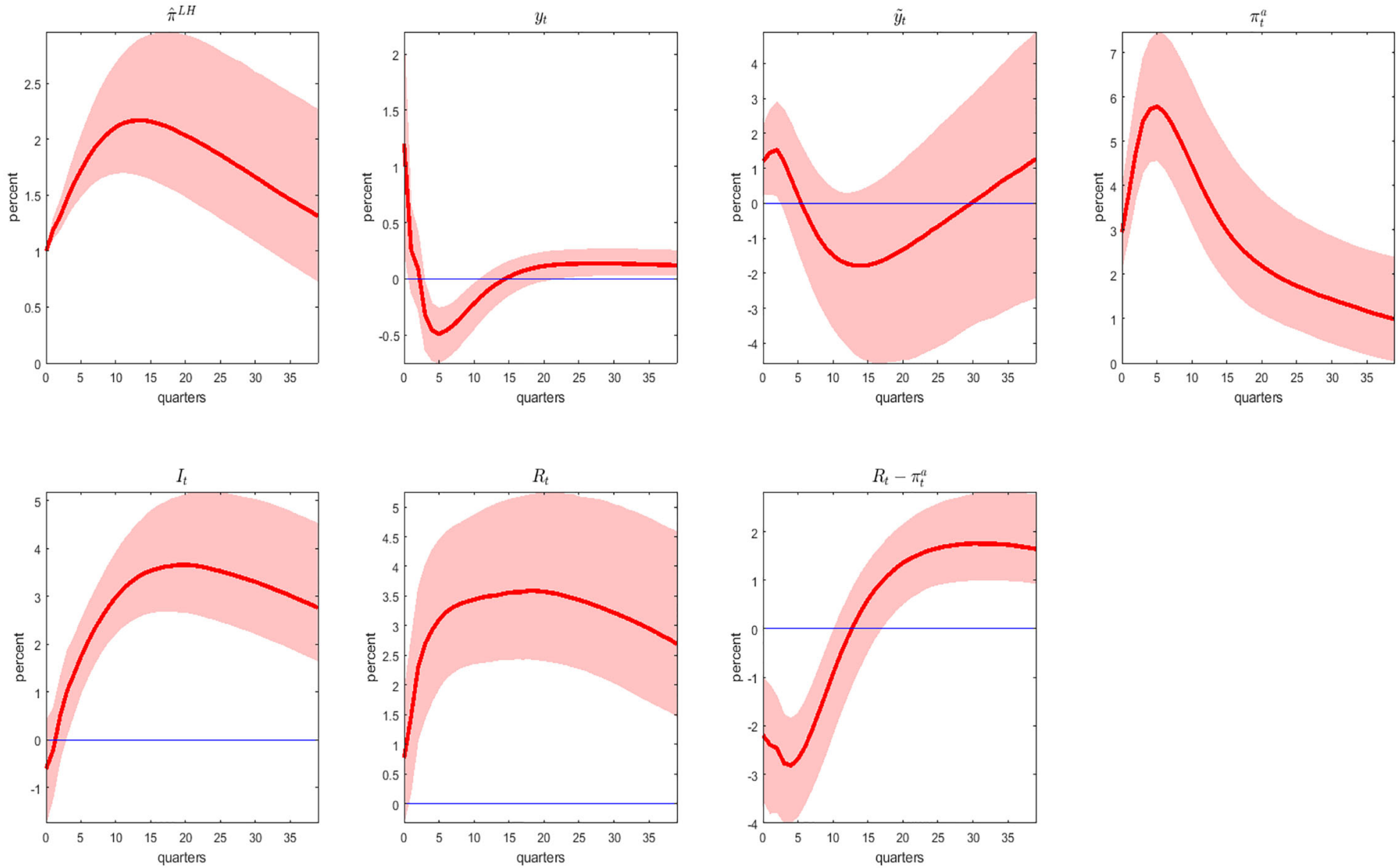
Figure 5 displays the estimated response of consumption (C_t) and investment growth (inv_t). The target shock is associated with a sharp increase in both variables, with the rise in inv_t more persistent of the two. Whereas the increase in the level of consumption is transient, the level of investment remains elevated for about four quarters before returning to base.

The transmission mechanism of the shock is as follows: the monetary authority announces an increase in the inflation target. Given that the central bank's credibility is unquestionable, both households' and firms' long-term inflation expectations increase. Output is demand-driven in the short run, and the only way for high inflation to occur is via more robust demand (relative to supply). Elevated consumption and investment demand can only exist via real rates that are lower relative to steady state. Reduced real rates finance higher aggregate demand, which translates to higher labour and capital demand and, consequently, to higher working capital expenses (i.e., wages and the cost of capital) given supply. Current inflation starts rising because the marginal cost increases. The output gap also increases, given that the potential supply is unaffected by inflation target shocks. Higher current inflation and output gap result in higher current and future policy rates. Expectations about higher policy rates drive up long-term interest rates. As the policy rate increases by less than inflation initially, real interest rates are negative but increase and become positive as inflation declines.[5]

To check the robustness of these results to the measure of long-horizon inflation expectations, we reestimate the VAR model using the series based on the blue chip forecasts and the Livingstone survey as an additional endogenous variable. As discussed above, this VAR model entails the estimation of missing inflation expectations data, as well as the VAR parameters. Note also that the estimation sample excludes the 1970s due to the unavailability of the blue chip measure. Given the shorter sample and to keep the state-space parsimonious, we fix the lag length to 2. The target shock is identified as the disturbance that makes the largest contribution to the FEV of *both* inflation expectations measures at horizon $K = 40$. Note that the results remain virtually unchanged if only the FEV of the blue chip series is targeted during identification.

The impulse responses from this alternative model are shown in Figure 6. The null hypothesis of a zero response of GDP and inflation to this shock can be rejected at short and medium horizons. The magnitude of these two responses, however, is estimated to be different than those obtained from the benchmark model. The increase in GDP is more persistent than the benchmark, whereas inflation rises by a smaller amount. As in the benchmark model, the real rate declines initially, with the response reversing after one year. Both the short- and the long-term interest rate responses are large and persistent, albeit the peak response is estimated to be smaller than the benchmark case. In summary, the estimated responses from this model are qualitatively similar to the benchmark case.

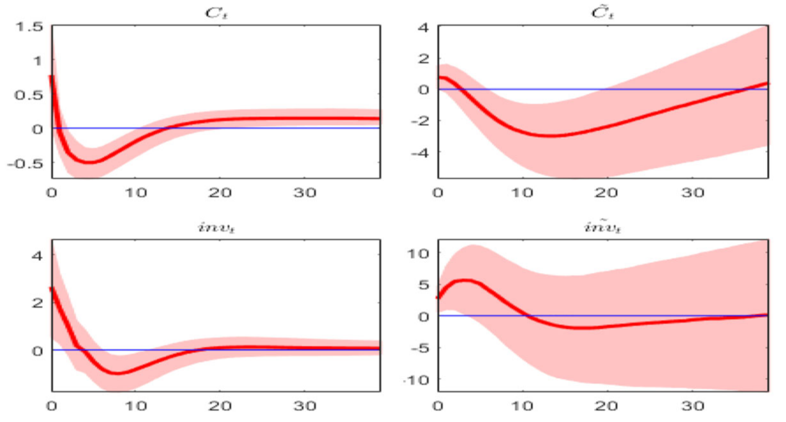
[5] The welfare implications of using this policy instrument by monetary institutions are not assessed in this study.



NOTES: The responses are shown for PTR ($\hat{\pi}^{LH}$), real GDP growth (y_t), real GDP level ($\tilde{y}_t$), CPI inflation (π_t^a), the 10-year government bond yield (I_t), the three-month treasury bill rate (R_t), and the real interest rate. The solid lines are posterior medians, whereas the shaded area is the 68% error band.

FIGURE 4

IMPULSE RESPONSE TO AN INFLATION TARGET SHOCK



NOTES: The responses are shown for real consumption expenditure growth (C_t), real fixed nonresidential investment growth (inv_t), real consumption level ($\tilde{C}_t$), and real investment level ($i\tilde{n}v_t$). The solid lines are posterior medians whereas the shaded area is the 68% error band.

FIGURE 5

IMPULSE RESPONSE TO AN INFLATION TARGET SHOCK

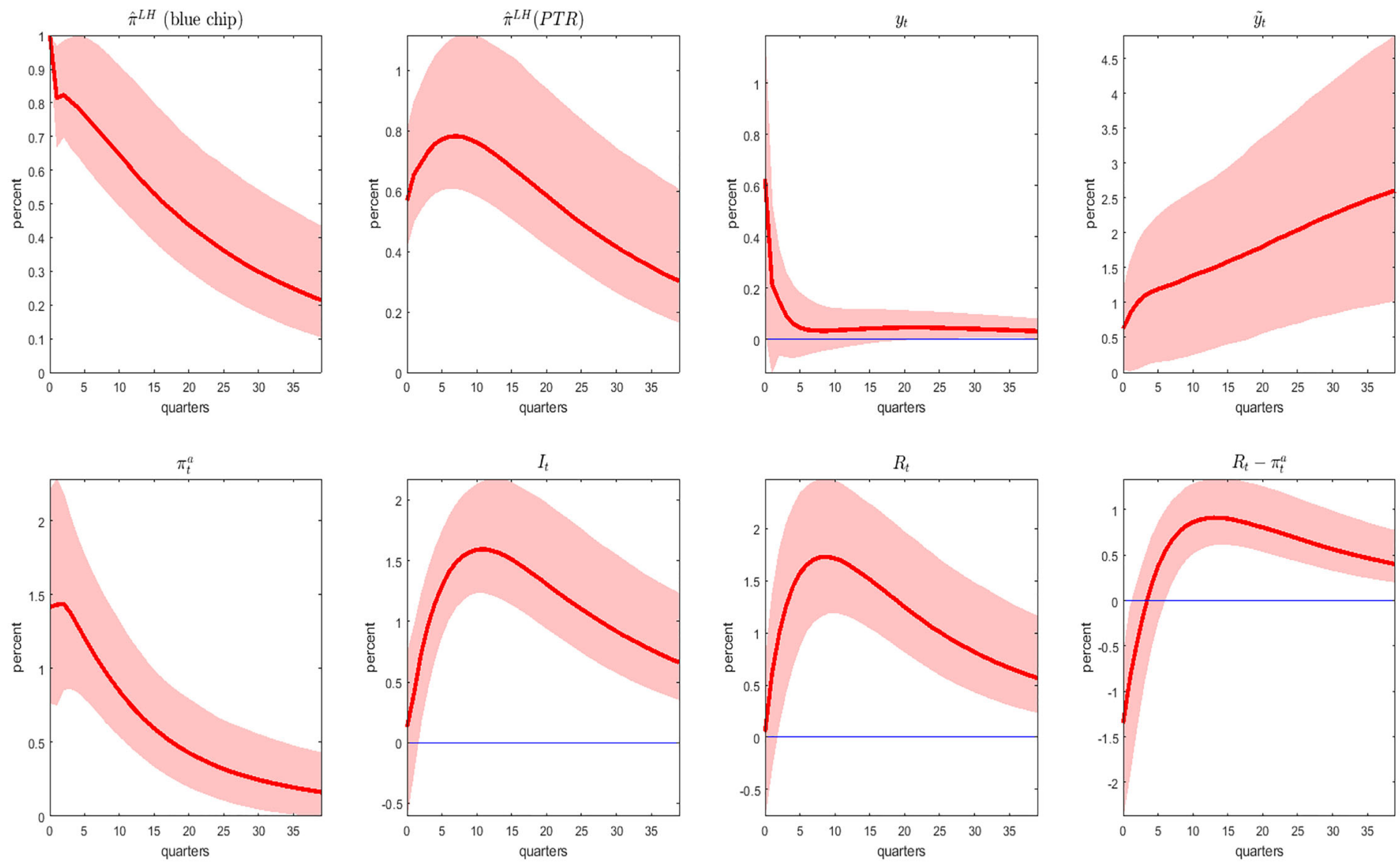
However, the estimated magnitude of the responses of the nominal variables is smaller than the benchmark, whereas GDP shows a more persistent increase. These differences may reflect the fact that the mixed frequency VAR treats some of the observations on $\hat{\pi}^{LH}$ as unobserved and requires the estimation of a larger number of parameters. An alternative explanation can be based on the observation that the post-1980 sample is dominated by the Great Moderation, and a change in the impact of structural shocks over this period is well documented in the literature (see, e.g., Galí and Gambetti, 2009). The difference in the responses might also be driven by measurement errors in PTR during the 1970s.[6] When we estimate the benchmark VAR (using PTR) on the post-1980 sample, the impulse responses of GDP is very similar to that obtained from the mixed frequency VAR (see Section 4 of the technical appendix). However, the response of the nominal variables is estimated to be larger. This would suggest that both the lower frequency of the blue chip/Livingstone series *and* the Great Moderation may be factors behind the change in the magnitude of the responses. In addition, one cannot fully rule out the influence of measurement errors. Nevertheless, even if the post-1980 responses are considered to be the more accurate estimate of the impact of this shock, the magnitude of the effect is large and clearly different from zero from a statistical perspective.

3.2.2. *Further robustness checks.* The results of the benchmark model are robust to variations in the identification scheme and changes in model specification. We summarize this analysis here, whereas the details of these additional robustness checks are given in the online technical appendix.

First, we augment the identification scheme with a zero restriction on the long-run impact of the target shock on real GDP and the real interest rate. This restriction incorporates the view that the target shock should not affect the real economy in the long run. As shown in the technical appendix, these additional restrictions do not materially affect the benchmark results. The main results also survive the addition of variables such as oil prices and principal components extracted from the FRED-QD database to account for potential information insufficiency (see Forni and Gambetti, 2014), estimation over the pre-2007 sample and changes in the prior specification.

We follow Ben Zeev and Pappa (2017) and consider the cross-correlation between the estimated target shock and shocks identified in the literature to be important for business cycle

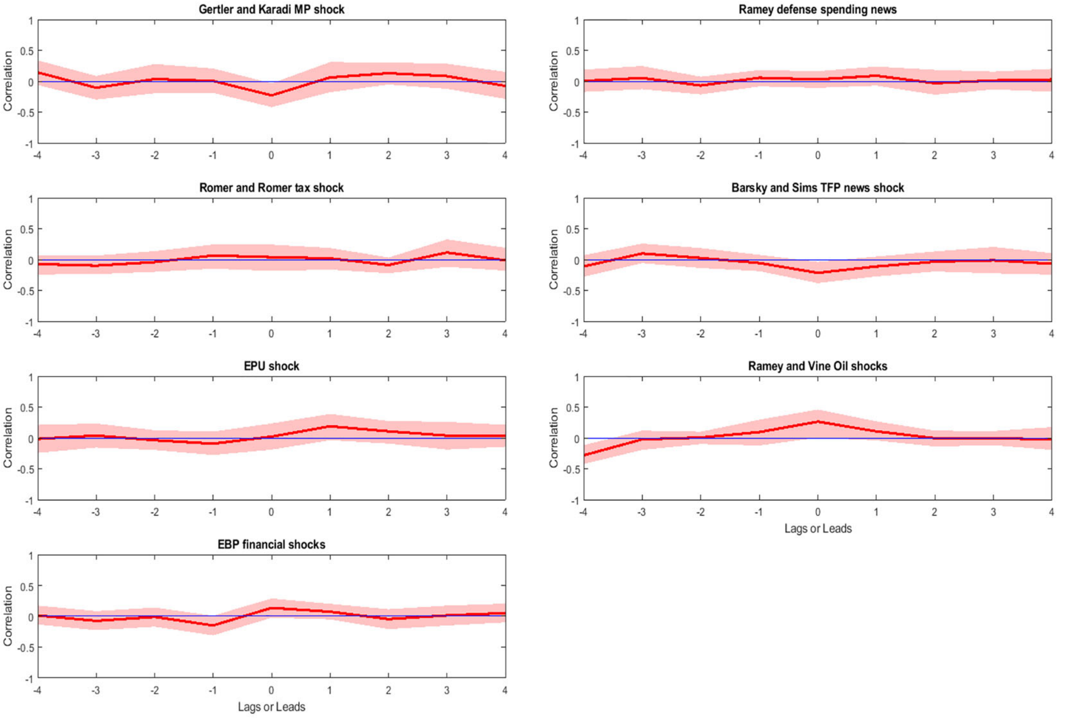
[6] Over this decade, PTR is based on the estimates of inflation expectations by Kozicki and Tinsley (2001).



NOTES: The responses are shown for Blue Chip/Livingstone survey ($\hat{\pi}^{LH}$ blue chip), PTR, ($\hat{\pi}^{LH}$ PTR) real GDP growth (y_t), real GDP level ($\tilde{y}_t$), CPI inflation (π_t^a), the 10-year government bond yield (I_t), the three-month treasury bill rate (R_t), and the real interest rate. The solid lines are posterior medians, whereas the shaded area is the 68% error band.

FIGURE 6

IMPULSE RESPONSE TO AN INFLATION TARGET SHOCK



NOTES: The solid line is the median correlation, whereas the error band represents the 95% confidence interval obtained via Bootstrap.

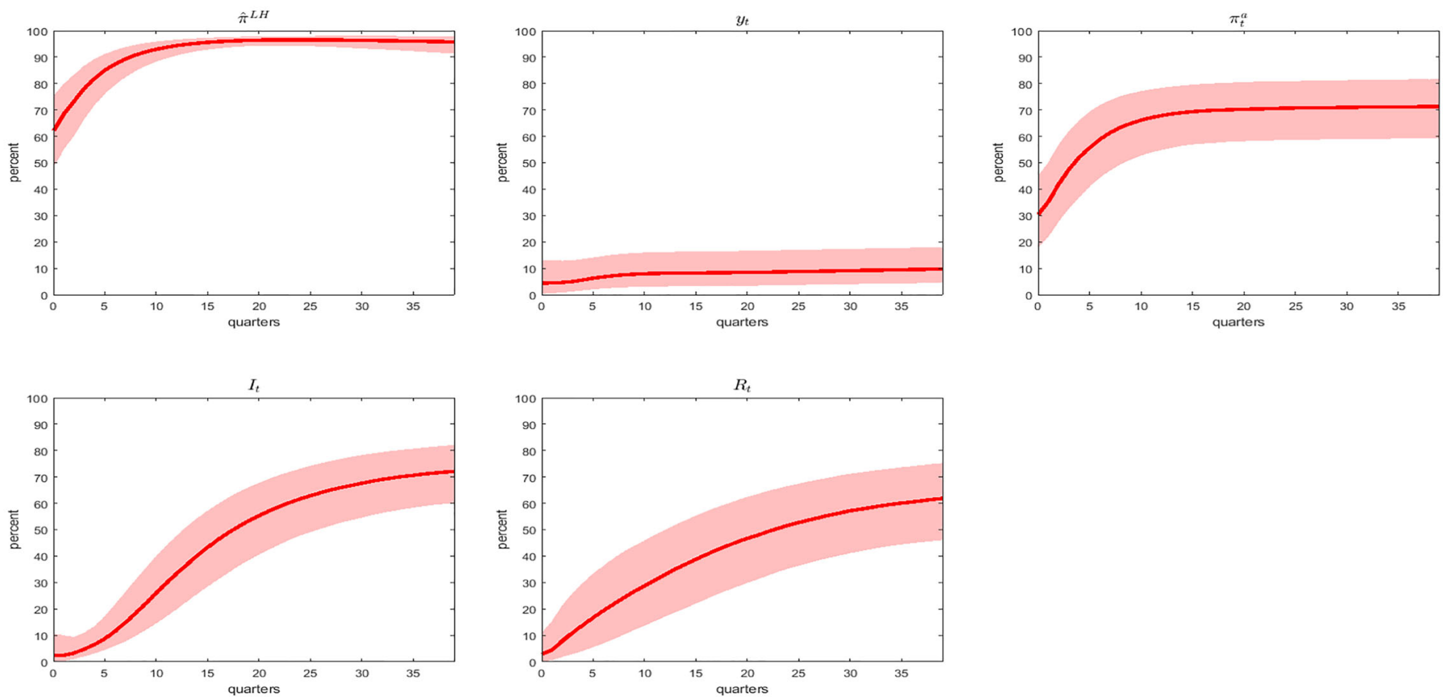
FIGURE 7

CORRELATION BETWEEN THE TARGET SHOCK AND OTHER STRUCTURAL SHOCKS

fluctuations. As shown in Figure 7, we consider monetary policy shocks identified by Gertler and Karadi (2015) and fiscal shocks taken from Ramey (2011) and Romer and Romer (2010). Policy uncertainty (EPU) shocks are proxied as residuals to an AR(4) model using the economic policy uncertainty index of Baker et al. (2016). Total Factor Productivity (TFP) news shocks are taken from Barsky and Sims (2011), whereas we use the measure of oil shocks constructed by Ramey and Vine (2011). Finally, we consider the innovations to the excess bond premium (see Gilchrist and Zakrajsek, 2012) obtained via a recursive VAR (using GDP, CPI, a short-term interest rate, and the excess bond premium) as a measure of financial shocks. Figure 7 shows that the estimated correlations are insignificant at most lags or leads. Moreover, the magnitude of the estimated correlations is small in all cases.[7] This provides evidence that the shock identified in our SVAR model is distinct from other policy and nonpolicy disturbances.

3.2.3. *Variance and historical decomposition.* Figure 8 shows the contribution of the inflation target shock to the FEV estimated using the benchmark model. By construction, the shock explains the bulk of the FEV of $\hat{\pi}^{LH}$. At the two-year horizon, the shock contributes about 7% to the FEV of GDP growth. The contribution to FEV of CPI inflation at this horizon is estimated to be about 61%. It is interesting to note that the contribution to the FEV of inflation is larger than that typically reported in the case of a monetary policy shock (see, e.g.,

[7] In the technical appendix, we show that extended versions of our VAR model where we identify the target shock, along with a monetary policy, oil, and TFP news shock, respectively, do not alter the main results.



NOTES: The contributions are shown for PTR ($\hat{\pi}^{LH}$), real GDP growth (y_t), CPI inflation (π_t^a), the 10-year government bond yield (I_t), and the three-month treasury bill rate (R_t). The solid lines are posterior medians, whereas the shaded area is the 68% error band.

FIGURE 8

CONTRIBUTION OF THE INFLATION TARGET SHOCK TO THE FEV

Bernanke et al., 2005). The bottom panels of the figure show that this shock makes an important contribution to the FEV of I_t and R_t explaining the bulk of the FEV at long horizons.[8]

A similar conclusion is reached when examining the contribution of this shock to the historical fluctuations in these interest rates. Figure 9 plots (detrended) data for the endogenous variables along with the counterfactual estimates from the VAR, assuming that the inflation target shock equals zero at each point in time. The second row of the figure shows that after the early 1990s the counterfactual estimate of the interest rates is above the observed data, implying that fluctuations in the implicit target of the Fed helped to keep these rates at depressed levels over the last two decades. The inflation target shock made a strong positive contribution to inflation during the mid and late-1970s. The great inflation is largely absent in the counterfactual scenario, and the impact of inflationary shocks in the early and the late-1970s is muted. The counterfactual estimate of inflation largely remains above the actual data after the mid-1980s providing some support for the hypothesis that systematic policy contributed to low inflation seen over the Great Moderation.

4. INFLATION TARGET SHOCKS IN A MODEL ECONOMY

The empirical results presented above suggest the following conclusion: an inflation target shock is estimated to have an impact on U.S. GDP growth, CPI inflation, the short- and long-term interest rate that is sizeable from an economic and statistical perspective.

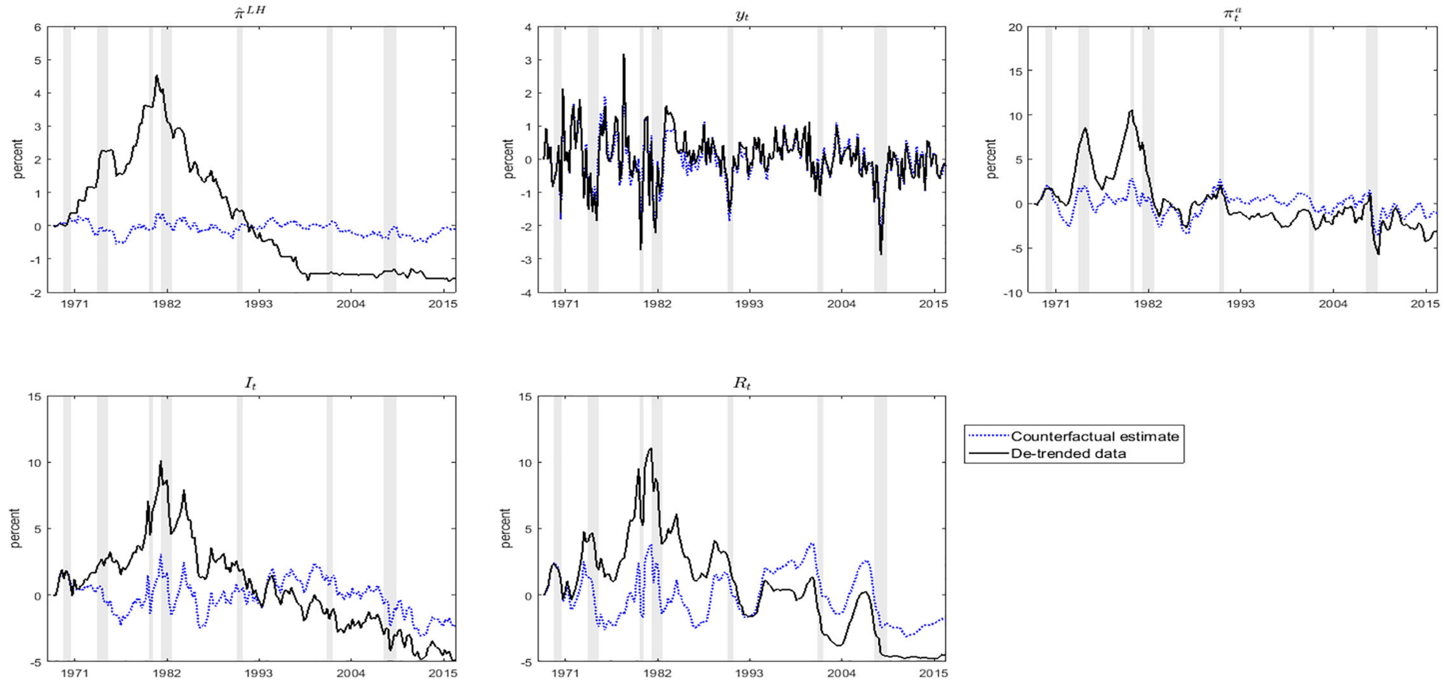
In this section, we explore the performance of the proposed identification scheme in a simulation setting. In particular, we generate artificial data from DSGE models that (i) incorporate shocks to the central bank's inflation target, (ii) allow for the fact that all agents may not directly observe the preferences of the central bank, and (iii) feature regime changes in the parameters of the monetary policy rule. We then check if a VAR model with the identification scheme proposed above can recover the responses to target shocks.

The DSGE model that we use as our benchmark DGP is based on De Graeve and Theodoridis (2016). This model nests the standard New Keynesian model and provides a more realistic representation of monetary policy. To be precise, the model allows the long-term interest rate to be a function of expectations of the policy rate *and* endogenously generated term premia.

Key Features of the Model:. This section briefly reviews the model, whereas the technical appendix contains a detailed description of the model equations. In this economy, households consume, supply labour, and accumulate capital—subject to an investment adjustment cost. Households have monopoly power over their wages. A fraction of them receives a random signal to set their wage optimally, with the remaining agents setting wages based on a backward-looking indexation rule. Households decide optimally about the degree of capital utilization, which is again subject to a cost that determines the level of capital services. Intermediate good producers hire labour and capital services from households in order to produce. They have a monopoly over the price they charge, with price setting subject to the same friction as wages. All the model features discussed so far are common with those in the literature (Christiano et al., 2005; Smets and Wouters, 2007; Justiniano et al., 2010). In addition, agents have access to both short- and long-term government debts that can be used to facilitate consumption smoothing across time.

Households:. The domestic economy is populated by a continuum of households that attain utility from consumption – $c_{\kappa,t+j}$ – and leisure – $h_{\kappa,t+j}$. Household's preferences are separable $E_t \sum_{j=0}^{\infty} \beta^j \{d_{t+j} \frac{(c_{\kappa,t+j} - bc_{\kappa,t+j-1})^{1-\sigma_c}}{1-\sigma_c} - \psi_{t+j} \Gamma_{t+j}^{1-\sigma_c} \frac{h_{\kappa,t+j}^{1+\varphi}}{1+\varphi} d\kappa\}$where $d_t = (1-\rho_d)d + \rho_d d_{t-1} + \sigma_d \omega_d$ is a discount factor shock, Γ_t $(\gamma_t = \ln(\frac{\Gamma_t}{\Gamma_{t-1}}) = (1-\rho_\gamma)\gamma + \rho_\gamma \gamma_{t-1} + \sigma_\gamma \omega_{\gamma,t})$

[8] As shown in the technical appendix, decomposition results based on the VAR that uses the blue chip–Livingstone inflation expectation series indicate that the inflation target shock is estimated to explain about 50% of the FEV of the short- and long-term interest rate.



NOTES: The contributions are shown for PTR ($\hat{\pi}^{LH}$), real GDP growth (y_t), CPI inflation (π_t^a), the 10-year government bond yield (I_t), and the three-month treasury bill rate (R_t). The shaded vertical bands show NBER recession dates.

FIGURE 9

CONTRIBUTION OF SHOCKS OTHER THAN INFLATION TARGET SHOCKS TO THE DETRENDED DATA is the nonstationary trend, $\psi_t = (1-\rho_\psi)\psi + \rho_\psi \psi_{t-1} + \sigma_\psi \omega_\psi$ is a stationary labor supply shock, β is the discount factor, φ the inverse of the Frisch elasticity, σ_c the inverse of intertemporal elasticity of substitution, and b the habit formation parameter. They also invest on fiscal capital ($\bar{k}_{t-1}$) that is rented to firms ($k_t = \upsilon_t \bar{k}_{t-1}$), where υ_t denotes the degree of capital utilization and capital accumulation is subject to investment adjustment cost ($\bar{k}_t = (1-\delta)\bar{k}_{t-1} + \phi_t(1 - \frac{\psi_I}{2}(\frac{i_t}{\gamma i_{t-1}} - 1))i_t$). Household's real budget constraint is given by $D^h_{\kappa,t} + c_{\kappa,t} + i_{\kappa,t} + \Upsilon_{\kappa,t} = \frac{r^h_{t-1}}{\pi_t} D^h_{\kappa,t-1} + w_{\kappa,t} h_{\kappa,t} + r^k_t \upsilon_{\kappa,t} \bar{k}_{\kappa,t-1} - u(\upsilon_{\kappa,t})\bar{k}_{\kappa,t-1} + F_{\kappa,t} - T_{\kappa,t}$. The household κ uses its labour income—$w_{\kappa,t} h_{\kappa,t}$, net return on capital services – $r^k_t \upsilon_{\kappa,t} \bar{k}_{\kappa,t-1} - u(\upsilon_{\kappa,t})\bar{k}_{\kappa,t-1}$, gross interest rate financial intermediary deposits—$\frac{r_{t-1}}{\pi^c_t} D^h_{\kappa,t-1}$, government transfers—$T_t$—and profits—$F_t$—to finance consumption, investment, and new purchases of financial assets—$c_{\kappa,t} + i_{\kappa,t} + D_{\kappa,t} + \Upsilon_{\kappa,t}$. The household maximizes its utility function with respect to $c_{\kappa,t}$, $i_{\kappa,t}$, $\bar{k}_{\kappa,t-1}$, and $D^h_{\kappa,t}$ subject to its budget and capital accumulation constraints.

Financial Intermediaries:. The financial intermediary firm issues deposits to households paying a gross interest rate r^h_t. The firm then purchases a portfolio of short- and long-term government issued bonds paying interest r^S_t and r^L_t. Similar to Andres et al. (2004), Chen et al. (2012), Harrison (2012), and Liu et al. (2019), we follow the formulation in Woodford (2001) and long-term bonds are perpetuities that cost $p_{L,t}$ at time t and pay an exponentially decaying coupon κ^s at time $t+s+1$ where $0 < \kappa \leq 1$. As explained in Woodford (2001) and Chen et al. (2012), the advantage of this formulation is that the price in period t of a bond issued s periods ago $p_{L-s,t}$ is a function of the coupon the current price $p_{L,t}$ ($p_{L-s,t} = \kappa^s p_{L,t}$). This relation allows us to express the balance sheet equation and government budget constraint (discussed below) in a familiar form that is easy to work with (see the discussion in Chen et al., 2012). Furthermore, in order to keep things simple, we rule out the possibility of a secondary market for long-term bonds, meaning that agents who buy long-term debt must hold it until maturity.[9] Finally, for simplicity, we assume that all government bonds issued are purchased by this firm. The intermediary's balance sheet is given by $b^h_{\kappa,t} = \frac{b^S_{\kappa,t}}{\varepsilon^{b^S}_t} + \frac{p_{L,t} b^L_{\kappa,t}}{\varepsilon^{b^L}_t}$or $b^h_{\kappa,t} = \frac{b^S_{\kappa,t}}{\varepsilon^{b^S}_t} + \frac{\bar{b}^L_{\kappa,t}}{\varepsilon^{b^L}_t}$. Motivated by the work of Smets and Wouters (2007), we assume the balance sheet equation is subject to two 'financial' shocks: a short and a long-term risk premium AR(1) stationary shocks denoted by $\varepsilon^{b^S}_t$ and $\varepsilon^{\bar{b}^L}_t$, respectively. Intermediary's profit function is then given by $\xi_t = \underbrace{b^h_{\kappa,t} + \frac{r^S_{t-1}}{\pi_t} b^S_{\kappa,t-1} + \frac{p_{L,t} r^L_t}{\pi_t} b^L_{\kappa,t-1}}_{\text{revenues}} - \underbrace{\frac{b^S_{\kappa,t}}{\varepsilon^{b^S}_t} - \frac{p_{L,t} b^L_{\kappa,t}}{\varepsilon^{\bar{b}^L}_t} - \frac{r^h_{t-1}}{\pi_t} b^h_{\kappa,t-1} - \frac{x}{2}(\delta^B_{\kappa,t-1} - \vartheta \delta^B_{t-2} - (1-\vartheta)\delta^B)^2 \frac{\Gamma_{t-1}}{\pi_t}}_{\text{expenditures}}$, where $\delta^B_{\kappa,t} = \frac{b^S_{\kappa,t}}{\bar{b}^L_{\kappa,t}}$. Intermediary's profits are subject to an adjustment cost that capture the "liquidity" expenses that occur as banks deviate from their steady-state long- to short-term debt ratio.

Wages:. We follow Erceg et al. (2000) and assume that each monopolistically competitive household supplies a differentiated labour service to the production section. They set their nominal wage and supply any amount of labour demanded by the firms at that wage rate. For convenience, we assume that there exists a representative firm that combines households' labour inputs into a homogeneous input good—h^d_t—using a Constant Elasticity of Substitution (CES) production function ($h^d_t = [\int_0^1 h_{\kappa,t}^{\frac{1}{\lambda_{w,t}}} d\kappa]^{\lambda_{w,t}}$), where $\lambda_{w,t} = (1-\rho_{\lambda_w})\lambda_w + \rho_{\lambda_w}\lambda_{w,t-1} + \sigma_{\lambda w}\omega_{\lambda w,t}$ is the time-varying wage markup. In each period, a function $(1-\xi_w)$ of households receive a random signal and they reset wages opti-

[9] See the discussion in Andres et al. (2004) for the advantages of that assumption.

mally (w_t^{new}), whereas the remaining (ξ_w) households can only partially index their wages by past inflation ($w_t = \pi_{t-1}^{\kappa_w}\bar{\pi}_t^{1-\kappa_w}\gamma w_{t-1}$). The problem of setting wages can be described as follows: $\max_{w_t^{new}} E_t \sum_{j=0}^{\infty}(\beta\xi_w)^j\{-\psi_{t+j}\Gamma_{t+j}^{1-\sigma_c}\frac{h_{\kappa,t+j}^{1+\varphi}}{1+\varphi} + \lambda_{t+j}\prod_{s=1}^{j}\frac{\pi_{t+s-1}^{\kappa_w}\bar{\pi}_t^{1-\kappa_w}\gamma}{\pi_{t+s}}w_{\kappa,t}h_{\kappa,t+j}\}$ subject to $h_{\kappa,t+j} = (\prod_{s=1}^{j}\frac{\pi_{t+s-1}^{\kappa_w}\bar{\pi}_{t+s}^{1-\kappa_w}\gamma}{\pi_{t+s}}\frac{w_{\kappa,t}}{w_{t+j}})^{-\frac{\lambda_{w,t}}{\lambda_{w,t}-1}}h_{t+j}^d$.

Firms:. The intermediate monopolistically competitive domestic firms use labour ($h_{i,t}^d$) and capital services ($k_{i,t}$) supplied by households to produce a differentiated good ($y_{i,t} = z_t(\Gamma_t h_{i,t}^d)^\alpha k_{i,t}^{1-\alpha}$), where $z_t = (1-\rho_z)z + \rho_z z_{t-1} + \sigma_z\omega_{z,t}$ denotes a stationary exogenous technological process. The output of this process is sold to a final good producer who employs a continuum of these differentiated goods in her constant elasticity of substitution—CES—production to deliver the final good ($y_t^d = [\int_0^1 y_{i,t}^{\frac{1}{\lambda_{y,t}}}di]^{\lambda_{y,t}}$) where $\lambda_{y,t} = (1-\rho_{\lambda_y})\lambda_y + \rho_{\lambda_y}\lambda_{y,t-1} + \sigma_{\lambda_y}\omega_{\lambda_y,t}$ is time-varying markup in the domestic good market. The intermediate firm selects $h_{i,t}^d$ and $k_{i,t}$ in order to minimize its production cost ($\min_{h_{i,t}^d,k_{i,t}} p_t w_t h_{i,t}^d + p_t r_t^k k_t + mc_{i,t}p_t[y_{i,t} - z_t(\Gamma_t h_{i,t}^d)^\alpha k_{i,t}^{1-\alpha}]$). A fraction $(1-\xi_y)$ of intermediate firms receives a random signal and resets prices optimally ($p_{i,t}^{new}$), whereas the remaining fraction (ξ_y) sets prices (p_t) based on backward-looking rule ($p_t = \pi_{t-1}^{\kappa_y}\bar{\pi}_t^{1-\kappa_y}p_{t-1}$), where $\pi_t = \frac{p_t}{p_{t-1}}$ is the gross inflation and κ_y is the indexation parameter. The optimal pricing behavior of firm i results as a solution to the following maximization problem: $\max_{p_{i,t}^{new}} E_t\sum_{j=0}^{\infty}(\beta\xi_y)^j\frac{\lambda_{t+j}}{\lambda_t}\{(\prod_{s=1}^{j}\pi_{t+s-1}^{\kappa_y}\bar{\pi}_{t+s}^{1-\kappa_y}\frac{p_{i,t}^{new}}{p_{t+j}} - mc_{t+j})y_{i,t+j}\}$ subject to $y_{i,t+j} = (\prod_{s=1}^{j}\pi_{t+s-1}^{\kappa_y}\bar{\pi}_{t+s}^{1-\kappa_y}\frac{p_{i,t}^{new}}{p_{t+j}})^{-\frac{\lambda_{y,t}}{\lambda_{y,t}-1}}y_{t+j}^d$.

Policy:. The Government's budget constraint is given by

$$b_t^S + \bar{b}_t^L + T_t = \frac{r_{t-1}^S}{\pi_t}b_{t-1}^S + \frac{r_t^L}{\pi_t}\frac{p_{L,t}}{p_{L,t-1}}\bar{b}_{t-1}^L + g_t y_t,$$

where the left-hand side is the total (short- plus long-term) debt issued by the government at time t plus lump-sum taxes (T_t) used to pay interest. Taxes are adjusted according to the following rule:

$$T_t = \Phi\left(\frac{b_{t-1}^S + \bar{b}_{t-1}^L}{b^S + \bar{b}^L}\right)^\theta. \tag{4}$$

The government spending (g_t) follows a stationary AR(1) process, whereas we assume that the supply of long-term debt is fixed ($b^L = 1$).

As in De Graeve et al. (2009), monetary authorities set policy based on the following rule:

$$\frac{\bar{\pi} r_t}{r\bar{\pi}_t} = \left(\frac{\bar{\pi} r_{t-1}}{r\bar{\pi}_{t-1}}\right)^{\phi_R}\left(\frac{\pi_t}{\bar{\pi}_t}\right)^{(1-\phi_R)\phi_\pi}\left(\frac{y_t}{y}\right)^{(1-\phi_R)\phi_y}e^{\sigma_R\omega_{R,t}}. \tag{5}$$

The inflation target shock evolves according to

$$\bar{\pi}_t - 0.999\bar{\pi}_{t-1} = \rho_{\bar{\pi}}(\bar{\pi}_{t-1} - 0.999\bar{\pi}_{t-2}) + \sigma_{\bar{\pi}}\omega_{\bar{\pi},t}. \tag{6}$$

The shocks kept active during the simulations presented below are : (i) the nonstationary productivity (γ_t), (ii) the interest rate policy ($\omega_{R,t}$), (iii) the short-term debt "hair-cut" financial ($\varepsilon_{\mathbf{t}}^{\mathbf{b^S}}$), (iv) the government spending (g_t), and (v) the inflation target ($\bar{\pi}_t$) shocks.

4.1. *Perceived versus Actual Inflation Target Shocks.* Agents in the model discussed above observe both the inflation target and monetary policy shocks. Following Erceg and Levin (2003), Gürkaynak et al. (2005) and Del Negro and Eusepi (2011), we also consider a version of the model where this assumption is relaxed. In this version, agents do not observe the source of departure of the (log-linearly approximated) policy rate from its rule, namely,

$$\hat{r}_t = \phi_R \hat{r}_{t-1} + (1 - \phi_R)(\phi_\pi \hat{\pi}_t + \phi_y \hat{y}_t) + \hat{o}_t, \tag{7}$$

where

$$\hat{o}_t = [1 - (1 - \phi_R)\phi_\pi]\hat{\bar{\pi}}_t - \phi_R \hat{\bar{\pi}}_{t-1} + \hat{m}_t. \tag{8}$$

In other words, agents in the economy observe $\hat{o}_t$ but not its individual components, however, they can obtain an estimate about the inflation target ($\hat{\bar{\pi}}_t^{KF}$) and monetary policy shock ($\hat{m}_t^{KF}$) shocks by solving a Kalman Filter extraction problem. In this economy, it is the Kalman Filter estimate of the inflation target shock ($\hat{\bar{\pi}}_t^{KF}$) that enters in the price and wage Phillips curve equations and not the actual inflation target process which is assumed to be unobserved.

4.2. *Active versus Passive Monetary Policy.* The benchmark model does not incorporate the possibility that over some periods, monetary policy may have been passive with $\phi_\pi < 1$.[10] Under these circumstances, inflation expectations are deanchored and respond persistently to structural shocks. To take this into account, we consider a Markov switching version of the benchmark model that allows for regime switches in the policy rule between an active/hawkish ($\phi_\pi > 1$) and passive/dovish ($\phi_\pi < 1$) state:

$$\hat{r}_t - \hat{\bar{\pi}}_t = \phi_R(s_t^c)\big(\hat{r}_{t-1} - \hat{\bar{\pi}}_{t-1}\big) + (1 - \phi_R(s_t^c))\big(\phi_\pi(s_t^c)\big(\hat{\pi}_t - \hat{\bar{\pi}}_t\big) + \phi_y(s_t^c)\hat{y}_t\big) + \hat{m}_t, \tag{9}$$

where s_t^c follows a first-order Markov chain with transition probabilities $P^c = \begin{bmatrix} p_{11}^c & 1 - p_{22}^c \\ 1 - p_{11}^c & p_{22}^c \end{bmatrix}$. As there is by now a large body of empirical evidence showing that uncertainty also evolves across time, we allow the standard deviation of all structural shocks to follow a Markov first-order process s_t^σ with a transition matrix $P^\sigma = \begin{bmatrix} p_{11}^\sigma & 1 - p_{22}^\sigma \\ 1 - p_{11}^\sigma & p_{22}^\sigma \end{bmatrix}$.

4.3. *Monte-Carlo Simulations.* We first consider the benchmark DSGE model. Note that the versions of the model that do not feature regime switching are estimated using standard Bayesian techniques (see An and Schorfheide, 2007). We use the data set of Smets and Wouters (2007) with the sample truncated at 2007Q4 to avoid issues with the zero lower bound. Information about the prior and posterior distribution of the structural parameter vector can be found in the technical appendix. Briefly, the prior moments of the structural parameters coincide with those in Smets and Wouters (2007) study, whereas the posterior ones are very similar to those in the existing literature.

The Monte-Carlo experiment is based on 1,000 simulated data sets of 200 observations.[11] At each replication, we simulate series for output, inflation, the short- and long-term interest rate, and 10-year-ahead inflation expectations. This set of endogenous variables is used to estimate a $VAR(P)$ model where the lag length is determined via the Schwarz criterion. The identification scheme discussed above is applied to identify the target shock and the resulting impulse responses are stored.

[10] Note that the inflation target reflects the preferences of the central bank regarding the level of inflation. Given the target, ϕ_π captures the degree to which the central bank tolerates deviations of inflation from the target.

[11] Actually 10,200 observations are simulated each time, and the first 10,000 pseudo-data points are dropped to eliminate the effects caused by the initial conditions.

Figure 10 shows the results from the experiment when the structural parameter vector for the benchmark DGP is set equal to the estimated posterior mode. The black line and the shaded area correspond to the pointwise 50, 5, and 95 percentiles of the simulated distribution using the proposed identification scheme. The blue circle line represents the underlying response to the inflation target shock in the DSGE model. A shock that increases the target causes the real interest rate to fall, stimulating real activity and inflation. The figure suggests that the VAR estimates of the response to this shock provide a close approximation of true responses in the DGP.

Next, we check if the performance of the identification scheme is robust to different DSGE parameter values. To this end, we draw 1,000 parameter vectors from the estimated DSGE posterior distribution and use them to simulate the 1,000 data sets for the experiment. Figure 11 illustrates again that the success of the VAR identification scheme does not depend on a particular DSGE parameter vector.[12]

Next, we investigate whether the econometrician can identify the inflation target shock successfully when the agents in the economy cannot observe the target directly. We repeat the simulation steps mentioned in the first experiment but we use the posterior mode estimates of the model where the inflation target and monetary policy shocks are unobserved. Figure 12 suggests that even in this case, the identification scheme performs remarkably well. This is because agents learn about the true shock, and the inference error does not survive long enough to have an effect on the *long-horizon* inflation expectations.[13]

Our next exercise examines the ability of the scheme to recover the true shocks when monetary authorities' preferences toward inflation switch stochastically between dovish and hawkish regimes, and shock variances are subject to heteroskedasticity. This version of the model is solved and estimated using the Rationality in Switching Environmnets (RISE) toolbox (see Maih, 2015). As documented in Maih (2015), RISE employs a perturbation solution for the switching DSGE model, with estimation carried out via Markov chain Monte Carlo (MCMC) methods. As shown in the technical appendix, the posterior estimates indicate large changes in the policy-rule coefficients across the two regimes. In particular, the posterior mode estimate of ϕ_π is 0.9 in the dovish regime and 1.8 in the hawkish state. The smoothed regime probabilities suggest that the hawkish regime prevailed after the mid-1980s—a result documented in most studies that consider regime-switching DSGE models (see, e.g., Bianchi, 2013). As before, we simulate data from this version of the model using the posterior mode of the structural parameters and estimate the SVAR and the response to target shocks.

Figure 13 presents the results of this simulation. The figure presents the regime-specific DSGE responses to the target shock and the generalized response (GIRF), which averages across the regimes. The median estimate from the SVAR estimation suggests that the identification scheme continues to perform remarkably well even in this environment. The median VAR responses are fairly close to the GIRF from the model. The Monte-Carlo distribution of the SVAR impulse response is somewhat wider in this experiment. However, this is not entirely unexpected, as the linear VAR ignores any nonlinear dynamics in the DGP. Note that the VAR identification scheme continues to perform well because when the sample is considered as a whole, the impact of dovish regimes is mitigated by the presence of regimes during which the monetary authority responds actively to inflation. As a consequence, inflation target shocks continue to exert a major influence on *long-horizon* inflation expectations in this economy.

4.4. *Additional Robustness Exercises and Monte-Carlo Simulations.* In the Online Appendix, we report the results from three additional experiments. The first two illustrate that

[12] In the technical appendix, we consider a version of the model where either the wage or the price markup shock, respectively, is assumed to be highly persistent. Even in this case, the identification scheme continues to successfully recover the inflation target shock.

[13] In the technical appendix, we present a further experiment that shows that the identification scheme continues to perform well when measurement error is added to the generated inflation expectations series.

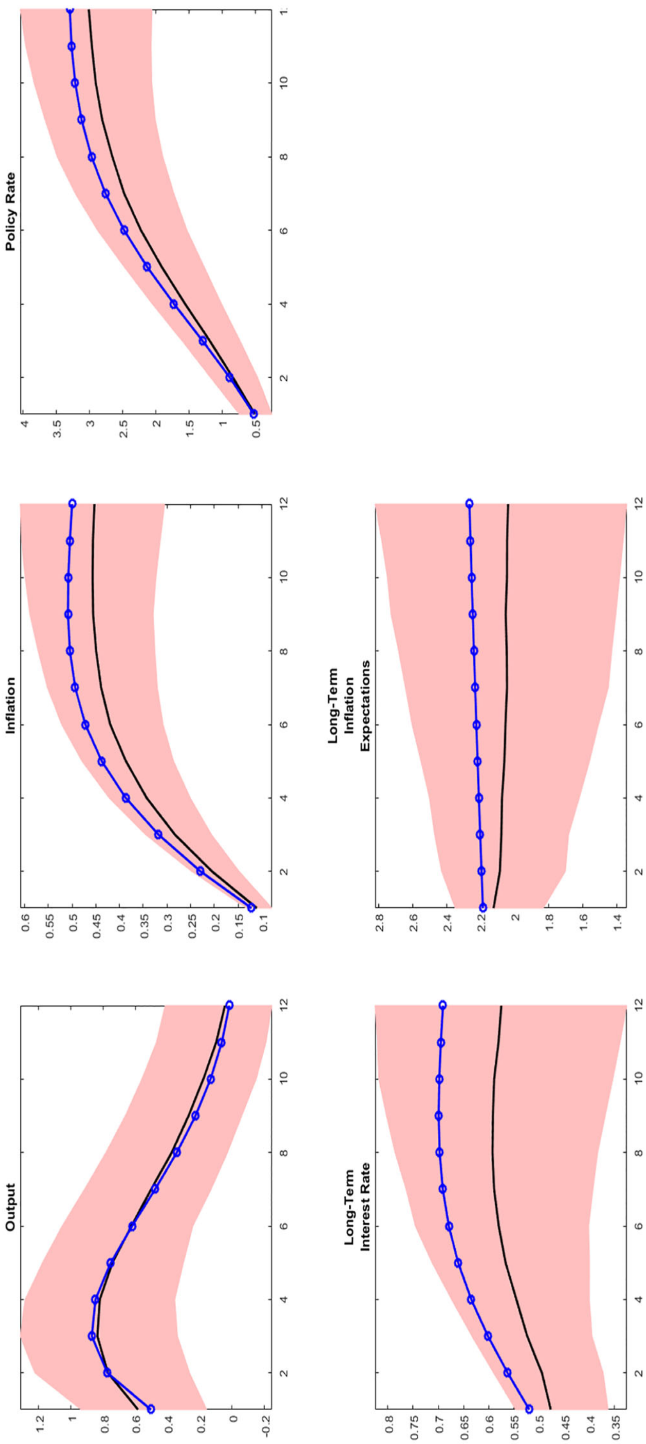
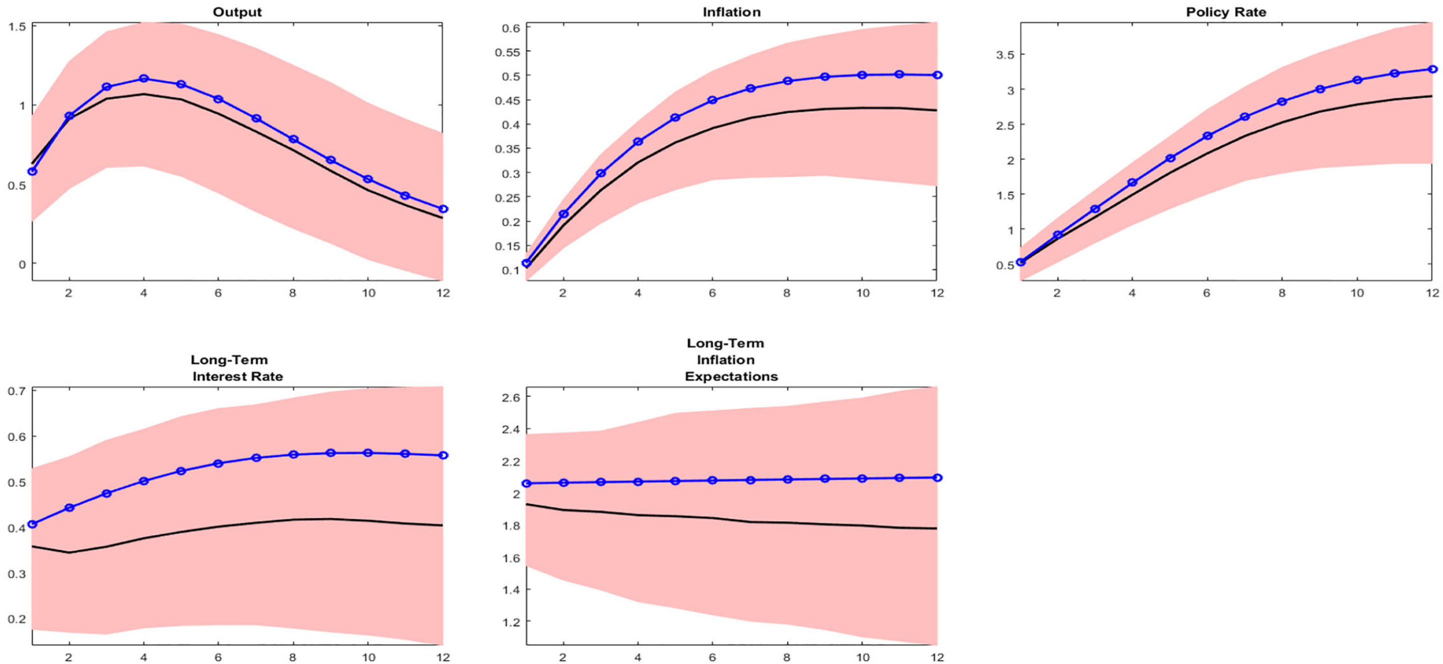


FIGURE 10

USING POSTERIOR MODE ESTIMATES

NOTES: The black line and the shadow pink area correspond to the pointwise 50, 5, and 95 percentiles of the simulated distribution. The blue circle line represents the DSGE true response to an inflation target shock. The responses are reported as percentage deviations from the steady state. The size of the shock is one time the standard deviation of the shock.



NOTES: See notes to Figure 10.

FIGURE 11

USING DRAWS FROM THE ESTIMATED DSGE POSTERIOR

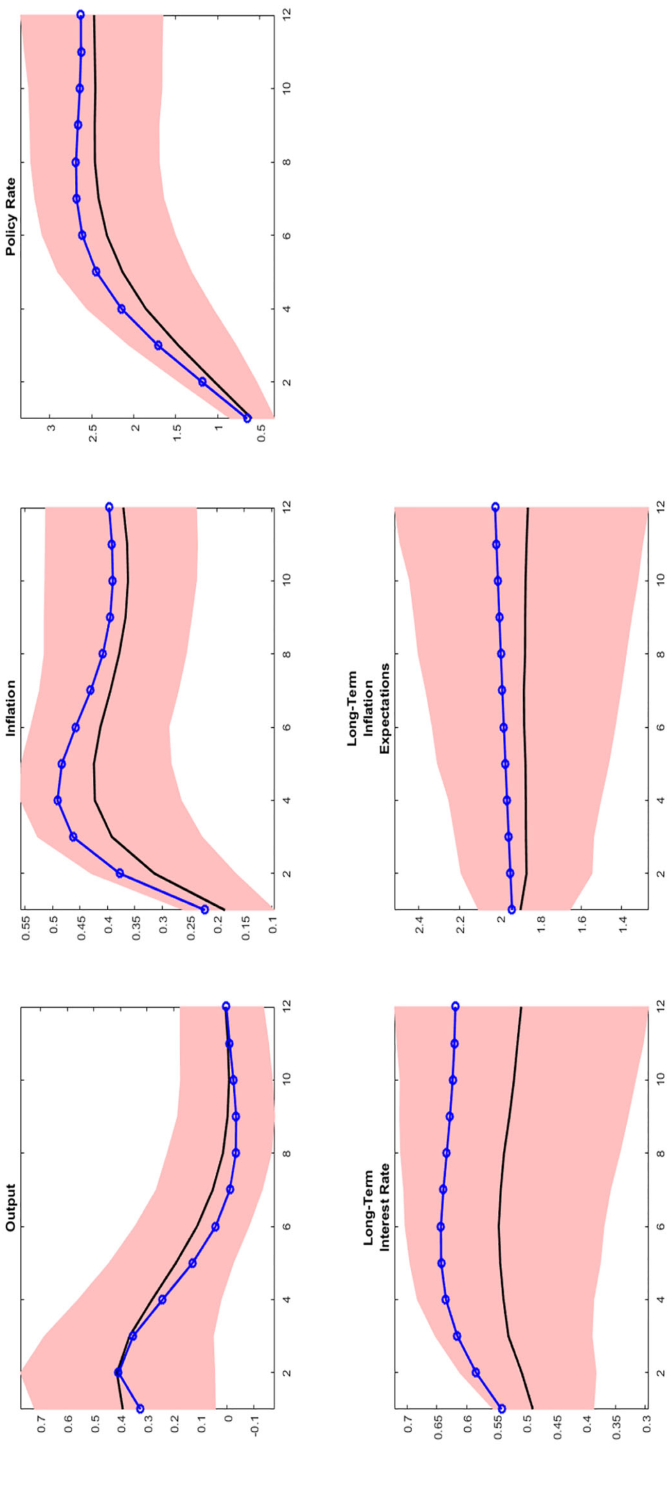


FIGURE 12

USING THE VERSION OF THE MODEL WITH UNOBSERVED TARGET AND POLICY SHOCK

NOTES: See notes in Figure 10.

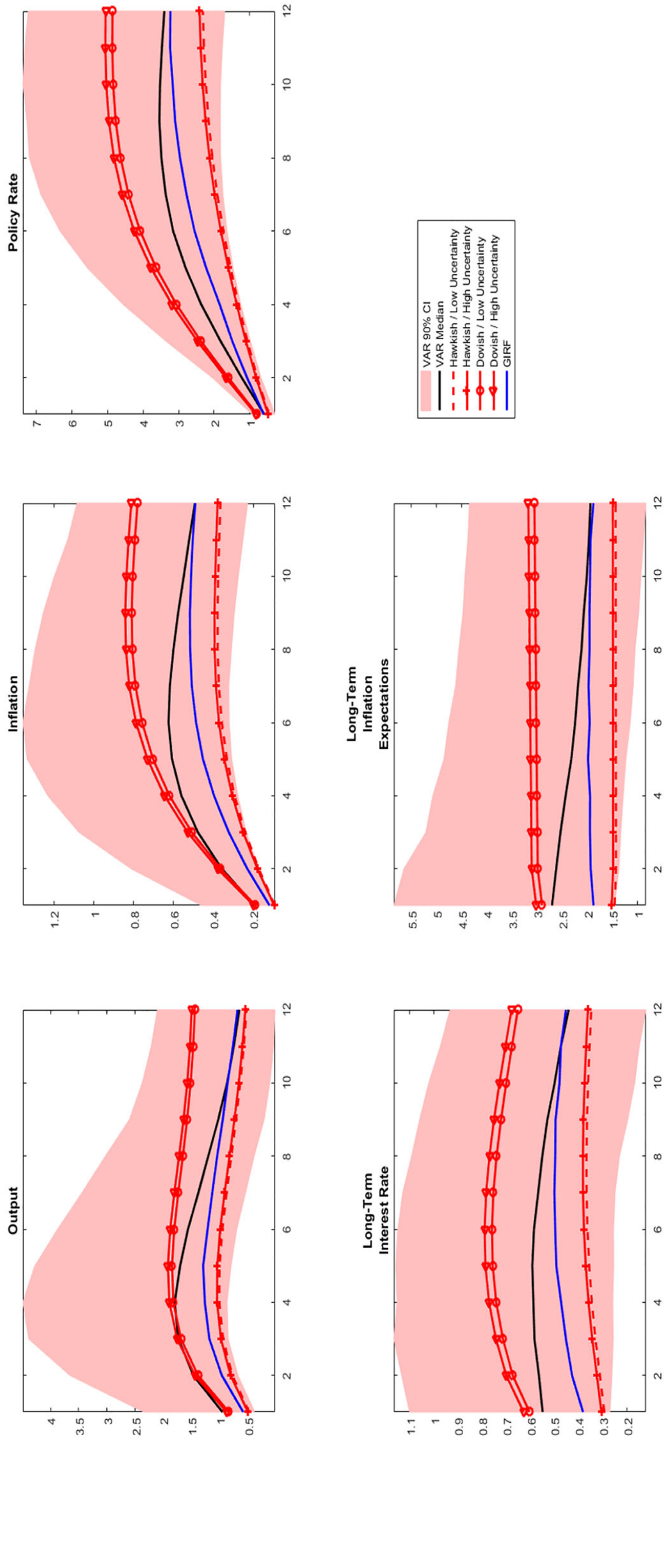


FIGURE 13

USING THE MARKOV SWITCHING DSGE MODEL AS THE DGP the scheme continues to perform well when one of the disturbances used for the simulation of the structural model is replaced by either a price or wage markup shock that is calibrated to be highly persistent. Finally, we study the performance of the SVAR when long-run restrictions are used to identify the inflation target shock.

Extremely Persistent Price or Wage Markup Shock:. Figures 12 and 14 (Section 6 Online Appendix) illustrate that even under the existence of a very persistent wage or price markup shock, the identification scheme continues to successfully recover the inflation target shock. As shown in Figure 13 (Section 6 Online Appendix), the markup shock lowers the level of the output below its steady-state trend by more than 15 years (i.e., it behaves as a permanent adverse shock). Even in this case, the performance of the scheme does not seem to be affected. This finding is consistent with the narrative that wants the central bank to be the nominal anchor, a feature embedded in New Keynesian models like the one presented employed in this study. In other words, in the presence of inflationary shocks, the central bank can keep price expectations well anchored by causing a severe recession. The central bank can achieve this objective by keeping the policy rate above the inflation persistently so the long-term real interest rate ($\rho_t^L = \frac{1}{40}\sum_{i=0}^{39} E_t(r_{t+i} - \pi_{t+1+i})$) that matters for households' consumption and firms' investment decision stays positive (see Figure 13, last subplot).

Identification via Long-Run Restrictions. In the technical appendix, we show that, in this experiment, when the shock is identified using long-run restrictions (as in Michelis and Iacoviello, 2016), the performance of SVAR deteriorates substantially. In particular, the estimated response of output is biased downward, and error bands for all variables are extremely wide. We argue in the Appendix that the bias in the output response could be related to the inability of the scheme to separately identify the permanent productivity from the permanent inflation target shock. Perhaps some additional information—in the form of extra identification restrictions—could improve the performance of the scheme. The upside skewness of the posterior distribution of the nominal variables could be related to the nature of the identification process. Under this scheme, inflation is a nonstationary variable, a feature that is inconsistent with the idea that the central bank can fully control the nominal trend. The simulations displayed in Figure 16 (Section 7, Online Appendix) illustrate exactly this property; that is, the central bank cannot always keep the long-term inflation expectations close to the target.

Inflation Target Shock Orthogonal to Natural Interest Rate. We illustrate (Figure 17 in the Online Appendix) that the identified inflation target shock is not correlated with shocks that could affect the natural interest rate. In this exercise, we augment the VAR model by including the measure of the natural interest rate derived by Holston et al. (2017), and we restrict the target shock to have a zero contemporaneous effect on the natural interest and to have no permanent effect on the level of GDP. Figure 17 in the Online Appendix illustrates that the responses are unchanged relative to those estimated using the benchmark scheme.

Inflation Target Shock Restring to have Long-Lasting Effect on Real Variable. We also illustrate in the Online Appendix (Section 9, Figure 18) that the VAR responses to an inflation target impulse remain unchanged when the identified shock is restricted to have:

- no permanent effect on the level of output (as in the previous exercise)
- no significant long-lasting effect (beyond 10 years) on the real interest rate

Inflation Target and Monetary, Oil, TFP News Shocks. Finally, we estimate an extended version of the VAR where we identify two shocks. As before, the first (main) shock is the inflation target shock, where the identification is based on FEV restrictions. The second shock is sequentially set to be monetary policy, oil, and TFP news, and the identification is carried out via an external instrument approach (Stock and Watson, 2012) in the first two cases and by

FEV restrictions in the final case. To identify monetary and oil shocks, we use the instruments by Gertler and Karadi (2015), Ramey and Vine (2011), respectively. The TFP news shock is identified using the restrictions on the FEV and contemporaneous responses introduced by Barsky and Sims (2011). We require the inflation target shock to be orthogonal to the second identified shock. The impulse responses from this exercise are shown in Figures 17 and 18 in the Online Appendix. The top panel of Figure 17 shows that identifying the monetary policy shock together with the target shock does not alter the main conclusions. The response of GDP is similar to the benchmark case. The response of inflation and interest rates is somewhat larger in magnitude, but the response of the real interest rate shows the same pattern as the benchmark case. The bottom panel of the figure shows that when the inflation target shock is identified together with the oil shock, the responses to the target shock remain similar to the benchmark. Figure 18 shows that a similar conclusion applies when the target shock is identified together with TFP news shocks.

5. CONCLUSIONS

We propose to identify shocks to the Fed's implicit inflation target as innovations in an SVAR that explain the bulk of the FEV of long-horizon inflation expectations. When this scheme is applied to data simulated from a DSGE model that features a time-varying inflation target, we are able to recover the target shock and estimate its transmission with precision. This result remains robust when the target is assumed to be unobserved by the agents in the model or the monetary policy rule is subject to regime shifts.

Application of this SVAR to U.S. data suggests that the impact of a 1% positive inflation target shock is large, with the peak effect on GDP and inflation estimated to be 1.2% and 1.5–5%, respectively. The shock has its largest impact on both the short- and long-term interest rate. Decompositions from the SVAR indicate that this shock was the major driving force behind the great inflation of the 1970s and contributed substantially to the persistent decline observed in long-term interest rates.

It may be interesting to consider in future work if this shock has spill-over effects on inflation and interest rates in other leading OECD countries. Given the possibility of changes in the outlook of the Fed under the new U.S. government, these conclusions can help in the analysis of OECD economic performance in the near future.

APPENDIX: DATA SOURCES

FRED is Federal Reserve Economic data (http://research.stlouisfed.org/fred2/), and GFD refers to Global Financial Data (http://www.globalfinancialdata.com/).

Data on inflation expectations.

- PTR. Downloaded from FRB/U.S. model webpage.
- Blue Chip/Livingstone survey. Available from the Philadelphia Fed.

Macroeconomic/Financial data for the United States.

- Real GDP: Real GDP (FRED series id GDPC1).
- CPI (FRED series id CPIAUCSL). We calculate inflation as the annual growth in CPI.
- Three-month Treasury Bill rate (FRED series id TB3MS).
- Ten-year government bond yield (GFD code IGUSA10D).

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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