DISCUSSION PAPER SERIES

DP16836

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Rüdiger Bachmann, Eric Sims and Isabel Goedl Hanisch

MONETARY ECONOMICS AND FLUCTUATIONS

ISSN 0265-8003

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Discussion Paper DP16836
Published 25 December 2021
Submitted 20 December 2021

Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

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JEL Classification: E31, E50, E52, E58

Keywords: identification, nowcasts, monetary policy shocks, local projections

Rüdiger Bachmann - rbachman@nd.edu
University of Notre Dame and CEPR

Eric Sims - esims1@nd.edu
University of Notre Dame

Isabel Goedl Hanisch - ihanisch@nd.edu
University of Notre Dame

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Rüdiger Bachmann
University of Notre Dame, CEPR, CESifo, and ifo

Isabel Gödl-Hanisch
University of Notre Dame

Eric R. Sims
University of Notre Dame and NBER

This version: November, 2021
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*Correspondence: ihanisch@nd.edu, rbachmann@nd.edu, esims@nd.edu (corresponding author).

1 Introduction

What is the effect of a monetary policy shock on the real economy? Policymakers and economists alike continue to have an ongoing interest in understanding the effects of monetary policy on prices and output. Theoretically, in a world with nominal rigidities, a temporary increase in the policy interest rate should lead to drops in both prices and output in the short run. In spite of this theoretical prediction, empirical evidence remains inconclusive, particularly so for the effect of policy shocks on inflation and the price level.

At the core of this issue is an endogeneity problem. To the extent that interest rates are set by central banks in response to aggregate economic conditions, it is difficult to discern the causal effects of policy rate changes on the macroeconomy. The literature has attempted to solve this identification problem in a number of ways; the recursive approach in vector autoregressions using timing restrictions (e.g., Christiano et al., 1999); the narrative approach using policy statements to isolate plausibly exogenous monetary policy changes (e.g., Romer and Romer, 2004); and the partial identification approach imposing sign restrictions (e.g., Uhlig, 2005). More recently, the literature has employed high-frequency financial market data around policy meetings to identify monetary policy shocks (Gertler and Karadi, 2015; Nakamura and Steinsson, 2018). As we show below, the recursive and narrative approaches can often result in a so-called price puzzle – that is, an increase in the price level in response to a monetary tightening – at least for some periods in the post-war U.S. economy.[1] A price puzzle stands in contrast to basic predictions from theory, and calls into question whether the various approaches heretofore employed in the literature have successfully dealt with the endogeneity problem.

This paper proposes a new identification approach that exploits the fact that the central bank has imperfect information at the time it must make decisions. Specifically, the central bank observes advance estimates and nowcasts of economic data, such as output and inflation. These nowcasts reflect a noisy measure of the actual state of the economy, which we assume is measured correctly by the final revised official statistics. Our empirical framework separates the part of the policy response that is due to the nowcast error and uses this to isolate exogenous variation in the monetary policy interest rate. To the extent that the central bank reacts to the nowcast error about economic conditions, the monetary impulse should be exogenous to economic conditions at the time of the impulse. In other

[1] In the original paper of Christiano et al. (1999) there is a mild price puzzle for most specifications. In Romer and Romer (2004) prices do not respond for almost two years after the shock.

words, we assume that the difference between real-time and final, revised estimates is unknown and unpredictable for the policymaker when setting policy. This identification approach comes with the advantage of not relying on (i) timing assumptions or (ii) potential subjectively interpretation of policymakers' statements.

To implement our empirical approach, we use historical data from the *Federal Reserve Bank of Philadelphia Greenbook data set* to approximate the Federal Reserve's information set in real-time from 1987:Q3 to 2008:Q2.[2] The analysis, consistent with many standard Taylor rule specifications, focuses on the nowcast errors in the output gap, output growth, and inflation as perceived by the Federal Reserve during the Federal Open Market Committee (FOMC) policy decision meeting. Our approach takes those nowcast errors as exogenous predictors for monetary policy in a two-step procedure. To identify the shock, we estimate the policy rate response due to nowcast errors. We then take the the monetary policy response due to nowcast errors and estimate its effects on contemporaneous and future output and inflation based on local projection methods (Jordà, 2005).

We find that the proposed identification procedure works well in the data and that our results are robust to a number of implementation details. Applying our procedure to U.S. data shows that a 25 basis point increase in the monetary policy interest rate leads to a brief decline in output and a persistent decline in prices. After four quarters, output reaches its peak decline of about 0.03 percent, and prices drop by about 0.05 percent. In particular, we do not find the price puzzle that arises when applying other identification approaches in the literature for the same time period, such as the narrative (Romer and Romer, 2004) and recursive approaches (Christiano et al., 1999).[3]

Finally, using a simple theoretical model, we validate our identification approach for a specific yet canonical data-generating process. We build on the New Keynesian (NK) model from Ireland (2004) and relax the assumption that the central bank observes economic variables in real-time without error. We therefore augment the Taylor rule with nowcast errors. We conduct a simulation exercise and show that our approach recovers the true reactions of output and prices in the model. We then evaluate the identification approach by comparing the results to established alternatives in the literature, such as the narrative (Romer and Romer, 2004) and recursive approaches (Christiano et al., 1999), and conclude that our approach performs better.

[2]Our baseline analysis starts with the first Greenbook output gap estimate in 1987 and ends in 2008 before the financial crisis and zero lower bound period. We provide robustness checks for an extension to 2015.

[3]Sims (1992) mitigates the price puzzle by adding commodity prices. Our approach does not rely on this.

The idea of using nowcast/measurement errors to isolate exogenous variation in policy variables has been employed in other settings. For example, Chodorow-Reich et al. (2019) decompose the state-level variation in the duration of unemployment benefits extensions into two parts, actual differences in economic conditions and measurement errors in the real-time data, concluding that exogenous benefit extensions have only a small impact on state-level macroeconomic outcomes.[4] Enders et al. (2020) investigate belief shocks, namely, shocks to perceived changes of fundamentals that do not materialize. In comparison, our paper focuses on the central bank's information set to identify exogenous monetary policy shocks. Finally, our paper has some relationship with Orphanides (2001) and Croushore and Evans (2006) in that this paper considers using real-time data sets for the estimation of monetary policy rules or VARs. However, these papers do not use nowcast errors to isolate exogenous variation in the policy rate.

The remainder of this paper is structured as follows: Section 2 explains the empirical strategy, Section 3 presents our findings using U.S. macroeconomic data, and Section 4 validates the identification approach using a simple NK model augmented with nowcast errors and evaluating its performance against other empirical strategies. Section 5 concludes.

2 Empirical strategy

Our empirical strategy is based on a two-step approach to overcome the inherent endogeneity problem when estimating the impact of monetary policy on the aggregate economy. Recall that the endogeneity problem arises because the central bank sets its monetary policy interest rate in response to the state of the economy, summarized, for example, by output or inflation. In this way, the policy rate and economic conditions become contemporaneously interdependent. To filter out the policy rate response to economic conditions, and highlight only exogenous movements in policy, we propose using a set of nowcast errors in the central bank's macroeconomic target variables. While nowcast errors in the central bank's macroeconomic variables are correlated with the interest rate decision, they are unlikely to be correlated with economic outcomes through any channel other than the policy rate.

[4] The critique by Hagedorn et al. (2016) of this approach does not apply to our setting, as we do not have to exploit discontinuities for identification.

To illustrate the intuition behind our approach, assume that the central bank sets its monetary policy interest rate in response to perceived current macroeconomic conditions, x_t^t, denoted by the superscript t, plus decision noise, ν_t. The central bank's perceived nowcast, x_t^t, is a noisy measure of the actual macroeconomic conditions, x_t^T, denoted by the superscript T, plus a nowcast error, u_t. We assume that u_t, and therefore x_t^T, is unknown to the central bank. Actual macroeconomic conditions, x_t^T, respond contemporaneously to the monetary policy interest rate with sensitivity ψ_x.

$$i_t = \psi_i x_t^t + \nu_t \tag{1}$$

$$x_t^t = x_t^T + u_t \tag{2}$$

$$x_t^T = \psi_x i_t \tag{3}$$

Combining (1) and (2) allows us to rewrite the policy rate in terms of an endogenous, x_t^T, and an exogenous policy reaction part, as shown in (4):

$$i_t = \underbrace{\psi_i x_t^T}_{\text{endogenous}} + \underbrace{\psi_i u_t + \nu_t}_{\text{exogenous}} \tag{4}$$

The exogenous part of the policy reaction can then serve to evaluate impact of policy on economic conditions. While the decision noise, ν_t, is unobservable in the data without the existence and the knowledge of a particular monetary policy reaction function, the nowcast error, u_t, can be extracted (ex-post) by analyzing the difference between the nowcast from the central bank, x_t^t, and the actual value, x_t^T. Central bank nowcast errors can thus help isolate exogenous movements in the policy rate.

Data sources. To approximate the information set of the Federal Reserve in real time, we use the *Federal Reserve Bank of Philadelphia Greenbook (Greenbook)*. For each FOMC meeting the Greenbook includes real-time estimates and projections by the staff of the Board of Governors (1987-2015).[5] We combine this data set with (i) the *Federal Reserve Bank of*

[5] According to Romer and Romer (1996) and McNees (1986), Greenbook forecasts are close to alternative private forecasts. According to Orphanides (2001), Greenbook forecasts are a good proxy for the appropriate forecast given the underlying information set at the time.

Philadelphia "Real-Time Data Set"[6] containing GDP and GDP deflator estimates of several vintages,[7] and, most importantly for our purposes, the final value for each variable that allows us to construct the Federal Reserves nowcast errors; and (ii) the *Congressional Budget Office (CBO)* final estimates of the output gap. Our analysis focuses on nowcast (current quarter) estimates of the following variables:

- Growth rate of real gross domestic product (GDP): g
- Growth rate of GDP deflator: π
- Output gap, that is, actual minus potential GDP divided by potential GDP: x.

Nowcast error construction. We construct the nowcast error, u_t, for each variable $X \in \{g, \pi, x\}$ at time t by taking the difference between the nowcast estimate of value X_t^t at point t and the final (true) value X_t^T at point T, each denoted by the superscript t and T:

$$u_t^X = \underbrace{X_t^t}_{\text{nowcast}} - \underbrace{X_t^T}_{\text{final}},$$

where the final value corresponds to the "most recent" value in the data set of the Federal Reserve Bank of Philadelphia (retrieved in June 2021) for GDP growth and GDP deflator inflation, and to the most recent value from the CBO for the output gap. Our analysis starts with the first Greenbook output gap estimate in 1987:Q3 and ends in 2008:Q2 before the financial crisis and the beginning of the zero lower bound period.[8] This has the added advantage that our final values are unlikely to be subject to further revisions. Throughout this paper, we work at the quarterly frequency. Therefore, following Orphanides (2001), we convert the Greenbook forecasts to quarterly values by focusing on fixed months (January, April, ...) instead of averaging, which has the advantage that time intervals are evenly spaced.[9]

[6]The Federal Reserve Bank of Philadelphia collects the U.S. Bureau of Economic Analysis (BEA) estimates across vintages over time.

[7]We use the GDP deflator for our analysis since alternative inflation measures like the one based on personal consumption expenditures (PCE) start to appear in the Greenbook data only in 2000.

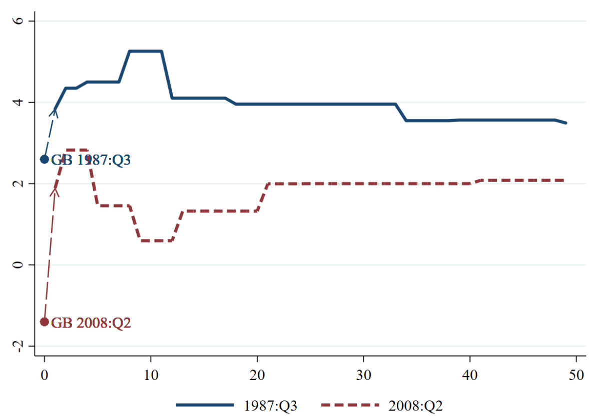
[8]We provide robustness checks based on the Wu and Xia (2016) shadow rate for 1987:Q3 to 2015:Q4 in Appendix A.1.

[9]Our results are robust to different time aggregation methods.

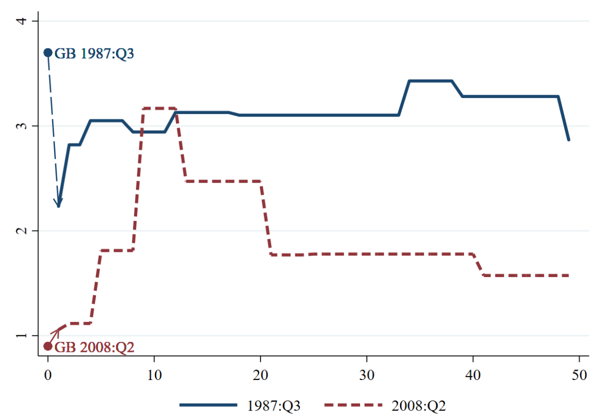
Analysis of the nowcast error series. Our analysis builds on the assumption that these nowcast errors are unknown to the policymaker in real-time. In theory, this assumption should be satisfied because we observe the central bank's expectations reflected by the Greenbook nowcast unless these expectations were uttered untruthfully or strategically. From a practical standpoint, the values of most macroeconomic variables get revised many times throughout the years, mainly due to updated statistical information. To illustrate this point, Panels (a) and (b) of Figure 1 present the estimates of GDP growth and GDP deflator inflation for two data points, the beginning and the end of our sample, across several vintages. The corresponding Greenbook nowcast is marked with a dot at the beginning of the time series graph. We observe that, over time, the nowcasts get revised many times, at least for 10 years before converging to a final value. The figure also demonstrates that the Greenbook forecast can substantially deviate even from the first BEA vintage. This makes it implausible that the Federal Reserve would know these nowcast errors in real time.

Figure 1: Estimates across vintages

(a) GDP growth



(b) GDP deflator inflation



Notes: Real GDP growth and GDP deflator inflation by vintage for different points in time. The Greenbook nowcast is indicated with a dot. The x-axis reflects the vintage since the first release of t expressed in quarters. All values are expressed in percent. *Sources:* Federal Reserve Bank of Philadelphia, Greenbook.

Furthermore, Table 1 below shows that for inflation the nowcast error is statistically unbiased because its average is statistically not different from zero. For output growth and the output gap, in contrast, one can reject the hypothesis that their averages are zero in a statistical sense. However, the economic magnitudes are small, and an ex-post regression of these nowcast errors is anyway not dispositive of the question of whether the central bank could have known better at the time.

Table 1: Summary statistics

	u^x	u^π	u^g
Constant	0.35***	-0.03	-0.66**
	(0.08)	(0.09)	(0.21)
N	84	84	84
min	-1.70	-2.21	-5.01
max	1.90	2.18	2.88
sd	0.73	0.82	1.92

Notes: $u_t = nowcast - final$. *Sources:* Greenbook, Federal Reserve Bank of Philadelphia, CBO. Output growth and inflation are annualized. All values are expressed in percent.

Empirical model. We implement our identification idea in two steps:

1. **Identifying the shock**

$$i_t = \alpha + \rho_x u_t^x + \rho_g u_t^g + \rho_\pi u_t^\pi + \epsilon_t \tag{5}$$

   To isolate the exogenous part of the monetary policy decision, the monetary policy interest rate, i_t, is regressed on the nowcast errors in the output gap, u_t^x, output growth, u_t^g, and inflation, u_t^π. This regression yields a fitted value for the monetary policy interest rate, $\widehat{i}_t$.

2. **Local projections**
   Using local projection methods (Jordà, 2005), we then regress the outcome variables of interest, output, y_{t+h}, prices, p_{t+h}, and the monetary policy interest rate, i_{t+h}, on the identified, exogenous part of the policy decision, $\widehat{i}_t$. Specifically, for each horizon $h \geq 0$, we estimate the following regressions:

$$\begin{aligned} y_{t+h} &= \alpha_h^y + \beta_h^y \widehat{i}_t + \gamma_h^y controls_t + \epsilon_{t+h}^y \\ p_{t+h} &= \alpha_h^p + \beta_h^p \widehat{i}_t + \gamma_h^p controls_t + \epsilon_{t+h}^p \\ i_{t+h} &= \alpha_h^i + \beta_h^i \widehat{i}_t + \gamma_h^i controls_t + \epsilon_{t+h}^i \end{aligned} \tag{6}$$

   In the baseline specification, $controls_t$ includes four lags of the dependent variable in the regressions of output and prices. We verify the robustness of our results using a broader set of controls in Section 3.3. The coefficients of interest are the β_h^z coefficients, for $z = y, p, i$. We scale the coefficients of interest to correspond to a 25 basis point increase in the monetary policy interest rate. Plotting these coefficients across time horizons gives an estimate of the impulse response function to a policy shock.

3 Empirical results

This section documents our findings based on U.S. data for the period from 1987:Q3 to 2008:Q2, using the two-step identification approach explained above.

3.1 Identifying the shock

We first examine the nowcast errors' individual and joint relevance as predictors of the federal funds rate. Table 4 reports the results obtained from estimating equation (5). Each column shows the coefficients based on a specification using individual or combinations of nowcast errors: (1) u_t^x, (2) u_t^π, (3) u_t^g, (4) u_t^x and u_t^g and u_t^π, and (5) u_t^x and u_t^π. The column (5′) represents robustness checks, explained in detail in Section 3.3.

Table 2: Constructing the shock: results (1987:Q3-2008:Q2)

	(1)	(2)	(3)	(4)	(5)	(5′)
u^x	1.58***			1.48***	1.35***	1.02**
	(0.28)			(0.31)	(0.29)	(0.33)
u^π		1.00***		0.48	0.59*	0.68*
		(0.27)		(0.27)	(0.26)	(0.28)
u^g			-0.04	-0.14		
			(0.13)	(0.11)		
R^2	0.276	0.142	0.001	0.332	0.319	0.228
F	31.27	13.56	0.10	13.24	18.96	11.81
N	84	84	84	84	84	83

Notes: Regression of the federal funds rate on individual or combinations of nowcast errors: (1) u_t^x, (2) u_t^π, (3) u_t^g, (4) u_t^x and u_t^g and u_t^π, and (5) u_t^x and u_t^π. (5′) uses u_t^π and the residual of u_t^x purged to the lagged output gap as predictors. Standard errors in parentheses. Constant included. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

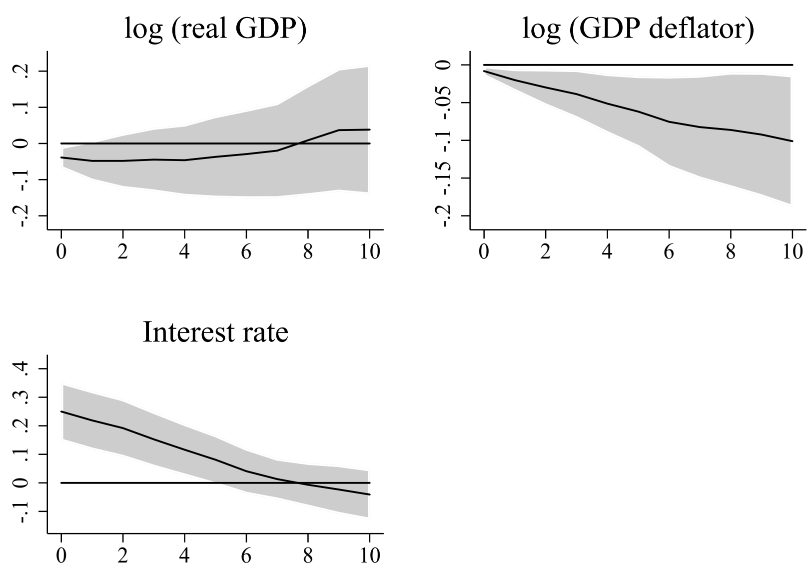
The coefficients on the output gap and inflation nowcast errors, u_t^x and u_t^π, are individually and jointly statistically significant. By contrast, this is not the case for the output growth nowcast error, u_t^g, which is individually and jointly insignificant. We therefore select specification (5), using only the output gap and inflation nowcast errors, u_t^x and u_t^π, as predictors of the policy rate as our benchmark specification.

3.2 Local projections

We measure output, y_{t+h}, as the log of real GDP and the price level, p_{t+h}, as the log of the GDP price deflator.[10] We present the impulse response function of output, prices, and the monetary policy interest rate to an exogenous monetary policy shock.

Figure 2 shows the impulse response functions to a monetary policy shock scaled to a 25 basis point impact increase in the policy rate. In the upper left panel, output declines initially in response to a contractionary monetary policy shock and slowly recovers over the next eight quarters. Similarly, prices decline slowly but persistently. The lower panel shows the effect of the monetary policy shock on the interest rate itself, which lasts about eight quarters. The response of output is statistically significant for a quarter or two, while the response of the price level is significant at all plotted horizons.

Figure 2: Local projections



Notes: Impulse response functions of the log of real GDP (in percent), the log of the GDP deflator (in percent), and the interest rate to a contractionary monetary policy shock scaled to a 25 bp increase in the impact interest rate. We use the nowcast error in the output gap and inflation as exogenous predictors for the policy rate. Regressions of the log of real GDP and the log of the GDP deflator include four lags of the dependent variable. 95% confidence bands. Newey-West standard errors with four lags.

[10] For the local projections, we retrieve the final outcome variables from Federal Reserve Economic Data (FRED): Real Gross Domestic Product (GDPC1) and Gross Domestic Product: Implicit Price Deflator (GDPDEF). The results are the same – no price puzzle – using the inflation rate instead of the price level.

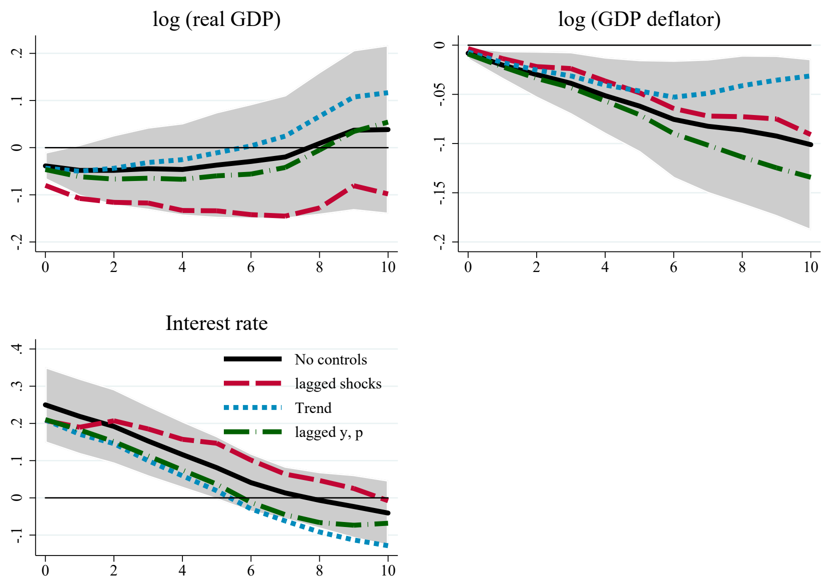
The responses plotted in Figure 2 are consistent with basic theory. A contractionary monetary policy results in a mild decline in output. There is an immediate reduction in prices that is long-lasting. Importantly, there is no price puzzle, wherein the price level initially reacts positively to a contractionary policy shock.

3.3 Robustness checks

To verify the robustness of our results to different specifications, we present two robustness checks. The first robustness check relates to the controls included in the local projections. The second robustness check pertains to the question of whether the nowcast errors are correlated with the business cycle.

Set of control variables. Although in principle not necessary – if one believes that a shock on the right hand side of local projection regression is truly exogenous – the literature often estimates local projections with a large set of controls (e.g., Ramey, 2016, and others). To confirm the robustness of our results, we estimate the local projections for several specifications controlling for (i) one lagged value of the shock, (ii) a quadratic time trend, and (iii) for four lagged values of log real GDP and log GDP deflator in all equations. Figure 10 presents the results.

Figure 3: Local projections with controls



Notes: Impulse response functions of the log of real GDP (in percent), the log of the GDP deflator (in percent), and the interest rate to a contractionary monetary policy shock scaled to a 25 bp increase in the interest rate. The black, solid lines reflect the results for the specification controlling for four lagged values of the dependent variables in the regression of the log of real GDP and the log of the GDP deflator; the red, dashed lines additionally control for one lagged value of the monetary policy shock; the blue, dotted lines additionally control for a quadratic time trend, and the green, dash-dotted lines control for four lagged values of log of real GDP and log of the GDP deflator in all regressions. 95 % confidence bands. Newey-West standard errors with four lags.

Solid lines show our benchmark estimated responses, while colored dashed lines include additional controls. Including additional controls in the local projection regression has no important qualitative effects on the impulse response function. One noticeable difference is that controlling for lagged shocks (dashed, red line) indicates a more significant and persistent decline in output vis-à-vis our benchmark; in contrast, controlling for a trend (dotted, blue line) results in a slightly smaller decline in output and prices vis-à-vis our benchmark.

Possible correlation with the business cycle. Our identification strategy requires that the nowcast errors are independent of the true state of the business cycle. Table 3 presents the results of regressing the output gap and inflation nowcast errors, u_t^x and u_t^π, on the final vintage measures of lagged inflation, π_{t-1}, lagged output growth, g_{t-1}, and the lagged output gap, x_{t-1}.[11]

[11]We use the lagged values of these variables as a measure of the state of the business cycle because, of course, their contemporaneous values are influenced by monetary policy, which is the relationship we are

Table 3: Correlation with lagged business cycle

	$\mathbf{u}^x$	$\mathbf{u}^\pi$
π_{t-1}	0.23	-0.19
	(0.35)	(0.42)
g_{t-1}	-0.17	-0.20
	(0.16)	(0.19)
x_{t-1}	0.18**	0.04
	(0.05)	(0.06)
R^2	0.130	0.016
F	3.89	0.43
N	82	82

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We find that the lagged output gap is a statistically significant predictor for the current output gap nowcast error, whereas lagged output growth and inflation are not. This suggests that the output gap nowcast error may be predictable, posing a threat to our identification. In contrast, Table 3 suggests that the inflation nowcast error is not predictable by the lagged state of the business cycle.

These observations suggest the following two robustness checks to our baseline results. First, we can investigate how, and to what extent, our results change when using only the inflation nowcast error in the first step as predictor for the policy rate. Second, we can replace the output gap nowcast error, u_t^x, with its residual, $u_t^{x,*}$, from a projection on the lagged output gap, x_{t-1}, which by construction is orthogonal to the true state of the business cycle. This transforms our baseline two-step procedure into the following three-step procedure:

1. Purging step: regress u_t^x on x_{t-1} to get innovation $u_t^{x,*}$.
2. First step: regress i_t on $u_t^{x,*}$ and u_t^π to get $\widehat{i_t}$.
3. LP step: regress y_{t+h}, p_{t+h}, and i_{t+h} on $\widehat{i_t}$ for different horizons, h.

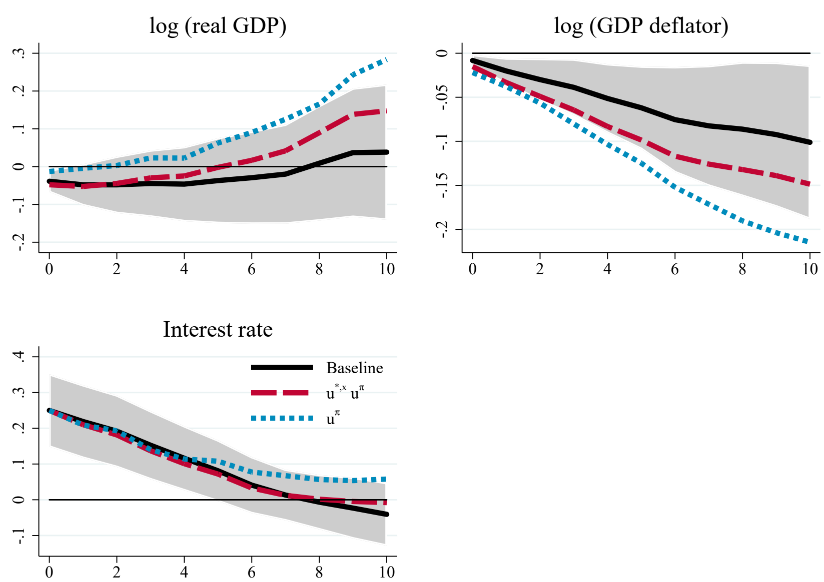
Column (5′) of Table 4 reports the results from estimating (5) with this modified procedure. The purged residual from the output gap remains a significant predictor of the policy rate, although the F statistic is lower.

attempting to estimate in this paper.

Figure 4 plots impulse responses estimated from the local projections of real GDP, the aggregate price level, and the policy rate to a monetary policy shock using both robustness exercises. The impulse responses with the inflation nowcast error as the single predictor of the policy rate are depicted with short-dashed, blue lines; the impulse responses from the three-step procedure are depicted with long-dashed, red lines. For comparison, we include the baseline impulse responses in solid black.

We find that the impulse responses from the three-step procedure are nearly identical to the baseline, suggesting that, while being a theoretical concern, a dependence of the nowcast errors on the state of the business cycle is of little practical relevance. The results with only the inflation nowcast error as a single predictor are qualitatively similar to the baseline but with some deviations, suggesting that the (purified) output gap nowcast error contains relevant information for the identification of monetary policy shocks.

Figure 4: Taking into account business cycle endogeneity

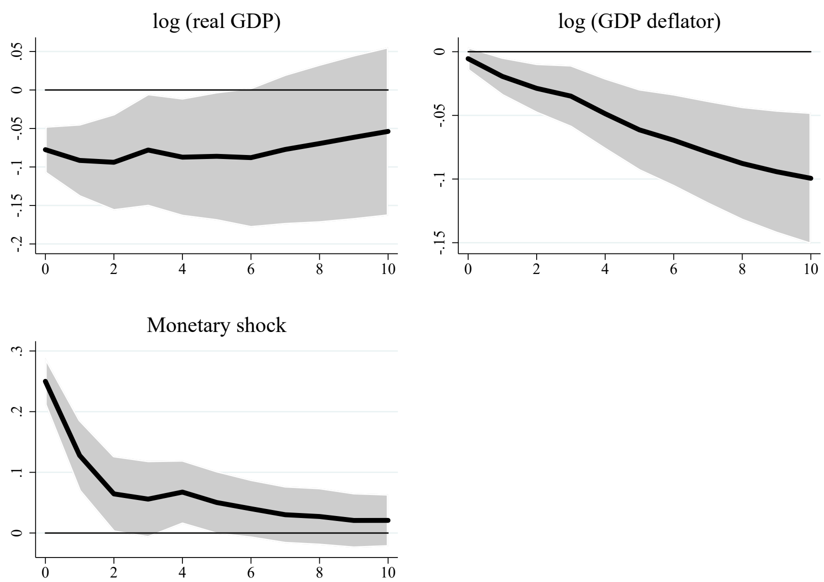


Notes: Impulse response functions of the log of real GDP (in percent), the log of the GDP deflator (in percent) and the interest rate to a contractionary monetary policy shock scaled to a 25 bp increase in the interest rate. The baseline specification uses the nowcast errors in output gap and inflation as exogenous predictors. $u^{*,x}u^{\pi}$ purges the output gap nowcast errors from the lagged output gap and uses the residuals as predictors for the policy rate. u^{π} uses the inflation nowcast errors only as predictors for the policy rate. Regressions of the log of real GDP and the log of the GDP deflator include four lags of the dependent variables. 95% confidence bands. Newey-West standard errors with four lags.

Local projections versus VAR method. To what extent do our results depend on the estimation technique? We present the results of our identification approach based on a VAR instead of local projection methods to verify that the estimation technique does not drive our results. Similar to before, we first identify the shock using the output gap and inflation as predictors or the policy rate. In the second step, however, we estimate a recursive VAR, ordering the shock variable first. This ordering implies that the shock can directly impact output and prices. The VAR is estimated for the same sample 1987:Q3-2008:Q2 and includes four lags.

Figure 5 shows the impulse responses of output, prices, and the monetary policy shock to an identified monetary policy shock using the output gap and inflation nowcast errors as exogenous predictors for the policy rate. In line with the local projection results presented in Figure 2, we observe that output declines briefly and prices decline persistently. We conclude that our approach based on nowcast errors robustly produces theory-consistent reactions of output and the aggregate price level to monetary policy shocks.

Figure 5: VAR results

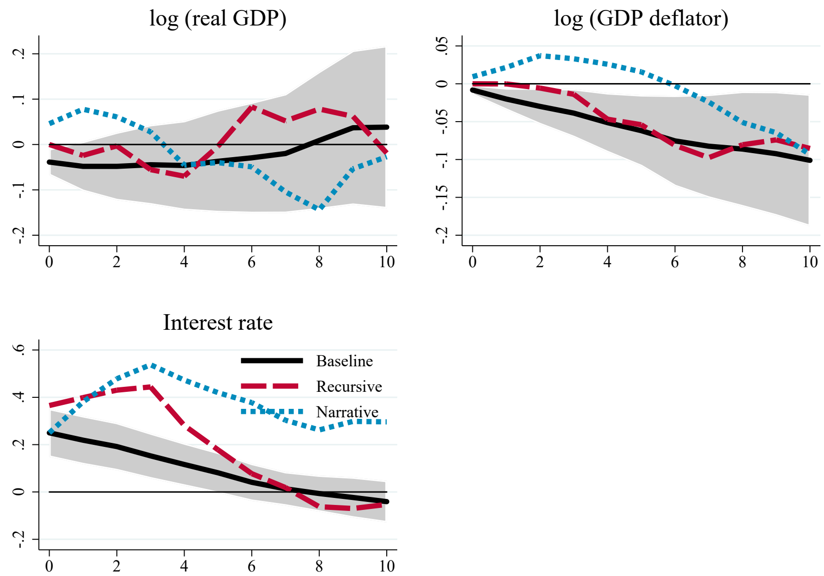


Notes: Impulse response functions of the log of real GDP (in percent), the log of the GDP deflator (in percent), and the monetary policy shock to a contractionary monetary policy shock based on a recursive VAR (including four lags). The exogenous monetary policy shock is ordered first. 95 % confidence bands.

3.4 Alternative identification approaches

Next, we compare our identification approach to two alternative identification approaches in the literature: the recursive approach used by Christiano et al. (1999) and the narrative approach pioneered by Romer and Romer (2004). We start this bridge to the literature by applying their methodologies to our sample (1987:Q3-2008:Q2), using our three variables, real GDP, the GDP deflator, the federal funds rate, and estimating local projections.[12]

Figure 6: Local projection results across identification approaches



Notes: Impulse response functions of the log of real GDP (in percent), the log of the GDP deflator (in percent), and the interest rate to a contractionary monetary policy shock scaled to a 25 bp increase in the interest rate based on local projection methods (Jordà, 2005). Regressions of the log of real GDP and the log of the GDP deflator include four lags of the dependent variable. 95 % confidence bands. Newey-West standard errors with four lags.

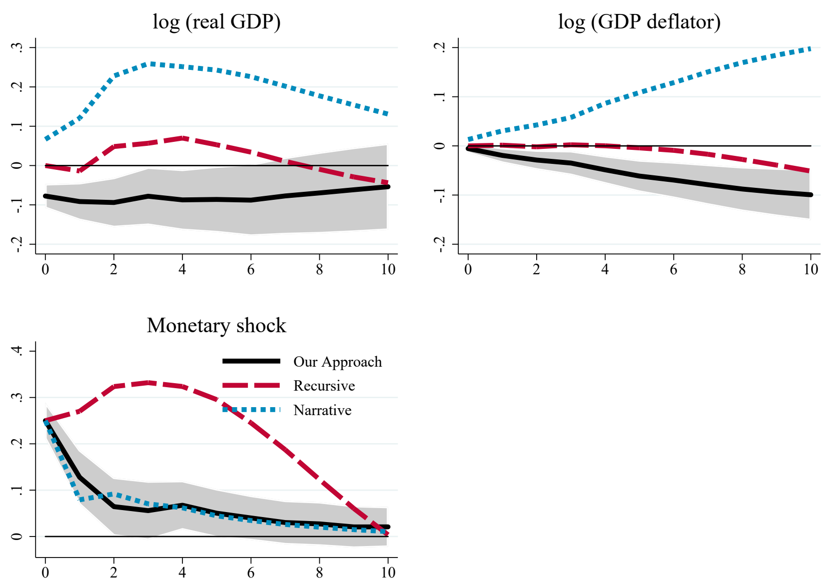
Figure 6 compares the results. In both alternative approaches, the recursive approach (red, dashed lines) and the narrative approach (dotted, blue lines), a contractionary monetary policy shock has no real effects (if anything it expands real GDP) and features a mild price puzzle. Similarly, in the original paper of Christiano et al. (1999) there is a mild price puzzle

[12] For the narrative approach, we use an updated Romer and Romer (2004) shock series, for which we thank Max Breitenlechner and Johannes Wieland. For the recursive approach, we estimate first a recursive VAR (Christiano et al., 1999) and use the identified monetary policy shock series then in the local projection as shock series.

for most specifications, but the negative output response is consistent with basic theory. In Romer and Romer (2004) prices do not respond at all for almost two years after the monetary policy shock, while the output response is negative. The difference between their original results and the results shown in Figure 6 is mainly due to the different samples: 1987-2008 in our replication versus 1965-1995 in Christiano et al. (1999) and 1969-1996 in Romer and Romer (2004).

Figure 7 shows that these features are, if anything, more pronounced when we use a recursively identified VAR instead of local projection methods to compute the impulse response functions.[13]

Figure 7: VAR results across identification approaches



Notes: Impulse response functions of the log of real GDP (in percent), the log of the GDP deflator (in percent), and the monetary policy shock to a contractionary monetary policy shock based on a recursive VAR (including four lags). We replace the federal funds rate with the monetary policy shock series when applying the narrative and our identification approach and order the shock first. The recursive approach ordering is: log real GDP, log GDP deflator, the federal funds rate. 95 % confidence bands.

[13] A further difference between our empirical specification and Christiano et al. (1999) is that the latter include commodity prices and a number of monetary aggregates into their VAR. Comparing their original and our sample shows that, for the output response this difference is immaterial: no matter whether one estimates their VAR with our three variables, our three variables plus an index of commodity prices, or their original seven variables (which include three monetary aggregates) the real effects of a monetary policy shocks are zero or mildly positive when estimated on our more recent sample and negative in the original older sample. For the response of prices, the inclusion of commodity prices in the VAR mitigates but does not eliminate the price puzzle.

4 Simulation results

To demonstrate the suitability of our approach to identifying monetary policy shocks, we build upon a simple yet canonical New Keynesian (NK) model by Ireland (2004), and relax the assumption that the central bank observes the economy in real time without error. We implement this by augmenting the central bank's macroeconomic target variables in the Taylor Rule with error terms. We then conduct a simulation exercise and show that our proposed estimation procedure works well with the simulated data.

The full model consists of a representative household with decisions over consumption, labor, bonds and money holdings, an intermediate good sector, a final good sector, and a central bank following a Taylor rule. Ireland (2004) describes the full model in detail. Appendix A.2 presents the linearized equilibrium conditions. For comparability with the empirical part, we compute the price level as the accumulated sum of the inflation rates. For a more detailed description, we refer the reader to his work and only highlight the key differences.

4.1 The Taylor rule

Conventional NK models such as Ireland (2004) assume that the central bank observes the state of the economy without noise. We depart from this assumption and postulate that the state of the economy as measured by output growth, g_t, inflation, π_t, and the output gap, x_t, is observed in real time t (denoted in the subscripts) with an orthogonal noise term, u_t^i for $i \in \{x, \pi, g\}$, for each. The augmented Taylor rule then takes the following form:

$$i_t = i_{t-1} + \rho_\pi \pi_t^t + \rho_g g_t^t + \rho_x x_t^t + \nu_t, \tag{7}$$

where the policy rate, i_t, is a function of the lagged policy rate, i_{t-1}, nowcast output growth, g_t^t, nowcast inflation, π_t^t, and the nowcast output gap, x_t^t, and the monetary policy shock proper, ν_t. The policy reaction is governed by the Taylor rule coefficients ρ_g, ρ_π, and ρ_x. The nowcasts denoted by the superscript t are a function of the true state denoted with the superscript T (and measured by the final vintage value of these variables) plus an orthogonal error term, $u_t^j \ \forall; \ j; \ \in \{x, g, \pi\}$:

$$x_t^t = x_t^T + u_t^x, \qquad g_t^t = g_t^T + u_t^g, \qquad \pi_t^t = \pi_t^T + u_t^\pi. \tag{8}$$

Combining (7) and (8) allows us to decompose the Taylor rule into the original part and the nowcast error part:

$$i_t = i_{t-1} + \rho_\pi \pi_t^T + \rho_g g_t^T + \rho_x x_t^T + \nu_t + \rho_\pi u_t^\pi + \rho_g u_t^g + \rho_x u_t^x, \tag{9}$$

where the first five terms on the right-hand side are standard and equivalent to the Taylor rule by Ireland (2004), and the subsequent terms correspond to the weighted nowcast errors. Note that the nowcast errors, u_t^π, u_t^g, and, u_t^x, enter the Taylor Rule linearly, which leads us to conclude that, up to a scaling parameter, the augmented nowcast error terms are isomorphic to the decision noise, ν_t.

4.2 Specification of error processes

We consider two different specifications of the error process underlying the nowcast errors. Our baseline calibration assumes that the error terms are independently and identically distributed (i.i.d.), that is, in particular, they are uncorrelated with each other. In a second specification, we allow for a more flexible covariance matrix.[14]

1. **Baseline calibration:** error terms are i.i.d and uncorrelated.

$$\Sigma = \begin{pmatrix} \sigma_{u_x}^2 & 0 & 0 \\ 0 & \sigma_{u_\pi}^2 & 0 \\ 0 & 0 & \sigma_{u_g}^2 \end{pmatrix}$$

$$\Sigma = \begin{pmatrix} 0.0072^2 & 0 & 0 \\ 0 & 0.002^2 & 0 \\ 0 & 0 & 0.0048^2 \end{pmatrix}$$

2. **Correlation calibration:** flexible structure on error term covariance.

$$\Sigma = \begin{pmatrix} \sigma_{u_x}^2 & \sigma_{u_x,u_\pi} & \sigma_{u_x,u_g} \\ \sigma_{u_x,u_\pi} & \sigma_{u_\pi}^2 & \sigma_{u_\pi,u_g} \\ \sigma_{u_x,u_g} & \sigma_{u_\pi,u_g} & \sigma_{u_g}^2 \end{pmatrix}$$

[14]The values presented below are based on the non-annualized, quarterly data in absolute terms (not percent).

$$\Sigma = \begin{pmatrix} 0.0072^2 & 0.0023^2 & 0.00294^2 \\ 0.0023^2 & 0.002^2 & -0.0014^2 \\ 0.00294^2 & -0.0014^2 & 0.0048^2 \end{pmatrix}$$

The baseline variance-covariance matrix is calibrated to match the standard deviation of the nowcast errors based on the baseline sample (1987:Q3-2008:Q2), as reported in Table 1, but adjusted to a quarterly frequency. The correlation calibration considers the correlation between the three nowcast errors observed in the data. The correlation between the output gap nowcast error and the inflation nowcast error is 0.35, the correlation between the output gap nowcast error and the output growth nowcast error is 0.25, and the correlation between the output growth nowcast error and the inflation nowcast error is -0.19.

4.3 Simulation

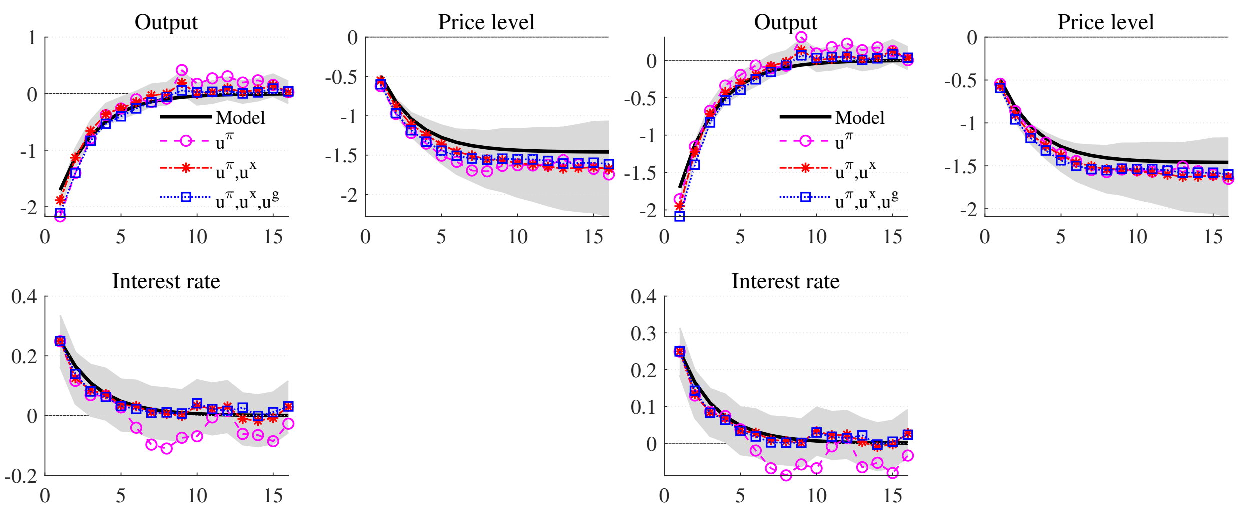
In addition to the covariance matrix of the nowcast errors described above, we calibrate the main model parameters to the post-1980 parameter estimates of Ireland (2004). We re-estimate, however, the shock processes for the sample from 1987:Q3 to 2008:Q2 in order to account for the lower aggregate volatility during the Great Moderation period (see Table 5 in Appendix A.3 for all the parameter values). For both model specifications, we simulate a sample of 10,000 periods and then apply our estimation approach, as well as estimations with a recursive identification and a narrative identification, respectively, on these simulated data.

4.3.1 Our identification approach

We present the impulse responses of output, prices, and the interest rate, to a monetary policy shock based on our identification approach and using local projection methods, estimated on the simulated data from the calibrated NK model specified above. Similar to the empirical part, we use the nowcast errors individually and jointly as predictors for the policy rate to obtain the monetary policy shock series. Specifically, we consider the following specifications, using (i) only the inflation nowcast error, u^{π} (pink, circles), (ii) the output gap nowcast error and inflation nowcast error, u^x and u^{π} (red, asterisks), which corresponds to our empirical baseline specification, and, (iii) all three nowcast errors, u^x, u^{π} and u^g (blue, squares), as predictors for the interest rate. To validate our identification approach, we compare our results to the theoretical impulse response function (black, solid). Panels (a) and (b) of Figure 8 show the estimated impulse responses based on the baseline and the correlation calibration. Similar to the empirical specification, the local projections include four lags of the dependent variable in the regressions of output and prices.

Figure 8: Local projections based on simulated data

(a) Baseline (b) Correlation calibration



Notes: Impulse responses to a contractionary monetary policy shock scaled to a 25 bp increase in the interest rate. u^π (pink, circles) uses the inflation nowcast error as the predictor for the interest rate, u^x, u^π (red, asterisks) uses the output gap nowcast error and inflation nowcast error as predictors for the interest rate, u^x, u^π, u^g (blue, squares) uses the output gap nowcast error, the inflation nowcast error, and the output growth nowcast error as predictors for the interest rate. *Model*, denotes the model-implied theoretical impulse response function. Regressions of output and the price level include four lags of the dependent variable. The 95 % confidence bands correspond to our baseline specification: u^x, u^π (red, asterisks) and based on conventional standard errors estimated by OLS.

We find that the estimated impulse responses based on the simulated data are close to the theoretical impulse response function, both for the baseline and correlation calibrations. Further, the 95 % confidence interval includes the model-implied responses for all variables and time horizons. We conclude that our procedure is able to recover the true reactions of output, the price level, and the interest rate in the model well. We can also see that our baseline empirical specification, which uses the inflation and output gap nowcast errors as predictors, performs slightly better than a specification using only the inflation nowcast error, which provides an additional justification for our empirical baseline. Adding the output growth nowcast error does not change the estimated impulse response functions, again consistent with the data.

4.3.2 Alternative identification approaches

In addition, we evaluate our identification and estimation approach by comparing it with the results from established alternatives in the literature: (i) the narrative approach (Romer and Romer, 2004), and (ii) the recursive approach (Christiano et al., 1999). We explain next the implementation of each alternative identification and estimation approach in detail:

1. *Narrative approach (Romer and Romer, 2004)*
   The narrative approach identifies monetary policy shocks by analyzing individual FOMC decisions, and obtains the exogenous monetary policy shock series by purging the change in the intended federal funds rate to observed, current and future economic conditions. The residual of this regression represents the *narrative* monetary policy shock. Romer and Romer (2004) attribute these monetary policy shocks to (i) beliefs of policymakers, (ii) time-varying operational procedures, and (iii) goals of the federal reserve. We implement their approach by estimating the following regression model using simulated data:

$$i_t = \alpha + \beta i_{t-1} + \sum_{i=-1}^{0} \gamma_{x,i} x_{t,i}^{obs} + \sum_{i=-1}^{0} \gamma_{g,i} g_{t,i}^{obs} + \gamma_{\pi,-1} \pi_{t,i}^{obs} + \varepsilon_t \tag{10}$$

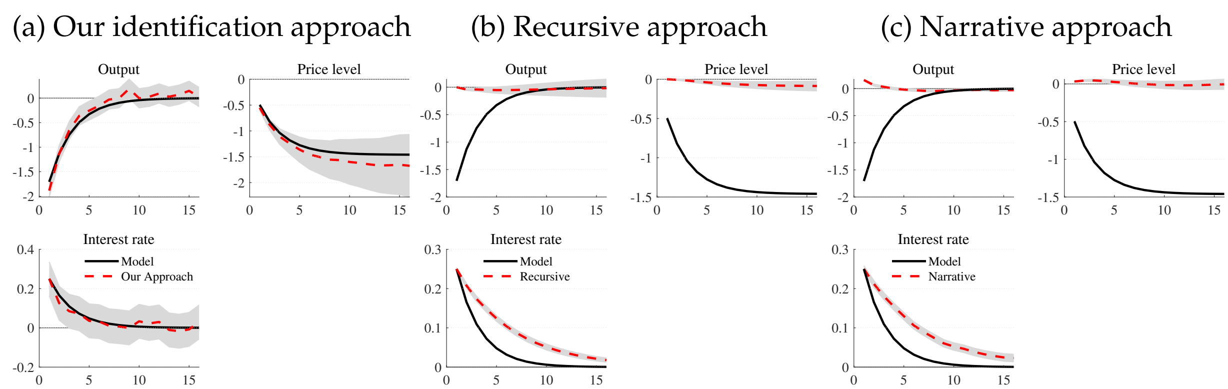
   where i_t reflects the interest rate, i_{t-1} the lag of the interest rate, $x_{t,i}^{obs}$ for $i \in \{-1, 0\}$ the lag and nowcast of the output gap, $g_{t,i}^{obs}$ for $i \in \{-1, 0\}$ the lag and nowcast of output growth, and $\pi_{t,i}^{obs}$ for $i \in \{-1\}$ the lag of inflation.[15] We then take the residual from Equation (10) as the shock variable in the local projection.

2. *Recursive identification approach*
   The recursive identification approach identifies monetary policy shocks using timing assumptions. To break the contemporaneous relationship, Christiano et al. (1999) assume that output and prices do not react contemporaneously to the interest rate. We therefore estimate a VAR with a recursive ordering of output, prices, and the policy interest rate on the simulated data, using four lags of the dependent variables.

[15]The forecasts are the model-implied rational expectations forecasts at the beginning of the period ($t-1$). Romer and Romer (2004) include also the one- and two-period ahead forecasts of the macroeconomic variables. In the model, the nowcast and the forecasts are multicollinear. Hence, we only include the nowcast of the observed value. Further, using the final instead of observed values does not alter the results significantly.

Figure 9 compares the impulse responses across all identification approaches, (a) our approach, (b) the recursive approach, and (c) the narrative approach, to the theoretical impulse response function.

Figure 9: Comparison of identification approaches (baseline)



Notes: Impulse responses to a contractionary monetary policy shock scaled to a 25 bp impact increase in the interest rate. *Our Approach* reflects our identification approach using the nowcast error in output growth and inflation as predictors for the policy rate; *Narrative*, the narrative approach (Romer and Romer, 2004); *Recursive*, the recursive approach (Christiano et al., 1999); and *Model*, the model-implied theoretical impulse response function. The regressions of output and the price level in (a) and (c) include four lags of the dependent variable. 95 % confidence bands in (a) and (c). Bootstrapped confidence bands (1,000 runs) in (b).

The recursive and narrative approaches, shown in Panels (b) and (c) of Figure 9, fail to recover the theoretically implied model responses in contrast to our identification approach, shown in Panel (a). Both alternative approaches significantly underestimate the model-implied impulse responses, that is, estimate a more muted response of output and prices to a monetary policy shock. The alternative approaches fail to identify the model-implied impulse responses because the restored monetary policy shock turns out to be a combination of all the shocks in the model. More precisely, the correlation of the derived "monetary policy shock" with the preference, cost-push, and technology shocks is significantly different from zero. Moreover, note that it is not the presence of the nowcast errors that is responsible for failing to recover the model-implied impulse responses, but rather the presence of the other shocks in the model. In fact, when the variances of the preference and cost-push shocks are set to zero, the narrative approach accurately recovers the model-implied impulse responses. Although we cannot recover the model-implied impulse responses using the recursive approach, we can improve the performance by aligning the expectation structure, i.e., assuming that prices and output are determined before the realization of the monetary policy shock, as shown in Carlstrom et al. (2009). However, the estimated impulse responses based on the modified expectation structure still underestimate the model-implied responses.

In Appendix A.4, Figure 11 displays the simulation results for the correlation calibration that are qualitatively similar to the baseline calibration. In sum, the results of our simulation exercise indicate that our approach to identifying monetary policy shocks works well on a standard NK model as the data-generating process, and better than narrative and recursive approaches.

5 Conclusion

We propose a new identification approach to estimate the effects of exogenous monetary policy shocks, exploiting the central bank's imperfect information at the point of decision making. We isolate the part of the policy response reaction due to the central bank's nowcast errors with respect to inflation and the output gap and use these as predictors for the interest rate. Our approach performs well in the data as well as in simulation exercises. Using the model from Ireland (2004), we confirm the viability of our identification approach. When we apply our identification approach to U.S. data, we find, in response to a 25 basis point increase in the interest rate, a brief decline in output, and a persistent decline in prices. In particular, we do not find the price puzzle that often plagues the empirical monetary policy literature.

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A Appendix

A.1 Extended sample (1987:Q3-2015:Q4)

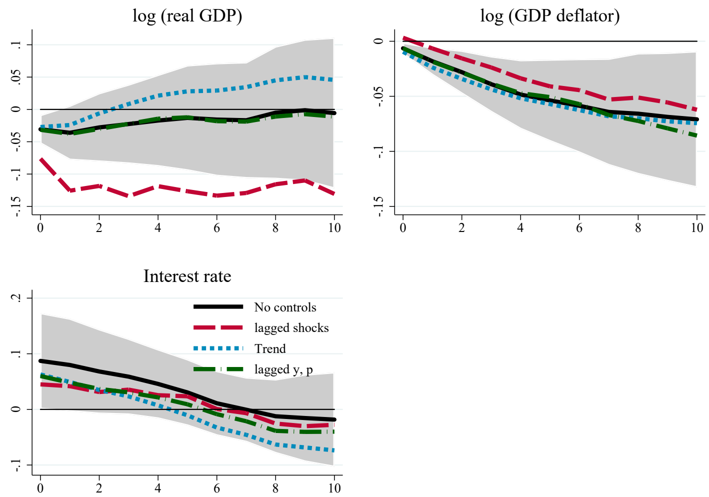
This section shows the results for the extended sample (1987:Q3-2015:Q4). We replace the federal funds rate with the Wu and Xia (2016) shadow rate during the zero lower bound (ZLB) period. To control for discontinuities, we include a dummy for the ZLB period in the local projection regression. The modified local projection regression equation is: $y_{t+h} = \alpha_h^y + \beta_h^y \widehat{i_t} + \gamma_h^y controls_t + \eta_h^y ZLB_t + \epsilon_{t+h}^y$.

Table 4: Constructing the shock: results (1987:Q3-2015:Q4)

	(1)	(2)	(3)	(4)	(5)	(5′)
u^x	1.78***			1.86***	1.79***	0.97**
	(0.21)			(0.22)	(0.22)	(0.36)
u^π		0.70*		-0.09	-0.07	0.30
		(0.35)		(0.28)	(0.29)	(0.37)
u^g			-0.26	-0.36**		
			(0.15)	(0.11)		
R^2	0.388	0.034	0.027	0.440	0.389	0.093
F	71.08	3.99	3.07	28.86	35.27	5.65
N	114	114	114	114	114	113

Notes: Regression of the shadow rate on individual or combinations of nowcast errors: (1) u_t^x, (2) u_t^π, (3) u_t^g, (4) u_t^x and u_t^g and u_t^π, and (5) u_t^x and u_t^π. (5′) uses u_t^π and the residual of u_t^x purged to the lagged output gap as predictors. Standard errors in parentheses. Constant included. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 10: Local projections: Baseline vs. controls (extended sample)



Notes: Impulse response functions of the log of real GDP (in percent), the log of the GDP deflator (in percent), and the shadow rate to a contractionary monetary policy shock scaled to a 25 bp increase in the interest rate based on local projection methods (Jordà, 2005). The black, solid lines reflect the results for the specification controlling for four lagged values of the dependent variables in the regression of the log of real GDP and the log of the GDP deflator; the red, dashed lines additionally control for one lagged value of the monetary policy shock; the blue, dotted lines additionally control for a quadratic time trend, and the green, dash-dotted lines control for four lagged values of log of real GDP and log of the GDP deflator in all regressions. 95 % confidence bands. Newey-West standard errors with four lags 95 % confidence bands. Newey-West standard errors with four lags.

A.2 Model equations

We present the linearized set of equations of the augmented NK model based on Ireland (2004). The nowcasts are denoted with the superscript t. The true state is denoted with the superscript T.

$$x_t^T = \alpha_x x_{t-1}^T + (1-\alpha_x)\mathbb{E}_t[x_{t+1}^T] - (i_t - \mathbb{E}_t[\pi_{t+1}^T]) + (1-\omega)(1-\rho_a)a_t \tag{11}$$

$$\pi_t^T = \beta(\alpha_\pi \pi_{t-1}^T + (1-\alpha_\pi)\mathbb{E}_t[\pi_{t+1}^T]) + \psi x_t^T - e_t \tag{12}$$

$$x_t^T = y_t - \omega a_t \tag{13}$$

$$g_t^T = y_t - y_{t-1} + \sigma_z \varepsilon_{z_t} \tag{14}$$

$$a_t = \rho_a a_{t-1} + \sigma_a \varepsilon_{a_t} \tag{15}$$

$$e_t = \rho_e e_{t-1} + \sigma_e \varepsilon_{e_t} \tag{16}$$

$$i_t = i_{t-1} + \rho_\pi \pi_t^t + \rho_g g_t^t + \rho_x x_t^t + \nu_t \tag{17}$$

$$\nu_t = \sigma_r \varepsilon_{r_t} \tag{18}$$

$$x_t^t = x_t^T + u_t^x \tag{19}$$

$$\pi_t^t = \pi_t^T + u_t^\pi \tag{20}$$

$$g_t^t = g_t^T + u_t^g \tag{21}$$

A.3 Model calibration

Table 5: Calibration

Parameter	Value
β	0.99
ψ	0.1
ω	0.0581
α_x	0.0000
α_π	0.0000
ρ_π	0.3866
ρ_g	0.3960
ρ_x	0.1654
ρ_a	0.8258 *
ρ_e	0.8363 *
σ_a	0.0175 *
σ_e	0.0006 *
σ_z	0.002 *
σ_r	0.0033 *
σ_x	0.0072
σ_π	0.002
σ_g	0.0048

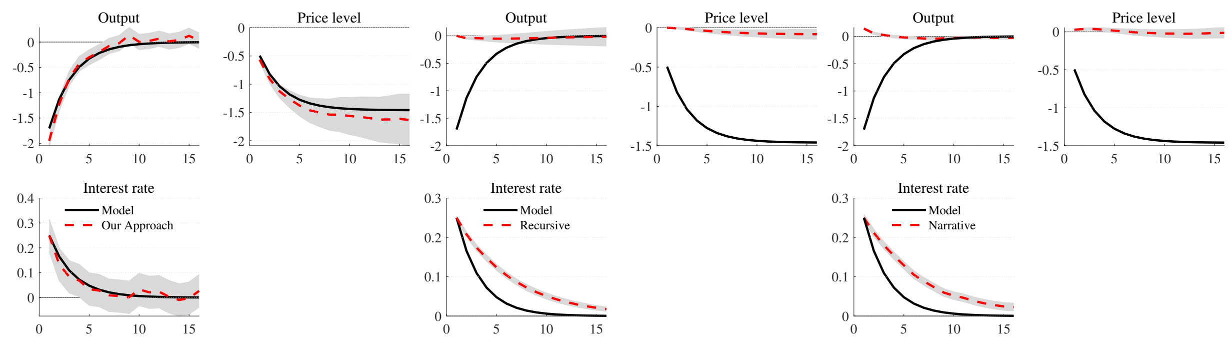
Notes: * denotes our estimates for the period from 1987:Q3 to 2008:Q2 using the demeaned time series of real GDP growth, the GDP deflator, the federal funds rate and the output gap at a quarterly frequency. The parameter values in the upper third section are taken from the post-1980 estimates of Ireland (2004). *Sources:* FRED, CBO.

A.4 Simulation results

This section presents the simulation results for the correlation calibration. We compare our identification, the narrative approach, and the recursive approach.

Figure 11: Comparison of identification approaches (correlation calibration)

(a) Our identification approach (b) Recursive approach (c) Narrative approach



Notes: Impulse responses to a contractionary monetary policy shock scaled to a 25 bp impact increase in the interest rate. *Our Approach* reflects our identification approach; *Narrative*, the narrative approach (Romer and Romer, 2004); *Recursive*, the recursive approach (Christiano et al., 1999); and *Model*, the model-implied theoretical solution. The regressions of output and the price level in (a) and (c) include four lags of the dependent variable. 95 % confidence bands in (a) and (c). Bootstrapped confidence bands (1,000 runs) in (b).