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Identifying monetary policy shocks using the central bank's information set[☆]

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A B S T R A C T

We identify monetary policy shocks by exploiting variation in the central bank's information set. To be specific, we use differences between nowcasts of the output gap and inflation with final, revised estimates of these series to isolate movements in the policy rate unrelated to economic conditions. We then compute the effects of a monetary policy shock on the aggregate economy using local projection methods. We find that a contractionary monetary policy shock has a limited negative effect on output but a persistent negative impact on prices. In contrast to alternative identification approaches, we do not observe a price puzzle when analyzing the period from 1987 to 2008. Further, we validate the identification approach in a simple New Keynesian model, augmented by the assumption that the central bank observes the ingredients of the Taylor rule with error.

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). For analyzing the effects of monetary policy in more recent periods, the literature has

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also employed high-frequency financial market data around policy meetings to identify monetary policy shocks (Cochrane and Piazzesi, 2002; Faust et al., 2003, 2004; Gertler and Karadi, 2015; Nakamura and Steinsson, 2018). As we show below, the recursive and narrative approaches 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 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) potentially subjective 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 meetings. 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 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 policy 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.

Related Literature.

Our paper fits into a large literature on the identification of monetary policy shocks.[4] Our paper is most closely related to a subset of this broader literature that investigates the importance of measurement error for monetary policy. A number of papers have taken seriously the fact that policy decisions must be made in real-time subject to potentially mismeasured data. One of the most prominent papers in this literature is Orphanides (2001), who argues that data revisions are important and that analyzing simple policy rules (such as the canonical Taylor rule) using ex-post data can lead to misleading conclusions about the desirability of such rules. Orphanides and Williams (2005) argue that the Fed reacted too much to perceived unemployment gaps based on poor real-time data in the 1970s, contributing to the subsequent Great Inflation. More generally, they caution against activist policies that react strongly to noisy real-time data. In a similar vein, Lubik and Matthes (2016) argue that the Fed may have inadvertently induced equilibrium indeterminacy in the 1970s. They analyze a model similar to our own, where the central bank reacts to perceived economic conditions (which are noisy measures of true conditions). Differently from us, they analyze an optimal policy problem, in which policy reaction coefficients change period-by-period. Similarly, Cukierman and Lippi (2005) study an optimal policy problem in which the central bank is uncertain about the extent to which fluctuations are driven by changes in potential output or cyclical demand shocks. Orphanides and Williams (2007) argue that in a world with real-time measurement issues, policy should be more inertial and less reactive to output/unemployment gaps.

[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.

[2] Our baseline analysis starts with the first Greenbook output gap estimate in 1987 and ends in 2008 before the zero lower bound period. We provide robustness checks for an extension to 2015 in Appendix A.1.

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

[4] It is beyond the scope of this paper to review that entire literature; for a comprehensive survey, see Ramey (2016).

On the empirical front, Croushore and Evans (2006) study the importance of using ex-post versus real-time data for conclusions about the effects of monetary policy shocks. They conclude that the use of revised data may not be of much practical concern for estimating the magnitudes and signs of macroeconomic responses to policy shocks using conventional identification approaches. Croushore (2019) analyzes the properties of revisions to the PCE deflator series and discusses the implications for monetary policy. More recently, Aruoba and Drechsel (2022) use machine learning techniques to fully capture the information set available to monetary policymakers in real-time. They then predict policy rates using their enhanced information set, identifying policy shocks as residuals from the actual policy rate in a procedure otherwise conceptually similar to Romer and Romer (2004). They emphasize that their identified policy shock series is relatively uncontaminated by the so-called “Fed information effect” (see, e.g., Nakamura and Steinsson, 2018 or Campbell et al., 2012).

Our paper differs from these in that we exploit real-time informational issues directly for the identification of policy shocks. The papers discussed above either analyze the implications of noisy measurement for the design of optimal rules (Orphanides, 2001 and Lubik and Matthes, 2016), analyze the effects of real-time versus ex-post macroeconomic time series for the performance of existing identification strategies (Croushore and Evans, 2006), or augment existing identification approaches with more data (Aruoba and Drechsel, 2022). We are unaware of any paper in the monetary policy literature that uses mismeasurement of real-time fundamentals as a way to identify exogenous variation in the policy rate. There are papers that make use of a this basic approach to identification in other areas, however. Our identification approach is very similar, for example, to Chodorow-Reich et al. (2019), who decompose state-level variation in the duration of unemployment benefit 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.[5] Similarly, Enders et al. (2021) use nowcast errors about output growth to identify belief shocks. We view our paper as providing a bridge between the empirical approach pioneered in Chodorow-Reich et al. (2019) to the monetary policy literature that focuses on challenges for policymaking in real-time but which has not heretofore used nowcast errors for the purposes of shock identification.

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 evaluates its performance against other popular empirical strategies. Section 5 concludes. Details, robustness checks, and additional results are available in the appendices.

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 targets are obviously correlated with the interest rate decision, they are unlikely to be correlated with economic outcomes through any channel other than the policy rate.

A stylized model.

To illustrate the intuition behind our approach, consider a stylized model. Though only meant for illustrative purposes, the simple, static model conveys the logic behind our approach of estimating the effects of a monetary policy shock using nowcast errors.

Suppose that the central bank sets its policy rate, i_t, as a function of perceived macroeconomic conditions at time t, denoted by x_t^t:[6]

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

In (1), $\psi_i \neq 0$ represents the central bank's response to perceived economic conditions. ν_t is a conventional monetary policy shock.

The central bank's perceived nowcast of current conditions, x_t^t, is a noisy measure of actual economic conditions, x_t^T, plus a nowcast error, u_t:

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

We assume that actual economic conditions, x_t^T, react to the policy rate via the parameter $\psi_x \neq 0$, as well as to a non-monetary shock, ϵ_t:

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

In (1)-(3), the exogenous shocks ν_t, u_t, and ϵ_t are assumed to be mean-zero and i.i.d with known variances.

[5] 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.

[6] For illustrative purposes, we suppose that perceived and actual economic conditions are described by scalars. It would be straightforward to extend the analysis to where x_t^t is instead a vector.

The parameter ψ_x measures the effect of an exogenous change in the interest rate on actual macroeconomic conditions. Suppose a researcher interested in estimating this parameter were to run a regression of x_t^T on the policy rate, i_t. This would not correctly recover the parameter of interest. In particular, so long as $\text{var}(\epsilon_t) \neq 0$, there would be simultaneity bias – ϵ_t would both directly affect x_t^T and indirectly affect it through the policy rate. This is the basic endogeneity problem described above.

In Appendix A.2, we show that the following two-step procedure will correctly uncover ψ_x. We assume that u_t can be measured as the difference between final release data, which we take to be a measure of x_t^T, and a real-time estimate, x_t^t, as in (2). In the first step, we regress the policy rate, i_t, on this nowcast error. This gives a fitted value, $\widehat{i_t}$. In the second step, we regress the final release data, x_t^T, on the fitted value. This procedure correctly uncovers the parameter of interest. The identifying assumption is that u_t only affects x_t^T through its impact on the policy rate. We do not require that u_t be orthogonal to x_t^T. In fact, it is precisely through the impact of u_t on the policy rate, and hence on economic conditions, that we can uncover the parameter ψ_x.

Data sources. To approximate the information set of the Federal Reserve in real time, we use the *Federal Reserve Bank of Philadelphia Greenbook* (Greenbook) and the *Output Gap and Financial Assumptions from the Board of Governors*.[7] For each FOMC meeting, the Greenbook includes real-time estimates and projections by the staff of the Board of Governors (1987–2015). We combine this data set with (i) the *Federal Reserve Bank of Philadelphia "Real-Time Data Set,"*[8] which contains GDP and GDP deflator estimates of several vintages,[9] 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.[10] 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 using only beginning-of-quarter values and thus focusing on fixed months (January, April, …) instead of averaging. This has the advantage that time intervals are evenly spaced.[11]

Analysis of the nowcast error series. Our analysis builds on the assumption that these nowcast errors are unknown to policymakers 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 formed 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 Fig. 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.

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

1. **Identifying the shock**

$$i_t = \alpha + \rho_x u_t^x + \rho_g u_t^g + \rho_\pi u_t^\pi + \epsilon_t \tag{4}$$

[7] To be clear, the output gap nowcasts were neither published nor mentioned in the Greenbook until January 2004. The output gap nowcasts that are now included in the Philadelphia Fed's dataset are from an internal output gap measure used by the staff of the Federal Reserve Board, as discussed by Orphanides (2001). We are grateful to an anonymous referee for pointing this out to us. Our results do not rely on the inclusion of the output gap. Appendix A.3 provides robustness checks using the inflation nowcast only.

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

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

[10] We provide robustness checks based on the Wu and Xia (2016) shadow rate for 1987:Q3 to 2015:Q4 in Appendix A.1. The reason the sample ends in 2015:Q4 is because the Greenback data are only available with a five-year lag.

[11] Our results are robust to different time aggregation methods and using monthly data. We present the results based on monthly data in Appendix A.4.

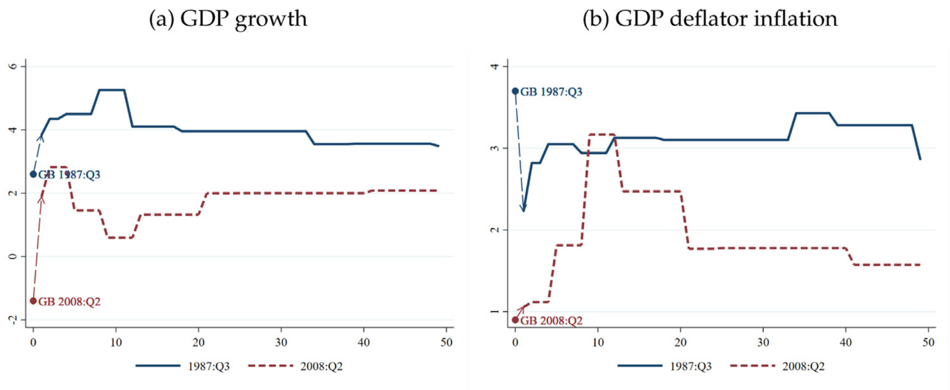

Fig. 1. Estimates across vintages.
Notes: Real GDP growth and GDP deflator inflation by vintage for different points in time. The Greenbook nowcast is indicated with a dot. The x-axis reflects the vintage since the first release of t expressed in quarters. All values are expressed in percent. *Sources:* Federal Reserve Bank of Philadelphia, Greenbook.

To isolate the exogenous part of the monetary policy decision, the policy 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 policy 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 policy rate, i_{t+h} – on the exogenous part of the policy decision, $\widehat{i_t}$. Specifically, for each horizon $h \geq 0$, we estimate the following regressions:

$$\begin{aligned} y_{t+h} &= \alpha_h^y + \beta_h^y \widehat{i_t} + \gamma_h^y controls_t + \epsilon_{t+h}^y \\ p_{t+h} &= \alpha_h^p + \beta_h^p \widehat{i_t} + \gamma_h^p controls_t + \epsilon_{t+h}^p \\ i_{t+h} &= \alpha_h^i + \beta_h^i \widehat{i_t} + \gamma_h^i controls_t + \epsilon_{t+h}^i \end{aligned} \tag{5}$$

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 policy 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 1 reports the results obtained from estimating Eq. (4). Each column shows the coefficients based on a specification using individual

Table 1
Constructing the shock: results (1987:Q3-2008:Q2).

	(1)	(2)	(3)	(4)	(5)	(5')	(5")	(5"')
u^x	1.62***			1.50***	1.36***	1.07**	1.04*	1.15*
	(0.27)			(0.30)	(0.28)	(0.32)	(0.44)	(0.45)
u^π		1.08***		0.56*	0.67**	0.75**	0.76*	0.87**
		(0.26)		(0.26)	(0.25)	(0.27)	(0.29)	(0.33)
u^g			-0.05	-0.15				
			(0.12)	(0.11)				
R^2	0.300	0.173	0.002	0.374	0.358	0.271	0.150	0.149
F	35.22	17.13	0.20	15.90	22.60	14.90	7.06	6.76
N	84	84	84	84	84	83	83	80

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^π and u_t^g, (5) u_t^x and u_t^π, (5') uses u^π and the residual of u_t^x purged to the lagged output gap as predictors. (5") and (5"') use the residual of u_t^x and u_t^π purged to its lagged first and four values as predictors. Standard errors in parentheses. Constant included. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

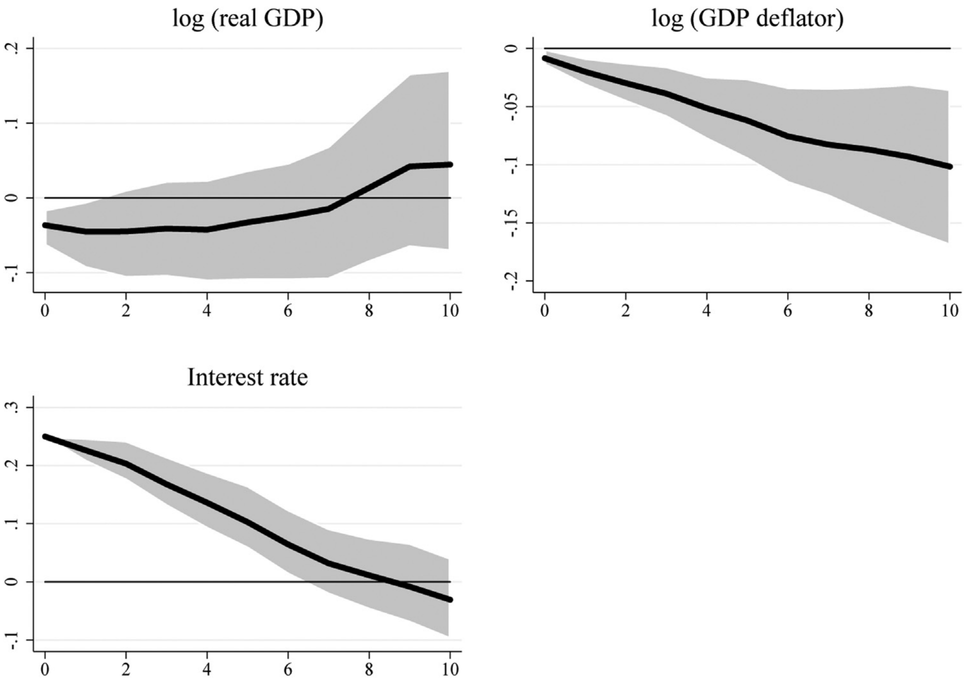

Fig. 2. Local projections.
Notes: Impulse response functions of the log of real GDP (in percent), the log of the GDP deflator (in percent), and the interest rate to a contractionary monetary policy shock scaled to a 25 bp increase in the interest rate on impact. We use the nowcast error in the output 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. Shaded areas are 95-percent bootstrap confidence bands.

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 columns (5'), (5"), and (5"') represent robustness checks, explained in detail in Section 3.3.

The coefficients on the output gap and inflation nowcast errors, u_t^x and u_t^π, are individually and jointly statistically significant. The signs of these coefficients correspond to standard Taylor rule logic: positive nowcast errors in the gap and inflation are associated with a higher policy rate. In contrast, the coefficient on the output growth nowcast error, u_t^g, is individually and jointly insignificant in all specifications. 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.[12] We present the impulse response functions of output, prices, and the policy rate to an exogenous monetary policy shock.

Fig. 2 shows the impulse response functions to a monetary policy shock scaled to a 25 basis point impact increase in the policy rate. Shaded areas are 95-percent confidence intervals from a bootstrap.[13] In the upper left panel, output declines initially and slowly recovers over the next eight quarters. Similarly, the price level declines slowly but persistently. The lower panel shows the effect of the 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 statistically significant at all plotted horizons.

The responses plotted in Fig. 2 are consistent with basic theory. A contractionary monetary policy results in a mild decline in output. There is an immediate reduction in the price level that is long-lasting. Importantly, there is no price puzzle, wherein the price level initially reacts positively to a contractionary policy shock.[14]

[12] 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). Our results are the same if we instead use the inflation rate rather than the price level on the left hand side.

[13] We implement the bootstrap using a standard fixed design pairs bootstrap following Montiel Olea and Plagborg-Møller (2021).

[14] In Appendix A.5, we show that we obtain qualitatively similar results when we instead use an external instruments approach.

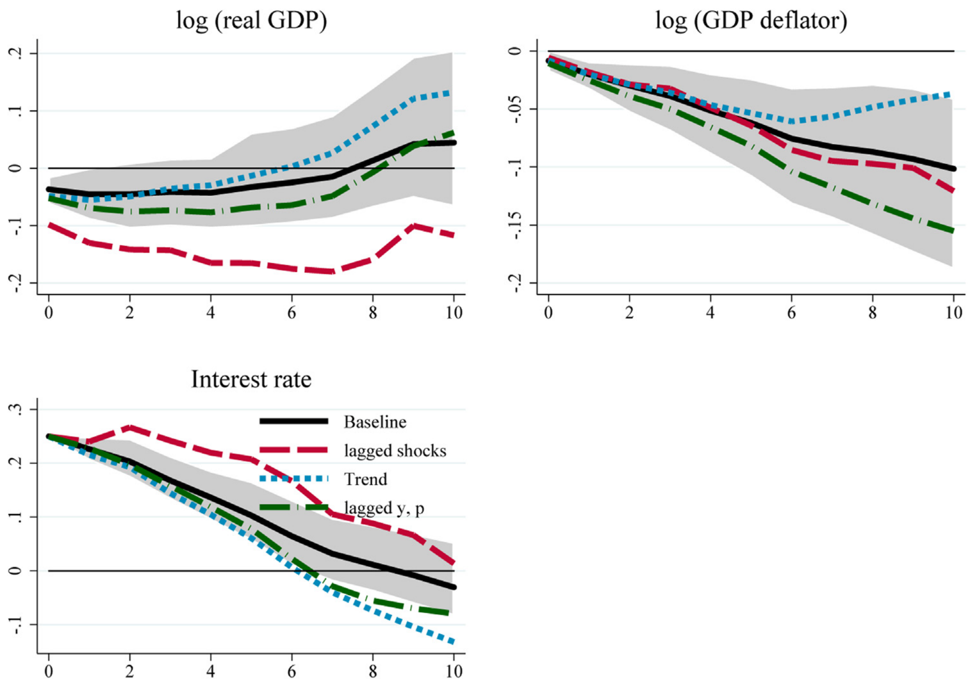

Fig. 3. Local projections with controls.
Notes: Impulse response functions of the log of real GDP (in percent), the log of the GDP deflator (in percent), and the interest rate to a contractionary monetary policy shock scaled to a 25 bp increase in the interest rate. The black, solid lines reflect the baseline 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. Shaded areas are 95-percent bootstrap confidence bands. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.3. Robustness checks

To verify the robustness of our results to different specifications, we present three additional sets of results. The first robustness check relates to the controls included in the local projections. The other robustness checks pertain to the question of whether the nowcast errors are correlated with the business cycle and whether they are unpredictable.

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. Fig. 3 presents the results.[15]

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 functions. One noticeable difference is that controlling for lagged shocks (dashed, red line) results in 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, other than through any effect operative through the policy rate. Table 2 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}.[16]

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, potentially posing a threat to our identification. We note, however, that ex-post predictability for the econometrician does not necessarily imply real-time predictability for the policymaker.

[15] Fig. A.5 in Appendix A.6 provides error bands for all individual responses.

[16] 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 attempting to estimate in this paper.

Table 2
Correlation with lagged business cycle.

	u^x	u^π
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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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.[17] 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 1 reports the results from estimating (4) 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.

Fig. 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.[18] 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.

Controlling for lagged nowcast errors. A second threat to identification would be if the Federal Reserve could predict its own nowcast errors. We have already shown in Fig. 1 that the data revision process takes a long time in practice, so that it is unlikely that the Federal Reserve knows its nowcast errors in real time. Nevertheless, we can ask what happens if the Federal Reserve observed its past nowcast errors and used them to predict its current nowcast errors?

To potentially correct for forecastability, we propose another three-step procedure. In particular, we regress the nowcast errors on their own lags, and then use the residual from this regression to isolate exogenous movement in the policy rate. We do this by postulating an AR(1) or an AR(4) structure.[19] Specifically,

1. Purging step: regress u_t^x and u_t^π on $\sum_{j=1}^{1(4)} u_{t-j}^x$ and $\sum_{j=1}^{1(4)} u_{t-j}^\pi$ to get the innovations, $u_t^{x,AR1(4)}$ and $u_t^{\pi,AR1(4)}$, respectively.
2. First step: regress i_t on $u_t^{x,AR1(4)}$ and $u_t^{\pi,AR1(4)}$ 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.

Columns (5") and (5"') of Table 1 report the results using the nowcast errors residuals, from, respectively, an AR(4) and AR(1), as predictors for the policy rate. The estimated coefficients are of smaller magnitude than the baseline model, but remain significant and have the same signs. The dotted, blue lines in Fig. 5 plot impulse responses from a local projection where the shock variable is constructed using nowcast error residuals from an AR(1). The dash-dotted, green lines do the same for nowcast error residuals from an AR(4).

[17] Appendix A.7 provides a robustness check in which we first project nowcast errors on lagged final values of all three series (inflation, the output gap, and output growth). Our results are similar.
[18] Fig. A.6 in Appendix A.6 provides error bands to all responses.
[19] The partial autocorrelations show that the nowcast errors are statistically significant at the five percent level up to one lag for the output gap nowcast error and up to four lags for the inflation nowcast error.

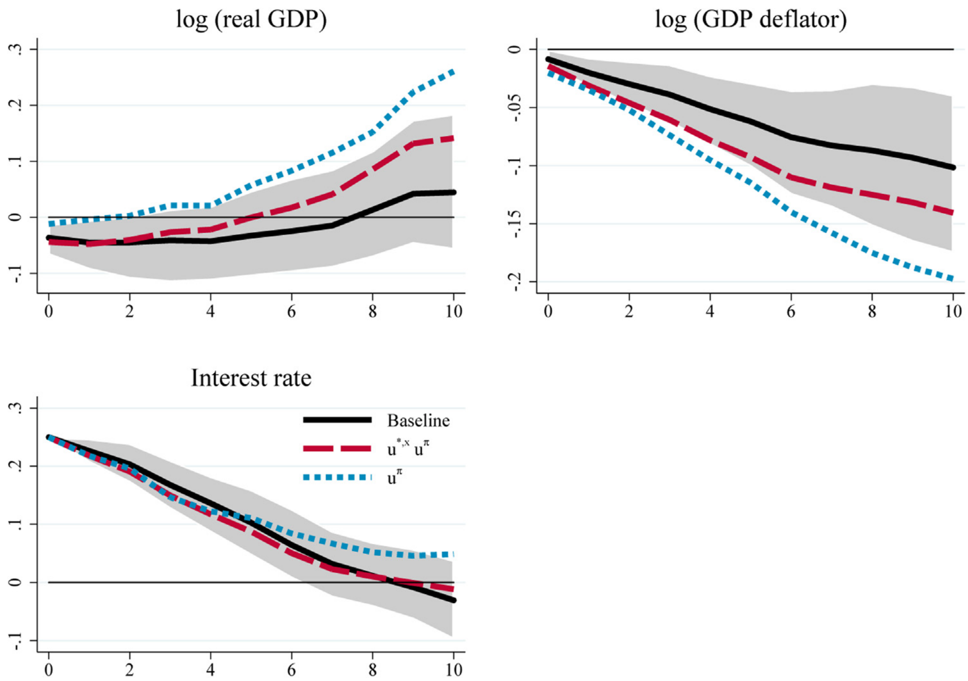

Fig. 4. Taking into account business cycle endogeneity.

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 to 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. Shaded areas are 95-percent bootstrap confidence bands.

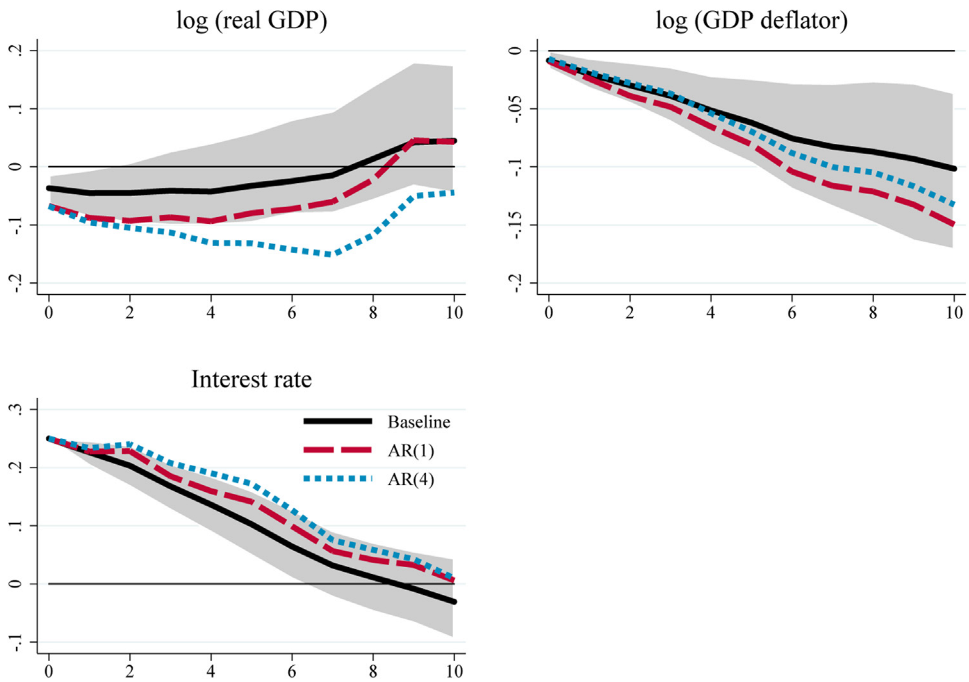

Fig. 5. Controlling for lagged nowcast errors.

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. In the baseline specification, we use the nowcast errors in output gap and inflation as predictors for the policy rate. AR(4) purges from the nowcast errors the last four lags and uses the residuals as predictors for the policy rate. AR(1) purges from the nowcast errors the first lag and uses the residuals as predictors for the policy rate. Shaded areas are 95-percent bootstrap confidence bands.

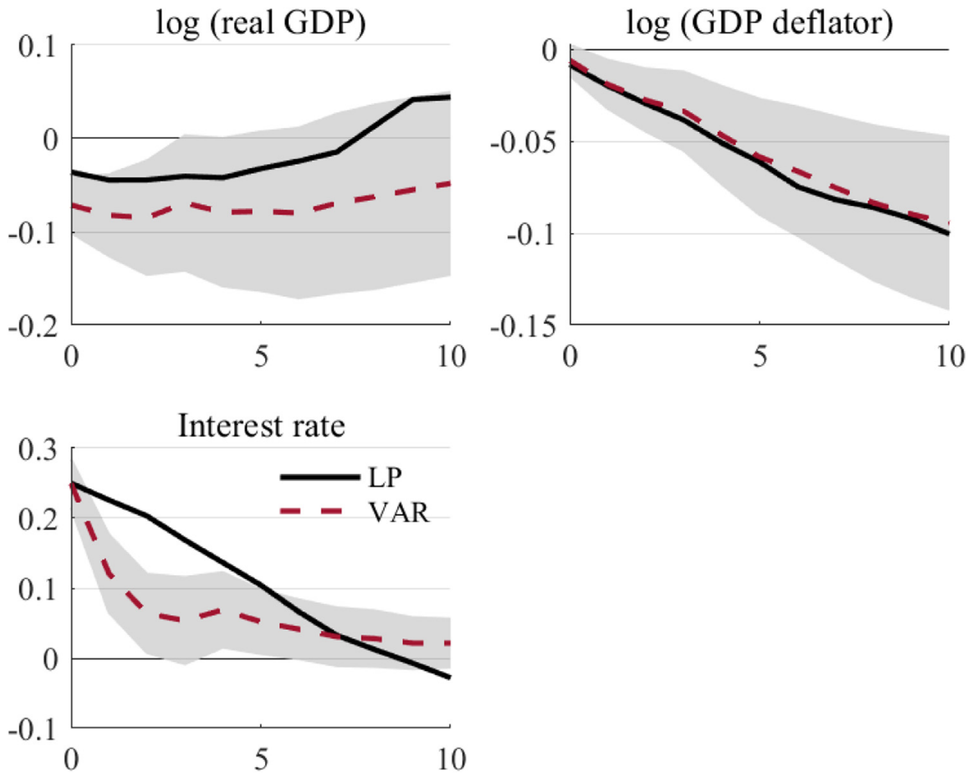

Fig. 6. VAR results.
Notes: Impulse response functions of the log of real GDP (in percent), the log of the GDP deflator (in percent), and the interest rate to a contractionary monetary policy shock based on local projections (LP) and a recursive VAR including four lags (VAR). The exogenous monetary policy shock is ordered first in the VAR. Shaded areas are 95-percent bootstrap confidence bands.

We observe only minor differences when comparing the baseline without controls in solid black to the specifications controlling for forecastability. The most significant differences appear for output, where we find that the output response is more significant when purging the nowcast errors to their lagged values. The other specifications are almost indistinguishable from the baseline, which leads us to conclude that our results are robust to controlling for these factors.

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 of 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.

Fig. 6 shows the impulse responses of output, prices, and the policy rate to an identified policy shock using the output gap and inflation nowcast errors as exogenous predictors for the policy rate. The recursive VAR results (in dashed red) indicate a brief contraction of output and a persistent decline in the price level, both of which are in line with the local projection results (in solid black). 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.

3.4. Alternative identification approaches

Next, we compare our identification approach to two alternatives common in the literature: the recursive approach used by Christiano et al. (1999) and the narrative approach pioneered by Romer and Romer (2004).[20] We follow the spirit of their methodologies and apply them to our sample period (1987:Q3-2008:Q2) using our three variables – real

[20] The Romer and Romer (2004) paper is a continuation of their earlier Romer and Romer (1989) paper that uses textual analysis to identify certain dates on which policy exogenously changed.

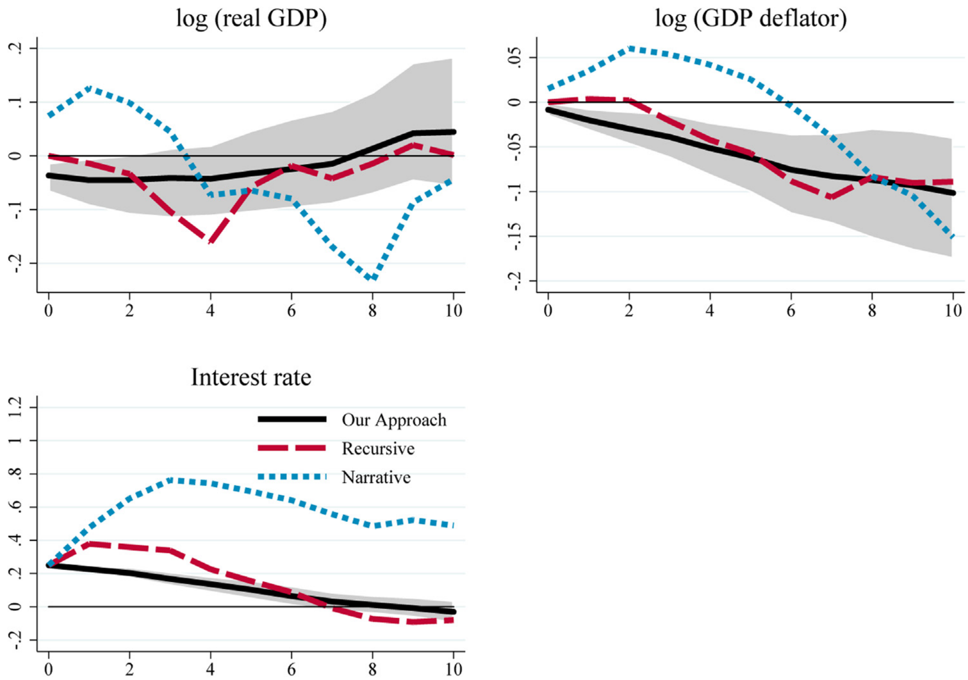

Fig. 7. Local projection results across identification approaches.
Notes: Impulse response functions of the log of real GDP (in percent), the log of the GDP deflator (in percent), and the interest rate to a contractionary monetary policy shock scaled to a 25 bp increase in the interest rate based on 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. Shaded areas are 95-percent bootstrap confidence bands.

GDP, the GDP deflator, the federal funds rate.[21] To facilitate comparison to our approach, we continue to estimate local projections.[22]

Fig. 7 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 initially) and features a mild price puzzle. Similarly, in the original paper of Christiano et al. (1999) there is a mild price puzzle 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. It is also the case that the quantitative magnitudes of the output responses that we present here (regardless of whether we use our approach or mimic other approaches) are smaller than in either Christiano et al. (1999) or Romer and Romer (2004). These differences are mainly due to the different samples: 1987–2008 in our analysis versus 1965–1995 in Christiano et al. (1999) and 1969–1996 in Romer and Romer (2004).

Fig. 8 shows that an initial output expansion and mild prize puzzle in the recursive and narrative approaches are, if anything, more pronounced when we use a recursively identified VAR instead of local projection methods to compute the impulse response functions.[23]

[21] Our implementation of the narrative approach, while similar, nevertheless differs from Romer and Romer (2004)'s VAR approach along a couple of dimensions: Romer and Romer (2004) use (i) monthly data, (ii) the producer price index for finished goods, (iii) a lag length of three years, (iv) the cumulative shock series, and (v) additionally impose a recursive ordering of the variables. Coibion (2012) shows that integrating the narrative shock series in a VAR instead of single-equation regressions and using a shorter lag length decreases the estimated output contraction in response to a monetary tightening. This brings the estimated output effects closer to the smaller size of our estimates.

[22] For the narrative approach, we use an updated Romer and Romer (2004) shock series as the forcing variable in the local projections regression. 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 in the local projection as shock series.

[23] 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 and larger 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. Compared to Christiano et al. (1999)'s original sample period (1965:Q3-1995:Q2), the output response using their approach in our sample period, 1987:Q3-2008:Q2, is much closer to zero.

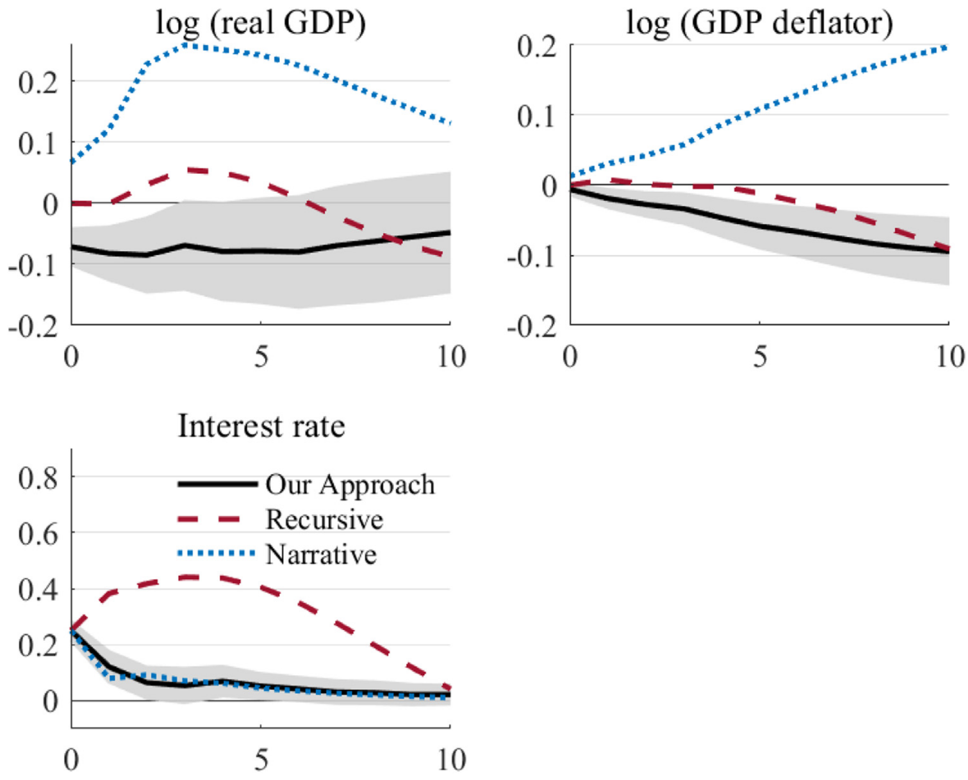

Fig. 8. VAR results across identification approaches.
Notes: Impulse response functions of the log of real GDP (in percent), the log of the GDP deflator (in percent), and the interest rate to a contractionary monetary policy shock based on a recursive VAR (including four lags). We replace the federal 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. Shaded areas are 95-percent bootstrap confidence bands.

4. Simulation results

To demonstrate the suitability of our approach to identifying monetary policy shocks, we build upon the 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.8 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:[24]

$$i_t = i_{t-1} + \rho_\pi \pi_t^t + \rho_g g_t^t + \rho_x x_t^t + \nu_t, \tag{6}$$

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

[24] Ireland (2004) assumes a coefficient of unity on the lagged interest rate in the Taylor rule. Replacing this assumption with a more conventional AR parameter (e.g. 0.85, or even zero) yields similar results to what follows.

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, $u_t^j\ \forall;\ j; \in \{x, g, \pi\}$:

$$x_t^t = x_t^T + u_t^x, \qquad g_t^t = g_t^T + u_t^g, \qquad \pi_t^t = \pi_t^T + u_t^\pi. \tag{7}$$

Combining (6) and (7) allows us to decompose the Taylor rule into the original part and the nowcast error part:

$$i_t = i_{t-1} + \rho_\pi \pi_t^T + \rho_g g_t^T + \rho_x x_t^T + \nu_t + \rho_\pi u_t^\pi + \rho_g u_t^g + \rho_x u_t^x \tag{8}$$

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.[25]

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

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

$$\Sigma = \begin{pmatrix} 0.00005272 & 0 & 0 \\ 0 & 0.00000423 & 0 \\ 0 & 0 & 0.00002295 \end{pmatrix}$$

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

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

$$\Sigma = \begin{pmatrix} 0.00005272 & 0.00000519 & 0.00000873 \\ 0.00000519 & 0.00000423 & -0.00000192 \\ 0.00000873 & -0.00000192 & 0.00002295 \end{pmatrix}$$

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). 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 0.3476, the correlation between the output gap nowcast error and the output growth nowcast error is 0.2510, and the correlation between the output growth nowcast error and the inflation nowcast error is -0.1950.

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 A.3 in Appendix A.9 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.

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

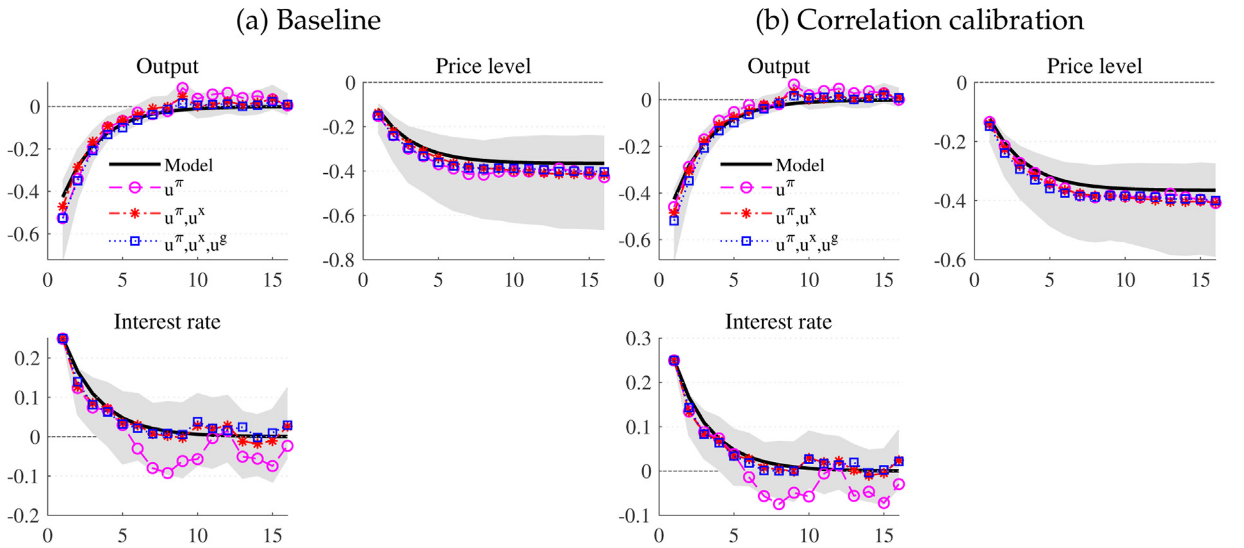

Fig. 9. Local projections based on simulated data.
Notes: Impulse responses to a contractionary monetary policy shock scaled to a 25 bp increase in the interest rate. u^π (pink, circles) uses the inflation nowcast error as the predictor for the interest rate, u^x, u^π (red, asterisks) uses the output 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. On the left-hand side of the regressions, we use the true macroeconomic variables, not the ones with measurement errors, as in our empirical exercises. The 95-percent bootstrap confidence bands correspond to our baseline specification: u^x, u^π (red, asterisks). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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 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 functions (black, solid). Panels (a) and (b) of Fig. 9 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.

We find that the estimated impulse responses based on the simulated data are close to the theoretical impulse response functions, both for the baseline and correlation calibrations. Further, the 95-percent 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

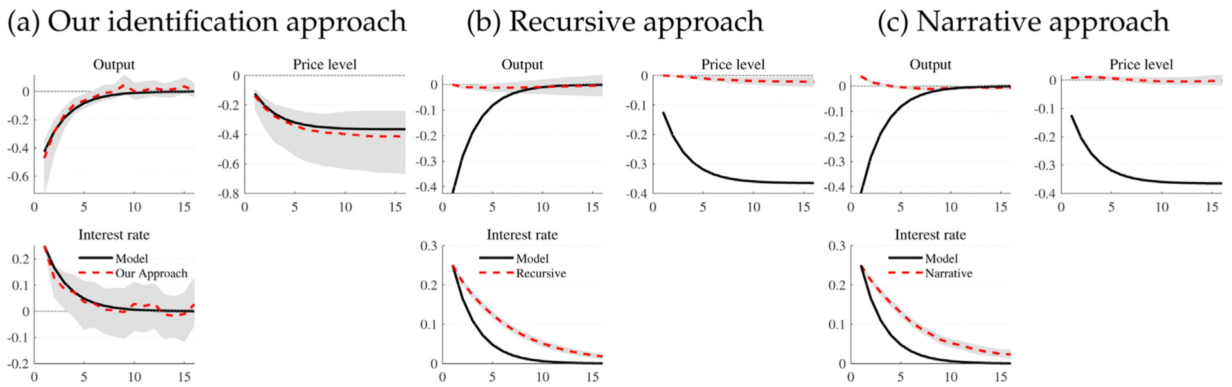

Fig. 10. Comparison of identification approaches (baseline).
Notes: Impulse responses to a contractionary monetary policy shock scaled to a 25 bp impact increase in the interest rate. *Our Approach* reflects our identification approach using the nowcast error in output growth and inflation as predictors for the policy rate; *Narrative* is the narrative approach (Romer and Romer, 2004); *Recursive* is the recursive approach (Christiano et al., 1999); and *Model* is 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. On the left-hand side of the regressions, we use the true macroeconomic variables, not the ones with measurement errors, as in our empirical exercises. 95-percent bootstrap confidence bands.

using simulated data:

$$i_t = \alpha + \beta i_{t-1} + \sum_{i=-1}^{0} \gamma_{x,i} x_{t,i}^{obs} + \sum_{i=-1}^{0} \gamma_{g,i} g_{t,i}^{obs} + \gamma_{\pi,-1} \pi_{t,i}^{obs} + \varepsilon_t \tag{9}$$

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.[26]
We then take the residual from Eq. (9) 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.

Fig. 10 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.

The recursive and narrative approaches, shown in Panels (b) and (c) of Fig. 10, 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.10, Fig. A.8 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. In particular, we exploit the central bank's imperfect information at the point of decision making. We isolate the part of the policy response

[26] Romer and Romer (2004) also include the one- and two-period ahead forecasts of the macroeconomic variables. In the model, the nowcast and these further-ahead forecasts are multicollinear. Hence, we only include model nowcasts to compute the model-implied narrative shocks.

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 policy 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.

Appendix A

A1. 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

Table A.1
Constructing the shock: results (1987:Q3-2015:Q4).

	(1)	(2)	(3)	(4)	(5)	(5')	(5")	(5"')
u^x	1.80***			1.90***	1.82***	1.02**	0.81	0.74
	(0.21)			(0.22)	(0.23)	(0.36)	(0.50)	(0.51)
u^π		0.70		-0.10	-0.08	0.28	0.41	0.35
		(0.35)		(0.28)	(0.30)	(0.37)	(0.38)	(0.40)
u^g			-0.30*	-0.40***				
			(0.15)	(0.11)				
R^2	0.390	0.034	0.035	0.453	0.390	0.098	0.039	0.030
F	71.53	3.92	4.02	30.37	35.50	5.96	2.26	1.68
N	114	114	114	114	114	113	113	110

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^π and u_t^g, (5) u_t^x and u_t^π, (5') uses u^π and the residual of u_t^x purged to the lagged output gap as predictors. (5") and (5"') use the residual of u_t^x and u_t^π purged to its lagged first and four values as predictors. Standard errors in parentheses. Constant included. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

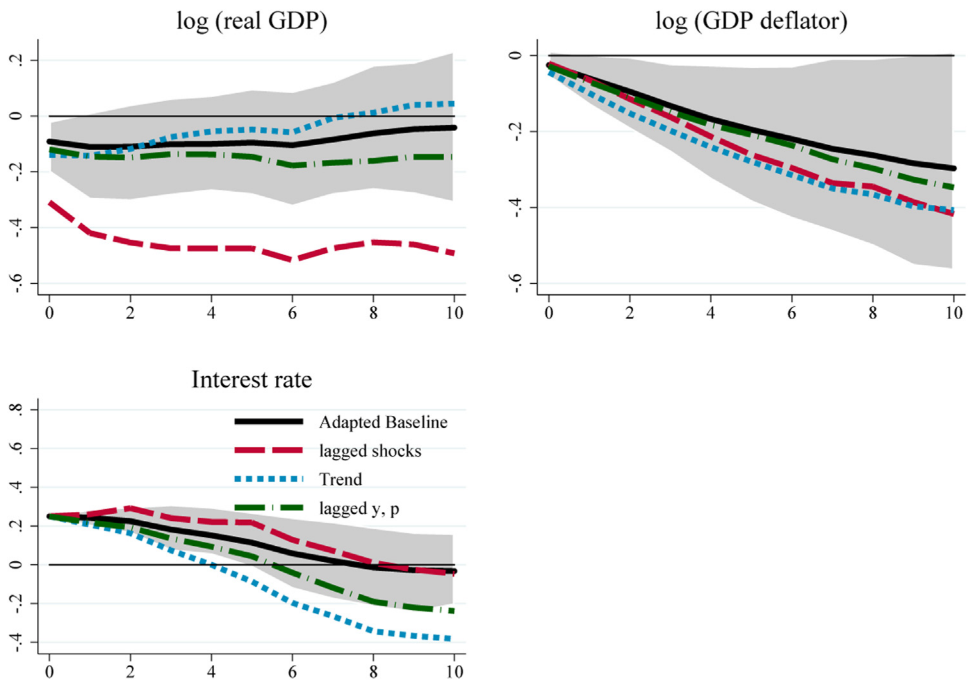

Fig. A.1. Local projections: Baseline vs. additional controls (extended sample).
Notes: Impulse response functions of the log of real GDP (in percent), the log of the GDP deflator (in percent), and the shadow rate to a contractionary monetary policy shock scaled to a 25 bp increase in the interest rate 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. Shaded areas are 95-percent bootstrap confidence bands. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

dummy for the ZLB period in the local projection regression. The modified local projection regression equation is: $y_{t+h} = \alpha_h^y + \beta_h^y \widehat{i_t} + \gamma_h^y controls_t + \eta_h^y ZLB_t + \epsilon_{t+h}^y$.

A2. Analytics in the stylized model

Consider the stylized model characterized by (1)–(3). It is straightforward to express the endogenous variables (i_t, x_t^t, and x_t^T) as functions of exogenous shocks (ν_t, u_t, and ϵ_t), which we assume are all i.i.d:

$$x_t^T = \frac{1}{1-\psi_x\psi_i}[\psi_x\psi_i u_t + \psi_x \nu_t + \epsilon_t] \tag{10}$$

$$x_t^t = \frac{\psi_x}{1-\psi_x\psi_i}\nu_t + \frac{1}{1-\psi_x\psi_i}\epsilon_t + \frac{1}{1-\psi_x\psi_i}u_t \tag{11}$$

$$i_t = \frac{1}{1-\psi_x\psi_i}\nu_t + \frac{\psi_i}{1-\psi_x\psi_i}\epsilon_t + \frac{\psi_i}{1-\psi_x\psi_i}u_t \tag{12}$$

An econometrician would like to identify ψ_x, the partial effect of an exogenous change in the interest rate on economic conditions. So long as $\text{var}(\epsilon_t) \neq 0$, a regression of x_t^T on i_t will not correctly uncover this parameter. ϵ_t both directly affects x_t^T and indirectly affects it through the policy rate, so there is a classic simultaneity problem.

Since the shocks are mutually uncorrelated, looking at (12), in a sufficiently large sample, a regression of i_t on u_t will result in a fitted value of:

$$\widehat{i_t} = \frac{\psi_i}{1-\psi_x\psi_i}u_t \tag{13}$$

Now, suppose one estimates a regression of x_t^T on $\widehat{i_t}$:

$$x_t^T = \alpha\widehat{i_t} + e_t \tag{14}$$

Using (13), we can write this as:

$$x_t^T = \alpha\frac{\psi_i}{1-\psi_x\psi_i}u_t + e_t \tag{15}$$

Hence, the regression in (15) is a regression of x_t^T on a scaled version of u_t. But, from (10), in a sufficiently large sample we know that a regression of x_t^T on u_t will yield a coefficient of $\frac{\psi_x\psi_i}{1-\psi_x\psi_i}$. Hence, we will have:

$$\alpha\frac{\psi_i}{1-\psi_x\psi_i} = \frac{\psi_x\psi_i}{1-\psi_x\psi_i}, \tag{16}$$

which implies that:

$$\alpha = \psi_x \tag{17}$$

In other words, in this simple, stylized model our two-step procedure correctly uncovers the effect of a change in the interest rate on economic conditions, ψ_x. The nowcast error is *not* orthogonal to economic conditions; if it were, this procedure would not work. What we require is that the nowcast error *only* affects economic conditions through its influence on the policy rate.

A3. Inflation nowcast error as predictor for the policy rate

Fig. A.2 demonstrates the validity of the main results using inflation nowcast errors as the single predictor of the policy rate. The results are qualitatively similar to using both the output gap nowcast error and inflation nowcast error as predictors. While the output response is slightly smaller quantitatively and more transitory, the effect on prices remains significant and of similar magnitude.

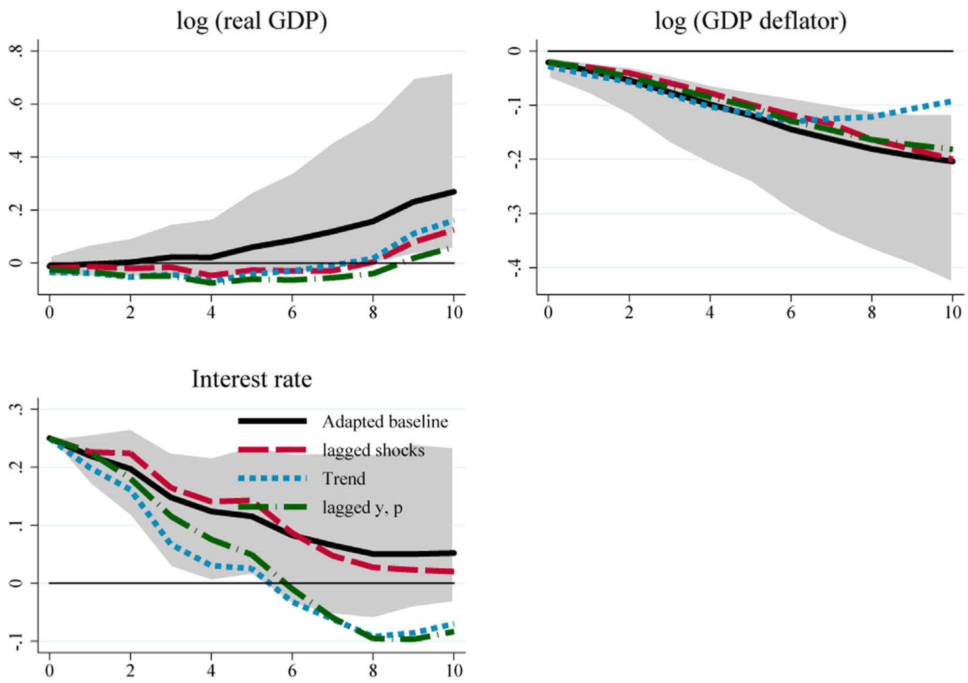

Fig. A.2. Local projections: Inflation nowcast error as predictor.
Notes: Impulse response functions of the log of real GDP (in percent), the log of the GDP deflator (in percent), and the interest rate to a contractionary monetary policy shock scaled to a 25 bp increase in the interest rate. The black, 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. Shaded areas are 95-percent bootstrap confidence bands. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

A4. Monthly data

This section presents the results using monthly data (1987:M7-2008:M8). To implement the monthly approach, we first obtain the shock series by regressing the federal funds rate on the nowcast errors at the FOMC meeting level (shown in Table A.2) and taking the fitted values as the monetary shock series.[27] We then estimate the response of output and prices to an exogenous monetary policy shock from the first stage using local projections. We measure output, y_{t+h}, as the log of Industrial Production, and prices, p_{t+h}, as the log of the Consumer Price Index.[28]

Table A.2
Constructing the shock: results (1987:M7-2008:M8).

	(1)	(2)	(3)	(4)	(5)	(5')	(5")	(5"')
u^x	1.62***			1.53***	1.39***	1.14***	0.81	0.83
	(0.20)			(0.21)	(0.21)	(0.23)	(0.43)	(0.44)
u^π		1.02***		0.51**	0.61**	0.68***	0.65**	0.61*
		(0.19)		(0.19)	(0.18)	(0.19)	(0.24)	(0.25)
u^g			-0.10	-0.19*				
			(0.09)	(0.08)				
R^2	0.277	0.142	0.007	0.346	0.323	0.254	0.069	0.060
F	64.06	27.65	1.24	29.12	39.55	28.07	6.16	5.18
N	169	169	169	169	169	168	168	165

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^π and u_t^g, (5) u_t^x and u_t^π, (5') uses u^π and the residual of u_t^x purged to the lagged output gap as predictors. (5") and (5"') use the residual of u_t^x and u_t^π purged to its lagged first and four values as predictors. Standard errors in parentheses. Constant included. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

[27] In line with the literature using high-frequency data (e.g., Gertler and Karadi, 2015; Nakamura and Steinsson, 2018) and Romer and Romer (2004)'s narrative approach, the shock is zero in months without an FOMC meeting.

[28] For the local projections, we retrieve the final outcome variables from Federal Reserve Economic Data (FRED): Industrial Production (INDPRO), and Consumer Price Index (CPALCY01USM661N).

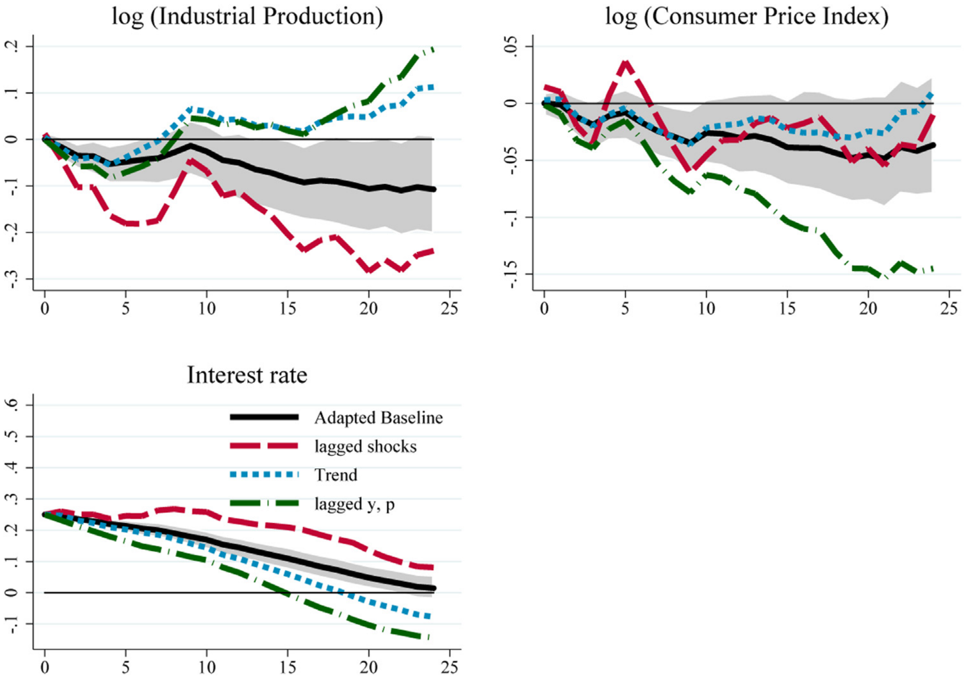

Fig. A.3. Local projections: Baseline vs. additional controls (monthly data).
Notes: Impulse response functions of the log of Industrial Production (in percent), the log of the Consumer Price Index (in percent), and the federal funds rate to a contractionary monetary policy shock scaled to a 25 bp increase 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 Industrial Production and the log of the Consumer Price Index; 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 Industrial Production and log of the Consumer Price Index in all regressions. Shaded areas are 95-percent bootstrap confidence bands. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

A5. External instrument approach

This appendix produces impulse responses to a policy shock following the external instrument literature; see e.g., Stock and Watson (2012, 2018).

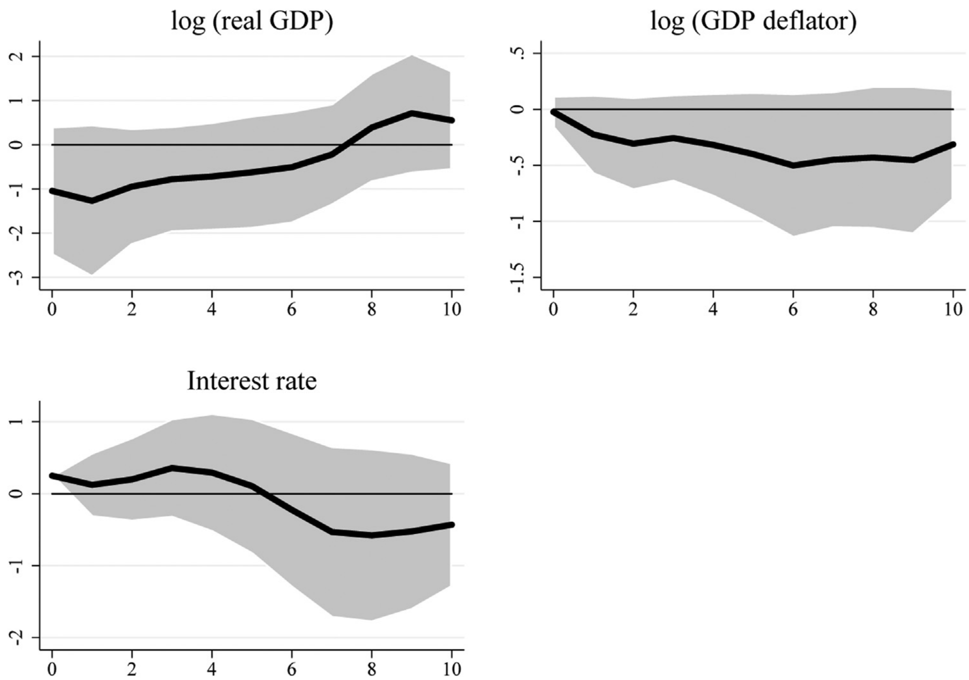

Fig. A.4. External instrument approach.
Notes: Impulse response functions of the log of real GDP (in percent), the log of the GDP deflator (in percent) and the interest rate to a contractionary monetary policy shock scaled to a 25 bp increase in the interest rate. All regressions include the four lagged values of log real GDP, the log GDP deflator, and the interest rate as controls, using the output gap and inflation nowcast errors as external instruments for the policy rate. Shaded areas are 95-percent confidence bands.

Fig. A.4 presents the impulse responses. The responses of real GDP and the price level are qualitatively similar to our baseline in Fig. 2; importantly, there is no price puzzle. Quantitatively, the responses of output and the price level are much larger (arguably implausibly so), and have less statistical precision, in the external instrument approach compared to our baseline.

A6. Responses with confidence bands

Fig. A.5 and A.6 provide the error bands for all responses in Figs. 3 and 4, respectively.

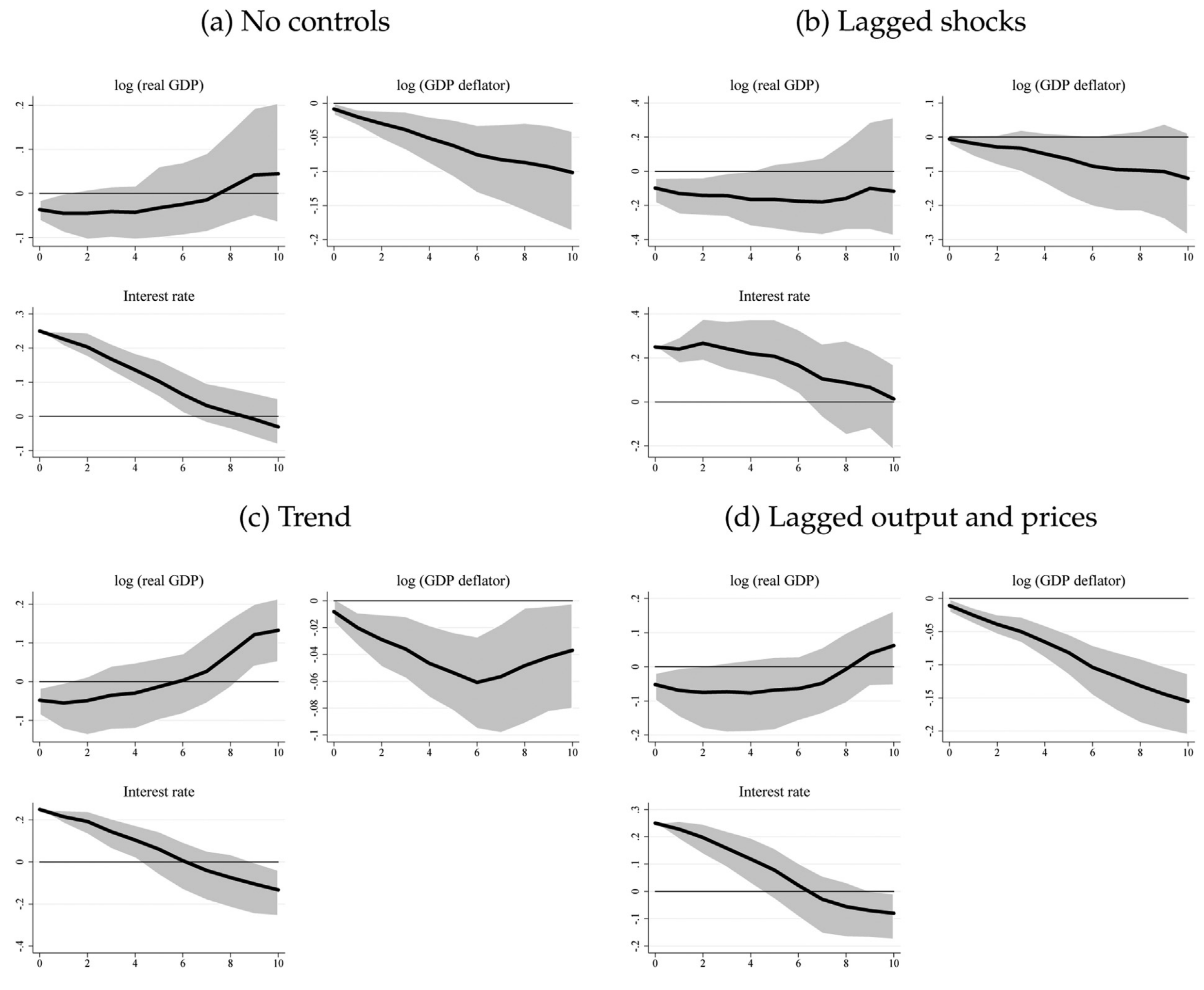

Fig. A.5. Local projections with controls.
Notes: Impulse response functions of the log of real GDP (in percent), the log of the GDP deflator (in percent), and the interest rate to a contractionary monetary policy shock scaled to a 25 bp increase in the interest rate. Panel (a) presents the results for 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; Panel (b) additionally controls for one lagged value of the monetary policy shock; Panel (c) additionally controls for a quadratic time trend, and Panel (d) controls for four lagged values of log of real GDP and log of the GDP deflator in all regressions. Shaded areas are 95-percent bootstrap confidence bands.

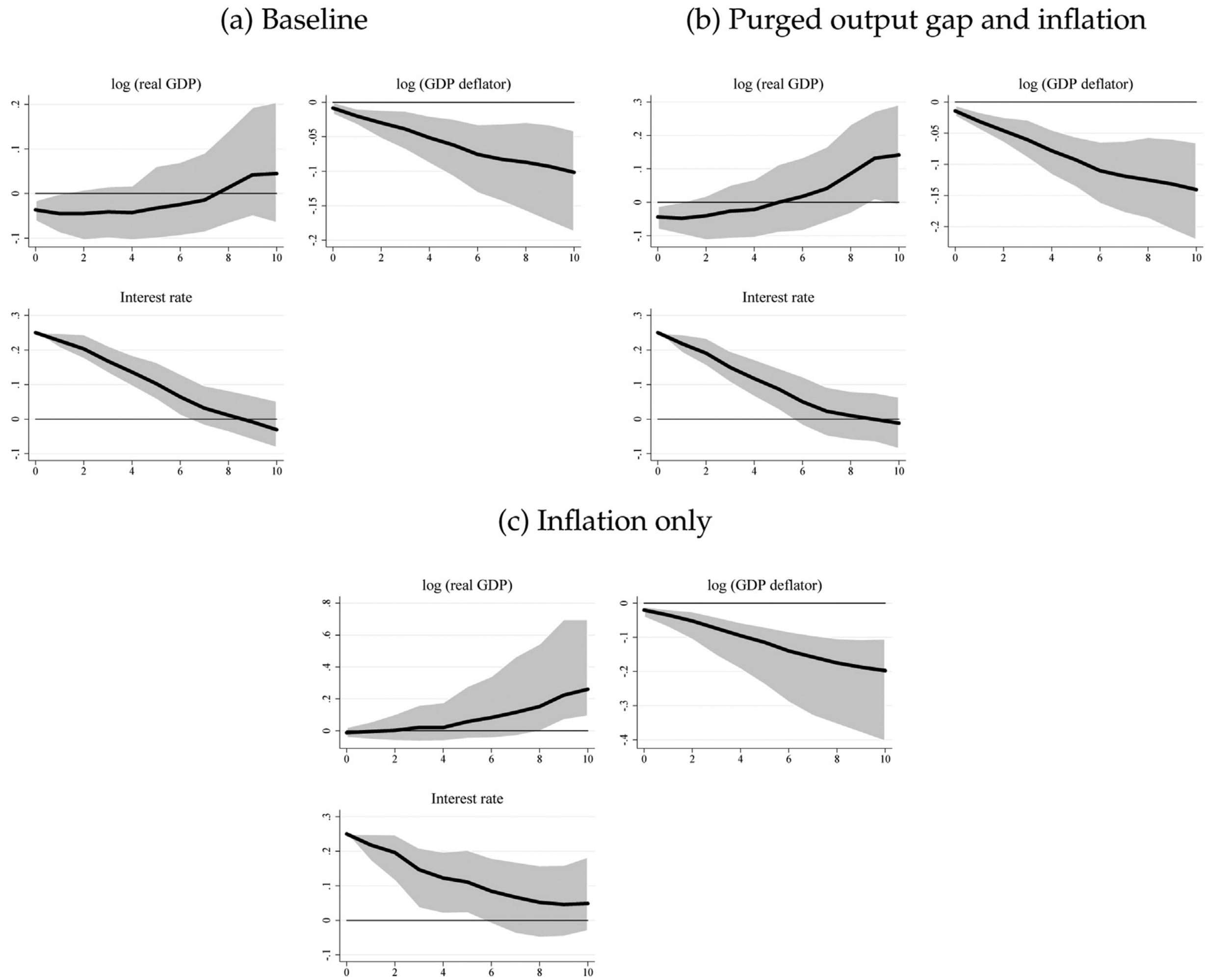

Fig. A.6. Taking into account business cycle endogeneity.
Notes: Impulse response functions of the log of real GDP (in percent), the log of the GDP deflator (in percent) and the interest rate to a contractionary monetary policy shock scaled to a 25 bp increase in the interest rate. Panel (a) uses the nowcast errors in output gap and inflation as exogenous predictors. Panel (b) purges the output gap nowcast errors to the lagged output gap and uses the residuals as predictors for the policy rate. Panel (c) 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. Shaded areas are 95-percent bootstrap confidence bands.

A7. Business cycle endogeneity (II)

To further verify that the difference between final and real-time data constitutes exogenous variation that can be exploited for identification, the nowcast errors are purged from their lagged final values. We use the lagged values of these

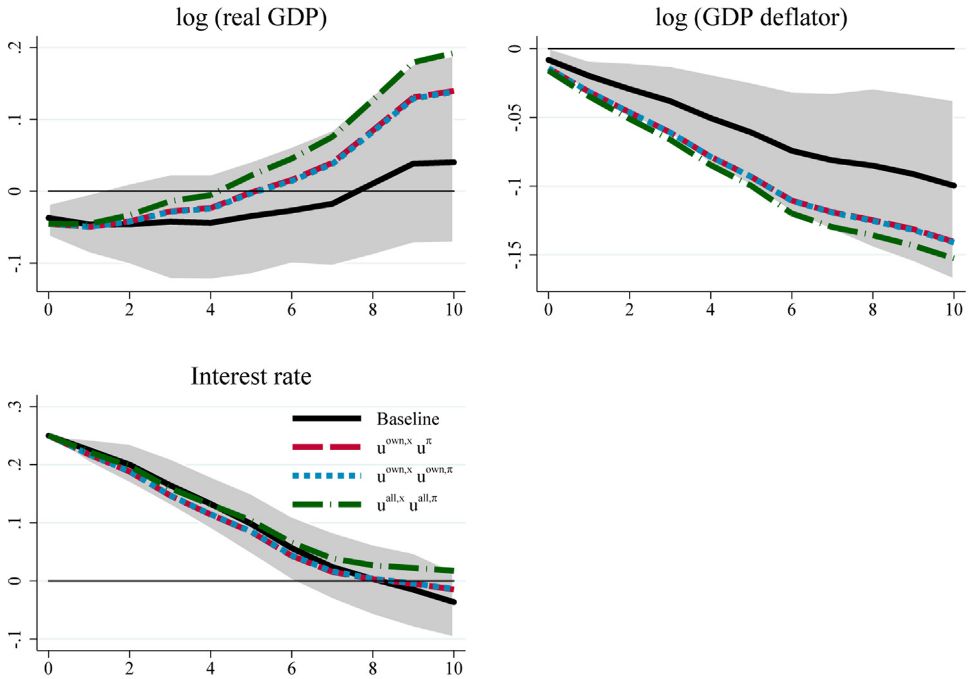

Fig. A.7. Taking into account business cycle endogeneity (II).
Notes: Impulse response functions of the log of real GDP (in percent), the log of the GDP deflator (in percent), and the interest rate to a contractionary monetary policy shock scaled to a 25 bp increase in the interest rate. The baseline specification uses the nowcast errors in the output gap and inflation as exogenous predictors. $u^{own.x}$ and $u^{own.\pi}$ purge the nowcast errors to their own lagged final vintage values and use the residuals as exogenous predictors. $u^{all.x}$ and $u^{all.\pi}$ purge the nowcast errors to the lagged final values of the output gap output growth and inflation and use the residuals as exogenous predictors. Regressions of the log real GDP and the log GDP deflator include four lags of the dependent variables. Shaded areas are 95-percent bootstrap confidence bands.

variables because - by construction - their contemporaneous values are influenced by monetary policy, which is the relationship we are attempting to estimate in this paper. Fig. A.7 shows that our results are unaffected by controlling for lagged final values.

A8. 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.

$$x_t^T = \alpha_x x_{t-1}^T + (1-\alpha_x)\mathbb{E}_t[x_{t+1}^T] - (i_t - \mathbb{E}_t[\pi_{t+1}^T]) + (1-\omega)(1-\rho_a)a_t \tag{18}$$

$$\pi_t^T = \beta(\alpha_\pi \pi_{t-1}^T + (1-\alpha_\pi)\mathbb{E}_t[\pi_{t+1}^T]) + \psi x_t^T - e_t \tag{19}$$

$$x_t^T = y_t - \omega a_t \tag{20}$$

$$g_t^T = y_t - y_{t-1} + \sigma_z \varepsilon_{z_t} \tag{21}$$

$$a_t = \rho_a a_{t-1} + \sigma_a \varepsilon_{a_t} \tag{22}$$

$$e_t = \rho_e e_{t-1} + \sigma_e \varepsilon_{e_t} \tag{23}$$

$$i_t = i_{t-1} + \rho_\pi \pi_t^t + \rho_g g_t^t + \rho_x x_t^t + \nu_t \tag{24}$$

$$\nu_t = \sigma_r \varepsilon_{r_t} \tag{25}$$

$$x_t^t = x_t^T + u_t^x \tag{26}$$

$$\pi_t^t = \pi_t^T + u_t^\pi \tag{27}$$

$$g_t^t = g_t^T + u_t^g \tag{28}$$

A9. Model calibration

Table A.3
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.

A10. Simulation results

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

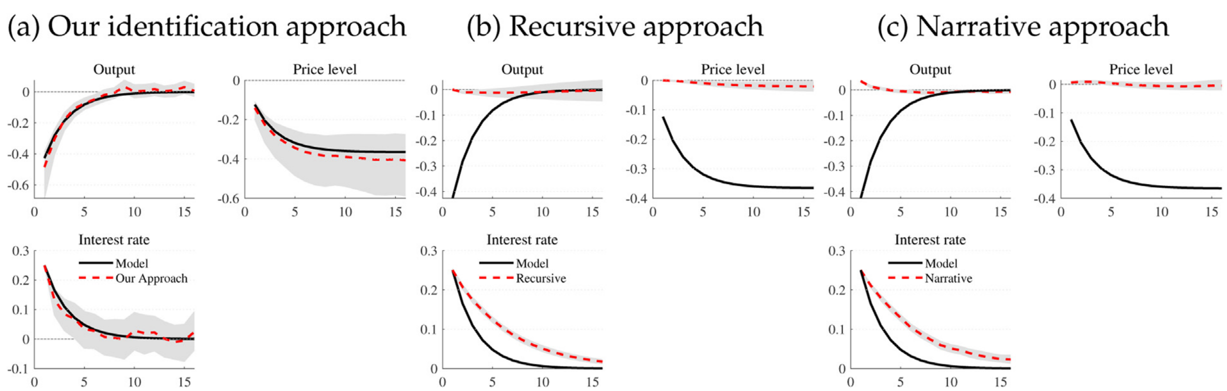

Fig. A.8. Comparison of identification approaches (correlation calibration).
Notes: Impulse responses to a contractionary monetary policy shock scaled to a 25 bp impact increase in the interest rate. *Our Approach* reflects our identification approach; *Narrative* is the narrative approach (Romer and Romer, 2004); *Recursive* is the recursive approach (Christiano et al., 1999); and *Model* is the model-implied theoretical solution. The regressions of output and the price level in (a) and (c) include four lags of the dependent variable. On the left-hand side of the regressions, we use the true macroeconomic variables, not the ones with measurement errors, as in our empirical exercises. 95-percent bootstrap confidence bands.

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