American Economic Journal: Macroeconomics 2016, 8(4): 75–102
http://dx.doi.org/10.1257/mac.20150093

The Macroeconomic Effects of Monetary Policy: A New Measure for the United Kingdom†

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This paper estimates the effects of monetary policy based on a new, extensive real-time dataset for the United Kingdom. Employing the Romer–Romer identification approach we construct a new measure of monetary policy innovations and find that a 1 percentage point increase in the policy rate reduces output by 0.6 percent and inflation by up to 1 percentage point after 2 to 3 years. Our use of forecast data is shown to be crucial and that their omission generates the well-known price puzzle. Our estimates are more comparable to the wider VAR literature but we also reconcile our findings with the Romer–Romer estimates for the United States. (*JEL* E23, E31, E32, E52)

The efficacy of monetary policy has often been the subject of heated debate and despite considerable research in the academic literature there remains disagreement about its effect on the macroeconomy. A range of empirical estimates have emerged in the literature and the effects on prices and output of a 1 percentage point innovation to the policy rate tend to be between 0.5 and 1 percent. A notable exception—the so-called narrative method pioneered by Romer and Romer (2004)—is often cited as finding larger effects.[1] This approach uses rich new data sources to identify monetary policy innovations and has a number of advantages. Despite the attention given to the results for the United States, however, there have been no other applications. This paper fills that gap using a newly constructed series of monetary policy innovations for the United Kingdom based on a rich real time and forecast dataset.

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† Go to http://dx.doi.org/10.1257/mac.20150093 to visit the article page for additional materials and author disclosure statement(s) or to comment in the online discussion forum.

[1] This method follows earlier work using a slightly different narrative identification strategy in Romer and Romer (1989). Narrative approaches have also been employed to identify tax shocks (Romer and Romer 2010; Cloyne 2013) and government spending shocks (Ramey and Shapiro 1998; Ramey 2011).

Identifying the effects of changes in monetary policy requires confronting at least three econometric issues. First, monetary policy instruments, interest rates, and other macroeconomic variables are determined simultaneously as policymakers respond to macroeconomic fluctuations with the intent that their decisions affect the economy. Second, policymakers are likely to react to expected future economic conditions as well as current and past information. Third, policymakers base their decisions on real-time data, not ex post data often used in other empirical studies.

A major advantage of the Romer and Romer (2004) approach is that we can directly tackle all three of these empirical challenges. First we need to disentangle cyclical movements in short-term market interest rates from policymakers' intended changes in the policy target rate. A particular advantage of studying the United Kingdom is that the Bank of England's policy rate—Bank Rate—*is* the intended policy target rate. We therefore do not need to construct the implied policy target rate from central bank minutes as in Romer and Romer (2004). As a second step, the target rate series is purged of discretionary policy changes that were responding to the changes in macroeconomic variables within the policymakers' information set. This information set may include real-time data and forecasts that determine the policy reaction to anticipated economic conditions. We therefore use historical sources to reconstruct a proxy for the information set on which policy decisions were made.[2] Specifically we construct an extensive new dataset of historical Bank of England forecasts, private sector forecasts, and real-time data. Our detailed new dataset and shock series should provide a useful resource in itself.

Furthermore, many studies rely on ex post data that were not the data available to policymakers at the time of their decision. Rudebusch (1998) argues that conventional VAR analyses have been "too cavalier about the real time information set of the central bank" and Orphanides (2001) shows that this can significantly affect estimates of the response of monetary policy to macroeconomic variables. Since our data are real-time, we naturally address this concern.

We perform a first-stage regression to purge the intended policy target rate of systematic policy changes, producing a new series of monetary policy innovations. The academic literature has typically referred to these as structural monetary policy shocks. We show that this series is unpredictable on the basis of various macroeconomic time series and it is uncorrelated with other structural shocks.

Armed with our new series of monetary policy innovations, and following Romer and Romer (2004) and Coibion (2012), we use our new shock measure in a vector autoregression. We find that a 1 percentage point contractionary shock to the policy target rate leads to a peak decline in output of 0.6 percent[3] and a 1.0 percentage point fall in inflation. These empirical estimates are therefore in line with the magnitudes found elsewhere in the VAR literature. Unlike many VAR-based studies,

[2] The Romer and Romer (2004) approach is often referred to as *narrative* because the intended change in the target policy rate for the United States is constructed from the reading of historical FOMC minutes. While this is not necessary for the United Kingdom—as we already have a measure of the target policy rate—our approach still follows Romer and Romer (2004) as we discuss above. In particular, we use historical documents to construct a detailed real time and forecast dataset to proxy the policymakers' information set at the time for their decision. For both these reasons we refer to our shock series as following the *narrative* tradition.

[3] As measured by monthly industrial production. For quarterly GDP the peak effect is −0.5 percent.

however, and in keeping with Romer and Romer (2004) for the United States, we also find a negative, significant and theoretically plausible response for inflation and prices. We therefore solve the so-called "price puzzle"—first documented in Sims (1992)—for the United Kingdom, where prices and inflation increase following a monetary contraction in conventional VARs. Investigating the issue further, we find that including forecast data in our methodology is crucial for this result echoing, among others, Castelnuovo and Surico (2010) who explore the US price puzzle.[4]

Wider Literature.—Many VAR studies, following Christiano, Eichenbaum, and Evans (1996, 1999), are based on a recursiveness assumption with the policy instrument (typically interest rates) ordered last. Intuitively, this identification strategy allows all variables to contemporaneously affect interest rates, but interest rates have a lagged effect on the other macroeconomic variables. In response to a 1 percentage point contractionary monetary policy innovation, these studies typically find an effect on output of around 0.5 to 1 percent at the peak and similar for prices.[5] However, as noted above, there is sometimes a sizable short-term increase in prices in response to a monetary tightening, which has led some to question the result. When we employ the common recursive VAR approach, where Bank Rate is ordered last and monetary policy is assumed to affect the economy with a lag, we also find a large price puzzle for the United Kingdom. The price puzzle remains even after controlling for commodity prices, oil prices and exchange rates.

Bernanke, Boivin, and Eliasz (2005) argue that typical VARs use too narrow information sets. These authors use factor augmented VARs (FAVARs) to exploit a wide range of US data, finding a peak decline in GDP of 0.6 percent and in prices of 0.7 percent, to a 1 percentage point monetary contraction. Ellis, Mumtaz, and Zabczyk (2014) estimate a FAVAR model for the United Kingdom, finding a maximum GDP decrease of 0.5 percent and a price level decline of up to 2 percent.[6] An advantage of our approach is that forecasts can be seen as summary statistics of the policymakers' information set. Consequently, this approach does not require the very large datasets used in the FAVAR literature, many of which are only available at a quarterly frequency.

Another strand of the literature, following Uhlig (2005), has proposed using sign restrictions on the direction of the impulse responses. Specifically, a contractionary innovation to monetary policy is assumed to lower prices and output on impact. For a monetary contraction of 1 percent, Uhlig (2005) finds a GDP peak decrease of 0.3 percent and a maximum decline in prices of 1.0 percent for the US economy, when also imposing a 0-restriction on real GDP on impact. Mountford (2005), applying this methodology to the United Kingdom, finds a maximum GDP fall of 0.6 percent and a decline in the GDP deflator of 0.15 percent.[7]

[4] Although they specifically argue this is necessary in periods of indeterminacy where policy did not respect the Taylor Principle.

[5] For the United States, Christiano, Eichenbaum, and Evans (1999) find a decline in industrial production of 0.7 percent and a peak decline in prices of 0.6 percent. For the United Kingdom, Dedola and Lippi (2005) find a drop in industrial production of 0.5 percent and an insignificant price response.

[6] The GDP effect is similar across their two subsamples. The inflation effect, however, is considerably smaller in the 1975–1991 sample at around −0.5 percentage points at the peak.

[7] Although, one potential drawback of this approach is that the impulse responses are only set-identified.

A growing literature has also attempted to isolate surprises in monetary policy from forward-looking financial market data as in Kuttner (2001); Faust, Swanson, and Wright (2004); Bernanke and Kuttner (2005); Gürkaynak, Sack, and Swanson (2005); Wingender (2011); Barakchian and Crowe (2013); and Gertler and Karadi (2015). Recently, Barakchian and Crowe (2013) construct a measure of policy surprises based on Fed funds futures. Using this measure in a VAR specification, the authors report that a 1 percent monetary contraction causes a fall in industrial production of around 0.9 percent, although a small price puzzle emerges. In related work, Gertler and Karadi (2015) combine high frequency identification (HFI) with a VAR approach including the Gilchrist and Zakrajšek (2012) excess bond premium variable. One advantage of their approach is that they do not rely on timing restrictions in conventional VARs and they find that inflation can move on impact. Approaches that make use of financial market data also have various strengths, and we see it as a complementary approach to the identification discussed here, but, given a number of data availability issues with UK financial markets measures, we leave this for future work.[8] Instead, our focus is on providing a measure of monetary policy shocks by constructing a novel real-time dataset capturing the information available to policymakers at the time of their decisions.

Romer and Romer (2004) find that a 1 percentage point monetary tightening in the United States has much larger effects than typically reported in the rest of the literature. For example, in their baseline single equation estimation approach, industrial production falls by 4.3 percent and the level of consumer prices falls by 3.6 percent.[9] More recently, however, Coibion (2012) has shown that these magnitudes may be overstated. Two important issues are the sample period and the persistence of the policy rate itself following a Romer–Romer shock, and we discuss these further when comparing our findings to the results for the United States.

The remainder of this paper is structured as follows. Section I addresses the econometric challenges in more detail and presents our new real-time database. Section II estimates our new monetary policy measure and investigates its properties. Section III presents the baseline results. Section IV shows that our results are robust to a variety of different specifications and how the conduct and effects of policy may have changed over time. This section also shows that forecast data are important for our results. Section V concludes.

I. Methodology

A. *Identification and the First-Stage Regression*

In estimating the effects of monetary policy the researcher needs to overcome at least three econometric challenges. First, interest rates and other macroeconomic

[8] Ideally, for this alternative approach, we would like to extract a financial markets measure for the United Kingdom but unfortunately data limitations make this no small task. While the yield curve for overnight index swaps may provide the closest equivalent to Federal Funds Futures, this is unavailable before 2004. Other measures, such as those based on Libor, are only readily available back to 1997.

[9] The level of producer prices falls by nearly 6 percent. These effects are based on the original Romer and Romer (2004) sample from 1969 to 1996.

variables (e.g., output, inflation) are determined simultaneously, generating a challenging identification problem. Second, policymakers are likely not only to react to the current state of the economy, but also to anticipated future macroeconomic conditions. Third, policymakers base their decision on real-time data, whereas many studies employ final revised data.

More formally, we aim to isolate the innovations m_t from the systematic movements in the intended policy variable S_t in the following equation:

$$S_t = f(\Omega_t) + m_t. \tag{1}$$

The systematic component of S_t is driven by the policymakers' response to data in their information set Ω_t, where $f(\cdot)$ is a function capturing the systematic reaction and the term m_t reflects unexpected shifts in monetary policy.

The VAR literature has mainly tackled the simultaneity problem of interest rates and macroeconomic fluctuations. Often this literature has imposed a timing restriction: macroeconomic variables do not contemporaneously (within the period) react to interest rates (e.g., Christiano, Eichenbaum, and Evans 1996, 1999). The equation of the VAR that describes interest rates is therefore directly related to equation (1) above. Other papers in the literature have used sign restrictions—following Uhlig (2005)—to identify m_t. This method assumes that a contractionary monetary policy shock is one that, for example, raises interest rates but lowers output and inflation on impact.

Two further issues are often overlooked in commonly applied approaches. First, forward-looking policymakers may well include forecasts in their information set Ω_t and central banks devote a great deal of resources forecasting the future path of the economy. Moreover, since contemporaneous estimates of the state of the economy are rarely available in real-time, the policymakers' forecasts also include a forecast of the current period. It is worth noting that, in practice, the forecasts may be based on additional information and judgments not readily available to the econometrician.

Second, since monetary policy responds to information available to policymakers at the time of the decision, any regression designed to recover the structural shocks to policy m_t should be based on the real-time data rather than ex post revised data. As noted, key papers in the existing literature, among these Christiano, Eichenbaum, and Evans (1999) and Uhlig (2005), have employed ex post data. Orphanides (2001, 2003) and Molodtsova, Nikolsko-Rzhevskyy, and Papell (2008) show that estimated monetary policy reaction functions based on ex post revised data are considerably different when using real-time data.[10]

We apply the Romer and Romer (2004) approach to identify monetary policy innovations m_t. Following the literature we refer to this as a narrative approach because it makes careful use of historical documents to construct the intended policy target rate and the information set of the policymakers prior to their decisions. The first stage of this approach requires constructing a measure of the intended policy target rate (S_t) at *each policy decision*. Romer and Romer (2004) construct the target rate from

[10] Ex post data for some variables, such as real output growth, often turn out to differ substantially from real-time estimates, as shown in online Appendix A.

minutes of the *Federal Open Market Committee* meetings. One advantage of the UK monetary framework is that the policy rate—Bank Rate—is the intended policy target. Batini and Nelson (2009), in their extensive history of UK monetary policy, argue that short-term interest rates have always implicitly been an intended target, even in the periods where the government publicly emphasized money supply or exchange rates.[11]

Armed with a series for the intended policy rate we then estimate a first-stage regression addressing the econometric challenges discussed above. The precise regression estimated is

$$(2)\quad \Delta i_m = \alpha + \beta i_{t-d14} + \sum_{j=-1}^{2} \gamma_j \hat{y}^F_{m,j} + \sum_{j=-1}^{2} \varphi_j \pi^F_{m,j} + \sum_{j=-1}^{2} \delta_j (\hat{y}^F_{m,j} - \hat{y}^F_{m-1,j}) + \sum_{j=-1}^{2} \vartheta_j (\pi^F_{m,j} - \pi^F_{m-1,j}) + \sum_{j=1}^{3} \rho_j u_{t-j} + \epsilon_m,$$

where the dependent variable is measured at a meeting-by-meeting frequency as indicated by subscript m. For forecast and real-time data, the subscript j denotes the quarter of the forecast relative to the meeting date. In particular, we follow Romer and Romer (2004) and regress the change in the intended policy target (Δi_m) around the policy decision (in practice, between two meetings) on the one and two quarter ahead forecasts of real GDP growth $(\hat{y}^F_{m,j})$ and inflation $(\pi^F_{m,j})$ as well as the real-time backdata of the previous period and the forecast for the current period. We also include revisions in the forecasts relative to the previous round of forecasts (e.g., $\hat{y}^F_{m,j} - \hat{y}^F_{m-1,j}$). In addition, we control for recent economic conditions by including interest rates two weeks before the meeting (i_{t-d14}) and the unemployment rates of the previous three months (u_{t-j}).

It is also worth noting that in collecting forecast data for the UK economy we are directly constructing a real-time dataset to capture the information set of policymakers at each period in time. We therefore take seriously the concerns raised by Orphanides (2001) and others about using ex post revised data.

To include forecasts in a regression such as equation (1) they need to be orthogonal to m_t.[12] To achieve this, we carefully exploit the timing of forecast releases to ensure they do not already include the effects of the relevant (subsequent) policy change. We therefore aim to capture the information set of policymakers *prior* to the policy decision.

Using forecast data to identify monetary policy innovations also has a further advantage. In principle, the researcher may need to include a large number of time series in the VAR as many variables could enter the information set Ω_t. This is the motivation behind the data-rich FAVAR approach of Bernanke, Boivin, and Eliasz

[11] Bank Rate is not an overnight *market* rate but the policy rate as announced by policymakers. This makes it similar to the target federal funds rate that Romer and Romer (2004) have to construct from the FOMC minutes and different to the effective federal funds rate that moves around at high frequency even without policy changes. Previously Bank Rate was also referred to as Minimum Lending Rate/Repo Rate/Official Bank Rate.

[12] In our specification in equation (2) the forecasts need to be orthogonal to ϵ_m. Later we transform the residual to a monthly shock series that we denote m_t.

(2005). Forecasts are particularly useful, however, because they neatly summarize a wider range of macroeconomic information, as well as the anticipated movements in the macroeconomy.

The estimated residuals of the first-stage regression are our new exogenous monetary policy shock measure. Our definition of a monetary policy "shock" therefore captures an unpredictable surprise that is not taken in response to information about current and future economic developments.[13] As such, the "shock" reflects an unpredictable surprise movement in the target variable and could represent a variety of factors including deliberately induced policy surprises, over- and under-reactions or temporary shifts in the preferences of policymakers. This new meeting-by-meeting measure of monetary policy shocks is converted to a monthly series and, in second stage regressions, is used to estimate the effect of monetary policy on the macroeconomy.

B. *Data Construction*

As noted above, the official Bank Rate series serves as our intended policy target rate. This is available from the Bank of England website.

Since 1997 the Bank of England has had operational independence in setting interest rates to meet an inflation target. To capture the information set of policymakers the natural starting point is to use official Bank of England forecasts for inflation and output growth. Since the Bank of England actually began inflation targeting in 1993, forecasts are available from the quarterly *Inflation Report* (IR) and the forecasts themselves provide quarterly projections for several years ahead.[14]

The Bank of England publishes two sets of forecasts. One set is conditioned on a constant interest rate path, which, ex post, includes the effect of the Monetary Policy Committee's (MPC) Bank Rate decision. The other set is conditioned on a path for Bank Rate implied by market interest rates *prior* to the meeting. As discussed above, a crucial assumption to ensure identification is that forecasts do not already contain the effect of the policy decision (in other words, they are uncorrelated with the error term ϵ_m). If the forecasts already included the effect of the policy change the regression results would be biased. We therefore use the latter set of forecasts and we assign these data to the relevant meeting of the MPC.[15]

Before 1997 monetary policy decisions were made by the UK Treasury. Official Treasury forecasts were produced but only two per year are publicly available and the published forecast is not detailed enough for our purposes. Furthermore, monetary policy was not set at a regular meeting but was changed periodically as deemed

[13] Given that the relevant endogeneity of the target rate is with respect to variables in the policymakers' information set, the relevant forecasts are those of the policymakers. It may still be the case that endogenous policy changes are surprises relative to the forecasts of the private sector. We address this issue in the robustness section.

[14] Until 2003 the inflation target was defined in terms of the retail prices index excluding mortgage interest payments (RPIX)—first as a band, then as a point target of 2.5 percent at an annual rate after 1997. After 2003 the inflation target was specified in terms of the consumer prices index (CPI), with a target of 2 percent annual rate.

[15] In addition, MPC minutes are published shortly after the Bank Rate decision, providing further insights into the decision making process.

necessary. To tackle this problem we also collect forecasts produced by the *National Institute of Economic and Social Research* (NIESR).[16]

NIESR is Britain's longest established independent economic research institute, which is widely respected and close to the UK policy debate. Furthermore, unlike forecasts from other professional bodies, NIESR forecasts are available for a long time period, at a quarterly frequency, and for a large number of possible variables of interest.

We collect NIESR forecasts for our full sample, even for periods when we have Bank of England forecasts. The reason for doing so is twofold. First, we can confirm that the NIESR and Bank of England Inflation Report forecasts are highly correlated.[17] Second, we are able to re-estimate our results using only NIESR forecasts for the full sample. Later we show this makes little difference to the results. NIESR forecasts therefore appear to be good proxies for official forecasts. Moreover, new releases of NIESR forecasts have received much attention in the media (e.g., the *Financial Times*) indicating that these are likely to be known to the private sector and policymakers.

All data were collected from NIESR or historical copies of the *National Institute Economic Review*. We use forecast data for real GDP growth and inflation. The relevant inflation index varied over our sample. We therefore use the consumer prices deflator (1975–1987), retail prices index (RPI) (1987–1992), retail prices index excluding mortgage interest payments (1993–2003), and the consumer prices index (2003–2007).

To address the possible endogeneity of forecasts to the policy change we collect all the forecast embargo dates and finalization dates from the historical hard copies. We also consult historical editions of the *Financial Times* archive to confirm the forecast release date. We are therefore able to ensure that a forecast did not already contain the effects of the relevant policy change.

As noted above, we use the forecast for the current period (real-time estimates of the current period were rarely available to policymakers) and the forecasts for the two quarters ahead. We collect the relevant real-time backdata, which may also differ from the final revised series. These are available either from the forecast publications themselves or the Bank of England's real-time dataset. Our new dataset contains a number of variables, all at quarterly frequency from 1975:I to 2007:IV. We exclude the most recent years after 2007 when interest rates were maintained close to the zero lower bound. We go back to 1975, which produces a time series with a sizable number of observations. Before 1975 the availability of the forecast data becomes increasingly varied, we therefore start our data collection in the mid-1970s. This is a rich dataset, which should also prove useful for future research (for further details see Table A2 in online Appendix A).

Since our first-stage regression is conducted at a decision-by-decision frequency, the new real-time forecast dataset is carefully matched to relevant Bank

[16] We use Bank of England forecasts from 1993 to 1997, where available, as we regard them as a closer proxy for Treasury forecasts.

[17] The correlation between NIESR and Bank of England's real-time data and forecasts for inflation as well as real GDP growth ranges between 0.7 and 0.9 for up to two quarter ahead forecasts in the overlapping sample period (1993:I–2007:IV).

TABLE 1—ASSIGNMENT OF FORECASTS TO BANK RATE DECISIONS

Bank Rate	Current quarter	$\hat{y}^F_{m,t-1}$	$\hat{y}^F_{m,t}$	$\hat{y}^F_{m,t+1}$	$\hat{y}^F_{m,t} - \hat{y}^F_{m-1,t}$
15/03/83	1983:I	$\mathcal{F}^{N[Q4,82]}_{24-02-83}$	$\mathcal{F}^{N[Q1,83]}_{24-02-83}$	$\mathcal{F}^{N[Q2,83]}_{24-02-83}$	$\mathcal{F}^{N[Q1,83]}_{24-02-83} - \mathcal{F}^{N[Q1,83]}_{30-11-82}$
⋮					
06/05/97	1997:II	$\mathcal{F}^{IR[Q1,97]}_{13-05-97}$	$\mathcal{F}^{IR[Q2,97]}_{13-05-97}$	$\mathcal{F}^{IR[Q3,97]}_{13-05-97}$	$\mathcal{F}^{IR[Q2,97]}_{13-05-97} - \mathcal{F}^{IR[Q2,97]}_{12-02-97}$
06/06/97	1997:II	$\mathcal{F}^{IR[Q1,97]}_{13-05-97}$	$\mathcal{F}^{IR[Q2,97]}_{13-05-97}$	$\mathcal{F}^{IR[Q3,97]}_{13-05-97}$	$\mathcal{F}^{IR[Q2,97]}_{13-05-97} - \mathcal{F}^{IR[Q2,97]}_{12-02-97}$
10/07/97	1997:III	$\mathcal{F}^{IR[Q2,97]}_{13-05-97}$	$\mathcal{F}^{IR[Q3,97]}_{13-05-97}$	$\mathcal{F}^{IR[Q4,97]}_{13-05-97}$	$\mathcal{F}^{IR[Q3,97]}_{13-05-97} - \mathcal{F}^{IR[Q3,97]}_{12-02-97}$
⋮					

Notes: Forecasts are denoted by $\mathcal{F}^j_m$, $m =$ Publication date, $j =$ Source[Forecast quarter, Forecast year], where we distinguish between the source (IR/NIESR), the quarter and the year the forecast was prepared for (t), and the forecast publication date (m). The remaining variables are matched following the same procedure indicated in this table.

Rate decisions. In the first part of our sample Bank Rate is not changed at regular intervals, whereas meetings are held on a monthly basis after 1997. Table 1 illustrates the construction of our dataset using both sources—Bank of England forecasts and NIESR forecasts. The first column lists the date of the Bank Rate decision and the second column specifies the contemporaneous quarter. Forecasts are denoted by $\mathcal{F}^{\text{Source[Forecast quarter, Forecast year]}}_{\text{Publication date}}$, where we distinguish between the source (IR/NIESR), the quarter and the year the forecast was produced for, and the forecast publication date.[18]

A complication we face is that we do not have new forecasts for every Bank Rate decision as policy meetings take place at higher frequency: there are more Bank Rate decisions than forecast releases. This is also true, although to a lesser degree, in Romer and Romer (2004). There are a few possible ways to deal with this issue. One option is to only consider Bank Rate changes after a new quarterly release of forecasts (and exclude all other changes). However, this procedure reduces the number of observations substantially. Alternatively we could assign the latest available forecast to each policy meeting, while still controlling for developments between the last forecast and the policy decision, for example by including unemployment data.

A further issue arises in the earlier sample when we have a new forecast and no change in policy, but we do not know whether there was a meeting to decide to leave the rate unchanged. We could either treat the forecast release itself as a decision to keep the rate fixed in the face of new economic developments, or we could disregard these cases.

On balance, our preferred specification is to keep all Bank Rate decisions and assign the latest available forecast to that decision. We disregard, however, the cases where new forecasts are available but we do not observe a Bank Rate change (since

[18] As noted, Bank of England forecasts are officially published *after* the Bank Rate decision they were prepared for. For example, the Bank Rate decision on May 6, 1997 was based on Bank of England forecasts published on May 13, 1997. We assign the 1997:II forecast to the contemporaneous quarter, i.e., $\hat{y}_{m,i}$, since it is conditioned on the market path for interest rates prior to the policy announcement. NIESR forecasts released after the policy decision would be endogenous. Therefore, NIESR forecasts are assigned to the Bank Rate decision that is *subsequently* implemented.

we cannot be sure these are genuine monetary policy *decisions*). This approach maintains a large number of observations and is closest to the implementation in Romer and Romer (2004).[19]

II. The New Measure of Monetary Policy Shocks

A. *Stripping Out the Systematic Component*

After assigning the real-time forecast data to Bank Rate decisions, we isolate innovations to Bank Rate that are orthogonal to the real-time information set of policymakers that we consider. We include all Bank Rate changes between 1975 and 2007, except those taking place at very high frequency (i.e., within the same two weeks). The sample covers 235 Bank Rate decisions.

Table 2 reports the results from estimating equation (2). The estimation results indicate that UK monetary policy was conducted countercyclically over the sample. Summing up the coefficients on the real GDP growth forecasts yields 0.15 for the *level* and 0.23 for the *change* in the growth forecast. Thus, a 1 percentage point increase in the real GDP growth forecast from one forecast release to the next was associated with an increase in Bank Rate of 39 basis points. The effect on Bank Rate is comparable to the US results of Romer and Romer (2004), who find a response of 29 basis points in the intended target rate. The response to a 1 percentage point increase in the inflation forecast leads to a rise in the Bank Rate of 30 basis points, of which 3 basis points are due to the absolute change in inflation forecasts and 27 basis points are due to the change relative to the last forecast release. The policy target rate in the United Kingdom reacts more strongly (30 basis points) than the intended federal funds rate in the United States (which increases by 7 basis points) to a 1 percentage point change in the inflation forecasts. A 1 percentage point increase in the unemployment rate in each of the past three months keeping everything else equal reduces the policy target rate by around 5 basis points in the UK economy.

In summary, the point estimates for the United Kingdom and those for the United States in Romer and Romer (2004) are qualitatively similar, although not identical. The results in Table 2 also appear to have reasonable and expected signs and magnitudes. Importantly, having stripped out the systematic component of policy, the residual of equation (2) is our new measure of monetary policy changes orthogonal to the information set of policymakers.

B. *Properties of the New Shock Series*

We now transform the first-stage residuals into a monthly series of monetary policy innovations that we use to estimate the macroeconomic effects of changes in monetary policy. Note that the residuals from the first-stage regression are dated

[19] In the online Appendix, we confirm that our baseline results are robust to the following alternative cases: (i) including dates where there was no change in Bank Rate but where a new forecast was released and (ii) only including cases where Bank Rate decisions were accompanied by a new forecast, this essentially produces a shock series at quarterly frequency.

TABLE 2—DETERMINANTS OF THE CHANGE IN BANK RATE

Variable	Coefficient	Standard error
Constant (α)	−0.177	0.279
Initial Bank Rate (i_{t-d14})	−0.002	0.026
Forecasted output growth ($\hat{y}^F_{m,j}$), Quarters ahead		
−1	0.011	0.035
0	0.073	0.041
1	0.049	0.047
2	0.019	0.060
Forecasted inflation ($\hat{\pi}^F_{m,j}$), Quarters ahead		
−1	0.131	0.065
0	−0.200	0.104
1	0.003	0.104
2	0.099	0.075
Change in forecasted output growth ($\hat{y}^F_{m,j} - \hat{y}^F_{m-1,j}$), Quarters ahead		
−1	0.061	0.030
0	0.062	0.033
1	0.034	0.040
2	0.077	0.049
Change in forecasted inflation ($\pi^F_{m,j} - \pi^F_{m-1,j}$), Quarters ahead		
−1	0.035	0.114
0	0.354	0.182
1	−0.208	0.169
2	0.090	0.100
Change in unemployment rate (u_{t-j}), Months		
−1	−0.953	0.496
−2	0.242	0.797
−3	0.659	0.492

Notes: Dependent variable: Change in policy target rate Δi_m. $R^2 = 0.29$, D.W. $= 1.80$, F-Statistic $= 4.40$, $N = 235$. Sample covers all Bank Rate changes over the period 1975:M3 to 2007:M12 that are at least two weeks apart. The estimated equation is: $\Delta i_m = \alpha + \beta i_{t-d14} + \sum_{j=-1}^{2} \gamma_j \hat{y}^F_{m,j} + \sum_{j=-1}^{2} \varphi_j \pi^F_{m,j} + \sum_{j=-1}^{2} \delta_j \left(\hat{y}^F_{m,j} - \hat{y}^F_{m-1,j}\right) + \sum_{j=-1}^{2} \vartheta_j \left(\pi^F_{m,j} - \pi^F_{m-1,j}\right) + \sum_{j=1}^{3} \rho_j u_{t-j} + \epsilon_m$.

according to the policy decision (given that we have the exact date of the decision). We therefore transform the residuals into a monthly series as follows. In a month without a Bank Rate decision we set the observation to zero. Otherwise we assign the shock to the respective month in which the policy change occurred. For months with multiple policy changes, we sum the shocks. Figure 1 shows our new monthly series of exogenous monetary policy shocks. As above, we denote the monthly shock series by m_t.[20]

The new series is more volatile in the first half of the sample until 1993. This observation fits well with the view that there was a regime change around 1993. Since October 1992, the Bank of England has explicitly targeted inflation. The policy making process also has become more transparent due to regular publications

[20] We find no evidence of serial correlation in the residuals based on the ACF/PACF correlogram at a 1 percent significance level.

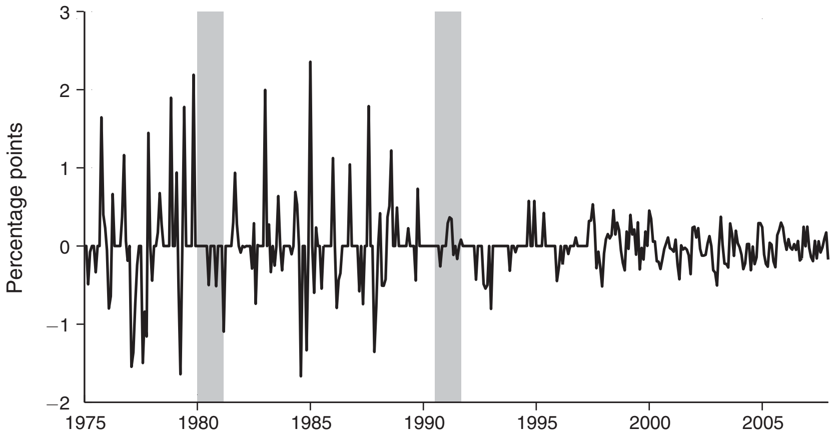

Figure 1. New Monthly UK Monetary Policy Innovation Series

of the Inflation Report (since 1993) and MPC Minutes (since 1997). It is therefore interesting that we find a decrease in the volatility of the new innovation series. Since the independence of the Bank of England in 1997, we find no large surprise monetary policy innovations.[21] One interpretation of equation (2) is as a policy rule and Figure A1 in online Appendix A.A1 compares the exogenous Bank Rate path to the actual path of Bank Rate. This chart shows that looser policy than predicted by equation (2) can be seen in the mid-1970s, as well as a tighter policy throughout the 1980s. Policy also seemed somewhat tight after 1997 and neutral in the mid-2000s. Interestingly, the path implied by shocks from a conventional VAR (which we discuss later) produces quite different results. As noted earlier, conventional VARs for the United Kingdom also produce a number of puzzling empirical results, so it is unsurprising the shock series generates a different path in Figure A1.

C. *Predictability of the New Measure of Monetary Policy Shocks*

Our constructed monthly shocks series should, in principle, be unpredictable from movements in ex post revised data.[22] Before proceeding, it is worth confirming this using a series of Granger causality tests. Specifically, we regress the monetary innovations m_t on a set of lagged macroeconomic variables including industrial production, inflation, and the unemployment rate:

$$m_t = c + \sum_{i=1}^{I} \beta_i x_{t-i} + u_t. \tag{3}$$

[21] Larger shocks in the first part of the sample also might reflect that the average level of Bank Rate was higher than in the second part of the sample.

[22] We also checked whether our new monetary shock series is correlated with a range of other structural shocks. Reassuringly, we confirm that our new monetary shock series is uncorrelated with other structural shocks, among these narrative UK tax shocks (−0.07), narrative monetary shocks for the United States (0.00) from Romer and Romer (2004), and oil price shocks (−0.02) from Kilian (2009).

Table 3—Predictability of Monetary Policy Innovations

	I = 3 lags		I = 6 lags	
Variable	*F*-statistics	*p*-values	*F*-statistics	*p*-values
Change in industrial production	0.34	0.80	0.66	0.68
Monthly inflation	1.04	0.38	0.82	0.55
Unemployment rate	0.00	1.00	0.50	0.81
Money growth M4	0.35	0.79	0.44	0.85
Commodity price inflation	1.32	0.27	0.81	0.57
Change in FTSE	0.52	0.67	0.59	0.74

Notes: The table reports *F*-statistics and *p*-values for the null hypothesis that all coefficients β_i are equal to zero. Data on money growth M4 are only available from 1982:6 onward. The standard errors are corrected for the possible presence of serial correlation and heteroskedasticity using a Newey-West variance covariance matrix.

The null hypothesis is that our new measure of monetary innovations is not predictable from lags of these macroeconomic variables. Table 3 reports *F*-statistics and *p*-values for the null hypothesis based on estimation of equation (3). With all *p*-values well above 25 percent (and mostly above 50 percent) we cannot statistically reject the hypothesis of unpredictability of the shock series. The lack of predictability is reassuring and suggests our shock series is a suitable new measure to use to identify the effect of monetary policy.[23]

III. The Macroeconomic Effects of Monetary Policy

A. *Baseline Results*

Armed with our new measure of monetary policy innovations, we estimate the effects on output and inflation for the full sample from 1975 to 2007. The wider literature on the effects of monetary policy tends to employ Vector Autoregressions (VARs).[24] To compare our results with this literature, we follow Romer and Romer (2004) and Coibion (2012) in using our shock series in a VAR framework.[25] A further advantage, as noted in Coibion et al. (2012), is that including the lagged dependent variables and controlling for other shocks may yield more precise estimates in shorter samples. The VAR framework allows us to control for the joint dynamics of other variables, including controlling for commodity prices, which has generated much debate in the literature.[26]

[23] For the post-1992 sample considered later in the paper the shock series is also not predictable. Table E.E1 in the online Appendix reports the *p*-values for this subsample 1992–2007.

[24] A recent literature pioneered by Stock and Watson (2012) and Mertens and Ravn (2013) uses externally identified shocks as instruments for the structural residuals in VARs. While appealing, it is not clear our shocks are best used in this way. Typical instruments employed in this literature are derived from other historical sources. For example, narrative tax shocks are constructed directly from official budget documents and Mertens and Ravn (2013) argue that these are noisy proxies for the true structural shock. Our shock series, in contrast, is the product of a first-stage regression, and the motivation for the information set used in equation (2) is that common VARs have insufficient information to identify the shocks, see Kliem and Kriwoluzky (2013). Our method therefore constructs a direct measure of the structural shock, rather than a proxy, and, as such, we use this new measure directly.

[25] For completeness, we explicitly consider the single equation approach also employed in Romer and Romer (2004) in the robustness section below.

[26] If there is any residual endogeneity of the shock measure with respect to the ex post revised data the VAR will strip this out as well.

We consider a parsimonious VAR specification using four macroeconomic variables: the log of output as measured by industrial production (seasonally adjusted) (y_t), a measure of prices based on the retail prices index excluding mortgage interest payments (p_t),[27] a measure of log commodity prices (com_t), and our new measure of monetary policy. This is the same VAR specification as in Romer and Romer (2004), with commodity prices added. While not important for our results, it will be useful to control for commodity prices for our later discussion regarding the price puzzle in standard VARs. Online Appendix B.B3 shows that our results are robust to a larger specification, including adding unemployment and the actual policy rate. Precise data definitions are given in online Appendix A.

We estimate the effects of monetary policy based on the following VAR:

$$\mathbf{X}_t = \mathbf{B}(\mathbf{L})\,\mathbf{X}_{t-1} + \epsilon_t, \tag{4}$$

where $\mathbf{B}(\mathbf{L})$ is a lag polynomial with P lags. The vector of observables is $\mathbf{X}_t = [y_t, p_t, com_t, cum.shock_t]'$. In the estimation we also allow for a constant and a time trend, although the results are robust to excluding the trend.[28]

Since conventional VARs are based on interest rates in levels (Bank Rate for the United Kingdom), we follow Romer and Romer (2004) and Coibion (2012) and cumulate our new monetary policy series ($cum.shock_t = \sum_{i=0}^{t} m_i$) and order this series last in the VAR, assuming that the nonpolicy variables in the VAR do not react within the month to a change in policy.[29] We follow the Romer and Romer (2004) and Coibion (2012) method of using the cumulated series to make our results as comparable as possible. The data are monthly and we estimate the VAR with $P = 24$ lags. The VAR in Romer and Romer (2004) includes 36 lags, but their single equation regressions are based on including lags of two years for the endogenous variables. We therefore prefer to include two years of lags to estimate fewer parameters. We also experimented with different values for P and show that the results are robust (as shown in online Appendix B.B5). All figures below report impulse responses together with 68 and 95 percent bootstrapped confidence intervals using 2,000 replications.

In terms of quantitative magnitudes, Figure 2 presents the main result of this paper. In response to a 1 percentage point positive innovation to the monetary policy target rate, the inflation rate falls by up to -1.00 percentage points.[30] Industrial production has a peak decline of -0.61 percent. In Section IV, we show a similar effect on GDP using a quarterly version of the VAR. The drop in industrial production peaks 10 months after the shock. Inflation does not react strongly on impact, but

[27] The price measures we have considered are: the seasonally adjusted log price index, the 12-month inflation rate, and the 1-month inflation rate. The main figures show the results based on the 12-month inflation rate but, for reference, Figure B5 in the online Appendix shows that the results are very similar using all three measures. A seasonally adjusted (at source) price-level series is not available for the United Kingdom, and we therefore adjust it ourselves. Using the 12-month inflation rate produces tighter standard errors. We therefore prefer to use this variable in our baseline results in Figure 2.

[28] The results are extremely similar excluding the trend, as shown in Figure B3 in the online Appendix.

[29] Importantly, we relax this assumption later. That said, estimating a monthly VAR as we do, the assumption is less restrictive when compared with quarterly VARs.

[30] The results are robust to using the alternative price measures RPI and CPI as presented in Figure B4 in online Appendix B.B5.

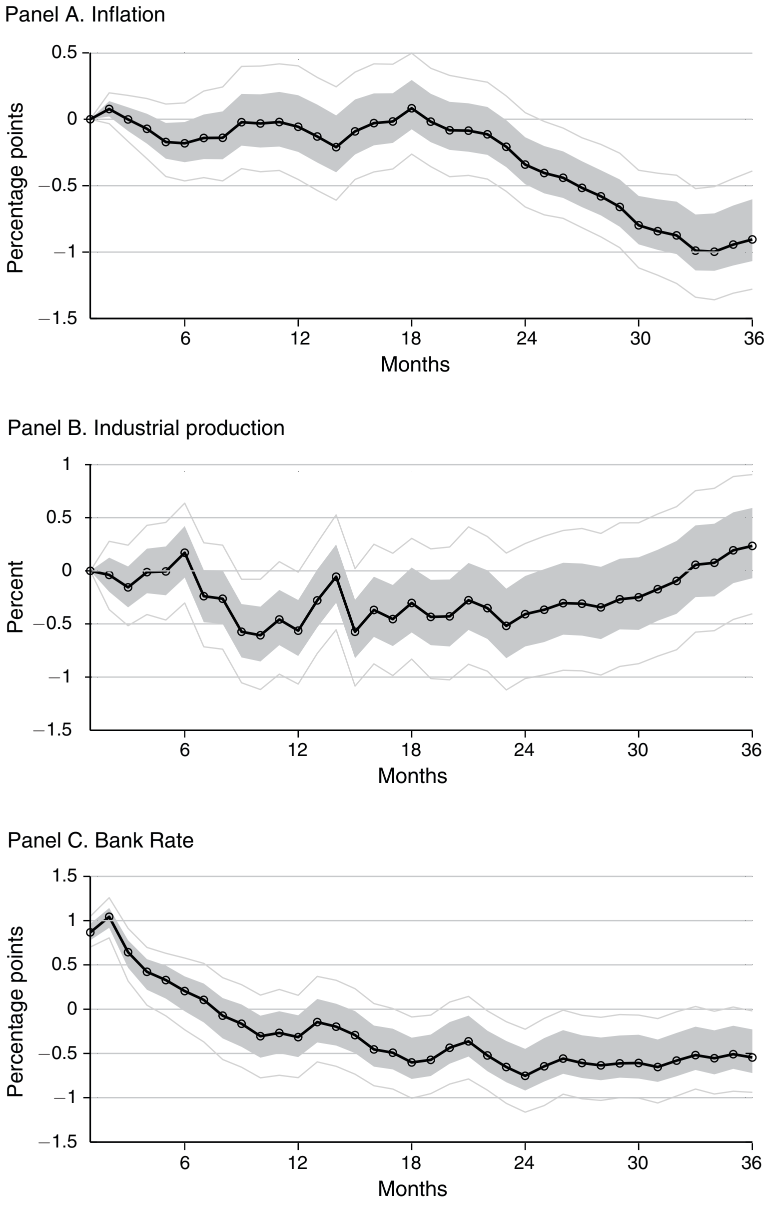

Figure 2. The Macroeconomic Effects of a Monetary Policy Innovation

Notes: Impulse responses to a 1 percentage point contractionary monetary policy shock. VAR with industrial production, inflation rate (RPIX12m), commodity prices, and our new monetary policy measure. For reference, we added Bank Rate ordered last in our baseline VAR in the bottom panel. Online Appendix B.B3 shows that our results are robust to a larger specification. $P = 24$. Sample: 1975–2007. Confidence bands indicate 68 and 95 percent intervals.

declines sharply 18 months after the shock, reaching its peak effect after 34 months. The industrial production response is significant at 95 percent between periods 9 and 12 and the inflation response becomes highly significant after about 2 years.

We also investigate the contribution of monetary policy shocks to economic fluctuations. A forecast error variance decomposition suggests that monetary policy shocks account for 11 percent of output volatility and 38 percent of inflation fluctuations at the 4-year horizon. In line with our empirical findings, the wider literature has also documented that the contribution of monetary policy shocks to output fluctuations is rather small. Our results mirror the finding in Coibion (2012) who shows that even after considering a range of specifications, the Romer and Romer (2004) shocks account for a reasonable degree of the variability of inflation, but much less of the variation in measures of real activity.

B. *Comparison to the Literature*

There is, of course, a wider literature on the empirical effects of monetary policy using VAR methods (such as the recursive method or sign-restrictions discussed in the introduction). Much of this research has been for the United States, but there exists a smaller range of VAR studies for the United Kingdom, and it is interesting to briefly consider how our results compare.

For the United Kingdom, Dedola and Lippi (2005) also report a fall of around 0.5 percent in industrial production. Mountford (2005) and Ellis, Mumtaz, and Zabczyk (2014) find that GDP falls by 0.6 and 0.5 percent, respectively. These results are in line with our findings. However, there is much more disparity in the estimated response of inflation and prices. For example, in Dedola and Lippi (2005), the price level rises following a monetary contraction. Below we also show a "price puzzle" exists using the recursive Cholesky identification methodology in a conventional VAR with Bank Rate as the policy variable (rather than our series).

Most studies conducted for the United States and other countries also find that real activity as measured by industrial production or total output declines between 0.5 and 1 percent to a one percentage point increase in the interest rate. A concise overview of key studies can be found in Table A3 in the online Appendix.

In summary, the main conclusion we draw from this wider literature is that our shock series produces results for the United Kingdom that are of the order of magnitude found by other VAR-based methods in the literature.

A further question is how closely our results line-up with estimates for the United States using the Romer and Romer (2004) shock series. As noted in the introduction, the Romer and Romer results are commonly seen as being larger than the rest of the literature. The original dataset of Romer and Romer (2004) is based on the sample from 1969 to 1996. To make the results as comparable as possible across countries, we use an extended Romer and Romer (2004) shock series up to 2007 and use the same sample period, i.e., from 1975 to 2007.[31]

Figure 3 shows the VAR results for the United Kingdom (black lines) and the United States (grey lines) of a 1 percentage point contractionary monetary policy shock. Interestingly, we find similar results for the United Kingdom and the United States for both the dynamics and the peak effects. The responses for the United

[31] Using data from Coibion (2012), Coibion et al. (2012), and our own reading of the Federal Reserve Greenbook data. Extending the US sample to 1969–2007 does not alter the results.

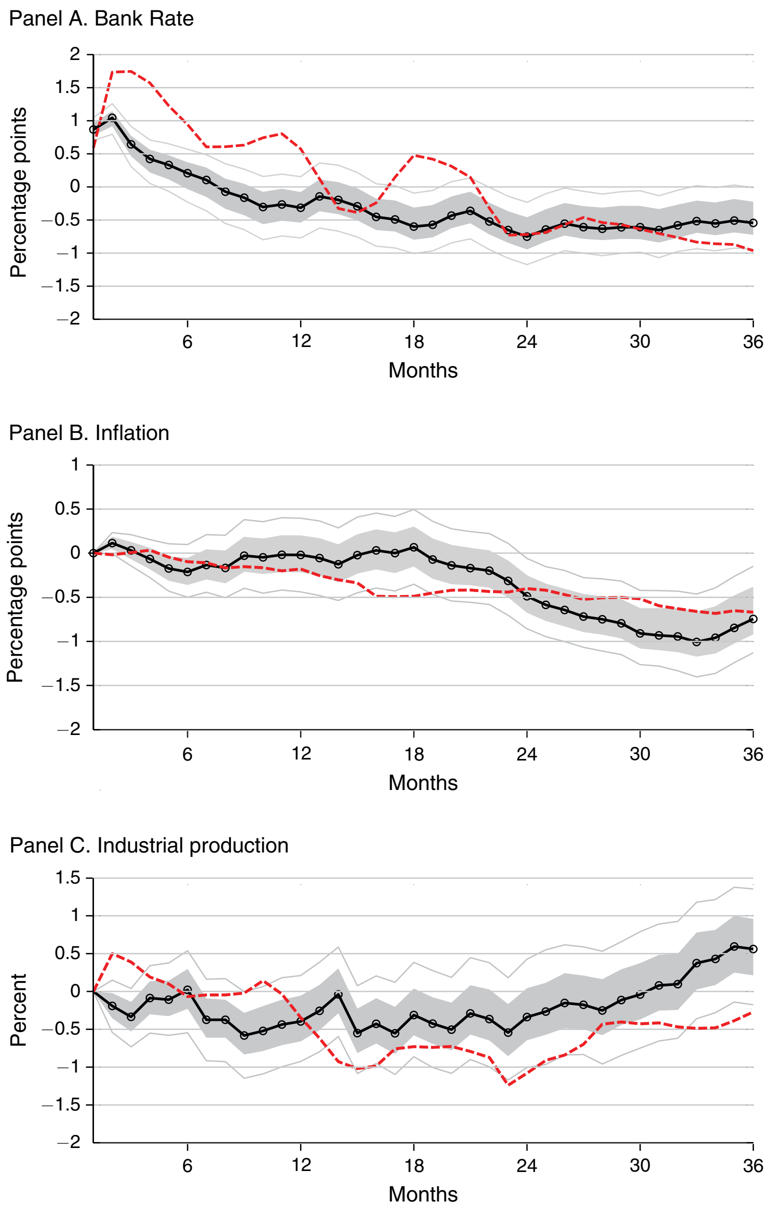

FIGURE 3. VAR WITH NARRATIVE SHOCK SERIES FOR THE UNITED KINGDOM AND THE UNITED STATES

Notes: Impulse responses to a 1 percentage point contractionary monetary policy shock. VAR with industrial production, inflation rate (UK RPIX12m and US CPI12m), commodity prices, narrative monetary policy measure, and policy rate (UK Bank Rate and US effective FFR). $P = 24$. Sample: 1975–2007. Confidence bands indicate 68 and 95 percent intervals.

States are largely within the 95 percent confidence bands for the United Kingdom estimates. The peak effect for industrial production is still a bit larger for the United States. There is a small output puzzle for the United States, although we do not see this for the United Kingdom. While United States inflation responds slightly more quickly, the effects two to three years after the shock are still broadly similar in magnitude and the overall fall in the level of prices is comparable.

Romer and Romer (2004) also employ single equation regressions to estimate the effect of monetary policy shocks and these tend to produce larger results than commonly found in the literature. In the robustness section, for completeness, we also show the results for the United Kingdom using this approach. In the online Appendix, we demonstrate that these results can also be reconciled with the Romer and Romer's (2004) findings for the United States and with the UK VAR-based estimates reported in the previous section once we harmonize the policy experiment as in Coibion (2012).

C. *The Price Puzzle*

Conventional VARs, which employ observed interest rates and the recursive identification strategy of Christiano, Eichenbaum, and Evans (1996, 1999), often generate a substantial and persistent price puzzle—a monetary policy tightening is followed by an increase in the price level and/or inflation rate. This observation, first documented in Sims (1992) and dubbed the “price puzzle” by Eichenbaum (1992), has raised doubts about the recursive identification scheme, being at odds with conventional intuition and theory. A large literature has proposed various methods to resolve this puzzle, such as expanding the VAR with oil prices and commodity prices or to use FAVARs. The motivation behind these approaches is that conventional VARs do not contain enough observables to capture the information actually available to policymakers and driving the changes in interest rates.

For the UK economy, we also find that a VAR with Bank Rate as the policy instrument (rather than our measure) and employing the recursive identification assumption produces a large and persistent price and inflation puzzle.[32] As a robustness check we add a variety of extra variables to this VAR including oil prices, unemployment, money supply, and various exchange rate measures. However, adding these variables does not solve the UK price puzzle. Figure 4 shows the inflation response to a 1 percentage point increase in Bank Rate in our baseline VAR (dashed line) and compares it to the response based on our new series. Using the standard recursive method, the inflation response is positive for around 2 years and lies outside of the 95 percent confidence intervals of our baseline results.[33]

Romer and Romer (2004) also document a large price puzzle for the United States using the conventional recursive VAR methodology, and show that their new shock measure solves this issue. It therefore seems a robust feature of both the United States and United Kingdom that applying the narrative identification strategy resolves the puzzling results in conventional VAR studies. While constructing a detailed real-time and forecast dataset is no small task, this approach provides different results than conventional VAR approaches and novel insights on the macroeconomic effects of monetary policy.

[32] In our procedure, we replace Bank Rate in the VAR specification with our new monetary shock measure.
[33] Online Appendix B.B6 shows the response of inflation in the recursive VAR, together with standard errors.

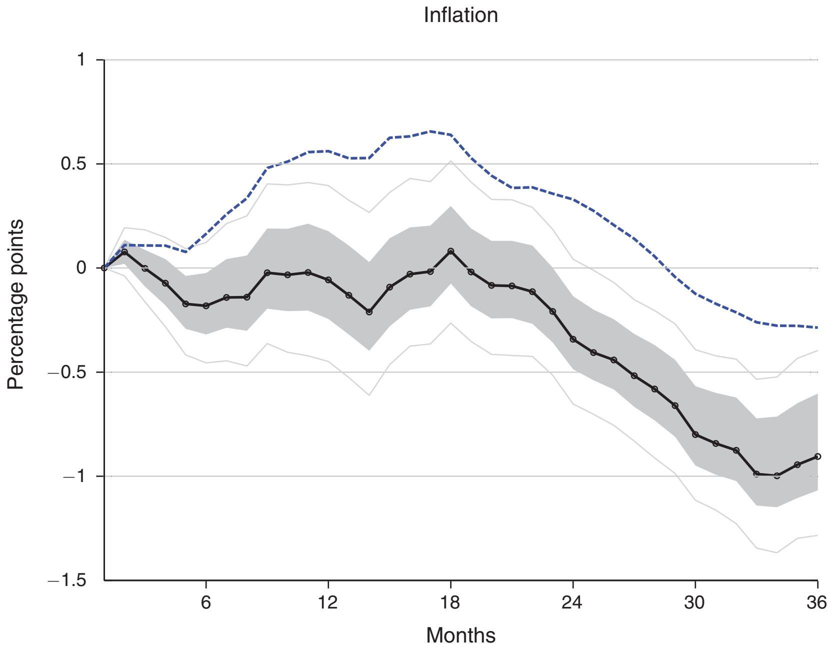

Figure 4. Response of Inflation in VAR with the New Innovation Measure versus a Conventional, Recursive VAR with Bank Rate (*dashed line*)

Notes: Impulse responses to a 1 percentage point contractionary monetary policy shock. VAR with industrial production, inflation rate (RPIX12m), commodity prices and shock measure. $P = 24$. Sample: 1975–2007. The circled line is the inflation response based on the new shock measure together with the respective confidence bands. The dashed line is the inflation response based on a conventional, recursive VAR with Bank Rate. Confidence bands indicate 68 and 95 percent intervals.

IV. Robustness and Extensions

A. *Do the Forecasts Matter?*

Previously we argued that forecasts provide summary statistics of the policymakers' information set. Forecasts also allow us to control for policy reactions designed to offset future business cycle movements. If policy did not respond to forecasted conditions, or if the VAR already contains sufficient information to make their inclusion redundant, excluding the forecasts from our first-stage regression would not alter our baseline results. To examine this possibility we estimate the first-stage regression only including lagged real-time variables. Panel A in Figure 5 shows the results of this exercise. With forecasts excluded we find a substantial and pronounced price puzzle and the industrial production response is slightly stronger. These findings suggest that policymakers do respond to anticipated movements in the macroeconomy and that this information is not adequately summarized by conventional macroeconomic variables used in VARs.

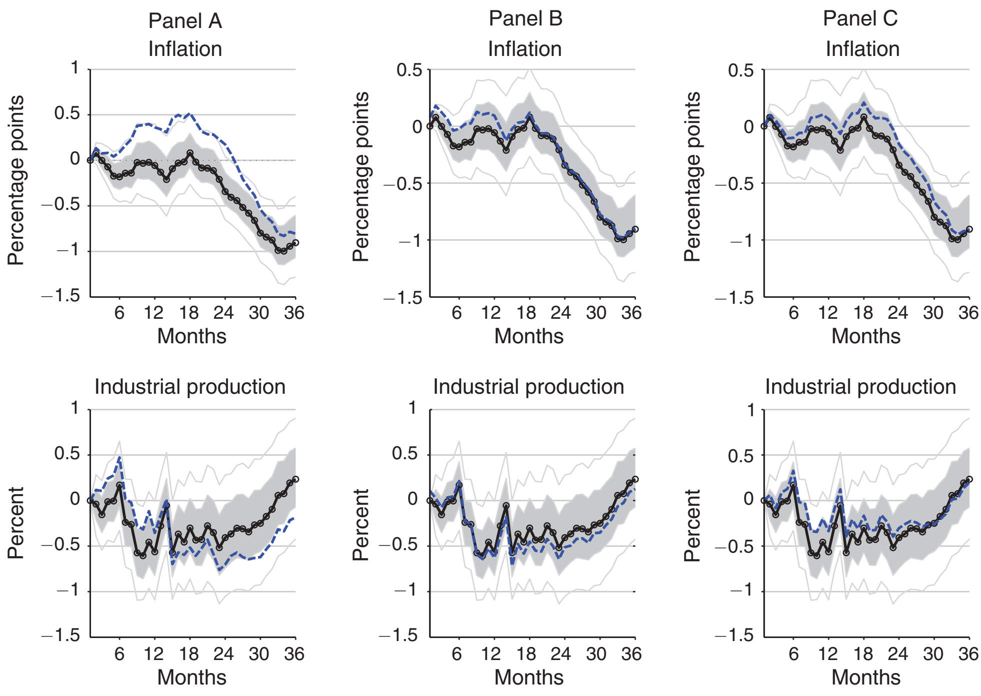

Figure 5. Robustness to Excluding Forecasts, Timing Assumptions, and Using NIESR Forecasts

Notes: Impulse responses to a 1 percentage point contractionary monetary policy shock (dashed line) using an alternative specification compared to baseline specification (circled line) with corresponding 68 and 95 percent confidence intervals. The baseline specification uses industrial production, RPIX12m inflation, commodity prices, and our shock measure. Panel A: first stage regression with only lagged variables (dashed line). Panel B: non-recursive VAR allowing for contemporaneous effect (dashed line). Panel C: using only NIESR forecasts (dashed line) in the first-stage regression.

As a further experiment, we estimate the first-stage regression excluding real-time backdata and forecasts of the current period.[34] Interestingly, the dynamics are very similar to our baseline results in Section IV. It is therefore the inclusion of the forecasts that seems key for removing the price puzzle.

In a related contribution, Castelnuovo and Surico (2010) provide compelling evidence that the omission of expected inflation in a VAR can account for the price puzzle in indeterminate monetary regimes. In essence, excluding forecasts causes omitted variable bias and the empirical evidence for the UK economy in this section is in line with their finding.

B. *Alternative Timing Assumptions in the VAR*

So far we have followed the previous literature (Christiano, Eichenbaum, and Evans 1996, 1999; Romer and Romer 2004; Coibion 2012) imposing that the policy change does not contemporaneously affect macroeconomic variables. We relax

[34] In practice, we estimate equation (2) with the forecast horizon $i = 1, 2$ instead of $i = -1, 0, 1, 2$.

this assumption for the following reason. The regressors in the first-stage regression capture the real-time information set of policymakers prior to the policy rate decision. As discussed, we carefully ensure that the forecasts do not include the consequences of the policy change. If we have correctly captured the information set that policymakers used to form their decision, our new measure m_t should be contemporaneously exogenous. Rather than assuming movements in policy do not contemporaneously affect other variables in the second stage VAR, we should, in principle, be able to relax this assumption.[35]

We therefore estimate our baseline VAR with the new monetary policy measure ordered first in the recursive ordering. This implies that contemporaneous macroeconomic fluctuations do not affect the policy decision other than via the forecasts. This seems reasonable given the discussion above. We can now identify the contemporaneous effects of our monetary policy changes.

Panel B of Figure 5 presents the results based on this new identification assumption (dashed line). Our results are virtually identical, suggesting that the effects of monetary policy are indeed very protracted, building up slowly over time.

C. *Private Sector Forecasts*

A possible concern is whether NIESR forecasts (for periods where official forecasts were unavailable) are suitable substitutes for official forecasts. Ideally we would like to have used official forecasts for the full sample, but these were unavailable further back. Previously we noted that NIESR and Bank of England forecasts are highly correlated at short forecast horizons. Moreover, if private sector forecasts are a good proxy for official forecasts we should expect very similar results using NIESR forecasts in our first stage regression for the full sample. To investigate the validity of employing private forecasts, we therefore estimate the first-stage regression using only NIESR data. Panel C in Figure 5 shows that the impulse responses based on NIESR data (in the blue dashed lines) for the full sample are almost identical and lie well within the 95 percent confidence bands of our baseline results (solid line). The results are virtually unchanged suggesting that NIESR forecasts are indeed a useful econometric proxy for the policymakers' own forecasts.

D. *Quarterly VAR with GDP*

In earlier sections we used industrial production as our measure of output. This is useful because it is available monthly and correlates strongly with GDP. To provide an estimate of how strongly monetary policy innovations affect the total economy, as measured by GDP, we estimate a quarterly VAR with National Accounts data in the first column of Figure 6.[36] In line with our baseline results the peak decline in inflation is 0.88 percentage points. GDP significantly falls below 0 to a minimum of −0.5 percent, slightly smaller than the effect on industrial production found earlier.

[35] Further motivation comes from papers such as Gertler and Karadi (2015) who find that prices do, in certain specifications, move on impact.

[36] We include GDP, RPIX inflation, commodity prices, and our new measure cumulated to a quarterly series.

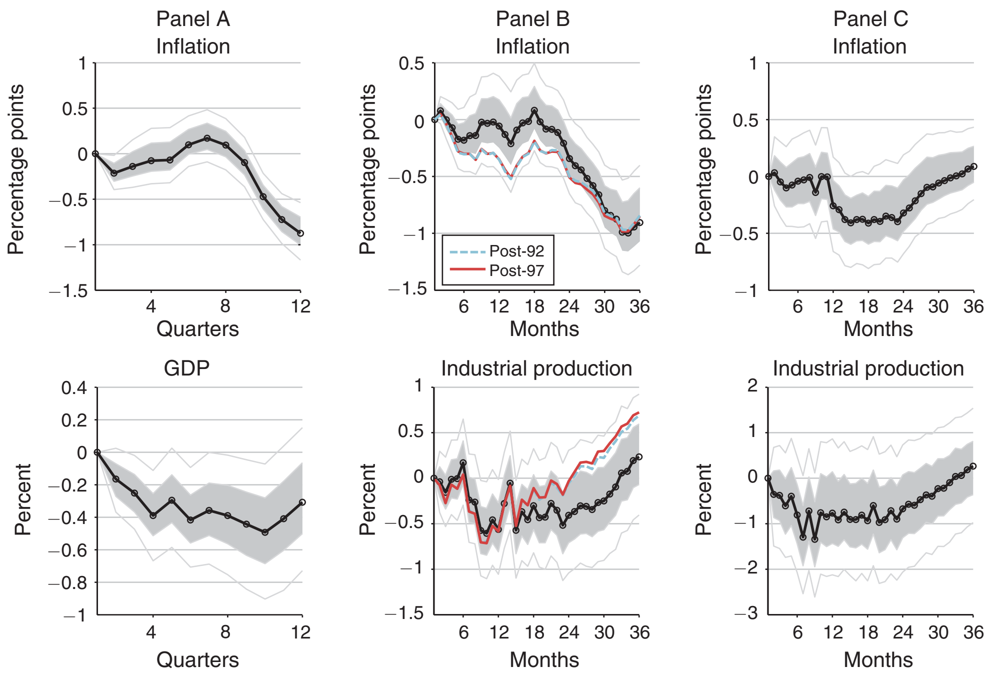

FIGURE 6. ROBUSTNESS TO QUARTERLY VAR AND FIRST-STAGE AND SECOND-STAGE SUBSAMPLE STABILITY

Notes: Impulse responses to a 1 percentage point contractionary monetary policy shock (circled line) with corresponding 68 and 95 percent confidence intervals. The baseline specification uses industrial production, RPIX12m inflation, commodity prices, and our shock measure. Panel A: quarterly VAR with GDP. Panel B: using spliced shock series with break in 1993 (dashed line) and in 1997 (solid line). Panel C: hybrid VAR based on inflation targeting sample: 1993–2007.

A smaller peak effect on GDP as compared to industrial production is in line with the UK result of Ellis, Mumtaz, and Zabczyk (2014). The GDP response is more clearly significant at 95 percent than the industrial production results, although the standard errors remain relatively wide.

E. *Subsample Stability of First-Stage Regression*

So far we have assumed constant coefficients over the full sample in our first-stage regression. To the extent that there have been changes in the central bank's reaction function over time, we should consider estimating different regimes separately. This section therefore explores the issue of breaks in the first-stage regression. While we could estimate the first-stage regression with time-varying parameters, we prefer to directly consider sample splits at dates where the conduct of UK monetary policy is likely to have discretely changed (rather than considering smooth transitions often favored by time-varying parameter models). In particular, we consider two different scenarios: first we split the sample in 1992 when the Bank of England officially started inflation targeting. The second sample split is in 1997 when the Bank of England became operationally independent. We run the first-stage regression on each subsample, and then splice together the resulting new shock series, which we then use in our full-sample baseline VAR.

We report our results in panel B of Figure 6. After allowing for breaks in the reaction function in 1992 or in 1997, the dynamics of inflation and output lie within the 95 percent confidence bands of our baseline results (circled line). While inflation responds slightly faster when allowing for breaks, the peak effects of both inflation and output remain very similar to our baseline results. This similarity suggests that our shocks and their effects do not seem to be significantly biased by not explicitly considering breaks. Of course, the transmission mechanism itself may have changed over time and we discuss this issue in the next section.

F. *Effects of Monetary Policy under Inflation Targeting*

After 1992 the United Kingdom established an official inflation target. From 1992 until the recent crisis, the UK economy experienced low and stable inflation together with consistent positive output growth.[37] The inflation targeting period is also reflected in our monetary policy shock series: the volatility of the series clearly decreases after the early 1990s. An interesting question, therefore, is whether the effects of monetary policy after-1992 change markedly from the effects we find using the full sample.

To generate a specific post-1992 shock series, we re-estimate our first-stage regression only on the inflation targeting period.[38] We then use this series in the VAR employed in Section III.[39]

The third column of Figure 6 shows the results for the post-1992 sample. The inflation response is faster and has a smaller peak effect by the second year. However, this suggests the overall effect on the price level is similar across the two samples after two years.[40] The industrial production response is a bit larger than in the full sample, although not significantly so given the noisy response. This is also true for the response of GDP which peaks at -0.8 percent in a quarterly VAR specification.

Given the change in the monetary regime, the response of the economy is likely to be affected by the conduct of monetary policy following the initial contraction. After 1992 the policy rate is indeed cut slightly more aggressively, suggesting that monetary policy acted more quickly to offset the contractionary effect of the initial innovation over time.

The paradox of more stabilizing monetary policy is that, in reducing volatility, it may become harder to precisely identify the effects of monetary policy on the economy. Furthermore, any innovations would be more quickly offset, making it more

[37] In the United States, this period of low aggregate volatility has been dubbed the Great Moderation in the literature (e.g., Benati and Surico 2009; Boivin and Giannoni 2006; Mavroeidis 2010).

[38] Results of the predictability tests are shown in online Appendix E.E1. For the post-1992 sample our dataset also contains forecasts for output and inflation more than two quarters ahead. As the results do not change, to remain comparable with the previous literature we prefer our baseline specification employing up to two quarter ahead forecasts. Even when including up to six quarter ahead forecasts, the results are very similar.

[39] Because we have halved the sample size, we employ half the lags in the regressions in this section compared to the full sample.

[40] As in the full sample, our new measure of monetary policy innovations delivers a negative response of inflation after 1992, contrary to the conventional VAR results shown in online Appendix E.E2.

challenging to identify the effects in our later sample period. Mirroring this logic, the results after 1992 are not very significant. This partly reflects the smaller sample but, as noted above, it could also be driven by the diminished volatility of interest rates and policy surprises after 1992. However, this does not mean that monetary policy was ineffective post-1992, in fact quite the opposite.

Our points estimates, and the results in Ellis, Mumtaz, and Zabczyk (2014), suggest GDP effects that are similar pre- and post-1992. Turning to our results for inflation, although our peak inflation effect post-1992 is smaller than the results in Ellis et al. (2014), they also find that the response of inflation is faster in the more recent period. Furthermore, given the dynamics of inflation in Figure 6, the overall effect on the level of prices appears similar in both samples.

G. *Results from the Single Equation Approach*

This section considers whether a single equation approach affects our findings. Our preferred approach so far has been to use our shock series within a VAR framework. An alternative is to use our shock series in a simple autoregressive distributed lag (ADL) model and this single equation approach is used by Romer and Romer (2004) to produce their baseline results.[41] This method regresses the change in a variable of interest on a distributed lag of the monetary policy shocks.

One potential drawback of the single equation approach as typically estimated is the possibility of errors in the long-run response induced by differencing. To address this concern while still maintaining a single equation specification, we employ the local projections method following Jordá (2005).[42] Specifically, we estimate the following empirical model:

$$(5) \quad x_{t+h} - x_t = c + \Psi_h(L)\, z_{t-1} + \beta_h shock_t + \epsilon_{t+h} \qquad \text{for } h = 0, 1, 2 \ldots ,$$

where x is the variable of interest, z_{t-1} is a vector of control variables, $\Psi_h(L)$ is a polynomial lag operator, and *shock* refers to our new measure of monetary policy shocks. In particular, the variables of interest are industrial production and inflation, and the vector of control variables is the same that we use in our VAR baseline specification.[43]

Figure 7 shows the results from estimating the single equation model specified in equation (5) using local projections.[44] The effects on industrial production and inflation are qualitatively similar to our baseline results. One feature of these responses, however, is that they appear quantitatively somewhat larger than our VAR-estimates. As noted in Coibion (2012), this setup tends to produce a more persistent effect on

[41] Note that online Appendix D contains a full set of results estimating an ADL model as in Romer and Romer (2004).

[42] We thank one of our anonymous referees for pointing out that the possible counterintuitive permanent effects on output resulting from an OLS ADL specification could be ameliorated by using a more flexible approach such as local projections.

[43] The results are not sensitive to the choice of lags for the control variables but in Figure 7 four lags are used. Results are also robust to excluding these extra controls. To be cautious we include four years of lags of our shock measure, as in Romer and Romer (2004). One advantage of local projections is that it is straightforward to consider a range of controls and lag structures while still maintaining a single equation approach.

[44] Interestingly, the results are very similar when employing an instrumental variable approach as suggested by Ramey and Zubairy (2014) where we use our shock series as an instrument for the policy variable.

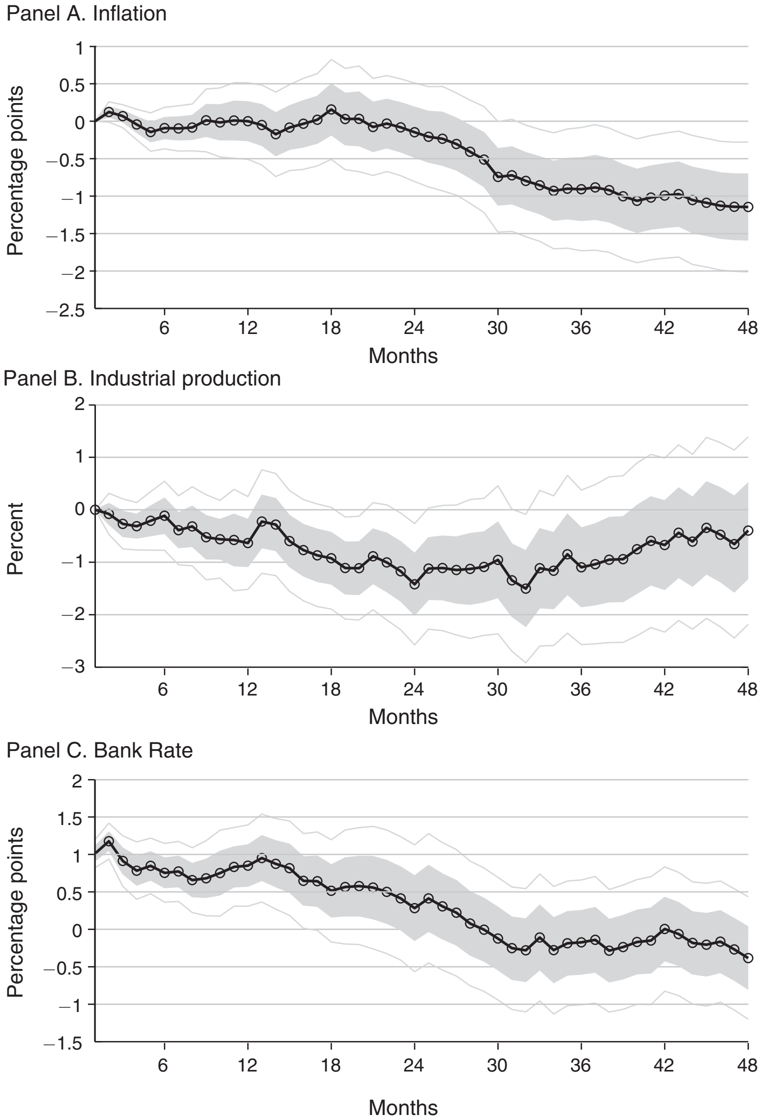

Figure 7. Single Equation Approach

Notes: Impulse responses to a 1 percentage point contractionary monetary policy shock based on single equation regression using local projections with corresponding 68 and 95 percent confidence intervals. The specification uses industrial production, RPIX12m inflation, commodity prices, and our shock measure.

the policy rate, and this can also be seen in Figure 7. The larger effects are therefore not especially surprising. Figure C1 in the online Appendix shows that after adjusting for the differential effects on the policy rate, the VAR and single equation methods produce very similar results. For completeness, and mirroring our baseline VAR results, we also reconcile responses from the US and UK single equation approaches in the online Appendix.

V. Conclusion

Identifying exogenous variation in monetary policy is challenging. This paper tackles this issue for the United Kingdom by applying the identification strategy of Romer and Romer (2004). While numerous studies employ more conventional VAR methodologies, to our knowledge, there have been no other applications of the RR strategy. There is also comparatively little evidence of the macroeconomic effects of monetary policy for the UK economy.

A study of this kind requires high quality data along a number of dimensions and the United Kingdom is an excellent country for such an exercise: the Bank of England's policy rate *is* the intended target rate and there is a wealth of UK real-time and forecast data available. We construct a new, extensive real-time forecast database and carefully match these data to relevant Bank Rate decision. We therefore reconstruct the policymakers' information set prior to the policy change, allowing us to identify monetary policy innovations from a first stage regression.

We find that a 1 percentage point tightening leads to a maximum decline in industrial production of 0.6 percent and a fall in inflation of 1.0 percentage point after 2 to 3 years. Monetary policy changes have a protracted effect on the economy. Our results also suggest that GDP responds by a comparable magnitude as industrial production—around 0.5 percent at the peak.

The VAR literature that relies on a commonly employed recursive ordering exhibits a large price puzzle in the United Kingdom. This occurs even after controlling for a range of other variables, including commodity prices. In keeping with Romer and Romer (2004), we are able to resolve the price puzzle for the United Kingdom, and we show that the narrative approach employed here, in particular the use of forecast data, is crucial for this result.

The effect of changes in monetary policy continues to be keenly debated, both in academic and policy circles. At the Jackson Hole conference on August 28, 2010, Deputy Governor of the Bank of England Charles Bean argued that in times of financial stress asset purchases are a suitable last resort at the zero lower bound, but there are reasons to primarily rely on short-term interest rates in normal times (see Bean et al. 2010). It therefore seems likely that interest rates will remain a key tool of monetary policy in the future as economies recover from the Great Recession. Our new estimates therefore contribute to this ongoing debate. In doing so, we provide a rich new dataset and a new monetary policy innovations measure for the United Kingdom. We hope both will provide exciting scope for future research.

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