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HIGH FREQUENCY IDENTIFICATION OF MONETARY NON-NEUTRALITY:
THE INFORMATION EFFECT

Emi Nakamura
Jón Steinsson

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ABSTRACT

We present estimates of monetary non-neutrality based on evidence from high-frequency responses of real interest rates, expected inflation, and expected output growth. Our identifying assumption is that unexpected changes in interest rates in a 30-minute window surrounding scheduled Federal Reserve announcements arise from news about monetary policy. In response to an interest rate hike, nominal and real interest rates increase roughly one-for-one, several years out into the term structure, while the response of expected inflation is small. At the same time, forecasts about output growth also increase—the opposite of what standard models imply about a monetary tightening. To explain these facts, we build a model in which Fed announcements affect beliefs not only about monetary policy but also about other economic fundamentals. Our model implies that these information effects play an important role in the overall causal effect of monetary policy shocks on output.

Emi Nakamura
Columbia Business School
3022 Broadway, Uris Hall 820
New York, NY 10027
and NBER
enakamura@columbia.edu

Jón Steinsson
Department of Economics
Columbia University
1026 International Affairs Building
420 West 118th Street
New York, NY 10027
and NBER
jsteinsson@columbia.edu

1 Introduction

A central question in macroeconomics is how monetary policy affects the economy. The key empirical challenge in answering this question is that most changes in interest rates happen for a reason. For example, the Fed might lower interest rates to counteract the effects of an adverse shock to the financial sector. In this case, the effect of the Fed's actions are confounded by the financial shock, making it difficult to identify the effects of monetary policy. The most common approach to overcoming this endogeneity problem is to attempt to control for confounding variables. This is the approach to identification in VAR studies such as Christiano, Eichenbaum, and Evans (1999) and Bernanke, Boivin, and Elias (2005), and also in the work of Romer and Romer (2004). The worry with this approach is that despite efforts to control for important confounding variables, some endogeneity bias remains (see, e.g., Rudebusch, 1998).

An alternative approach—the one we pursue in this paper—is to focus on movements in bond prices in a narrow window around scheduled Federal Open Market Committee (FOMC) meetings. This high frequency identification approach was pioneered by Cook and Hahn (1989), Kuttner (2001), and Cochrane and Piazzesi (2002). It exploits the fact that a disproportionate amount of monetary news is revealed at the time of the eight regularly scheduled FOMC meetings each year. The lumpy way in which monetary news is revealed allows for a discontinuity-based identification scheme.

We construct monetary shocks using unexpected changes in interest rates over a 30-minute window surrounding scheduled Federal Reserve announcements. All information that is public at the beginning of the 30-minute window is already incorporated into financial markets, and, therefore, does not show up as spurious variation in the monetary shock. Such spurious variation is an important concern in VARs. For example, Cochrane and Piazzesi (2002) show that VAR methods (even using monthly data) interpret the sharp drop in interest rates in September 2001 as a monetary shock as opposed to a reaction to the terrorist attacks on 9/11/2001.

A major strength of the high-frequency identification approach we use is how cleanly it is able to address the endogeneity concern. As is often the case, this comes at the cost of reduced statistical power. The monetary shocks we estimate are quite small (they have a standard deviation of only about 5 basis points). This “power problem” precludes us from directly estimating their affect on future output. Intuitively, output several quarters in the future is influenced by a myriad of other shocks, rendering the signal-to-noise ratio in such regressions too small to yield reliable inference.

We can, however, measure the response of variables that respond contemporaneously such as

financial variables and survey expectations. Since the late 1990's it has been possible to observe the response of real interest rates via the Treasury Inflation Protected Securities (TIPS) market. This is important since the link between nominal interest rates and real interest rates is *the* distinguishing feature of models in which monetary policy affects real outcomes. All models—Neoclassical and New Keynesian—imply that *real* interest rates affect output. However, New Keynesian and Neoclassical models differ sharply as to whether monetary policy actions can have persistent effects on real interest rates. In New Keynesian models, they do, while in Neoclassical models real interest rates are decoupled from monetary policy. By focusing on the effects of monetary policy shocks on real interest rates, we are shedding light on the core empirical issue in monetary economics.

We use the term structure of interest rates at the time of FOMC meetings to show that the monetary shocks we identify have large and persistent effects on expected real interest rates as measured by TIPS. Nominal and real interest rates respond roughly one-for-one several years out into the term structure in response to our monetary shocks. The effect on real rates peaks at around 2 years and then falls monotonically to zero at 10 years. In sharp contrast, the response of break-even inflation (the difference between nominal and real rates from TIPS) is essentially zero at horizons up to three years. At longer horizons, the response of break-even inflation becomes modestly, but significantly, negative. A tightening of monetary policy therefore eventually reduces inflation—as standard theory would predict. However, the response is small and occurs only after a long lag.

What can we conclude from these facts? Under the conventional interpretation of monetary shocks, these facts imply a great deal of monetary non-neutrality. Intuitively, a monetary-policy-induced increase in real interest rates leads to a drop in output relative to potential, which in turn leads to a drop in inflation. The response of inflation relative to the change in the real interest rates is determined by the slope of the Phillips curve (as well as the intertemporal elasticity of substitution). If the inflation response is small relative to the change in the real rates, the slope of the Phillips curve must be small implying large nominal and real rigidities and, therefore, large amounts of monetary non-neutrality.

There is, however, an additional empirical fact that does not fit this interpretation. We document that in response to an unexpected increase in the real interest rate (a monetary tightening), survey estimates of expected output growth rise. Under the conventional interpretation of monetary shocks, a tightening of policy should lead to a fall in output growth. Our empirical finding regarding output growth expectations is therefore the *opposite* direction from what one would expect from the conventional interpretation of monetary shocks.

A natural interpretation of this evidence is that FOMC announcements lead the private sector to

update its beliefs not only about the future path of monetary policy, but also about other economic fundamentals. For example, when the Fed Chair announces that the economy is strong enough to withstand higher interest rates, market participants may react by reconsidering their own beliefs about the economy. Market participants may contemplate that perhaps the Fed has formed a more optimistic assessment of the economic outlook than they have and that they may want to reconsider their own assessments. Following Romer and Romer (2000), we refer to the effect of FOMC announcements on private sector views of non-monetary economic fundamentals as “Fed information effects.”

The Fed information effect calls for more sophisticated modeling of the effects of monetary shocks than is standard. The main challenge is how to parsimoniously model these information effects. We present a new model in which monetary shocks affect not only the trajectory of the real interest rate, but also private sector beliefs about the trajectory of the *natural rate* of interest. This is a natural way of modeling the information content of Fed announcements since optimal monetary policy calls for interest rates to track the natural rate in simple models. Since the Fed is attempting to track the natural rate, it is natural to assume that Fed announcements contain information about the path of the natural rate.

Our “Fed information model” implies less monetary non-neutrality through conventional channels than a model that ignores Fed information. The reason is that the response of inflation is determined by the response of the real interest rate *gap*—the gap between the response of real interest rates and the natural real rate—which is smaller than the response of real interest rates themselves. Intuitively, some of the increase of real rates is interpreted not as a tightening of policy relative to the natural rate—which would push inflation down—but rather as an increase in the natural rate itself—which does not.

If the Fed information effect is large, even a large response of real interest rates to a monetary shock is consistent with the conventional channel of monetary non-neutrality being modest (since the real interest rate movement is mostly due to a change in the natural real rate). However, this does not mean that the Fed is powerless. To the contrary, if the Fed information effect is large, the Fed has a great deal of power over private sector beliefs about economic fundamentals, which may in turn have large effects on economic activity. If a Fed tightening makes the private sector more optimistic about the future, this will raise current consumption and investment in models with dynamic linkages. Depending on the strength of the Fed information effect, our evidence, therefore, suggests either that the Fed has a great deal of power over the economy through traditional channels or that the Fed has a great deal of power over the economy through non-traditional information

channels (or some combination of the two).

To assess the extent of Fed information and the nature of Fed power over the economy, we estimate our Fed information model using as target moments the responses of real interest rates, expected inflation, and expected output growth discussed above. Here, we follow in the tradition of earlier quantitative work such as Rotemberg and Woodford (1997) and Christiano, Eichenbaum, and Evans (2005), with two important differences. First, our empirical targets are identified using high-frequency identification as opposed to a VAR. Second, we allow for Fed information effects in our model.

Our estimates imply that the Fed information effect is large. Roughly 2/3 of the response of real interest rates to FOMC announcements are estimated to be a response of the natural rate of interest and only 1/3 a tightening of real rates relative to the natural rate. This large estimate of the Fed information effect allows us to simultaneously match the fact that beliefs about output growth rise following a monetary shock and inflation eventually falls. Beliefs about output growth rise because agents are more optimistic about the path for potential output. Inflation falls because a portion of the shock is interpreted as rates rising relative to the natural rate.

Once we allow for Fed information effects, the causal effect of monetary policy is much more subtle to identify. Our estimates imply that surprise FOMC monetary tightenings have large positive effects on expectations about output growth. Does this imply that the monetary announcements cause output to increase by large amounts? No, not necessarily. Much of the news the Fed reveals about non-monetary fundamentals would have eventually been revealed through other sources. To correctly assess the *causal* effect of monetary policy, one must compare versus a counterfactual in which the changes in fundamentals the Fed reveals information about occur even in the absence of the announcement. The causal effect of the Fed information is then limited to the effect on output of the Fed announcing this information earlier than it otherwise would have become known.

Our model makes these channels precise. Recent discussions of monetary policy have noted the Fed's reluctance to lower interest rates for fear it might engender pessimistic expectations that would fight against its goal of stimulating the economy. Our analysis suggests that these concerns may be well-founded at least at the zero lower bound.¹ Moreover, our model suggests that the implications of systematic monetary policy actions are quite different from those of monetary shocks. The reason is that systematic monetary policy actions don't entail information effects since, by definition, they are not based on private information. In other words, there is an important external

¹Revealing information about natural rates, even bad news, is likely to be welfare improving as long as the Fed can vary interest rates to track the natural rate. At the zero lower bound, the Fed however loses its ability to track the natural rate. Withholding bad news may then be optimal.

validity problem whenever researchers use monetary shocks to try to infer the effects of systematic monetary policy. We use a structural model to solve this external validity problem.

Our measure of monetary shocks is based not only on surprise changes in the federal funds rate but also changes in the path of future interest rates in response to FOMC announcements. This is important since over the past 15 years forward guidance has become an increasingly important tool in the conduct of monetary policy (Gurkaynak, Sack, and Swanson, 2005). This also implies that it is important to focus on a narrow 30-minute window as opposed to the 1-day or 2-day windows more commonly used in prior work. We make use of Rigobon's (2003) heteroskedasticity-based estimator to show that OLS results based on monetary shocks constructed from longer-term interest rate changes over one-day windows around FOMC announcements are confounded by substantial "background noise" that lead to unreliable inference and in particular can massively overstate the true statistical precision of the estimates. In contrast, OLS yields reliable results when a 30-minute window is used.

An important question about our empirical estimates is whether some of the effects of our monetary shocks on longer-term real interest rates reflect changes in risk premia as opposed to changes in expected future short-term real interest rates. We use three main approaches to analyze this issue: direct survey expectations of real interest rates, an affine term structure model, and an analysis of mean reversion. None of these pieces of evidence suggest that movements in risk premia at the time of FOMC announcements play an important role in our results. In other words, our results suggest that the expectations hypothesis of the term structure is a good approximation in response to our monetary shocks, even though it is not a good approximation unconditionally. This is what we need for our analysis to be valid.

Another important (and related) question is whether there might be a predictable component of the monetary shocks we analyze and how this might affect the interpretation of our results. In our analysis of real interest rates, the *dependent variables* are high frequency changes. The error terms in these regressions, therefore, only contain information revealed in that narrow window, and the identifying assumption is that our monetary shock is orthogonal to this limited amount of information. This methodology has the advantage that we need not assume that our monetary shock is orthogonal to macro shocks occurring on other days or to slow-moving confounding variables. The identifying assumptions are stronger when we analyze the effects of our monetary shocks on survey expectations from the Blue Chip data. In that analysis the dependent variable is a monthly change and the identifying assumption is that the monetary shock is orthogonal to confounders over the whole month. Similar (stronger) assumptions are required when high frequency monetary

shocks are used as external instruments in a VAR—as in Gertler and Karadi (2015)—since the outcome variables are changes over several months. Additionally, predictability is difficult to establish convincingly due to data mining and peso problem concerns.

Our paper relates to several strands of the literature in monetary economics. The seminal empirical paper on Fed information is Romer and Romer (2000). Faust, Swanson, and Wright (2004) present a critique of their findings. More recently, Campbell et al. (2012) show that an unexpected tightening leads survey expectations of unemployment to fall. The theoretical literature on the signaling effects of monetary policy is large. Early contributions include Cukierman and Meltzer (1986) and Ellingsen and Soderstrom (2001). Recent contributions include Berkelmans (2011), Melosi (2017), Tang (2015), Frankel and Kartik (2017), and Andrade et al. (2016). The prior literature typically assumes that the central bank must communicate only through its actions (e.g., changes in the fed funds rate), whereas we allow the Fed to communicate through its words (FOMC statements).

Our estimates of the effects of monetary announcements on real interest rates using high-frequency identification are related to recent work by Hanson and Stein (2015) and Gertler and Karadi (2015). We make different identifying assumptions than Hanson and Stein, use a different definition of the monetary shock, and come to quite different conclusions about the long-run effects of monetary policy.² There are also important methodological differences between our work and that of Gertler and Karadi (2015). They rely on a VAR to estimate the dynamic effects of monetary policy shocks. They are therefore subject to the usual concern that the VAR they use may not accurately describe the dynamic response of key variables to a monetary shock. Our identification approach is entirely VAR-free. Our paper is also related to several recent papers that have used high-frequency identification to study the effects of unconventional monetary policy during the recent period over which short-term nominal interest rates have been at their zero lower bound (Gagnon et al., 2010; Krishnamurthy and Vissing-Jorgensen, 2011; Wright, 2012; Gilchrist et al., 2015, Rosa, 2012).

The paper proceeds as follows. Section 2 describes the data we use in our analysis. Section 3 presents our empirical results regarding the response nominal and real interest rates and TIPS break-even inflation to monetary policy shocks. Section 4 presents our empirical evidence on output growth expectations. Section 5 presents our Fed information model, describes our estimation methods, and presents the results of our estimation of the Fed information model. Section 6 discusses how to think about the causal effect of the monetary announcement in the face of Fed information. Section 7 concludes.

²In earlier work, Beechey and Wright (2009) analyze the effect of unexpected movements in the federal funds rate at the time of FOMC announcements on nominal and real 5-year and 10-year yields and the five-to-ten year forward over the period February 2004 to June 2008. Their results are similar to ours for the 5-year and 10-year yields.

2 Data

To construct our measure of monetary shocks, we use tick-by-tick data on federal funds futures and eurodollar futures from the CME Group (owner of the Chicago Board of Trade and Chicago Mercantile Exchange). These data can be used to estimate changes in expectations about the federal funds rate at different horizons after an FOMC announcement (see Appendix A). The tick-by-tick data we have for federal funds futures and eurodollar futures is for the sample period 1995-2012. For the period since 2012 we use data on changes in the prices of the same five interest rate futures over the same 30-minute windows around FOMC announcements that Refet Gurkaynak graciously shared with us.

We obtain the dates and times of FOMC meetings up to 2004 from the appendix to Gurkaynak, Sack, and Swanson (2005). We obtain the dates of the remaining FOMC meetings from the Federal Reserve Board website at <http://www.federalreserve.gov/monetarypolicy/fomccalendar.htm>. For the latter period, we verified the exact times of the FOMC announcements using the first news article about the FOMC announcement on *Bloomberg*. We cross-referenced these dates and times with data we obtained from Refet Gurkaynak and in a few cases used the time stamp from his database.

To measure the effects of our monetary shocks on interest rates, we use several daily interest rate series. To measure movements in Treasuries at horizons of 1 year or more, we use daily data on zero-coupon nominal Treasury yields and instantaneous forward rates constructed by Gurkaynak, Sack, and Swanson (2007). These data are available on the Fed's website at <http://www.federalreserve.gov/pubs/feds/2006/200628/200628abs.html>. We also use the yields on 3M and 6M Treasury bills. We retrieve these from the Federal Reserve Board's H.15 data release.

To measure movements in real interest rates, we use zero-coupon yields and instantaneous forward rates constructed by Gurkaynak, Sack, and Wright (2010) using data from the TIPS market. These data are available on the Fed's website at <http://www.federalreserve.gov/pubs/feds/2008/200805/200805abs.html>. TIPS are "inflation protected" because the coupon and principal payments are multiplied by the ratio of the reference CPI on the date of maturity to the reference CPI on the date of issue.³ The reference CPI for a given month is a moving average of the CPI two and three months prior to that month, to allow for the fact that the Bureau of Labor Statistics publishes these data with a lag.

TIPS were first issued in 1997 and were initially sold at maturities of 5, 10 and 30 years, but only

³This holds unless cumulative inflation is negative, in which case no adjustment is made for the principle payment.

the 10-year bonds have been issued systematically throughout the sample period. Other maturities have been issued more sporadically. While liquidity in the TIPS market was initially poor, TIPS now represent a substantial fraction of outstanding Treasury securities. We start our analysis in 2000 to avoid relying on data from the period when TIPS liquidity was limited. For 2- and 3-year yields and forwards we start our analysis in 2004. Gurkaynak, Sack, and Wright (2010) only report zero-coupon yields for these maturities from 2004 onward. One reason is that to accurately estimate zero-coupon yields at this maturity it is necessary to wait until longer maturity TIPS issued several years earlier have maturities in this range. To facilitate direct comparisons between nominal and real interest rates, we restrict our sample period for the corresponding 2- and 3-year nominal yields and forwards to the same time period.

To measure expectations, we use data on expectations of future nominal interest rates, inflation and output growth from the *Blue Chip Economic Indicators*. Blue Chip carries out a survey during the first few days of every month soliciting forecasts of these variables for up to the next 8 quarters. We use the mean forecast for each variable. We also use data on Greenbook forecasts from the Philadelphia Fed. These data are hosted and maintained on the dataset, <https://www.philadelphiafed.org/research-and-data/real-time-center/greenbook-data/philadelphia-dataset>. We use the real GDP growth variable from this dataset.

To assess the role of risk premia, we use a daily decomposition of nominal and real interest rate movements into risk-neutral expected future rates and risk premia obtained from Abrahams, Adrian, Crump, and Moench (2015). To assess the robustness of our results regarding the response of real interest rates we use daily data on inflation swaps from *Bloomberg*. Finally, we estimate the response of stock prices to monetary announcements using daily data on the level of the S&P500 stock price index obtained from *Yahoo Finance*.

3 Response of Interest Rates and Expected Inflation

Our goal in this section is to identify the effect of the monetary policy news contained in scheduled FOMC announcements on nominal and real interest rates of different maturities. Specifically, we estimate

$$\Delta s_t = \alpha + \gamma \Delta i_t + \epsilon_t, \tag{1}$$

where Δs_t is the change in an outcome variable of interest (e.g., the yield on a five year zero-coupon Treasury bond), Δi_t is a measure of the monetary policy news revealed in the FOMC announcement,

ϵ_t is an error term, and α and γ are parameters. The parameter of interest is γ , which measures the effect of the FOMC announcement on Δs_t relative to its effect on the policy indicator Δi_t .

To identify a pure monetary policy shock, we consider the change in our policy indicator (Δi_t) in a 30-minute window around scheduled FOMC announcements.⁴ The idea is that changes in the policy indicator in these 30-minute windows are dominated by the information about future monetary policy contained in the FOMC announcement. Under the assumption that this is true, we can simply estimate equation (1) by ordinary least squares. We also present results for a heteroskedasticity based estimation approach (Rigobon, 2003; Rigobon and Sack, 2004) which is based on a weaker identifying assumption to verify that our baseline identifying assumption is reasonable. In our baseline analysis, we focus on only scheduled FOMC announcements, since unscheduled meetings may occur in reaction to other contemporaneous shocks.

The policy indicator we use is a composite measure of changes in interest rates at different maturities spanning the first year of the term structure. Until recently, most authors used unanticipated changes in the federal funds rate (or closely related changes in very short term interest rates) as their policy indicator. The key advantage of our measure is that it captures the effects of “forward guidance.” Forward guidance refers to announcements by the Fed that convey information about future changes in the federal funds rate. Over the past 15 years, the Federal Reserve has made greater and greater use of such forward guidance. In fact, changes in the federal funds rate have often been largely anticipated by markets once they occur. Gurkaynak, Sack, and Swanson (2005) convincingly argue that unanticipated changes in the federal funds rate capture only a small fraction of the monetary policy news associated with FOMC announcements in recent years (see also, Campbell et al., 2012).

The specific composite measure we use as our policy indicator is the first principle component of the unanticipated change over the 30-minute windows discussed above in the following five interest rates: the federal funds rate immediately following the FOMC meeting, the expected federal funds rate immediately following the next FOMC meeting, and expected 3-month eurodollar interest rates at horizons of two, three and four quarters. We refer to this policy indicator as the “policy news shock.” We use data on federal funds futures and eurodollar futures to measure changes in market expectations about future interest rates at the time of FOMC announcements. The scale of the policy news shock is arbitrary. For convenience, we rescale it such that its effect on the 1-year nominal Treasury yield is equal to one. Appendix A provides details about the construction of the policy

⁴Specifically, we calculate the monetary shock using a 30-minute window from 10 minutes before the FOMC announcement to 20 minutes after it.

news shock.⁵

3.1 Baseline Estimates

Table 1 presents our baseline estimates of monetary shocks on nominal and real interest rates and break-even inflation. Each estimate in the table comes from a separate OLS regression of the form discussed above—equation (1). In each case the independent variable is the policy news shock measured over a 30-minute window around an FOMC announcement, while the change in the dependent variable is measured over a one-day window.⁶

The first column of Table 1 presents the effects of the policy news shock on nominal Treasury yields and forwards. Recall that the policy news shock is scaled such that the effect on the one-year Treasury yield is 100 basis points. Looking across different maturities, we see that the effect of the shock is somewhat smaller for shorter maturities, peaks at 110 basis points for the 2-year yield and then declines monotonically to 38 basis points for the 10-year yield. Since longer-term yields reflect expectations about the average short-term interest rate over the life of the long bond, it is easier to interpret the time-path of the response of instantaneous forward rates. Abstracting from risk premia, these reveal market expectations about the short-term interest rate that the market expects to prevail at certain points in time in the future.⁷ The impact of our policy news shock on forward rates is also monotonically declining in maturity from 114 basis points at 2-years to -8 basis points at 10-years. We show below that the negative effect on the 10-year nominal forward rate reflects a decline in break-even inflation at long horizons.⁸

The second column of Table 1 presents the effects of the policy news shock on real interest rates measured using TIPS. While the policy news shock affects nominal rates by construction, this is not the case for real interest rates. In neoclassical models of the economy, the Fed controls the nominal interest rate but has no impact on real interest rates. In sharp contrast to this, we estimate the impact of our policy news shock on the 2-year real yield to be 106 basis points, and the impact on the 3-year real yield to be 102 basis points. Again, the time-path of effects is easier to interpret by viewing

⁵Our policy news shock variable is closely related to the “path factor” considered by Gurkaynak, Sack, and Swanson (2005). The five interest rate futures that we use to construct our policy news shock are the same five futures as Gurkaynak, Sack, and Swanson (2005) use. They motivate the choice of these particular futures by liquidity considerations. They advocate the use of two principle components to characterize the monetary policy news at the time of FOMC announcements—a “target factor” and a “path factor.” We focus on a single factor for simplicity. See also Barakchian and Crowe (2013).

⁶The longer window for the dependent variable adds noise to the regression without biasing the coefficient of interest.

⁷For example, the effect on the 2-year instantaneous forward rate is the effect on the short-term interest rate that the market expects to prevail in 2 years time.

⁸Our finding that long-term inflation expectations decline in response to contractionary monetary policy shock is consistent with Beechey, Johannsen, and Levin (2011) and Gürkaynak, Levin, and Swanson (2010).

Table 1: Response of Interest Rates and Inflation to the Policy News Shock

	Nominal	Real	Inflation
3M Treasury Yield	0.67 (0.14)		
6M Treasury Yield	0.85 (0.11)		
1Y Treasury Yield	1.00 (0.14)		
2Y Treasury Yield	1.10 (0.33)	1.06 (0.24)	0.04 (0.18)
3Y Treasury Yield	1.06 (0.36)	1.02 (0.25)	0.04 (0.17)
5Y Treasury Yield	0.73 (0.20)	0.64 (0.15)	0.09 (0.11)
10Y Treasury Yield	0.38 (0.17)	0.44 (0.13)	-0.06 (0.08)
2Y Treasury Inst. Forward Rate	1.14 (0.46)	0.99 (0.29)	0.15 (0.23)
3Y Treasury Inst. Forward Rate	0.82 (0.43)	0.88 (0.32)	-0.06 (0.15)
5Y Treasury Inst. Forward Rate	0.26 (0.19)	0.47 (0.17)	-0.21 (0.08)
10Y Treasury Inst. Forward Rate	-0.08 (0.18)	0.12 (0.12)	-0.20 (0.09)

Each estimate comes from a separate OLS regression. The dependent variable in each regression is the one day change in the variable stated in the left-most column. The independent variable is a change in the policy news shock over a 30 minute window around the time of FOMC announcements. The sample period is all regularly scheduled FOMC meetings from 1/1/2000 to 3/19/2014, except that we drop July 2008 through June 2009. For 2Y and 3Y yields and real forwards, the sample starts in January 2004. The sample size for the 2Y and 3Y yields and forwards is 74. The sample size for all other regressions is 106. In all regressions, the policy news shock is computed from these same 106 observations. Robust standard errors are in parentheses.

estimates for instantaneous forward rates. The effect of the shock on the 2-year real forward rate is 99 basis points. It falls monotonically at longer horizons to 88 basis points at 3 years, 47 basis points at 5 years, and 12 basis point at 10 years (which is not statistically significantly different from zero). Evidently, monetary policy shocks can affect real interest rates for substantial amounts of time (or at least markets believe it can). However, in the long-run, the effect of monetary policy shocks on real interest rates is zero as theory would predict.

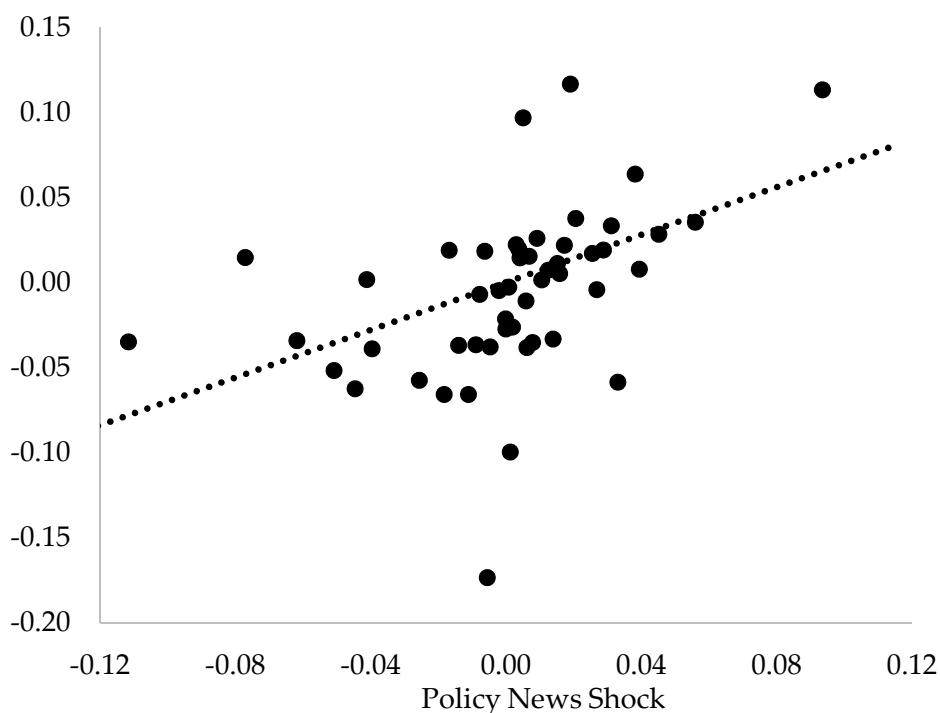
The third column of Table 1 presents the effect of the policy news shock on break-even inflation as measured by the difference between nominal Treasury rates and TIPS rates. The first several rows provide estimates based on bond yields, which indicate that the response of break-even inflation is small. The shorter horizon estimates are actually slightly positive but then become negative at longer horizons. None of these estimates are statistically significantly different from zero. Again, it is helpful to consider instantaneous forward break-even inflation rates to get estimates of break-even inflation at points in time in the future. The response of break-even inflation implied by the 2 year forwards is slightly positive, though statistically insignificant. The response is negative at longer horizons: for maturities of 3, 5 and 10 years, the effect is -6, -21 and -20 basis points, respectively. It is only the responses at 5 and 10 years that are statistically significantly different from zero. Our evidence thus points to break-even inflation responding modestly and quite gradually to monetary shocks that have a substantial effect on real interest rates.

Table 1 presents results for a sample period from January 1st 2000 to March 19th 2014, except that we drop the period spanning the height of the financial crisis in the second half of 2008 and the first half of 2009.⁹ We choose to drop the height of the financial crisis because numerous well-documented asset pricing anomalies arose during this crisis period, and we wish to avoid the concern that our results are driven by these anomalies. However, similar results obtain for the full sample including the crisis, as well as a more restrictive data sample ending in 2007, and for a sample that also includes unscheduled FOMC meetings (see Table A.1). The results for the sample ending in 2007 show that our results are unaffected by dropping the entire period during which the zero-lower-bound is binding and the Fed is engaged in quantitative easing. Table A.2 presents results analogous to those of Table 1 but using the unexpected change in the fed funds rate as the policy indicator.

Figure 1 presents a binned scatter plot of the relationship between the policy news shock and the 5-year real yield (the average expected response of the short-term real interest rates over the next 5

⁹The sample period for 2- and 3-year yields and forwards is somewhat shorter (it starts in 2004) because of data limitations (see section 2 for details).

Figure 1: Binned Scatter Plot for 5-Year Real-Yield Regression



years). The variation in the policy new shock ranges from -11 basis points to +10 basis points. The relationship between the change in the 5-year real yield and the policy news shock does not seem to be driven by a few outliers.

3.2 Background Noise in Interest Rates

A concern regarding the estimation approach we describe above is that other non-monetary news might affect our monetary policy indicator during the window we consider around FOMC announcements. If this is the case, it will contaminate our measure of monetary shocks. This concern looms much larger if one considers longer event windows than our baseline 30-minute window. It has been common in the literature on high frequency identification of monetary policy to consider a one- or two-day window around FOMC announcements (e.g., Kuttner, 2001; Cochrane and Piazzesi, 2002; Hanson and Stein, 2015). In these cases, the identifying assumption being made is that no other shocks affect the policy indicator in question during these one or two days. Especially when the policy indicator is based on interest rates several quarters or years into the term structure—as has recently become common to capture the effects of forward guidance—the assumption that no other shocks affect this indicator over one or two days is a strong assumption. Interest rates at these maturities fluctuate substantially on non-FOMC days, suggesting that other

shocks than FOMC announcements affect these interest rates on FOMC days. There is no way of knowing whether these other shocks are monetary shocks or non-monetary shocks.

To assess the severity of this problem, Table 2 compares estimates of equation (1) based on OLS regressions to estimates based on a heteroskedasticity-based estimation approach developed by Rigobon (2003) and Rigobon and Sack (2004). We do this both for a 30-minute window and for a 1-day window. The heteroskedasticity-based estimator is described in detail in Appendix B. It allows for “background” noise in interest rates arising from other shocks during the event windows being considered. The idea is to compare movements in interest rates during event windows around FOMC announcements to other equally long and otherwise similar event windows that do not contain an FOMC announcement. The identifying assumption is that the variance of monetary shocks increases at the time of FOMC announcements, while the variance of other shocks (the background noise) is unchanged.

The top panel of Table 2 compares estimates based on OLS to those based on the heteroskedasticity-based estimator (Rigobon estimator) for a subset of the assets we consider in Table 1 when the event window is 30-minutes as in our baseline analysis. The difference between the two estimators is very small, both for the point estimates and the confidence intervals.¹⁰ This result indicates that there is in fact very little background noise in interest rates over a 30-minute window around FOMC announcements and the OLS identifying assumption—that only monetary shocks occur within the 30-minute window—thus yields a point estimate and confidence intervals that are close to correct. Table A.3 presents a full set of results based on the Rigobon estimator and a 30-minute window. It confirms that OLS yields very similar results to the Rigobon estimator for all the assets we consider when the event window is 30 minutes.

In contrast, the problem of background noise is quite important when the event window being used to construct our policy news shocks is one day. The second panel of Table 2 compares estimates based on OLS to those based on the Rigobon estimator for policy news shocks constructed using a one-day window. In this case, the differences between the OLS and Rigobon estimates are substantial. The point estimates in some cases differ by dozens of basis points and have different signs in three of the six cases considered. However, the most striking difference arises for the confidence intervals. OLS yields much narrower confidence intervals than those generated using the

¹⁰The confidence intervals for the Rigobon estimator in Table 2 are constructed using a procedure that is robust to inference problems that arise when the amount of background noise is large enough that there is a significant probability that the difference in the variance of the policy indicator between the sample of FOMC announcements and the “control” sample is close to zero. In this case, the conventional bootstrap approach to constructing confidence intervals will yield inaccurate results. Appendix C describes the method we use to construct confidence intervals in detail. We thank Sophocles Mavroeidis for suggesting this approach to us.

Table 2: Allowing for Background Noise in Interest Rates

	2-Year Forward		5-Year Forward		10-Year Forward	
	Nominal	Real	Nominal	Real	Nominal	Real
<i>Policy News Shock, 30-Minute Window:</i>						
OLS	1.14 [0.23, 2.04]	0.99 [0.41, 1.57]	0.26 [-0.12, 0.64]	0.47 [0.14, 0.80]	-0.08 [-0.43, 0.28]	0.12 [-0.12, 0.36]
Rigobon	1.10 [0.31, 2.36]	0.96 [0.45, 1.82]	0.22 [-0.14, 0.64]	0.46 [0.15, 0.84]	-0.12 [-0.46, 0.24]	0.11 [-0.13, 0.35]
<i>Policy News Shock, 1-Day Window:</i>						
OLS	1.24 [0.80, 1.69]	1.00 [0.57, 1.43]	0.44 [0.18, 0.70]	0.48 [0.20, 0.76]	0.05 [-0.20, 0.29]	0.15 [-0.10, 0.39]
Rigobon	0.93 [-0.64, 2.08]	0.82 [0.38, 3.20]	-0.11 [-1.23, 0.33]	0.33 [-0.07, 1.12]	-0.51 [-1.93, -0.08]	-0.04 [-0.51, 0.45]
<i>2-Year Nominal Yield, 1-Day Window</i>						
OLS	1.23 [1.07, 1.38]	0.94 [0.69, 1.20]	0.64 [0.43, 0.84]	0.54 [0.31, 0.76]	0.18 [0.01, 0.35]	0.20 [0.02, 0.38]
Rigobon (90% CI)	1.14 [0.82, 1.82]	0.82 [0.62, 2.98]	-0.11 [-7.94, 0.60]	0.33 [-0.01, 7.48]	-0.51 [-10.00, -0.21]	-0.04 [-4.57, 0.38]

Each estimate comes from a separate "regression." The dependent variable in each regression is the one day change in the variable stated at the top of that column. The independent variable in the first panel of results is the 30-minute change in the policy news shock around FOMC meeting times, in the second panel it is the 1-day change in the policy news shock, and in the third panel it is the 1-day change in the 2-Year nominal yield. In each panel, we report results based on OLS and Rigobon's heteroskedasticity based estimation approach. We report a point estimate and 95% confidence intervals except in the last row of Rigobon estimates which reports 90% confidence intervals. The sample of "treatment" days for the Rigobon method is all regularly scheduled FOMC meeting days from 1/1/2000 to 3/19/2014—this is also the period for which the policy news shock is constructed in all "regressions." The sample of "control" days for the Rigobon analysis is all Tuesdays and Wednesdays that are not FOMC meeting days over the same period of time. In both the treatment and control samples, we drop July 2008 through June 2009 and 9/11/2001-9/21/2001. For 2Y forwards, the sample starts in January 2004. Confidence intervals for the OLS results are based on robust standard errors. Confidence intervals for the Rigobon method are calculated using the weak-IV robust approach discussed in the appendix with 5000 iterations.

Rigobon method. According to OLS, the effects on the 5-year nominal and real forwards are highly statistically significant, while the Rigobon estimator indicates that these effects are far from being significant.

This difference between OLS and the Rigobon estimator indicates that there is a large amount of background noise in the interest rates used to construct the policy news shock over a one day window. The Rigobon estimator is filtering this background noise out. The fact that the confidence intervals for the Rigobon estimator are so wide in the 1-day window case implies that there is very little signal left in this case. The OLS estimator, in contrast, uses all the variation in interest rates (both the true signal from the announcement and the background noise). Clearly, this approach

massively overstates the true statistical precision of the effect arising from the FOMC announcement when a 1-day window is used.

The difference between OLS and the Rigobon estimator is even larger when a longer-term interest rate is used as the policy indicator that proxies for the size of monetary shocks. The third panel of Table 2 compares results based on OLS to those based on the Rigobon estimator when the policy indicator is the change in the two-year nominal yield over a one day window. Again, the confidence intervals are much wider using the Rigobon estimator than OLS. In fact, here we report 90% confidence intervals for the Rigobon estimator since the 95% confidence intervals are in some cases infinite (i.e., we were unable to find any value of the parameter of interest that could be rejected at that significance level).

An important substantive difference arises between the OLS and Rigobon estimates in the case of the 10-year real forward rate when the 2-year nominal yield is used as the policy indicator. Here, OLS estimation yields a statistically significant effect of the monetary shock on forward rates at even a 10-year horizon. This result is emphasized by Hanson and Stein (2015). However, the Rigobon estimator with appropriately constructed confidence intervals reveals that this result is statistically insignificant. Our baseline estimation approach using a 30-minute window and the policy news shock as the proxy for monetary shocks yields a point estimate that is small and statistically insignificant.¹¹

3.3 Risk Premia or Expected Future Short-Term Rates?

One question that arises when interpreting our results is to what extent the movements in long-term interest rates we identify reflect movements in risk premia as opposed to changes in expected future short-term interest rates. A large literature suggests that changes in risk premia do play an important role in driving movements in long-term interest rates in general. Yet, for our analysis, the key question is not whether risk premia matter in general, but rather how important they are in explaining the abrupt changes in interest rates that occur in the narrow windows around the FOMC

¹¹Hanson and Stein (2015) also present an estimator based on instrumenting the 2-day change in the 2-year rate with the change in the two-year rate during a 60-minute window around the FOMC announcement. This yields similar results to their baseline. Since this procedure is not subject to the concerns raised above, it suggests that there are other sources of difference between our results and those of Hanson and Stein than econometric issues. One possible source of difference is that we use different monetary shock indicators. Their policy indicator (the change in the 2-year yield) is further out in the term structure and may be more sensitive to risk premia. As we discuss in section 3.3, our measure of monetary shocks is uncorrelated with the risk premia implied by the affine term structure model of Abrahams et al. (2015), whereas Hanson and Stein's monetary shocks are associated with substantial movements in risk premia. The difference could also arise from the fact that Hanson and Stein focus on a 2-day change in long-term real forwards; which could yield different results if the response of long-term bonds to monetary shocks is inertial.

announcements that we focus on.¹²

In Appendix D, we present three sets of results that indicate that risk premium effects are not driving our empirical results. First, the impact of our policy news shock on direct measures of expectations from the *Blue Chip Economic Indicators* indicate that our monetary shocks have large effects on expected short-term nominal and real rates. Second, the impact of our policy news shock on risk-neutral expected short rates from the state-of-the-art affine term structure model of Abrahams et al. (2015) are similar to our baseline results. Third, the impact of our policy news shock on interest rates over longer event windows do not suggest that the effects we estimate dissipate quickly (although the standard errors in this analysis are large).

We also consider an alternative, market-based measure of inflation expectations based on inflation swap data.¹³ The sample period for this analysis is limited by the availability of swaps data to begin on January 1st 2005. Unfortunately, due to the short sample available to us, the results are extremely noisy, and are therefore not particularly informative. As in our baseline analysis, there is no evidence of large negative responses in inflation to our policy news shock (as would arise in a model with flexible prices). Indeed the estimates from this approach (which are compared to our baseline results in Table A.4) suggest a somewhat larger “price puzzle”—i.e., positive inflation response—at shorter horizons, though this is statistically insignificant.

4 The Fed Information Effect

The results in section 3 show that variation in nominal interest rates caused by monetary policy announcements have large and persistent effects on real interest rates. The conventional interpretation of these facts is that they imply that prices must respond quite sluggishly to shocks. We illustrate this in a conventional business cycle model in Appendix E. This conventional view of monetary shocks has the following additional prediction that we can test using survey data: A surprise increase in interest rates should cause expected output to fall. To test this prediction, we run our baseline empirical specification—equation (1)—at a monthly frequency with the monthly change in

¹²Piazzesi and Swanson (2008) show that federal funds futures have excess returns over the federal funds rate and that these excess returns vary counter-cyclically at business cycle frequencies. However, they argue that high frequency changes in federal funds futures are likely to be valid measures of changes in expectations about future federal funds rates since they difference out risk premia that vary primarily at lower frequencies.

¹³An inflation swap is a financial instrument designed to help investors hedge inflation risk. As is standard for swaps, nothing is exchanged when an inflation swap is first executed. However, at the maturity date of the swap, the counterparties exchange $R_t^x - \Pi_t$, where R_t^x is the x -year inflation swap rate and Π_t is the reference inflation over that period. If agents were risk neutral, therefore, R_t would be expected inflation over the x year period. See Fleckenstein, Longstaff, and Lustig (2014) for an analysis of the differences between break-even inflation from TIPS and inflation swaps.

Table 3: Response of Expected Output Growth Over the Next Year

	1995-2014	2000-2014	2000-2007	1995-2000
Policy News Shock	1.01 (0.32)	1.04 (0.35)	0.95 (0.32)	0.79 (0.63)
Observations	120	90	52	30

We regress changes from one month to the next in survey expectations about output growth over the next year from the Blue Chip Economic Indicators on the policy news shock that occurs in that month (except that we drop policy news shocks that occur in the first week of the month since we do not know whether these occurred before or after the survey response). Specifically, the dependent variable is the change in the average forecasted value of output growth over the next three quarters (the maximum horizon over which forecasts are available for the full sample). See Appendix F for details. We present results for four sample periods. The longest sample period we have data for is 1995m1-2014m4; this is also the period for which the policy news shocks is constructed. We also present results for 2000m1-2014m4 (which corresponds to the sample period used in Table 1), 2000m1-2007m12 (a pre-crisis sample period), and 1995m1-1999m12. As in our other analysis, we drop data from July 2008 through June 2009. Robust standard errors are in parentheses.

Blue Chip survey expectations about output growth as the dependent variable and the policy news shock that occurs in that month as the independent variable.¹⁴

Table 3 reports the resulting estimates. The dependent variable is the monthly change in expected output growth over the next year (see Appendix F for details). In sharp contrast to the conventional theory of monetary shocks, policy news shocks that raise interest rates lead expectations about output growth to *rise* rather than fall.¹⁵ We present results for four sample periods. The longest sample period for which we are able to construct our policy new shock is 1995-2014. We also present results for the sample period 2000-2014, which corresponds to the sample period we use in most of our other analysis. For robustness, we also present results for two shorter sampler periods (1995-2000 and 2000-2007). The results are similar across all four sample periods, but of course less precisely estimated for the shorter sampler periods.

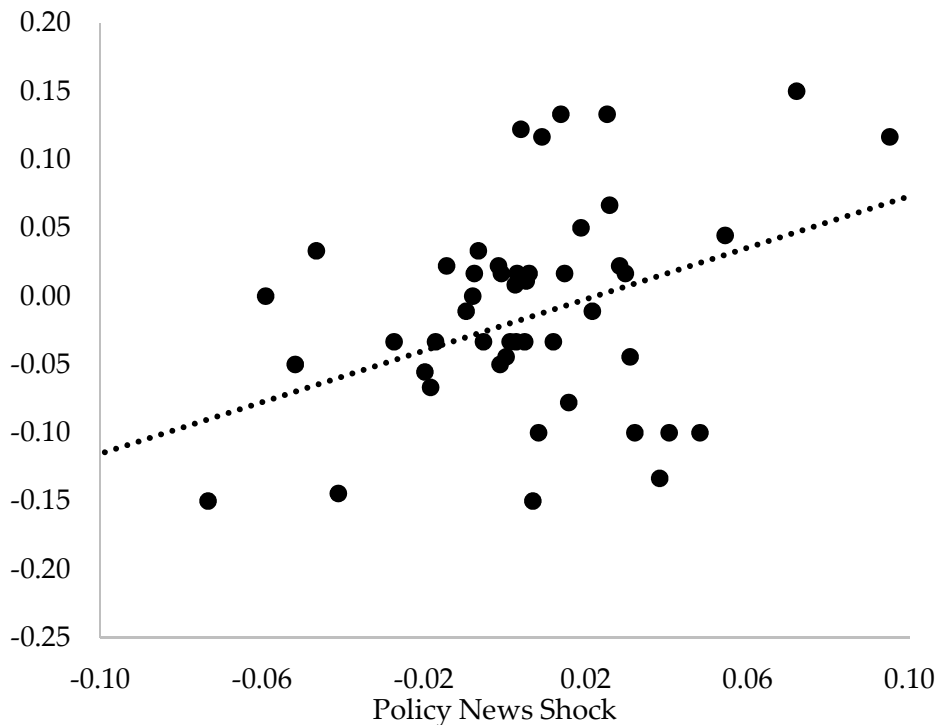
Figure 2 presents a binned scatter plot of the relationship between changes expected output growth and our policy news shock over the 1995-2014 sample period. This scatter plot shows that the results in Table 3 are not driven by outliers. Finally, Table A.5 presents the response of output growth expectations separately for each quarter that the Blue Chip survey asks about. These are noisier but paint the same picture as the results in Table 3.

A natural interpretation of this evidence is that FOMC announcements lead the private sector to update its beliefs not only about the future path of monetary policy, but also about other economic

¹⁴We exclude policy news shocks that occur in the first week of the month because in those cases we do not know whether they occurred before or after the survey response.

¹⁵Campbell et al. (2012) present similar evidence regarding the effect of surprise monetary shocks on Blue Chip expectations about unemployment.

Figure 2: Binned Scatter Plot for Expected Output Growth Regression



fundamentals. For example, when an FOMC announcement signals higher interest rates than markets had been expecting, market participants may view this as implying that the FOMC is more optimistic about economic fundamentals going forward than they had thought, which in turn may lead the market participants themselves to update their own beliefs about the state of the economy. We refer to effects of FOMC announcements on private sector views of non-monetary economic fundamentals as “Fed information effects.”

The idea that the Fed can have such information effects relies on the notion that the FOMC has some knowledge regarding the economy that the private sector doesn’t have or has formulated a viewpoint about the economy that the private sector finds valuable. Is it reasonable to suppose that this is the case? In terms of actual data, the FOMC has access to the same information as the private sector with minor exceptions.¹⁶ However, the Fed does employ a legion of talented, well-trained economists whose primary role is to *process and interpret* all the information being released about the economy. This may imply that the FOMC’s view about how the economy will evolve contains a perspective that affects the views of private agents. This is the view Romer and Romer (2000) argue

¹⁶The FOMC may have some advance knowledge of industrial production data since the Federal Reserve produces these data. It also collects anecdotal information on current economic conditions from reports submitted by bank directors and through interviews with business contacts, economists, and market experts. This information is subsequently published in reports commonly known as the Beige Book.

for in their classic paper on Federal Reserve information.¹⁷

The idea that the Fed can influence private sector beliefs through its analysis of *public* data is somewhat unconventional in macroeconomics. However, the finance literature on analyst effects suggests this is not implausible. This literature finds that the most influential analyst announcements can have quite large effects on the stock market (see, e.g. Loh and Stulz, 2011). Loh and Stulz note: “Kenneth Bruce from Merrill Lynch issued a recommendation downgrade on Countrywide Financial on August 15, 2007, questioning the giant mortgage lenders ability to cope with a worsening credit crunch. The report sparked a sell-off in Countrywides shares, which fell 13% on that day.” If Kenneth Bruce can affect the market’s views about Countrywide, perhaps it is not unreasonable to believe that the Fed can affect the market’s views about where the economy is headed.

If Fed information is important, one might expect that contractionary monetary shocks would disproportionately occur when the Fed is more optimistic than the private sector about the state of the economy. In Appendix G, we test this proposition using the Fed’s Greenbook forecast about output growth as a measure of its optimism about the economy.¹⁸ We find that, indeed, our policy news shocks tend to be positive (i.e., indicate a surprise increase in interest rates) when the Greenbook forecast about current and future real GDP growth is higher than the corresponding Blue Chip forecast (panel A of Table G.1). We furthermore find that the difference between Greenbook and Blue Chip forecasts tends to narrow after our policy news shocks occur (panel B of Table G.1). This suggests that private sector forecasters may update their forecasts based on information they glean from FOMC announcements.

5 Characterizing Monetary Non-Neutrality with Fed Information

The evidence we present in section 4 calls for more sophisticated modeling of the effects of monetary announcements than is standard in the literature. Rather than affecting beliefs only about current and future monetary policy, FOMC announcements must also affect private sector beliefs about other economic fundamentals.

An important consequence of this is that our evidence does not necessarily point to nominal and real rigidities being large. It may be that the responses of real interest rates that we estimate

¹⁷This does not necessarily imply that the Fed should be able to forecast the future evolution of the economy better than the private sector. The private sector, of course, also processes and interprets the information released about the economy. It may therefore also be able to formulate a view about the economy that the Fed finds valuable. In other words, information can flow both ways with neither the Fed nor the private sector having a clear advantage.

¹⁸The Greenbook forecast is an internal forecast produced by the staff of the Board of Governors and presented at each FOMC meeting. Greenbook forecasts are made public with a five year lag.

in response to FOMC announcements mostly reflect changes in private sector expectations about the natural rate of interest. If this is the case, the fact that we find that our shocks have little effect on inflationary expectations may be consistent with small nominal and real rigidities, since the tightening of policy relative to the natural rate is small.¹⁹

But even if this is true—that the responses of real interest rates that we estimate mostly reflect changes in private sector expectations about the natural rate of interest—this does not imply that the Fed is powerless. Quite to the contrary, in this case, the Fed has enormous power over beliefs about economic fundamentals, which may in turn have large effects on economic activity.

Our evidence on the response of real interest rates and expected inflation to a monetary announcement, therefore, implies that either 1) nominal and real rigidities are large, or 2) the Fed can affect private sector beliefs about future non-monetary fundamentals by large amounts. In other words, it implies that the Fed is powerful, either through the conventional channel or a non-conventional channel (or some combination).

To make these arguments precise, we now present a New Keynesian model of the economy augmented with Fed information effects. We then estimate this model to match the responses of interest rates, expected inflation, and expected output growth to FOMC announcements calculated above. Finally, we use the estimated model to assess the degree of monetary non-neutrality implied by our evidence and to assess how much of this monetary non-neutrality arises from traditional channels versus information effects.

5.1 A New Model with Fed Information Effects

Most earlier theoretical work on the signaling effect of monetary policy has made the very restrictive assumption that the Fed can only signal through its actions. The focus of much of this literature has been on the limitations of what the Fed can signal with its actions. The recent empirical literature on monetary policy has, however, convincingly demonstrated that the Fed also signals through its statements (Gurkaynak, Sack, and Swanson, 2005). This implies that the Fed’s signals can be much richer; they can incorporate forward guidance, and they can distinguish between different types of shocks. With a much richer signal structure, the key question becomes: What information would the Fed like to convey?

We model FOMC announcements as affecting private sector beliefs about the path of the “natural rate of interest,” the real interest rate that would prevail absent pricing frictions. This is a natural

¹⁹This idea is explained in more detail below and in Appendix E.

choice since tracking the natural rate is optimal in the model we consider absent information effects. If the Fed's goal is to track the natural rate of interest, it seems natural that announcements by the Fed about its current and future actions provide information about the future path of the natural rate of interest.

Apart from including a Fed information effect, the model we use differs in two ways from the textbook New Keynesian model: households have internal habits, and we allow for a backward-looking term in the Phillips curve. These two features allow the model to better fit the shapes of the impulse responses we have estimated in the data. Detailed derivations of household and firm behavior in this model are presented in Appendix H. There, we show that private sector behavior in this model can be described by a log-linearized consumption Euler equation and Phillips curve that take the following form:

$$\hat{\lambda}_{xt} = E_t \hat{\lambda}_{xt+1} + (\hat{i}_t - E_t \hat{\pi}_{t+1} - \hat{r}_t^n), \quad (2)$$

$$\Delta \hat{\pi}_t = \beta E_t \Delta \hat{\pi}_{t+1} + \kappa \omega \tilde{\zeta} \hat{x}_t - \kappa \tilde{\zeta} \hat{\lambda}_{xt}. \quad (3)$$

Hatted variables denote percentage deviations from steady state. $\Delta \hat{\pi}_t = \hat{\pi}_t - \hat{\pi}_{t-1}$. The variable $\hat{\lambda}_{xt} = \hat{\lambda}_t - \hat{\lambda}_t^n$ denotes the marginal utility gap (the difference between actual marginal utility of consumption $\hat{\lambda}_t$ and the "natural" level of marginal utility $\hat{\lambda}_t^n$ that would prevail if prices were flexible), $\hat{x} = \hat{y}_t - \hat{y}_t^n$ denotes the "output gap", $\hat{\pi}_t$ denotes inflation, \hat{i}_t denotes the gross return on a one-period, risk-free, nominal bond, and \hat{r}_t^n denotes the "natural rate of interest," which is a function of exogenous shocks to technology. The parameter β denotes the subjective discount factor of households, while κ , ω , and $\tilde{\zeta}$ are composite parameters that determine the degree of nominal and real rigidities in the economy. With internal habits, the marginal utility gap is

$$\hat{\lambda}_{xt} = -(1 + b^2 \beta) \sigma_c \hat{x}_t + b \sigma_c \hat{x}_{t-1} + b \beta \sigma_c E_t \hat{x}_{t+1}, \quad (4)$$

where b governs the strength of habits and $\sigma_c = -\sigma^{-1}/((1-b)(1-b\beta))$, where σ is the intertemporal elasticity of substitution.

We assume that the monetary authority sets interest rates according to the following simple rule:

$$\hat{i}_t - E_t \hat{\pi}_{t+1} = \bar{r}_t + \phi_\pi \hat{\pi}_t, \quad (5)$$

with \bar{r}_t following an AR(2) process

$$\bar{r}_t = (\rho_1 + \rho_2)\bar{r}_{t-1} - \rho_1\rho_2\bar{r}_{t-2} + \epsilon_t, \quad (6)$$

where ρ_1 and ρ_2 are the roots of the lag polynomial for \bar{r}_t and ϵ_t is the innovation to the \bar{r}_t process. Here ϵ_t is the monetary shock. Notice that it can potentially have a long-lasting effect on real interest rates through the AR(2) process for \bar{r}_t . We choose this specification to be able to match the effects of the monetary shocks we estimate in the data. The shocks we estimate in the data have a relatively small effect on contemporaneous interest rates but a much larger effect on future interest rates (see Table 1)—i.e., they are mostly but not exclusively forward guidance shocks. The AR(2) specification for \bar{r}_t can capture this if ρ_1 and ρ_2 are both large and positive leading to a pronounced hump-shape in the impulse response of \bar{r}_t (and therefore a pronounced hump-shape across the term structure in the contemporaneous response of longer-term interest rates as in Table 1).²⁰

As we discuss above, the way in which we model the Fed information effect is by assuming that FOMC announcements may affect the private sector's beliefs about the path of the natural rate of interest. The simplest way to do this is to assume that private sector beliefs about the path of the natural rate of interest shifts by some fraction ψ of the change in \bar{r}_t . Formally, in response to a monetary announcement

$$E_t \hat{r}_{t+j}^n = \psi E_t \bar{r}_{t+j}. \quad (7)$$

Moreover, we assume that the shock to expectations about the current value of the natural rate of output is proportional to the shock to expectations about the current monetary policy with the same factor of proportionality, i.e., $E_t \hat{y}_t^n = \psi E_t \bar{r}_t$.²¹

Here the parameter ψ governs the extent to which monetary announcements have information effects versus traditional effects. A fraction ψ of the shock shows up as an information effect, while a fraction $1 - \psi$ shows up as a traditional gap between the path for real interest rates and the (private sector's beliefs about) the path for the natural rate of interest.²²

²⁰How should the monetary shocks ϵ_t be interpreted? A natural interpretation is the following: The Fed seeks to target the natural rate of interest. When the Fed makes an announcement, it seeks to communicate changes in its beliefs about the path of the natural rate to the public. The changes in beliefs sometimes surprise the public and therefore lead to a shock.

²¹Here we assume that the FOMC meeting occurs at the beginning of the period, before the value of \hat{y}_t^n is revealed to the agents. In reality, uncertainty persists about output in period t until well after period t , due to heterogeneous information. We abstract from this.

²²This way of modeling the information effect has the crucial advantage that it is simple and parsimonious enough to allow us to account for the effects of FOMC announcements on the entire path of future interest rate expectations—i.e., the role of forward guidance. This is a distinguishing feature versus previous work. Ellingsen and Soderstrom (2001) present a model in which the signaling effect derives from announcements about the current interest rate.

5.2 Estimation Method

We estimate four key parameters of the model using simulated method of moments. The four parameters we estimate are the two autoregressive roots of the shock process (ρ_1 and ρ_2), the information parameter (ψ) and the “slope of the Phillips curve” ($\kappa\hat{\zeta}$). We fix the remaining parameters at the following values: We choose a conventional value of $\beta = 0.99$ for the subjective discount factor. Our baseline value for the intertemporal elasticity of substitution is $\sigma = 0.5$, but we explore robustness to this choice. We fix the Taylor rule parameter to $\phi_\pi = 0.01$. This is roughly equivalent to a value of 1.01 for the more conventional Taylor rule specification without the $E_t\hat{\pi}_{t+1}$ term on the left-hand-side of equation (5). We choose this value to ensure that the model has a unique bounded equilibrium but at the same time limit the amount of endogenous feedback from the policy rule. This helps ensure that the response of the real interest rate dies out within 10 years as we estimate in the data.²³ We set the elasticity of marginal cost with respect to own output to $\omega = 2$. This value results from a Frisch labor supply elasticity of one and a labor share of 2/3. Finally, we set the habit parameter to $b = 0.9$, a value very close to the one estimated by Schmitt-Grohé and Uribe (2012).

To ease the computational burden of the simulated method of moments estimation we use a two stage iterative procedure. In the first stage, we estimate the two autoregressive roots of the monetary shock process (ρ_1 and ρ_2) to fit the hump-shaped response of real interest rates to our policy news shock. We do this for fixed values of the information parameter and the slope of the Phillips curve. The moments we use in this step are the responses of 2, 3, 5, and 10 year real yields and forwards reported in Table 1. In the second step, we estimate the information parameter (ψ) and the slope of the Phillips curve ($\kappa\hat{\zeta}$) for fixed values of the two autoregressive roots. The moments we use in this step are the responses of 2, 3, 5, and 10 year break-even inflation (both yields and forwards) reported in Table 1 as well as the responses of output growth expectations reported in Table A.5. We then iterate back and forth between these steps until convergence.

In both steps, we use a loss function that is quadratic in the difference between the moments discussed above and their theoretical counterparts in the model.²⁴ We use a weighting matrix with the inverse standard deviations of the moments on the diagonal, and with the off-diagonal values set to zero. We use a bootstrap procedure to estimate standard errors. Our bootstrap procedure is

²³Recent work has shown that standard New Keynesian models such as the one we are using are very sensitive to interest rate movements in the far future (Carlstrom, Fuerst, and Paustian, 2015; McKay, Nakamura, and Steinsson, 2016).

²⁴The theoretical counterparts are the responses of the corresponding variable to a monetary shock in the model. Since the magnitude of the shock in our simulations is arbitrary, we make sure to rescale all responses from the model in such a way that the 3Y real forward rate is perfectly matched. We use the methods and computer code described in Sims (2001) to calculate the equilibrium of our model.

to re-sample the data with replacement, estimate the empirical moments on the re-sampled data, and then estimate the structural parameters as described above using a loss function based on the estimated empirical moments for the re-sampled data.²⁵ We repeat this procedure 1000 times and report the 2.5% and 97.5% quantiles of the statistics of interest. Importantly, this procedure for constructing the confidence intervals captures the statistical uncertainty associated with our empirical estimates in Tables 1 and A.5.

5.3 Results and Intuition

Our primary interest is to assess the extent to which FOMC announcements contain Fed information and how this affects inference about other key aspects of the economy such as the slope of the Phillips curve. Table 4 presents our parameter estimates, while Figures 3-5 illustrate the fit of the model. As in the data, the estimated model generates a persistent, hump-shaped response of nominal and real interest rates with a small and delayed effect on expected inflation (see Figure 3). To generate this type of response, we estimate that both of the autoregressive roots of the monetary shock process are large and positive, and we estimate a small slope of the Phillips curve.

We also estimate that the monetary shock leads to a pronounced increase in expectations about output growth as in the data (see Figure 4). The model can match the increase in expected growth following a surprise increase in interest rates by estimating a large information effect. We estimate that roughly 2/3 of the monetary shock is a shock to beliefs about future natural rates of interest (see Figure 5).

As Figure 4 illustrates, our monetary shock simultaneously leads to an increase in expectations about output growth and a decrease in output relative to the natural rate of output (i.e., a decrease in the output gap). This is a consequence of the fact that the information effect is large but still substantially smaller than the overall increase in interest rates. Output growth expectations rise because the monetary shock is interpreted as good news about fundamentals. But since the Fed increases interest rates by more than the private sector believes the natural rate of interest rose, private sector expectations about the output gap fall.

Despite estimating a large information effect, we estimate a very flat Phillips curve. This is consistent with prior empirical work. Mavroeidis, Plagborg-Moller, and Stock (2014) survey the

²⁵The re-sampling procedure is stratified since the empirical moments are estimated from different dataset and different sample periods. The stratification makes sure that each re-sampled dataset is consistent with the original dataset along the following dimensions: The number of observations for the yields and forwards before and after 2004 is the same as in the original dataset (since the sample period for the 2Y and 3Y yields and forwards starts in 2004). The number of Blue Chip observations that do not report 4- to 7-quarters ahead expected GDP growth are the same as in the original dataset, since Blue Chip only asks forecasters to forecast the current and next calendar year.

Table 4: Estimates of Structural Parameters

	ψ	$\kappa\zeta \times 10^{-5}$	ρ_1	ρ_2
<i>Baseline</i>	0.68	11.2	0.9	0.79
	[0.33, 0.84]	[0.0, 60.2]	[0.83, 0.96]	[-0.69, 0.89]
<i>No Information</i> ($\psi = 0$)	0.00	3.4	0.9	0.79
	--	[0.0, 24.1]	[0.83, 0.96]	[-0.69, 0.89]
<i>Full Information</i> ($\psi = 0.99$)	0.99	563	0.9	0.79
	--	[0, 12538]	[0.82, 0.96]	[-0.67, 0.89]
<i>Lower IES</i> ($\sigma = 0.25$)	0.67	13.7	0.9	0.79
	[0.25, 0.89]	[0.0, 94.6]	[0.83, 0.96]	[-0.69, 0.89]
<i>Higher IES</i> ($\sigma = 1$)	0.68	8.2	0.9	0.79
	[0.42, 0.81]	[0.0, 44.0]	[0.83, 0.96]	[-0.69, 0.89]
<i>No Habits</i> ($b = 0$)	1	1000	0.9	0.79
	[0.92, 1.00]	[0, 43236]	[0.83, 0.96]	[-0.69, 0.89]

The table reports our estimates of the structural parameters of the model that we estimate. We report 95% confidence intervals in square brackets below the point estimate for each parameter. These are based on the bootstrap procedure described in the text. In the No Information case and the Full Information case, the slope of the Phillips curve is estimated only off of inflation moments. In the other cases, the slope of the Phillips curve and the information parameter are estimated off of both inflation and GDP growth moments.

Figure 3: Responses of Nominal and Real Rates and Inflation to a Contractionary Shock

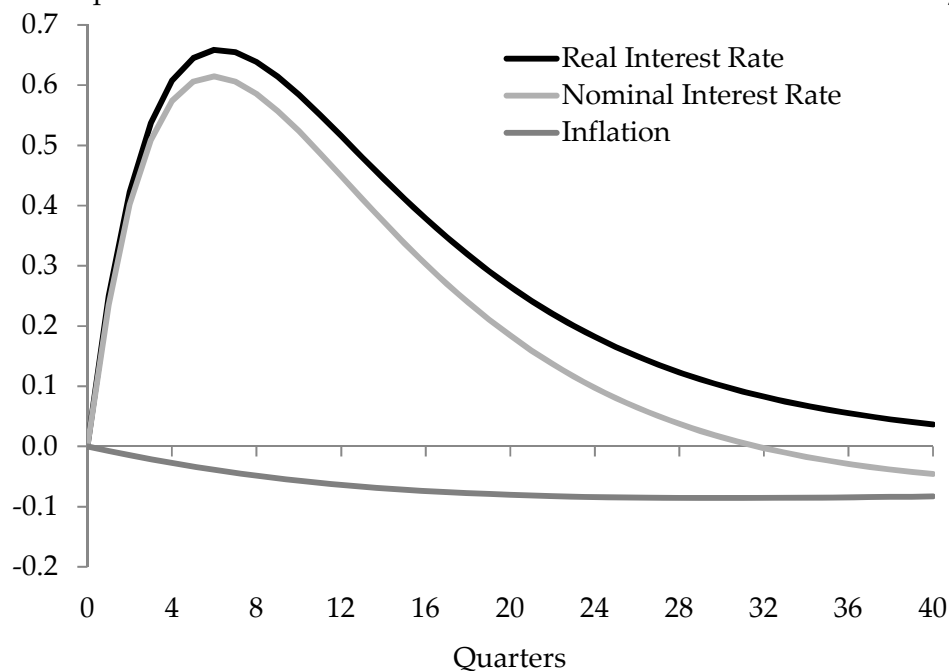


Figure 4: Responses of Expected Output Growth and Output Gap to a Contractionary Shock

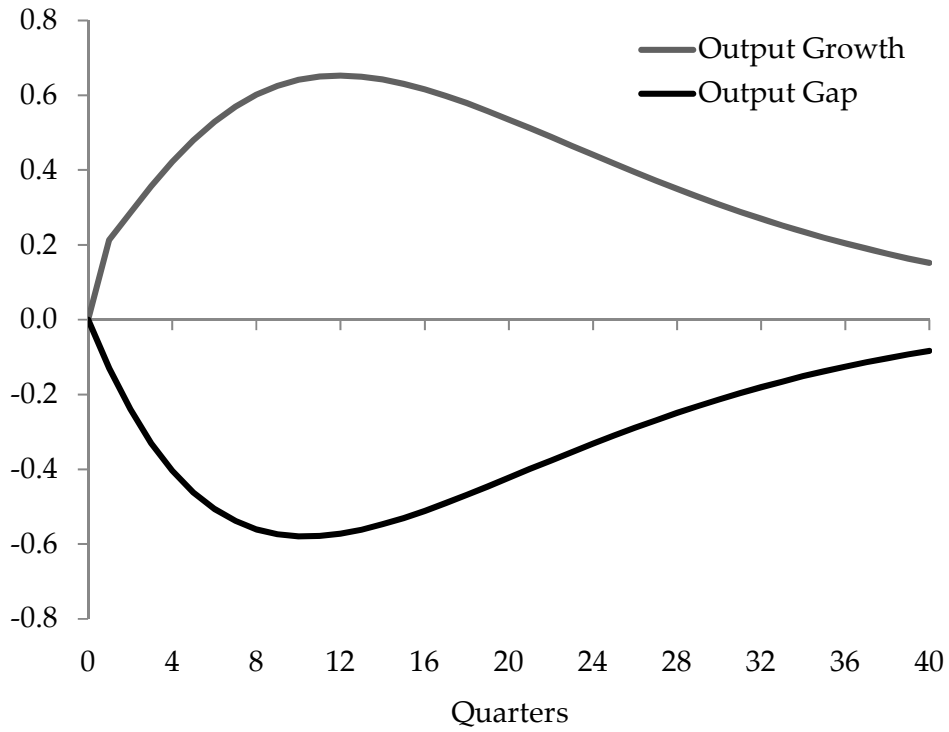
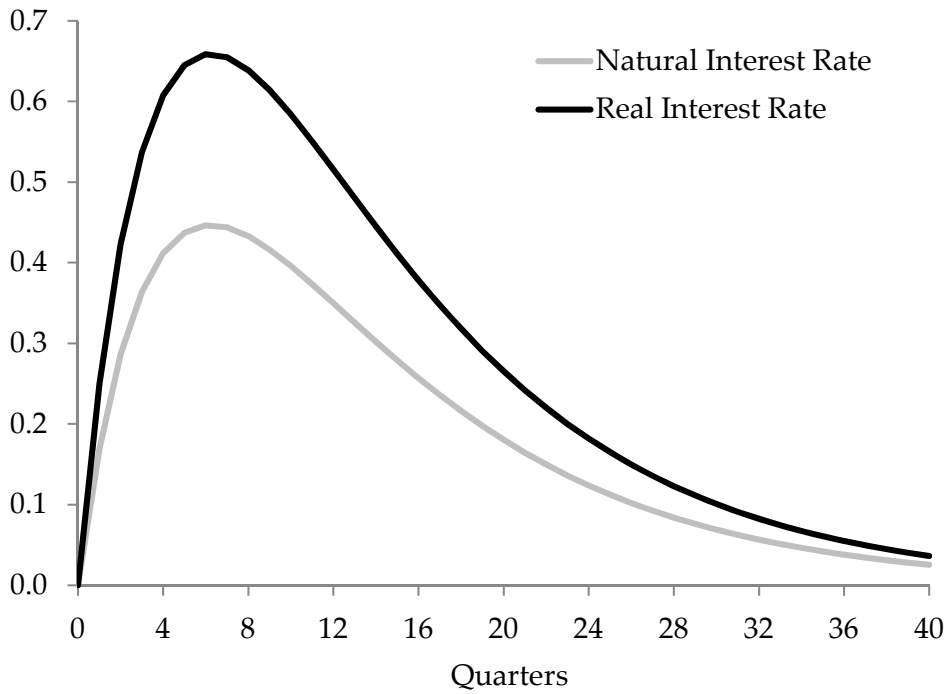


Figure 5: Decomposition of Real Rate in Interest Rate Gap and Natural Interest Rate



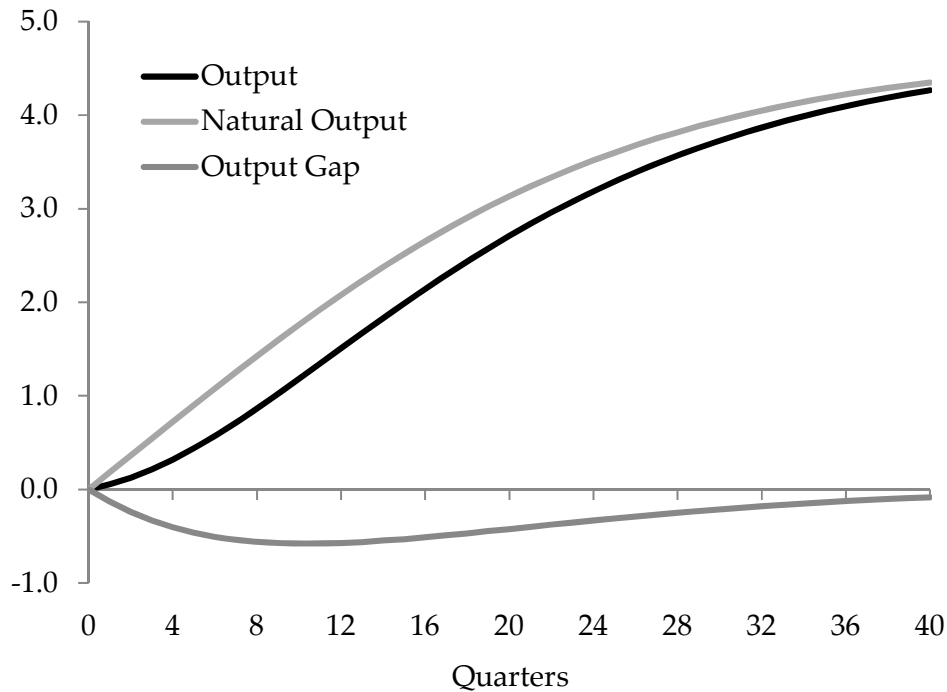
literature that has estimated Phillips curves and, using a common data set, run a huge number of a priori reasonable specifications which span different choices made in this literature. They find that the estimated values of the slope of the Phillips curve varies substantially across specifications and are symmetrically dispersed around a value of zero. One reason why our estimated Phillips curve is very flat is that the shocks that we estimate are substantially more persistent than most other identified monetary policy shocks (e.g., Christiano, Eichenbaum, and Evans, 2005). This means that our shocks imply forward guidance about interest rates quite far in the future. It has recently been shown that standard New Keynesian models implies that far future forward guidance has large effects on current outcomes (Carlstrom, Fuerst, and Paustian, 2015; McKay, Nakamura, and Steinsson, 2016).

To illustrate how allowing for the information effect affects our estimates, we reestimate the model setting the information effect to zero. In this case, we remove the expected output growth moments from the objective function of the estimation since these moments are impossible to match without an information effect. The second row in Table 4 presents the estimates for this case. We see that ignoring the information effect yields a substantially flatter Phillips curve—implying a substantial overestimate of nominal and real rigidities—relative to our baseline estimation. We also report a case where the information effect is set to a value close to one. In this case, the slope of the Phillips curve is estimated to be much steeper than in our baseline case.

Clearly, the information effect has an important effect on inference about the slope of the Phillips curve. This arises because the effect of the monetary shock on the interest rate gap—the gap between the interest rate and the natural rate of interest—is much smaller when the information effect is estimated to be large than it is when the information effect is estimated to be small. It is the response of the interest rate gap as opposed to the response of the real interest rate itself that determines the response of inflation (see equation (19) in Appendix E). The intuition is that, when the Fed raises rates, people perceive this as good news about economic fundamentals, and this counters the conventional channel of monetary policy whereby an interest rate hike lowers output.

Table 4 also reports alternative estimates where we vary the value of the intertemporal elasticity of substitution (IES) and the habit formation parameter. Varying the IES does not affect our estimates much. This may seem surprising. A smaller value of the IES implies that larger movements in the natural rate of interest are needed to match the movements in expected growth rates observed in the data. This would suggest that a lower value of the IES would yield a larger value of the information effect. However, in our model with substantial habit formation the IES and the information parameters also affect the shape of the response of output growth. These effects imply that similar

Figure 6: Response of Actual and Natural Expected Output



values of the information parameter are estimated for a wide range of values of the IES. In contrast, when we set the habit parameter to zero, we estimate that the entire change in interest rates is an information effect. As a consequence, we also estimate a much steeper Phillips curve. However, the fit of the model to the output growth moments is much worse without habit formation.

6 The Causal Effect of Monetary Shocks

The large information effect we estimate in section 5 fundamentally changes how we should interpret the response of output and inflation to monetary policy announcements. Figure 6 plots the response of private sector beliefs about output, the natural rate of output, and the output gap to a monetary shock that increases interest rates in our estimated model from section 5. The figure shows that this surprise monetary tightening leads to a large and permanent increase in expected output.

How can this be? Can monetary policy really have such huge effects on output 10 years in the future? Isn't monetary policy neutral in the long run? Shouldn't a monetary tightening decrease output? Here it is crucial to recognize that the information the Fed reveals about economic fundamentals is in large part (perhaps mostly) information that the private sector would have learned about eventually through other channels in the absence of the Fed's announcement. This intro-

duces an important subtlety into the assessment of the effect of monetary policy that has, to our knowledge, not been discussed in the existing literature. To correctly assess the *causal effect* of monetary policy on output, we need to compare versus a reasonable *counterfactual* that accounts for the fact that the changes in fundamentals that the Fed’s announcement reveals would have occurred even in the absence of the announcement. In other words, we want a counterfactual in which the path of productivity—the exogenous fundamental we assume the Fed provides information about—follows the same path as in the actual response.

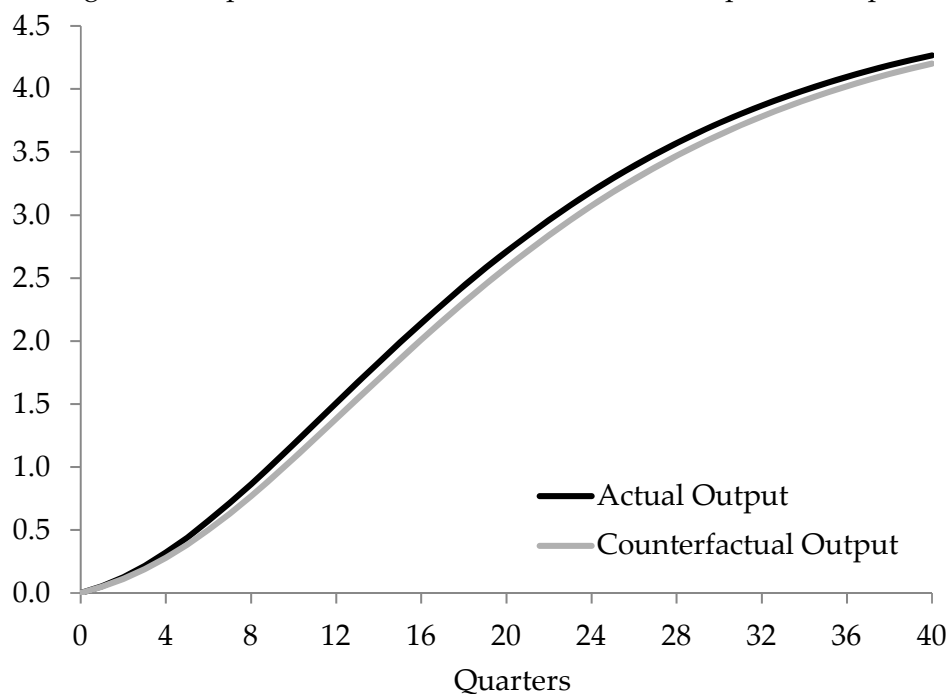
To construct this counterfactual, we must take a stand on when the private sector would have learned about the changes in fundamentals revealed by the Fed in the absence of the Fed announcement. We choose a particularly simple counterfactual. In this counterfactual, the private sector learns about changes in productivity when they occur and it believes that productivity follows a random walk. To be clear, this counterfactual represents our assumption about what would have happened regarding private sector beliefs about economic fundamentals in the absence of the Fed announcement. One could consider other counterfactuals. We don’t have any data to precisely pin down the counterfactual. But we think that our chosen counterfactual is reasonable and it serves the purpose of illustrating the main issue that one needs to use a counterfactual in which the changes in economic fundamentals that the Fed provides information about would occur even in the absence of the Fed announcement.

We must also make an assumption about how monetary policy reacts to changes in the natural rate of interest in the counterfactual. In keeping with the general assumption that the Fed seeks to track the natural rate of interest, we assume that monetary policy varies the interest rate to track the natural rate of interest in the counterfactual.

Figure 7 presents actual and counterfactual output growth constructed in this way. The figure reveals that most of the increase in output would have occurred anyway in the absence of the Fed announcement. Given this new counterfactual, the “causal effect” of the Fed on output growth—the difference between what happens following the monetary shock, and what would have happened as represented by the counterfactual—no longer looks so implausible. This difference is much more modest than the overall change in beliefs about the path of output (which includes the effects of the productivity shocks the Fed is informing the public about).

Figure 8 plots this measure of the causal effect of monetary shocks on output. The figure also decomposes it into two components: the effect on the output gap (which falls) and the effect on the natural rate of output (which rises). The effect on the output gap is the the conventional channel of monetary policy: an interest rate increase relative to the natural rate of interest leads to a drop

Figure 7: Response of Actual and Counterfactual Expected Output



in output relative to the natural rate of output. The second component is a novel effect of Fed information.

A positive shock to beliefs about economic fundamentals—which leads the future path of the natural rate of interest to rise—has a positive causal effect on output even *relative* to the counterfactual described above. Why is this? This effect arises because of the dynamic linkages in our model. In our model habit formation by households is important and households understand this. When consumers expect consumption to be high in the future, they want to consume more today to build up their habit. This implies that positive news about the *future* raises consumption and output today. Other dynamic linkages would yield similar effects of Fed information. For example, in a model with capital accumulation, news about high future productivity would cause an increase in investment upon announcement and thereby affect current output.

6.1 Policy Implications

The findings discussed above have important policy implications. The fact that the information effect of surprise Fed tightenings stimulates output implies that the Fed is “fighting against itself” when it surprises markets. Figure 8 shows that for our estimated parameters the overall effect of the two channels is for an interest rate increase to *raise* output—the opposite from the conventional view

Figure 8: Causal Effect of Monetary Shocks on Expected Output

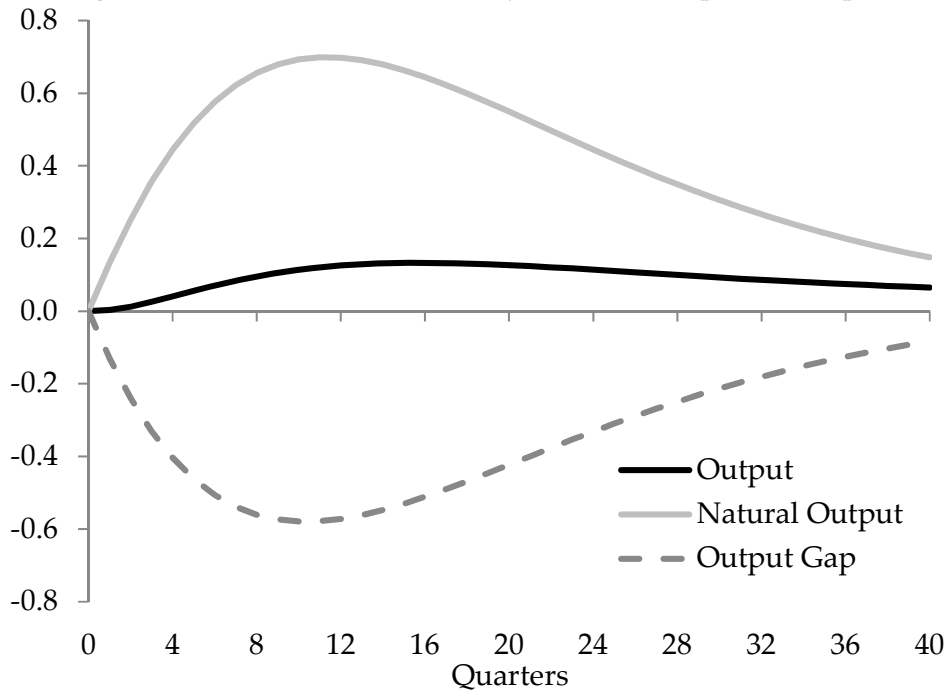
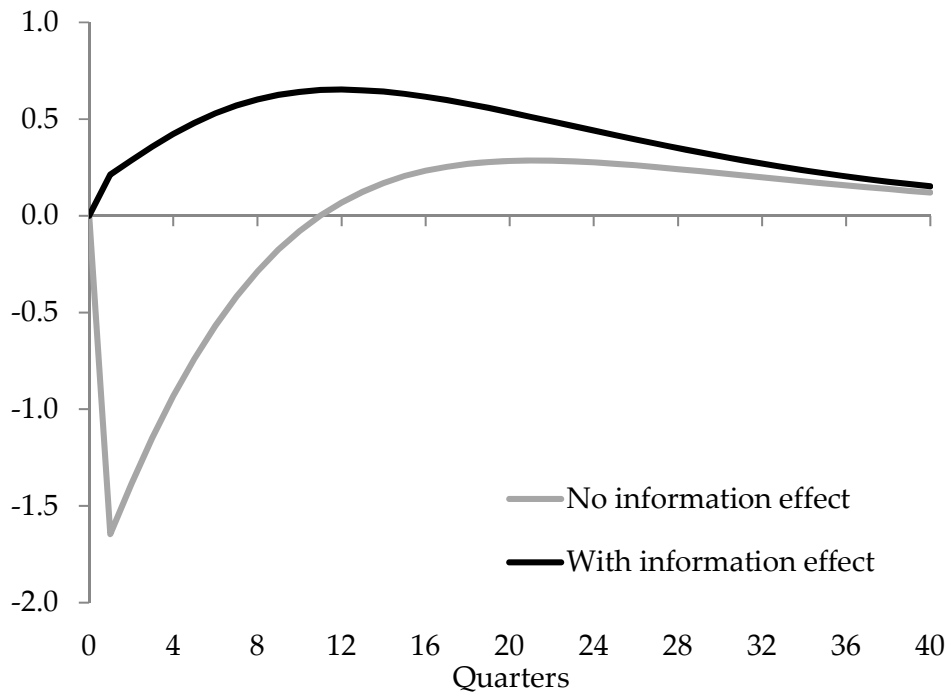


Figure 9: Expected Output Growth with and without the Information Effect



of how monetary policy works.²⁶ If the Fed would like to stimulate economic activity, a surprise policy easing may be counter-productive because the increase in pessimism that it causes itself pulls the economy further down.

This raises the question: Should the Fed withhold releasing bad news about the economy to avoid the increased pessimism this information would cause? A full analysis of this question is beyond the scope of this paper. But we would like to note two reasons why it may not be the case that the Fed should withhold bad news. First, an attempt by the Fed to systematically bias its signals is likely to be ineffective since the private sector will learn how to interpret what the Fed says and adjust for the bias. Second, advance knowledge about changes in fundamentals allows agents to prepare gradually for these changes, which is likely to improve welfare. A possible exception to this intuition is a circumstance when the Fed is not able to respond to the information it is revealing by tracking the updated natural rate, e.g., when interest rates are at the zero-lower-bound. In that case, it may be optimal for the Fed to withhold information.

The information effect also implies that there is an important distinction between interest rate changes associated with the monetary policy rule and deviations from this rule. The systematic response of monetary policy to public information—by definition—does not have information effects associated with it and therefore will not lead to the “perverse” effects on output discussed above. Figure 9 contrasts the consequences of an unexpected monetary shock with its associated information effect and the effects of a similarly sized change in interest rates that comes about due to the systematic component of monetary policy and therefore does not have an information effect associated with it.²⁷ The contrast is stark. Since our estimates imply considerable nominal and real rigidities, increases in interest rates associated with the monetary policy rule reduce output substantially.

This analysis makes clear that the information content of a monetary shock matters in determining its effects. Most of what the Fed does is anticipated by markets exactly because it depends in a systematic way on public information. The effects of this systematic component of monetary policy are likely to be more conventionally Keynesian than the effects of monetary surprises that contain significant information effects and are therefore a mix of the response to a conventional monetary

²⁶Recall that this result is not simply an implication of the fact that the Fed’s announcement is good news that raises output expectation. We are subtracting the counterfactual. The effect we are talking about here is the effect that learning the good news earlier has on the path of output.

²⁷It is important to understand that our empirical results can be used to think about both the effects of monetary policy shocks and changes in interest rates that come about due to the systematic component of policy. In the linear models we use, it does not matter why interest rates change (except for the information effect). In other words, the comparative static of a given change in interest rates on other variables is the same irrespective of the reason for the interest rate change (except for the information effect).

Table 5: Response of Stock Prices

	Stock Prices
Response in the Data	-6.5 (3.9)
Response in the Model	
Baseline	-6.8 [-11.5, -1.6]
No Fed Information Effect	-11.1 [-19.4, -2.5]

shock and the response to the non-monetary news contained in the Fed surprise.²⁸ The effects of monetary surprises will also vary depending on the amount and nature of the information they convey. In the case of the Volcker disinflation, for example, the narrative evidence suggests that few observers interpreted Volckers decision to raise interest rates as reflecting an optimistic view of the economic outlook. To the extent that the Volcker tightening was broadly interpreted as reflecting a different loss-function, or a greater degree of conservatism in dealing with inflation, then this too would have a small information effect. While we do not allow for any heterogeneity of this nature in our model, this strikes us as an interesting avenue for future research.

6.2 Stock Price Effects

We finish the paper with one additional piece of evidence that sheds light on the information content of FOMC announcements. Table 5 presents the response of stock prices to FOMC announcements. A pure tightening of monetary policy leads stock prices to fall for two reasons: higher discount rates and lower output. However, good news about future fundamentals can raise stock prices (if higher future cash-flows outweigh higher future discount rates). In the data, we estimate that the S&P500 index falls by 6.5% in response to a policy news shock that raises the 2-year nominal forward by 1%.²⁹ This estimate is rather noisy, with a standard error of 3.3%.

Table 5 also presents the response of stock prices to our monetary policy shock in our estimated model.³⁰ In the calibration of our model where monetary policy announcements convey information about both future monetary policy and future exogenous economic fundamentals, stock prices

²⁸This distinction is analogous to the local average treatment effect versus average treatment effect distinction in applied microeconomics.

²⁹Earlier work by Bernanke and Kuttner (2005) and Rigobon and Sack (2004) finds large responses of the stock market to surprise movements in the federal funds rate.

³⁰For simplicity, we model stocks as an unlevered claim to the consumption stream in the economy as is common in the asset pricing literature.

fall by 6.8% in response to the FOMC announcement. In contrast, if monetary policy is assumed not to convey information about future exogenous fundamentals, stock prices fall by 11%. The response of stock prices in the data is thus another indicator that favors the view that monetary policy conveys information to the public about future exogenous fundamentals.

7 Conclusion

We use a high-frequency identification approach to estimate the causal effect of monetary shocks. The monetary shocks that we identify have large and persistent effects on real interest rates. Real rates move essentially one-for-one with nominal rates several years into the term structure. Contractionary monetary shocks lead to no significant effect on inflation in the short-run and the effect becomes significantly negative only several years into the term structure. However, in sharp contrast with the implications of standard monetary models, contractionary shocks raise expectations about output growth.

We interpret the increase in expected output growth after a monetary tightening as evidence of a Fed “information effect.” When the Fed raises interest rates, this leads to increased optimism about economic fundamentals. We develop a model of this Fed information effect, in which the private sector interprets part of an unexpected increase in the interest rate as information about the natural rate. We estimate the model and find strong evidence for both channels: the conventional monetary policy channel and the information effect. One implication of our analysis is that the information content of a monetary shock matters in determining its causal effects.

A Construction of the Policy News Shock

The policy news shock is constructed as the first principle component of the change in five interest rates. The first of these is the change in market expectations of the federal funds rate over the remainder of the month in which the FOMC meeting occurs. To construct this variable we use data on the price of the federal funds futures contract for the month in question. The federal funds futures contract for a particular month (say April 2004) trades at price p and pays off $100 - \bar{r}$ where \bar{r} is the average of the effective federal funds rate over the month.³¹ To construct the change in expectations for the remainder of the month, we must adjust for the fact that a part of the month has already elapsed when the FOMC meeting occurs. Suppose the month in question has m_0 days and the FOMC meeting occurs on day d_0 . Let $f_{t-\Delta t}^1$ denote the price of the current month's federal funds rate futures contract immediately before the FOMC announcement and f_t^1 the price of this contract immediately following the FOMC announcement. Let r_{-1} denote the average federal funds rate during the month up until the point of the FOMC announcement and r_0 the average federal funds rate for the remainder of the month. Then

$$f_{t-\Delta t}^1 = \frac{d_0}{m_0} r_{-1} + \frac{m_0 - d_0}{m_0} E_{t-\Delta t} r_0,$$

$$f_t^1 = \frac{d_0}{m_0} r_{-1} + \frac{m_0 - d_0}{m_0} E_t r_0.$$

As a result

$$E_t r_0 - E_{t-\Delta t} r_0 = \frac{m_0}{m_0 - d_0} (f_t^1 - f_{t-\Delta t}^1).$$

When the FOMC meeting occurs on a day when there are 7 days or less remaining in a month, we instead use the change in the price of next month's fed funds futures contract. This avoids multiplying $f_t^1 - f_{t-\Delta t}^1$ by a very large factor.

The second variable used in constructing the policy news shock is the change in the expected federal funds rate at the time of the next scheduled FOMC meeting. Similar issues arise in constructing this variable as with the variable described above. Let m_1 denote the number of days in the month in which the next scheduled FOMC meeting occurs and let d_1 denote the day of the meeting. The next scheduled FOMC meeting may occur in the next month or as late as 3 months

³¹Fed funds futures have been traded since 1988. The effective federal funds rate is the rate that is quoted by the Federal Reserve Bank of New York on every business day. See the Chicago Board of Trade Reference guide [http://www.jamesgoulding.com/Research_II/FedFundsFutures/FedFunds\(FuturesReferenceGuide\).pdf](http://www.jamesgoulding.com/Research_II/FedFundsFutures/FedFunds(FuturesReferenceGuide).pdf) for a detailed description of federal funds futures contracts. On a trading day in March (say), the April federal funds futures contract is labeled as 2nd expiration nearby and also as 1st beginning nearby, in reference to the month over which \bar{r} is computed.

after the current meeting. Let $f_{t-\Delta t}^n$ denote the price of the federal funds rate futures contract for the month of the next scheduled FOMC meeting immediately before the FOMC announcement and f_t^n the price of this contract immediately following the FOMC announcement. Let r_1 denote the federal funds rate after the next scheduled FOMC meeting. Analogous calculations to what we present above yield

$$E_t r_1 - E_{t-\Delta t} r_1 = \frac{m_1}{m_1 - d_1} \left[(f_t^n - f_{t-\Delta t}^n) - \frac{d_1}{m_1} (E_t r_0 - E_{t-\Delta t} r_0) \right].$$

As with the first variable, if the next scheduled FOMC meeting occurs on a day when there are 7 days or less remaining in a month, we instead use the change in the price of next month's federal funds futures contract.

The last three variables used are the change in the price of three eurodollar futures at the time of the FOMC announcements. A eurodollar futures contract expiring in a particular quarter (say 2nd quarter 2004) is an agreement to exchange, on the second London business day before the third Wednesday of the last month of the quarter (typically a Monday near the 15th of the month), the price of the contract p for 100 minus the then current three-month US dollar BBA LIBOR interest rate. The contract thus provides market-based expectations of the three month nominal interest rate on the expiration date.³² We make use of eurodollar futures at horizons of n quarters in the future for $n = 2, 3, 4$ or, more precisely, the expiration date of the " n quarter" eurodollar future is between $n - 1$ and n quarters in the future at any given point in time.

We approximate the change in these variables over a 30-minute window around FOMC by taking the difference between the price in the last trade that occurred more than 10 minutes before the FOMC announcement and the first trade that occurred more than 20 minutes after the FOMC announcement. On control days in the analysis using the heteroskedasticity based estimation approach, we take the last trade before 2:05pm and the first trade after 2:35pm (since FOMC announcements tend to occur at 2:15pm). On some days (most often control days), trading is quite sparse and there sometimes is no trade before 2:05 or after 2:35. To limit the size of the windows we consider, we only consider trades on the trading day in question and until noon the next day. If we do not find eligible trades to construct the price change we are interested in within this window, we set the price change to zero (i.e., we interpret no trading as no price change).

³²Eurodollar futures began trading in the early 1980's. See the CME Group eurodollar futures reference guide <http://www.cmegroup.com/trading/interest-rates/files/eurodollar-futures-reference-guide.pdf> for more details about how eurodollar futures are defined.

B Rigobon's Heteroskedasticity-Based Estimator

Table 2 presents results from a heteroskedasticity-based estimator of the type developed by Rigobon (2003) and Rigobon and Sack (2004). The empirical model we consider in this analysis is the following. Let ϵ_t denote a pure monetary shock and suppose that movements in the policy indicator Δi_t we observe in the data is governed both by monetary and non-monetary shocks:

$$\Delta i_t = \alpha_i + \epsilon_t + \eta_t, \quad (8)$$

where η_t is a vector of all other shocks that affect Δi_t . Here α_i is a constant and we normalize the impact of ϵ_t and η_t on Δi_t to one. We wish to estimate the effects of the monetary shock ϵ_t on an outcome variable Δs_t . This variable is also affected by both the monetary and non-monetary shocks:

$$\Delta s_t = \alpha_s + \gamma \epsilon_t + \beta \eta_t. \quad (9)$$

The parameter of interest is γ , which should be interpreted as the impact of the pure monetary shock ϵ_t on Δs_t relative to its impact on Δi_t .

Our identifying assumption is that the variance of monetary shocks increases at the time of FOMC announcements, while the variance of other shocks is unchanged. Define $R1$ as a sample of narrow time intervals around FOMC announcements, and define $R2$ as a sample of equally narrow time intervals that do not contain FOMC announcements but are comparable on other dimensions (e.g., same time of day, same day of week, etc.). We refer to $R1$ as our "treatment" sample and $R2$ as our "control" sample. Our identifying assumption can then be written as

$$\sigma_{\epsilon, R1} > \sigma_{\epsilon, R2}, \text{ while } \sigma_{\eta, R1} = \sigma_{\eta, R2}.$$

Let Ω_{Ri} denote the variance-covariance matrix of $[\Delta i_t, \Delta s_t]$ in regime Ri . Then Ω_{Ri} is given by

$$\Omega_{Ri} = \begin{bmatrix} \sigma_{\epsilon, Ri}^2 + \sum_j \sigma_{\eta, j}^2 & \gamma \sigma_{\epsilon, Ri}^2 + \sum_j \beta_{s, j} \sigma_{\eta, j}^2 \\ \gamma \sigma_{\epsilon, Ri}^2 + \sum_j \beta_{s, j} \sigma_{\eta, j}^2 & \gamma^2 \sigma_{\epsilon, Ri}^2 + \sum_j \beta_{s, j}^2 \sigma_{\eta, j}^2 \end{bmatrix},$$

where j indexes the elements of η_t .

Notice that

$$\Delta \Omega = \Omega_{R1} - \Omega_{R2} = (\sigma_{\epsilon, R1}^2 - \sigma_{\epsilon, R2}^2) \begin{bmatrix} 1 & \gamma \\ \gamma & \gamma^2 \end{bmatrix}.$$

Thus,

$$\gamma = \frac{\Delta\Omega_{12}}{\Delta\Omega_{11}} = \frac{\text{cov}_{R1}(\Delta i_t, \Delta s_t) - \text{cov}_{R2}(\Delta i_t, \Delta s_t)}{\text{var}_{R1}(\Delta i_t) - \text{var}_{R2}(\Delta i_t)}. \quad (10)$$

This is the estimator we use to construct the results in Table 2 and Table A.3. Notice that if we set the variance of the “background noise” η_t to zero, then the heteroskedasticity-based estimator, equation (10) reduces to the coefficient from an OLS regression of Δs_t on Δi_t . Intuitively, the full heteroskedasticity-based estimator can be thought of as the simple OLS estimator, adjusted for the “normal” covariance between Δs_t and Δi_t and the “normal” variance of Δi_t .

C Weak Instruments Robust Confidence Intervals

The confidence intervals in Table 2 are constructed using a more sophisticated bootstrap procedure than is conventional. The reason is that the conventional bootstrap approach to constructing confidence intervals yields inaccurate results in the case when there is a significant probability that the difference in the variance of Δi_t between the treatment and control sample is close to zero.³³ Figure C.1 illustrates that this is the case for the 1-day window estimation but not the 30-minute window. The problem is essentially one of weak instruments. Rigobon and Sack (2004) show that the estimator in equation (10) can be formulated as an IV regression. When the difference in the variance of Δi_t between the treatment and control sample is small, the instrument in this formulation is weak, leading to biased point estimates and confidence intervals.

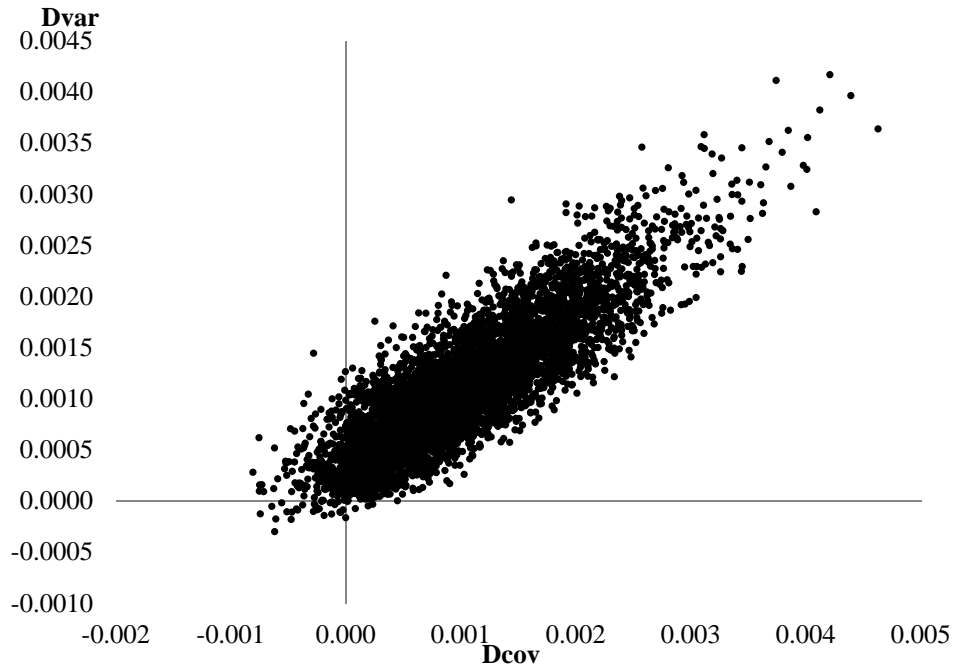
In Table 2, we, therefore, employ a weak-instruments robust approach to constructing confidence intervals. The approach we employ is a test inversion approach. A 95% confidence interval for our parameter of interest γ can be constructed by performing a hypothesis test for all possible hypothetical true values of γ and including those values that are not rejected by the test in the confidence interval.

The test statistic we use is

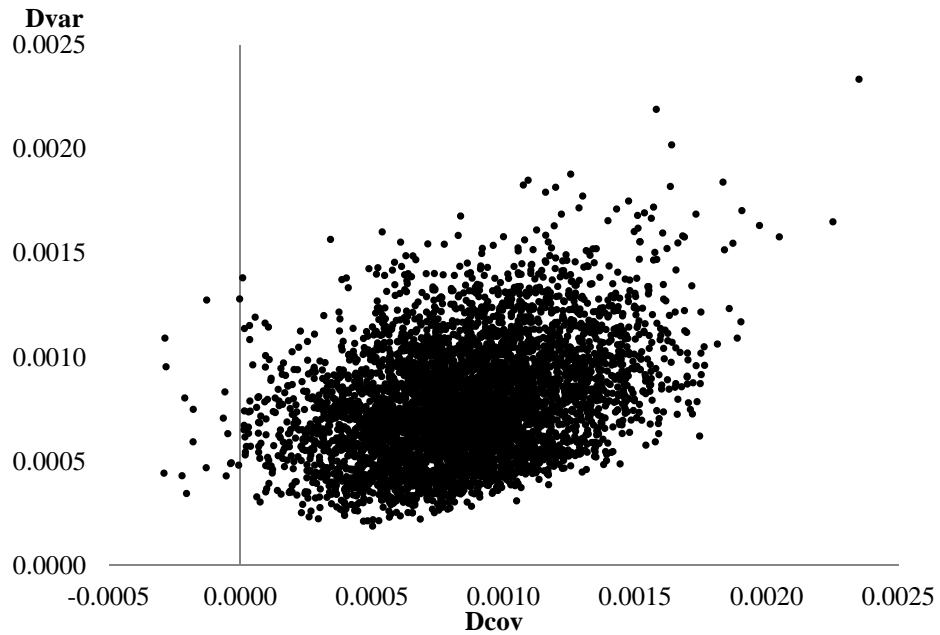
$$g(\gamma) = \Delta\text{cov}(\Delta i_t, \Delta s_t) - \gamma\Delta\text{var}(\Delta i_t), \quad (11)$$

where Δcov and Δvar denote the difference between the covariance and variance, respectively, in the treatment and control samples.

³³Recall that the Rigobon estimator—equation (10)—is a ratio with the difference in the variance of Δi_t between the treatment sample and the control sample in the denominator. If the distribution of this difference has significant mass in the vicinity of zero, the sampling distribution of the estimator will have significant mass at large positive and negative values.



Panel A: 1-Day Window



Panel B: 30-Minute Window

Figure C.1: Scatter of Joint Distribution of Dcov and Dvar for 2-Year Nominal Forward Rate

Notes: Each point in the figure is a draw from our bootstrap. Dvar denotes the difference in variance of our policy news shock between the treatment and control sample. Dcov denotes the difference in the covariance of our policy news shocks and the 2-year nominal forward rate between the treatment and the control sample.

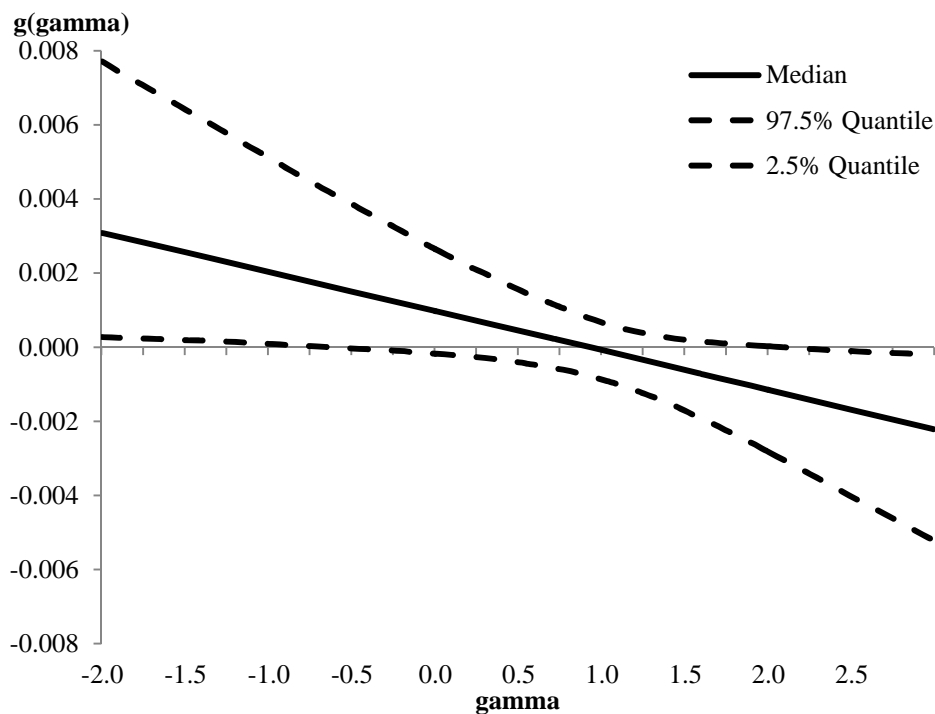


Figure C.2: Quantiles of the Distribution of $g(\gamma)$

Notes: Quantiles of the distribution of $g(\gamma)$ for different values of γ when estimating effect on the 2-year nominal forward rate using a 1-day window

Intuitively, $g(\gamma) = 0$ at the true value of γ . We estimate the distribution of $g(\gamma)$ for each hypothetical value of γ and include in our confidence interval values of γ for which $g(\gamma) = 0$ cannot be rejected. Figure C.2 plots the 2.5%, 50% and 97.5% quantiles of the distribution of $g(\gamma)$ as a function of γ for the 2-year nominal forward in the one-day window case. Values of γ for which the 2.5% quantile lies below zero and the 97.5% quantile lies above zero are included in the 95% confidence interval. This method for constructing confidence intervals is referred to as the Fieller method by Staiger, Stock, and Watson (1997) as it is an extension of an approach proposed by Fieller (1954). We use a bootstrap to estimate the joint distribution of Δcov and Δvar . Our approach is therefore similar to the grid bootstrap proposed by Hansen (1999) for a different application.

This more sophisticated procedure for constructing confidence intervals is not important for our baseline estimator based on changes in the policy news shock over a 30-minute window. In this case, the weak-IV robust confidence intervals coincide closely with the standard non-parametric bootstrap confidence interval reported in Table A.3. However, this weak-IV robust procedure is very important for the Rigobon estimator when the policy news shock is measured over a 1-day window.

D Risk Premia or Expected Future Short Rates

We present three sets of results that indicate that risk premium effects are not driving our empirical results: 1) the impact of our policy news shock on direct measures of expectations from the *Blue Chip Economic Indicators*; 2) the impact of our policy news shock on risk-neutral expected short rates from a state-of-the-art affine term structure model; and 3) the impact of our policy news shock on interest rates over longer event windows than in our baseline results.

Let us begin with our analysis of the Blue Chip forecast data. Blue Chip surveys professional forecasters on their beliefs about macroeconomic variables over the next two years in the first few days of every month. From this survey, it is possible to obtain direct measures of expectations that are not contaminated by risk premium effects. We use expectations about future values of the 3-month T-Bill rate as our measure of short-term nominal interest rate expectations and expectations about changes in the GDP deflator as our measure of expectations about inflation (and the difference between the two as our measure of expectations about short-term real rates).

We estimate the impact of monetary shocks on expectations by running regressions of the change from one month to the next in expectations regarding a particular forecast horizon on the policy news shock that occurs over the month except for those that occur in the first week of the month (because we do not know whether these occurred before or after the survey response). Unfortunately, Blue Chip asks respondents only about the current and subsequent calendar year on a monthly basis. So, fewer observations are available for longer-term expectations, leading to larger standard errors.³⁴ The sample period for this analysis is January 1995 to April 2014, except that we exclude the apex of the 2008-2009 financial crisis as we do in our baseline analysis.

Table D.1 presents the results from this analysis. The table shows that the policy news shock has a persistent impact on expected short-term interest rates, both nominal and real. The interest rate effects are somewhat larger than in our baseline results, but rather noisily estimated. The effect on expected inflation is small and statistically insignificant at all horizons. The much larger standard errors in Table D.1 arise from the fact that the Blue Chip variables are available only at a monthly frequency as opposed to a daily frequency. Overall, these estimates appear consistent with our baseline findings that monetary shocks have large effects on expected short-term nominal and real rates.

³⁴For example, towards the end of each year, forecasters are only asked about their beliefs a little more than 1-year in advance; while in the first quarter they are asked about their beliefs for almost the next full 2-years. Blue Chip also asks for longer-term inflation forecasts, but only twice a year (March and October) implying that there are too few observations to obtain meaningful estimates.

Table D.1: Effects of Monetary Shocks on Survey Expectations

	Nominal	Real	Inflation
1 quarter	1.05 (0.73)	1.17 (0.78)	-0.12 (0.24)
2 quarters	1.18 (0.75)	1.63 (0.78)	-0.44 (0.31)
3 quarters	0.99 (0.72)	1.29 (0.77)	-0.30 (0.24)
4 quarters	0.86 (0.71)	1.17 (0.69)	-0.32 (0.23)
5 quarters	0.73 (0.89)	0.59 (0.94)	0.14 (0.21)
6 quarters	1.84 (0.89)	1.60 (0.88)	0.23 (0.24)
7 quarters	4.45 (1.91)	4.29 (1.99)	0.17 (0.27)

Each estimate comes from a separate OLS regression. We regress changes in survey expectations from the *Blue Chip Economic Indicators* on the policy news shock. Since the Blue Chip survey expectations are available at a monthly frequency, we construct a corresponding monthly measure of our policy news shock. In particular, we use any policy news shock that occurs over the month except for those that occur in the first week (because we do not know whether these occurred before or after the survey response). The dependent variable is the change in the forecasted value of the variable listed at the top N quarters ahead, between this month's survey and last month's survey. See Appendix F for details. We consider the effects on expected future 3-month T-Bill rates, short-term real interest rates and inflation, where the inflation rate is the GDP deflator and the short-term real interest rate is calculated as the difference between the expected 3-month T-bill rate and the expected GDP deflator for a given quarter. The sample period is all regularly scheduled meetings between January 1995 and April 2014, except that we exclude the period from July 2008 through June 2009 and the aforementioned first-week meetings. The policy news shock is constructed on this sample period. The sample size is 120 for the first four rows of the table. It then falls to 75, 45, and 13 for rows 5 through 7, respectively. Robust standard errors are in parentheses.

Our second approach is to regress estimates of changes in expected future short rates from a state-of-the-art affine term structure model on our monetary policy shocks. Abrahams et al. (2015) employ an affine term structure model to decompose changes in both nominal and real interest rates at different maturities into changes in risk-neutral expected future short rates and changes in risk premia.³⁵ Table D.2 presents results based on their decomposition. The response of model-implied risk-neutral interest rates to our policy news shock is very similar to the response of raw interest rates in our baseline results. This piece of evidence, thus, points to our monetary shocks having large effects on future short-term nominal and real rates and small effects on expected inflation

³⁵What we refer to as the risk premia here is the difference between raw interest rate changes and changes in model-implied risk neutral interest rates. Abrahams et al. (2015) further decompose this difference into a term premium, a liquidity premium, and a model error term.

Table D.2: Response of Expected Future Short Rates and Risk Premia

	Expected Future Short Rates		Risk Premia	
	Nominal	Real	Nominal	Real
2Y Treasury Yield	1.01 (0.27)	0.86 (0.17)	0.09 (0.10)	0.20 (0.18)
3Y Treasury Yield	0.93 (0.26)	0.82 (0.18)	0.13 (0.15)	0.21 (0.19)
5Y Treasury Yield	0.76 (0.16)	0.60 (0.12)	-0.04 (0.11)	0.04 (0.14)
10Y Treasury Yield	0.50 (0.11)	0.40 (0.08)	-0.12 (0.14)	0.04 (0.14)
2Y Treasury Forward Rate	0.79 (0.24)	0.73 (0.22)	0.35 (0.26)	0.26 (0.21)
3Y Treasury Forward Rate	0.61 (0.19)	0.56 (0.17)	0.21 (0.29)	0.32 (0.25)
5Y Treasury Forward Rate	0.36 (0.08)	0.33 (0.08)	-0.11 (0.17)	0.14 (0.17)
10Y Treasury Forward Rat	0.10 (0.02)	0.09 (0.02)	-0.18 (0.18)	0.04 (0.12)

Each estimate comes from a separate OLS regression. The dependent variables in the first two columns are one-day changes in risk neutral yields and forwards from Abrahams et al. (2015) -- i.e., measures of expected future short rates. The dependent variables in the later two columns are the difference between one-day changes in raw yields and forwards and one-day changes in the risk neutral yields and forwards from Abrahams et al. (2015). We refer to this difference as the risk premia. It corresponds to the term premium, liquidity premium and model error in Abrahams et al. (2015). The independent variable is a change in the policy new shock over a 30 minute window around the time of FOMC announcements. The forward rates are one-year forwards at different horizons. The sample period is all regularly scheduled FOMC meetings from 1/1/2000 to 3/19/2014, except that we drop the period from July 2008 through June 2009. For 2Y and 3Y yields and real forwards, the sample starts in January 2004. The sample size for the 2Y and 3Y yields and forwards is 74. The sample size for all other regressions is 106—the same observations from which the policy news shock is constructed. Robust standard errors are in parentheses.

(even smaller than in our baseline results).

It is important to stress that the Abrahams et al. (2015) model by no means rules out the potential importance of risk premium effects. In fact, risk premia for long-term bonds are large and volatile in this model. While this model predicts that a large fraction of interest rate variation at other times *are* associated with risk premia, this is not the case for interest rate movements at the time of FOMC announcements. In this regard, our measure of the monetary shock appears to differ importantly from that of Hanson and Stein (2015). Our monetary shocks have virtually no effect on risk premia, as we describe above. In contrast, Hanson and Stein’s measure (based on the 2-day change in the 2-year nominal yield around FOMC announcements, as we describe in section 3.2) is associated with large changes in risk premia (Abrahams et al., 2015). This suggests that Hanson and Stein’s measure of monetary policy shocks is—either due to greater background noise, or because it picks up variation in interest rates further out in the yield curve—much more associated with movements in risk premia at the time of FOMC meetings than our policy news shock.

Our third approach to gauging the role of risk premia in our results is to consider longer event windows for the outcome variables of interest. Some models of liquidity premia (such as the one developed in Hanson and Stein (2015)) predict that we should see real interest rate effects dissipate quickly after the announcement.³⁶ Table D.3 presents the effects of our policy news shock on nominal and real interest rates over event windows of 1, 5, 10, 20, 60, 125, and 250 trading days.³⁷ While the estimates become very noisy as the event window becomes larger, there is little evidence that the effects on interest rates tend to dissipate over time. Indeed, in most cases, the point estimates appear to grow over time (though, again, the standard errors are quite large).

E A Conventional Model of Monetary Shocks

What do the empirical estimates in section 3 tell us about the economy? The conventional view of how monetary policy affects the economy can be decomposed into two parts. First, changes in nominal interest rates affect real interest rates. Second, changes in real interest rates affect output. The second of these components is a common feature of virtually all macroeconomic models and has nothing to do with monetary policy per se. In particular, both Neoclassical and New Keynesian models share the implication that changes in real interest rates affect output. In sharp contrast,

³⁶Hanson and Stein (2015) present a behavioral model in which “search for yield” generates significant risk premium effects of monetary shocks that dissipate over time.

³⁷In all cases, the policy news shock is measured over a 30-minute event window. We only vary the length of the event window for the dependent variables.

Table D.3: Mean Reversion

Horizon (Trading Days)	Nominal Yields			Real Yields		
	2-Year	3-Year	5-Year	2-Year	3-Year	5-Year
1	1.10 (0.34)	1.06 (0.39)	0.73 (0.21)	1.06 (0.28)	1.02 (0.31)	0.64 (0.19)
5	2.24 (1.09)	2.06 (1.07)	0.85 (0.50)	1.01 (0.64)	0.93 (0.68)	0.52 (0.38)
10	2.39 (1.07)	2.20 (1.05)	0.22 (0.80)	1.35 (0.55)	1.20 (0.57)	0.28 (0.53)
20	0.60 (1.22)	0.29 (1.16)	-0.01 (1.11)	0.88 (0.95)	0.43 (0.94)	0.04 (0.79)
60	3.41 (2.38)	2.80 (2.17)	-0.17 (1.46)	1.96 (2.13)	1.72 (1.92)	-0.10 (1.13)
125	9.42 (1.78)	8.02 (1.61)	3.20 (1.98)	6.16 (2.86)	5.22 (2.50)	2.47 (1.44)
250	13.52 (3.31)	11.56 (3.08)	4.72 (2.30)	9.58 (2.92)	8.22 (2.97)	4.13 (1.84)

Each estimate comes from a separate OLS regression. We regress the cumulative change in yields between the day before the FOMC announcement and 1, 5, 10, 20, 60, 125 and 250 trading days after the announcement on the policy news shock in the 30 minute interval surrounding the FOMC announcement. The first three columns present results for nominal zero coupon yields, and the next three columns present results for real zero coupon yields. The sample period is all regularly scheduled meetings from 1/1/2000 to 3/19/2014, except that we drop the period from July 2008 through June 2009. For 2Y and 3Y yields, the sample starts in January 2004. Going down the rows, the sample sizes for the 2Y and 3Y yields are 74, 73, 73, 73, 72, 69, and 65. The sample sizes for the 5Y yield are 106, 105, 105, 105, 104, 101, and 97. The policy news shock is constructed on the 2000-2014 sample used in Table 1. Newey-West standard errors with 4 lags are in parentheses.

Neoclassical and New Keynesian models have very different predictions regarding the extent to which changes in nominal interest rates caused by monetary policy can affect real interest rates. In a Neoclassical model, variation in nominal interest rates caused by monetary policy have *no* effect on the real interest rate, while in New Keynesian models, such movements in nominal interest rates can have large effects on real rates if prices are sufficiently sticky.

The evidence we present in section 3 shows that variation in nominal interest rates caused by monetary policy announcements does have large and persistent effects on real interest rates. In a conventional model of how monetary shocks affect the economy—i.e., one where monetary shocks only convey information about the future path of policy and don't change private sector views about other fundamentals of the economy—this evidence identifies key parameters governing the rigidity of prices. We can illustrate this very simply using the textbook New Keynesian model.

Consider a setting in which the behavior of households and firms can be described by the fol-

lowing Euler equation and Phillips curve:

$$\hat{x}_t = E_t \hat{x}_{t+1} - \sigma(\hat{i}_t - E_t \hat{\pi}_{t+1} - \hat{r}_t^n), \quad (12)$$

$$\hat{\pi}_t = \beta E_t \hat{\pi}_{t+1} + \kappa \zeta \hat{x}_t. \quad (13)$$

Hatted variables denote percentage deviations from steady state. The variable $\hat{x} = \hat{y}_t - \hat{y}_t^n$ denotes the “output gap”—the difference between actual output \hat{y}_t and the “natural” level of output \hat{y}_t^n that would prevail if prices were flexible— $\hat{\pi}_t$ denotes inflation, \hat{i}_t denotes the gross return on a one-period, risk-free, nominal bond, and \hat{r}_t^n denotes the “natural rate of interest.” The parameter σ in the Euler equation denotes the intertemporal elasticity of substitution, while β denotes the subjective discount factor of households, κ and ζ denote nominal and real rigidities, respectively. Both the natural rate of output and the natural rate of interest are functions of exogenous shocks to tastes and technology. Appendix H presents a detailed derivation of these equations from primitive assumptions about tastes and technology. Woodford (2003) and Galí (2008) present textbook treatments.

Suppose this economy starts off at a zero-inflation steady state and is then disturbed by a monetary shock. Assuming that the monetary shock has no effect on output in the long run, we can solve the Euler equation—equation (12)—forward and get that the response of the output gap to the monetary shock is,

$$\hat{x}_t = -\sigma \sum_{j=0}^{\infty} E_t \hat{r}_{t+j} = -\sigma \hat{r}_t^\ell. \quad (14)$$

where \hat{r}_{t+j} denotes the response of the short-term real interest rate at time $t + j$ —i.e., $\hat{r}_{t+j} = \hat{i}_{t+j} - E_{t+j} \hat{\pi}_{t+j+1}$ —and \hat{r}_t^ℓ denotes the response of the long-run real interest rate. Notice that $\hat{r}_t^n = 0$ in this case since the monetary shock has no effect on the natural rate of interest.

Similarly, we can solve forward the Phillips curve—equation (13)—and get that the response of inflation to the monetary shock is

$$\hat{\pi}_t = \kappa \zeta \sum_{j=0}^{\infty} \beta^j E_t \hat{x}_{t+j}. \quad (15)$$

Combining equations (14) and (15), we get a relationship between the response of inflation and the response of the real interest rates to the monetary shock:

$$\hat{\pi}_t = -\kappa \zeta \sigma \sum_{j=0}^{\infty} \beta^j E_t \hat{r}_{t+j}^\ell. \quad (16)$$

Recall that in section 3 we estimate the response of inflation and real interest rates to a monetary shock. These are exactly the two responses that appear in equation (16). Equation (16) therefore shows that in the textbook New Keynesian model the relative size of the response of inflation and real interest rates pins down the magnitude of the parameter triplet $\kappa\zeta\sigma$. Viewed through the lens of this model, the fact that we estimate a small response of inflation relative to the response of the real interest rate implies that either: 1) the Phillips curve must be very flat ($\kappa\zeta$ small), implying a lot of nominal and real rigidities, or 2) output must be very unresponsive to the real interest rate (σ small), or both.

Notice that in reaching these conclusions we do not need to fully specify the monetary policy rule. The only assumption we need to make about monetary policy is that monetary shocks do not have long-run effects on output. This is true of most common specifications of monetary policy rules used in the literature. In this respect, the conclusions reached above are quite robust.

Even so, let's consider whether this argument continues to hold even if the monetary shock leads to a shift in the long-run inflation target of the central bank (and therefore the long-run inflation rate). In this case, equation (16) becomes

$$\hat{\pi}_t = -\kappa\zeta\sigma \sum_{j=0}^{\infty} \beta^j E_t \hat{r}_{t+j}^{\ell} + \hat{\pi}_{\infty}, \quad (17)$$

where $\hat{\pi}_{\infty}$ denotes the change in the long-run inflation rate. The case we consider above assumed that $\pi_{\infty} = 0$. Even if this term is non-zero, however, it is important to recognize that it affects inflation in *every* period after the shock. Hence, it would not change the slope of the response of expected inflation. The extra term *does* have the potential to lead to a larger response of inflation to a monetary shock than in our baseline model. Empirically, however, the response of expected inflation to the monetary shock already appears to be very small. Adding this feature to the model would further increase the degree of rigidities we estimate in the data, and therefore, the degree of monetary non-neutrality.

In the analysis above, we did rely heavily on the conventional view of monetary shocks that they convey information only about the future path of policy but don't change private sector views about other fundamentals of the economy. In this view, monetary shocks may occur because the private sector is learning about the preferences of the policymakers, or because the private sector is learning about the policymaker's model of the world, or because the private sector is learning about the policymaker's views on the state of the economy. Crucially, however, the announcement by the policymaker cannot lead the private sector to update its own views about the state of the economy

or the model of the world. If it does, the monetary shocks contains an additional “information effect.”

If FOMC announcements affect not only beliefs about future monetary policy but also beliefs about future natural rates of interest, the conclusions reached above regarding what we can learn from the empirical evidence presented in section 3 can change dramatically. In this case, equation (14) becomes

$$\hat{x}_t = -\sigma \sum_{j=0}^{\infty} E_t(\hat{r}_{t+j} - \hat{r}_{t+j}^n) = -\sigma(\hat{r}_t^\ell - \hat{r}_t^{n\ell}), \quad (18)$$

where $\hat{r}_t^{n\ell}$ denotes the response to the monetary announcement of private sector beliefs about the long-term natural rate of interest, and equation (16) becomes

$$\hat{\pi}_t = -\kappa\zeta\sigma \sum_{j=0}^{\infty} \beta^j E_t(\hat{r}_{t+j}^\ell - \hat{r}_t^{n\ell}). \quad (19)$$

It is important to recognize that private sector behavior depends on private sector beliefs about the future path of the natural rate. The variables \hat{r}_{t+j}^n and $\hat{r}_t^{n\ell}$ denote the response of private sector beliefs about natural rates, and \hat{r}_{t+j} and \hat{r}_{t+j}^ℓ denote the response of private sector beliefs about actual real rates.

Notice that allowing for information effects, the response of the output gap and inflation to a monetary announcement is not determined by the response of real interest rates but rather by the response of the real interest rate *gap*—i.e., the gap between real interest rates and the natural rate of interest. This means that changes in real interest rates will not have as large effects on output and inflation if FOMC announcements have information effects since the movement in the interest rate gap will be only some fraction of the overall movement in interest rates. It also means that we will estimate larger values of the parameter triplet $\kappa\zeta\sigma$ —i.e., smaller values of nominal and real rigidities (for a given value of the IES)—since the sum on the right-hand-side of equation (19) will be smaller than if we ignored information effects.

F Expected Output Growth Regressions

The regressions in Tables 3 and A.5 are of the form

$$\Delta s_{t,t-1} = \alpha + \gamma \Delta i_{t-1} + \epsilon_t \quad (20)$$

with the policy news shock as the independent variable. In Table 3, the dependent variable is

$$\Delta s_{t,t-1} = \frac{gy_{t,q(t)+1} + gy_{t,q(t)+2} + gy_{t,q(t)+3}}{3} - \frac{gy_{t-1,q(t)+1} + gy_{t-1,q(t)+2} + gy_{t-1,q(t)+3}}{3} \quad (21)$$

where $gy_{t,q(t)+j}$ denotes the average forecast made in month t about output growth in quarter $q(t) + j$, where $q(t)$ is the quarter that month t belongs to. For example, t might be September 2008, in which case $q(t)$ is the third quarter of 2008, $q(t) + 2$ is the first quarter of 2009, and $gy_{t,q(t)+2}$ is the average forecast made in September 2008 about the value of output growth in the first quarter of 2009. In Table A.5, the dependent variable is

$$\Delta s_{t,t-1} = gy_{t,q(t)+j} - gy_{t-1,q(t)+j} \quad (22)$$

for $j \in \{0, 1, \dots, 7\}$.

G Greenbook Evidence

If Fed information is important, one might expect that contractionary monetary shocks would disproportionately occur when the Fed is more optimistic than the private sector about the state of the economy. The top panel of Table G.1 tests this proposition using the Fed's Greenbook forecast about output growth as a measure of its optimism about the economy.³⁸ We report estimates from the following regression:

$$\text{policy news shock}_t = \alpha + \beta (\Delta y_{t,q}^{GB} - \Delta y_{t,q}^{BC}) + \varepsilon_t, \quad (23)$$

where $\Delta y_{t,q}^{GB}$ is the Greenbook forecast of quarterly output growth (annualized) q quarters in the future made in month t , and $\Delta y_{t,q}^{BC}$ is the corresponding Blue Chip forecast. In words, we regress our policy news shock on the contemporaneous difference between the Greenbook and Blue Chip forecasts about real GDP growth at various horizons. The positive coefficients reported in the top panel of Table G.1 indicate that our policy news shocks tend to be positive (i.e., indicate a surprise increase in interest rates) when the Greenbook forecast about current and future real GDP growth is higher than the corresponding Blue Chip forecast.

³⁸The staff of the Board of Governors has presented the FOMC with analysis and forecasts of the US economy in the Greenbook (now, the Tealbook) since 1965. Conveniently, both the Greenbook and Blue Chip datasets make forecasts of the same variable: annualized real GDP growth. The Greenbook forecasts are finalized one week before each FOMC meeting.

Table G.1: Is Fed Information Reflected in Greenbook Forecasts?

Horizon (q):	-1	0	1	2	3	4	5	6	7
<i>Does Fed Relative Optimism Explain Monetary Shocks?</i>									
β	--	1.19	1.01	1.21	1.00	1.20	1.89	3.10	1.88
	--	(0.55)	(0.74)	(0.69)	(0.77)	(0.90)	(1.10)	(1.14)	(1.64)
N	--	90	90	90	90	90	66	42	22
<i>Does Fed Relative Optimism Reverse in Response to Monetary Shocks?</i>									
β	-7.26	-4.07	-0.45	-0.87	-0.46	-1.66	-3.58	-1.34	-3.04
	(3.63)	(1.80)	(1.53)	(1.30)	(1.08)	(1.11)	(1.31)	(1.30)	(2.44)
N	24	89	89	89	89	76	55	32	8

Each estimate comes from a separate OLS regression. In the first panel, we regress the policy news shock (scaled by 100) on the difference in forecasts about output growth q quarters ahead between the Fed's Greenbook forecast and the Blue Chip forecast. Since the Blue Chip forecasts are available at a monthly frequency, we construct a corresponding monthly measure of our policy news shock. In particular, we use any policy news shock that occurs over the month except for those that occur in the first week (because we do not know whether these occurred before or after the survey response). In the second panel, we regress the change in the difference between the Greenbook and Blue Chip forecast of output growth q quarters ahead on the news policy shock. The change is between the month of the policy shock and the month of the subsequent FOMC meeting. See Appendix F for details. The sample period is all regularly scheduled FOMC meetings from January 1995 to December 2009, except that we exclude the period from July 2008 through June 2009 and the aforementioned first-week meetings. The policy news shocks are constructed over the 1995-2014 sample used in Table A.5. Robust standard errors are in parentheses.

We furthermore find that the difference between Greenbook and Blue Chip forecasts tends to narrow after our policy news shocks occur. This suggests that private sector forecasters may update their forecasts based on information they glean from FOMC announcements. Building on the work of Romer and Romer (2000), we estimate the following regression:

$$[(\Delta y_{t+1,q}^{GB} - \Delta y_{t+1,q}^{BC}) - (\Delta y_{t,q}^{GB} - \Delta y_{t,q}^{BC})] = \alpha + \beta \text{policy news shock}_t + \varepsilon_{t+1}, \quad (24)$$

where time $t + 1$ is the month of the next FOMC meeting. In words, we assess whether our policy news shocks forecast a change in the difference between the Greenbook and the Blue Chip forecasts of output growth. The results of this regression are reported in the bottom panel of Table G.1. We find that a positive policy news shock forecasts a fall in the Greenbook forecast relative to the Blue Chip forecast (or equivalently a rise in the Blue Chip forecast relative to the Greenbook forecast). This change is statistically significant for the nowcast ($q = 0$) and for one of the longer-term forecasts ($q = 5$) but not statistically significant for the other horizons. Since positive monetary shocks tend to be associated with the Greenbook forecast being above the Blue Chip, the fact that the estimates are negative in this regression indicates that, indeed, our policy news shocks are associated

with a narrowing in the discrepancy between Fed and private sector views on the economy.

H Micro-Foundations for Our Model

This section lays out micro-foundations for the New Keynesian business cycle model we use in the paper. We do this in two steps. First we present a version of the model without internal habit and a backward-looking term in the Phillips curve. Then in sections H.4-H.6, we show how the model is modified to include internal habit and a backward-looking term in the Phillips curve. We end this appendix with a discussion of the determination of the natural rate of output and productivity in the full model. We note that none of the derivations in this section depend on whether there is an information effect or not. See Woodford (2003) and Gali (2008) for thorough expositions of New Keynesian models.

H.1 Households

The economy is populated by a continuum of household types indexed by x . A household's type indicates the type of labor supplied by that household. Households of type x seek to maximize their utility given by

$$E_0 \sum_{t=0}^{\infty} \beta^t [u(C_t, \xi_t) - v(L_t(x), \xi_t)], \quad (25)$$

where β denotes the household's subjective discount factor, C_t denotes household consumption of a composite consumption good, $L_t(x)$ denotes household supply of differentiated labor input x , and ξ_t denotes a vector of preference shocks. There are an equal (large) number of households of each type. The composite consumption good in expression (25) is an index given by

$$C_t = \left[\int_0^1 c_t(z)^{\frac{\theta-1}{\theta}} dz \right]^{\frac{\theta}{\theta-1}}, \quad (26)$$

where $c_t(z)$ denotes consumption of products of variety z . The parameter $\theta > 1$ denotes the elasticity of substitution between different varieties.

Households have access to complete financial markets. Households of type x face a flow budget constraint given by

$$P_t C_t + E_t[M_{t,t+1} B_{t+1}(x)] \leq B_t(x) + W_t(x) L_t(x) + \int_0^1 \Xi_t(z) dz - T_t, \quad (27)$$

where P_t is a price index that gives the minimum price of a unit of the consumption good C_t , $B_{t+1}(x)$ is a random variable that denotes the state contingent payoff of the portfolio of financial securities held by households of type x at the beginning of period $t + 1$, $M_{t,t+1}$ is the stochastic discount factor that prices these payoffs in period t ,³⁹ $W_t(x)$ denotes the wage rate received by households of type x in period t , $\Xi_t(z)$ denotes the profits of firm z in period t , and T_t is a lump-sum tax levied by the government. To rule out Ponzi schemes, household debt cannot exceed the present value of future income in any state of the world.

Households face a decision in each period about how much to spend on consumption, how many hours of labor to supply, how much to consume of each differentiated good produced in the economy and what portfolio of assets to purchase. Optimal choice regarding the trade-off between current consumption and consumption in different states in the future yields the following consumption Euler equation:

$$\frac{u_c(C_{t+j}, \xi_{t+j})}{u_c(C_t, \xi_t)} = \frac{M_{t,t+j} P_{t+j}}{\beta^j P_t} \quad (28)$$

as well as a standard transversality condition. The notation u_c denotes the partial derivate of the function u with respect to C_t . We use analogous notation for other partial derivatives below. Equation (28) holds state-by-state for all $j > 0$. Optimal choice regarding the intratemporal trade-off between current consumption and current labor supply yields a labor supply equation:

$$\frac{v_\ell(L_t(x), \xi_t)}{u_c(C_t, \xi_t)} = \frac{W_t(x)}{P_t}. \quad (29)$$

Households optimally choose to minimize the cost of attaining the level of consumption C_t . This implies the following demand curves for each of the differentiated products produced in the economy:

$$c_t(z) = C_t \left(\frac{p_t(z)}{P_t} \right)^{-\theta}, \quad (30)$$

where $p_t(z)$ denotes the price of product z and

$$P_t = \left[\int_0^1 p_t(z)^{1-\theta} dz \right]^{\frac{1}{1-\theta}}. \quad (31)$$

³⁹The stochastic discount factor $M_{t,t+1}$ is a random variable over states in period $t + 1$. For each such state it equals the price of the Arrow-Debreu asset that pays off in that state divided by the conditional probability of that state. See Cochrane (2005) for a detailed discussion.

H.2 Firms

There are a continuum of firms indexed by z in the economy. Firm z specializes in the production of differentiated good z , the output of which we denote $y_t(z)$. For simplicity, labor is the only variable factor of production used by firms. Each firm is endowed with a fixed, non-depreciating stock of capital. The production function of firm z is

$$y_t(z) = A_t f(L_t(z)), \quad (32)$$

where A_t denotes aggregate productivity. The function f is increasing and concave. It is concave because there are diminishing marginal return to labor given the fixed amount of other inputs employed at the firm. We follow Woodford (2003) in introducing heterogeneous labor markets. Each firm belongs to an industry x . There are many firms in each industry. The goods in industry x are produced using labor of type x and all firms in industry x change prices at the same time. This heterogeneous labor market structure is a strong source of real rigidities in price setting.

Firm z acts to maximize its value,

$$E_t \sum_{j=0}^{\infty} M_{t,t+j} [p_{t+j}(z) y_{t+j}(z) - W_{t+j}(x) L_{t+j}(z)]. \quad (33)$$

Firm z must satisfy demand for its product given by equation (30). Firm z is therefore subject to the following constraint:

$$C_t \left(\frac{p_t(z)}{P_t} \right)^{-\theta} \leq A_t f(L_t(z)). \quad (34)$$

Firm z takes its industry wage $W_t(x)$ as given. Optimal choice of labor demand by the firm is given by

$$W_t(x) = A_t f_\ell(L_t(z)) S_t(z), \quad (35)$$

where $S_t(z)$ denotes the firm's nominal marginal cost (the Lagrange multiplier on equation (34) in the firm's constrained optimization problem).

Firm z can reoptimize its price with probability $1 - \alpha$ as in Calvo (1983). With probability α , it must keep its price unchanged. Optimal price setting by firm z in periods when it can change its price implies

$$p_t(z) = \frac{\theta}{\theta - 1} E_t \sum_{j=0}^{\infty} \frac{\alpha^j M_{t,t+j} y_{t+j}(z)}{\sum_{k=0}^{\infty} \alpha^k M_{t,t+k} y_{t+k}(z)} S_{t+j}(z). \quad (36)$$

Intuitively, the firm sets its price equal to a constant markup over a weighted average of current

and expected future marginal cost.

H.3 A Linear Approximation of Private Sector Behavior

We seek a linear approximation of the equation describing private sector behavior around a zero-growth, zero-inflation steady state. We start by deriving a log-linear approximation for the consumption Euler equation that related consumption growth and a one-period, riskless, nominal bond. This equation takes the form $E_t[M_{t,t+1}(1 + i_t)] = 1$, where i_t denotes the yield on a one-period, riskless, nominal bond. Using equation (28) to plug in for $M_{t,t+1}$ and rearranging terms yields

$$E_t \left[\beta U_c(C_{t+1}, \xi_{t+1}) \frac{P_t}{P_{t+1}} \right] = \frac{U_c(C_t, \xi_t)}{1 + i_t}. \quad (37)$$

The zero-growth, zero-inflation steady state of this equation is $\beta(1 + \bar{i}) = 1$. A first order Taylor series approximation of equation (37) around this steady state is

$$\hat{c}_t = E_t \hat{c}_{t+1} - \sigma(\hat{i}_t - E_t \hat{\pi}_{t+1}) - \sigma E_t \Delta \hat{\xi}_{ct+1}, \quad (38)$$

where $\hat{c}_t = (C_t - C)/C$, $\hat{\pi}_t = \pi_t - 1$, $\hat{i}_t = (1 + i_t - 1 - \bar{i})/(1 + \bar{i})$, and $\hat{\xi}_{ct} = (U_{\xi c}/U_c)(\xi_t - 1)$. The parameter $\sigma = -U_c/(U_{cc}C)$ denotes the intertemporal elasticity of substitution of households.

We next linearize labor demand, labor supply, and the production function and combine these equations to get an expression for the marginal costs in period $t + j$ of a firm that last changed its price in period t . Let $\ell_{t,t+j}(x)$ denote the percent deviation from steady state in period $t + j$ of hours worked for workers in industry x that last was able to change prices in period t . Let other industry level variables be defined analogously. We assume that $f(L_t(x)) = L_t^\alpha(x)$.

A linear approximation of labor demand—equation (35)—in period $t + j$ for industry x that was last able to change its prices in period t is then

$$\hat{w}_{t,t+j}(x) = \hat{a}_{t+j} - (1 - a)\hat{\ell}_{t,t+j}(x) + \hat{s}_{t,t+j}(x), \quad (39)$$

where $\hat{w}_{t,t+j}(x)$ and $\hat{s}_{t,t+j}(x)$ denote the percentage deviation of real wages and real marginal costs, respectively, from their steady state values.

A linear approximation of labor supply—equation (29)—in period $t + j$ for industry x that was last able to change its prices in period t is

$$\hat{w}_{t,t+j}(x) = \eta^{-1}\hat{\ell}_{t,t+j}(x) + \sigma^{-1}\hat{c}_{t+j} + \hat{\xi}_{\ell,t+j} - \hat{\xi}_{c,t+j}, \quad (40)$$

where $\hat{\xi}_{\ell,t+j} = (V_{\ell\xi}/V_{\ell})(\xi_t - 1)$. The parameter $\eta = V_{\ell}/(V_{\ell\ell}L)$ is the Frisch elasticity of labor supply.

A linear approximation of the production function—equation (32)—in period $t + j$ for industry x that was last able to change its prices in period t is

$$\hat{y}_{t,t+j}(x) = \hat{a}_{t+j} + a\hat{\ell}_{t,t+j}(x). \quad (41)$$

Combining labor demand and labor supply—equations (39) and (40)—to eliminate $\hat{w}_{t,t+j}(x)$ yields

$$\hat{s}_{t,t+j}(x) = (\eta^{-1} + 1 - a)\hat{\ell}_{t,t+j}(x) + \sigma^{-1}\hat{c}_{t+j} - \hat{a}_{t+j} + \hat{\xi}_{\ell,t+j} - \hat{\xi}_{c,t+j}.$$

Using the production function—equation (41)—to eliminate $\hat{\ell}_{t,t+j}(x)$ yields

$$\hat{s}_{t,t+j}(x) = \omega\hat{y}_{t,t+j}(x) + \sigma^{-1}\hat{c}_{t+j} - (\omega + 1)\hat{a}_{t+j} + \hat{\xi}_{\ell,t+j} - \hat{\xi}_{c,t+j}, \quad (42)$$

where $\omega = (\eta^{-1} + 1 - a)/a$.

Taking logs of consumer demand—equation (30)—in period $t + j$ for industry x what was last able to change its prices in period t yields

$$\hat{y}_{t,t+j}(z) = -\theta\hat{p}_t(x) + \theta\sum_{k=1}^j\hat{\pi}_{t+k} + \hat{y}_{t+j}, \quad (43)$$

where we use the fact that $Y_t = C_t$ and $y_t(x) = c_t(x)$. Plugging this equation into equation (42) and again using the fact that $Y_t = C_t$ yields

$$\hat{s}_{t,t+j}(x) = -\omega\theta\hat{p}_t(x) + \omega\theta\sum_{k=1}^j\hat{\pi}_{t+k} + (\omega + \sigma^{-1})\hat{y}_{t+j} - (\omega + 1)\hat{a}_{t+j} + \hat{\xi}_{\ell,t+j} - \hat{\xi}_{c,t+j} \quad (44)$$

It is useful to derive the level of output that would prevail if all prices were flexible. Since our model does not have any industry specific shocks (other than the opportunity to change prices), marginal costs of all firms are the same when prices are flexible. Firm price setting in this case yields $p_t(x) = \mu S_t$, where $\mu = \theta/(\theta - 1)$. This implies that all prices are equal and that $S_t/P_t = 1/\mu$. Since real marginal cost is a constant, we have $\hat{s}_t = 0$. The flexible price version of equation (44) is then

$$(\omega + \sigma^{-1})\hat{y}_t^n = (\omega + 1)\hat{a}_t - \hat{\xi}_{\ell,t} + \hat{\xi}_{c,t}, \quad (45)$$

where we use the fact that output in all industries is the same under flexible prices and $\hat{y}_t = \hat{c}_t$ and

denote the rate of output under flexible prices as y_t^n . We will refer to y_t^n as the natural rate of output.

Combining equations (44) and (45) yields

$$\hat{s}_{t,t+j}(x) = -\omega\theta\hat{p}_t(x) + \omega\theta\sum_{k=1}^j\hat{\pi}_{t+k} + (\omega + \sigma^{-1})(\hat{y}_{t+j} - \hat{y}_{t+j}^n) \quad (46)$$

We next linearize the price setting equation—equation (36). This yields:

$$\sum_{j=0}^{\infty}(\alpha\beta)^j\hat{p}_t(x) - \sum_{j=0}^{\infty}(\alpha\beta)^jE_t\hat{s}_{t,t+j}(x) - \sum_{j=1}^{\infty}(\alpha\beta)^j\sum_{k=1}^jE_t\hat{\pi}_{t+k} = 0.$$

Manipulation of this equation yields

$$\hat{p}_t(x) = (1 - \alpha\beta)\sum_{j=0}^{\infty}(\alpha\beta)^jE_t\hat{s}_{t,t+j}(x) + \alpha\beta\sum_{j=1}^{\infty}(\alpha\beta)^{j-1}E_t\hat{\pi}_{t+j}. \quad (47)$$

Using equation (46) to eliminate $\hat{s}_{t,t+j}(x)$ in equation (47) and manipulating the resulting equation yields

$$\hat{p}_t(x) = (1 - \alpha\beta)\zeta\sum_{j=0}^{\infty}(\alpha\beta)^jE_t(\hat{y}_{t+j} - \hat{y}_{t+j}^n) + \alpha\beta\sum_{j=1}^{\infty}(\alpha\beta)^{j-1}E_t\hat{\pi}_{t+j}, \quad (48)$$

where $\zeta = (\omega + \sigma^{-1})/(1 + \omega\theta)$.

A linear approximation of the expression for the price index—equation (31)—yields

$$\hat{\pi}_t = \frac{1 - \alpha}{\alpha}\hat{p}_t(x). \quad (49)$$

Using this last equation to replace $\hat{p}_t(x)$ in equation (48) yields

$$\hat{\pi}_t = \kappa\zeta\sum_{j=0}^{\infty}(\alpha\beta)^jE_t(\hat{y}_{t+j} - \hat{y}_{t+j}^n) + (1 - \alpha)\beta\sum_{j=1}^{\infty}(\alpha\beta)^{j-1}E_t\hat{\pi}_{t+j},$$

where $\kappa = (1 - \alpha)(1 - \alpha\beta)/\alpha$. Quasi-differencing the resulting equation yields

$$\hat{\pi}_t - \alpha\beta E_t\hat{\pi}_{t+1} = \kappa\zeta(\hat{y}_t - \hat{y}_t^n) + (1 - \alpha)\beta E_t\hat{\pi}_{t+1},$$

which implies

$$\hat{\pi}_t = \beta E_t\hat{\pi}_{t+1} + \kappa\zeta(\hat{y}_t - \hat{y}_t^n). \quad (50)$$

Finally, we rewrite the household's Euler equation—equation (38) in terms of the output gap:

$$\hat{y}_t - \hat{y}_t^n = E_t(\hat{y}_{t+1} - \hat{y}_{t+1}^n) - \sigma(\hat{i}_t - E_t\hat{\pi}_{t+1} - r_t^n), \quad (51)$$

where r_t^n denotes the “natural rate of interest” as is given by

$$r_t^n = E_t\Delta\xi_{c,t+1} + \frac{1}{\sigma}E_t\Delta\hat{y}_{t+1}^n. \quad (52)$$

H.4 Household Behavior with Internal Habits

We now consider a case in which households form habits. Households of type x seek to maximize a utility function given by

$$E_0 \sum_{t=0}^{\infty} \beta^t [u(C_t - bC_{t-1}) - v(L_t(x))], \quad (53)$$

where the parameter b governs the strength of households' habit. We model household utility from consumption in period t as being affected by the amount that same household consumed in the previous period. Our model is therefore a model of “internal habit.” Notice also that relative to the derivations above, we have eliminated reference to the preferences shocks ξ_t since they play no role in the analysis in the body of the paper.

Households face the same budget constraint as in the simple model (equation (27)). They also face the same no-Ponzi condition as in the simple model. Maximization of utility subject to these constraints yields the following consumption Euler equation and labor supply equation:

$$\frac{\Lambda_{t+j}}{\Lambda_t} = \frac{M_{t,t+j}}{\beta^j} \frac{P_{t+j}}{P_t}, \quad (54)$$

$$\frac{v_\ell(L_t(x), \xi_t)}{\Lambda_t} = \frac{W_t(x)}{P_t}, \quad (55)$$

where Λ_t denotes marginal utility from consumption at time t and is given by

$$\Lambda_t = u_c(C_t - bC_{t-1}) - b\beta E_t u_c(C_{t+1} - bC_t). \quad (56)$$

H.5 Firm Price Setting with Inflation Inertia

In the simple model presented above, we assume that prices are either reoptimized (with probability $1 - \alpha$), or remain fixed (with probability α). As is well-known, this formulation yields a Phillips curve that implies that inflation reacts rapidly to news about future economic developments. Our

empirical evidence suggests that inflation responds very gradually to news about future economic conditions. To be able to match this aspect of our evidence, we now follow Christiano, Eichenbaum, and Evans (2005) in considering a formulation of price setting in which firms index the price of the good they produce to past inflation whenever they don't reoptimize the price. This formulation makes inflation sluggish.

Firm z can reoptimize its price with probability $1 - \alpha$ as in Calvo (1983). With probability α , it sets its price according to the following simple rule

$$p_t(z) = \frac{P_{t-1}}{P_{t-2}} p_{t-1}(z). \quad (57)$$

The firm's optimization problem is otherwise the same as in section H.2. Optimal price setting by firm z in periods when it can change its price implies

$$p_t(z) = \frac{\theta}{\theta - 1} E_t \sum_{j=0}^{\infty} \frac{\alpha^j M_{t,t+j} y_{t+j}(z)}{\sum_{k=0}^{\infty} \alpha^k M_{t,t+k} (P_{t+j-1}/P_{t-1}) y_{t+k}(z)} S_{t+j}(z). \quad (58)$$

The firm's labor demand equation is the same as in section H.2.

H.6 A Linearization of Private Sector Behavior in the Augmented Model

We seek a linear approximation of the equations describing private sector behavior with internal habits and price indexation. As before, we start by deriving a log-linear approximation for the consumption Euler equation that related consumption growth and a one-period, riskless, nominal bond. This equation may be written

$$E_t \left[\beta \Lambda_{t+1} \frac{P_t}{P_{t+1}} \right] = \frac{\Lambda_t}{1 + \hat{i}_t}. \quad (59)$$

The zero-growth, zero-inflation steady state of this equation is $\beta(1 + \bar{i}) = 1$. A first order Taylor series approximation of equation (37) around this steady state is

$$\hat{\lambda}_t = E_t \hat{\lambda}_{t+1} + (\hat{i}_t - E_t \hat{\pi}_{t+1}), \quad (60)$$

where $\hat{\lambda} = (\Lambda_t - \Lambda)/\Lambda$.

A linear approximation of labor supply—equation (55)—in period $t + j$ for industry x that was

last able to change its prices in period t is

$$\hat{w}_{t,t+j}(x) = \eta^{-1} \hat{\ell}_{t,t+j}(x) - \hat{\lambda}_{t+j}. \quad (61)$$

A linear approximation of marginal utility of consumption—equation (56)—is given by

$$\hat{\lambda}_t = -(1 + b^2\beta)\sigma_c \hat{c}_t + b\sigma_c \hat{c}_{t-1} + b\beta\sigma_c E_t \hat{c}_{t+1}, \quad (62)$$

where $\sigma_c = -\sigma^{-1}/((1-b)(1-b\beta))$.

Combining equation (61) with equations (39) (without the preference shock) and equation (41) yields

$$\hat{s}_{t,t+j}(x) = \omega \hat{y}_{t,t+j}(x) - \hat{\lambda}_{t+j} - (\omega + 1) \hat{a}_{t+j}. \quad (63)$$

With price indexation, consumer demand in period $t + j$ in an industry x that last changed its price in period t is

$$y_{t+j}(x) = \left(\frac{p_t(x)}{P_{t+j}} \frac{P_{t+j-1}}{P_{t-1}} \right)^{-\theta} Y_{t+j}. \quad (64)$$

A linear approximation of this equation is

$$\hat{y}_{t,t+j}(z) = -\theta \hat{p}_t(x) + \theta \sum_{k=1}^j \hat{\pi}_{t+k} - \theta \sum_{k=0}^{j-1} \hat{\pi}_{t+k} + \hat{y}_{t+j}. \quad (65)$$

Plugging this into equation (63) yields

$$\hat{s}_{t,t+j}(x) = -\omega\theta \hat{p}_t(x) + \omega\theta \sum_{k=1}^j \hat{\pi}_{t+k} - \omega\theta \sum_{k=0}^{j-1} \hat{\pi}_{t+k} + \omega \hat{y}_{t+j} - \hat{\lambda}_{t+j} - (\omega + 1) \hat{a}_{t+j}. \quad (66)$$

As in the simple model considered above, it is useful to derive a relationship between the natural level of output and marginal cost and the exogenous shocks in the model. With flexible prices all firms set the same price. In this case we have $p_t(x) = \mu S_t$ and $\hat{s}_t = 0$. This implies that the flexible price version of equation (66) is

$$\omega \hat{y}_{t+j}^n - \hat{\lambda}_{t+j}^n = (\omega + 1) \hat{a}_{t+j}. \quad (67)$$

Combining equations (66) and (67) yields

$$\hat{s}_{t,t+j}(x) = -\omega\theta\hat{p}_t(x) + \omega\theta\sum_{k=1}^j\hat{\pi}_{t+k} - \omega\theta\sum_{k=0}^{j-1}\hat{\pi}_{t+k} + \omega(\hat{y}_{t+j} - \hat{y}_{t+j}^n) - (\hat{\lambda}_{t+j} - \hat{\lambda}_{t+j}^n). \quad (68)$$

We next linearize the price setting equation—equation (58). This yields:

$$\sum_{j=0}^{\infty}(\alpha\beta)^j\hat{p}_t(x) - \sum_{j=0}^{\infty}(\alpha\beta)^jE_t\hat{s}_{t,t+j}(x) - \sum_{j=1}^{\infty}(\alpha\beta)^j\sum_{k=1}^jE_t\hat{\pi}_{t+k} + \sum_{j=1}^{\infty}(\alpha\beta)^j\sum_{k=0}^{j-1}E_t\hat{\pi}_{t+k} = 0.$$

Manipulation of this equation yields

$$\hat{p}_t(x) = (1 - \alpha\beta)\sum_{j=0}^{\infty}(\alpha\beta)^jE_t\hat{s}_{t,t+j}(x) + \alpha\beta\sum_{j=1}^{\infty}(\alpha\beta)^{j-1}E_t\hat{\pi}_{t+j} - \alpha\beta\sum_{j=0}^{\infty}(\alpha\beta)^jE_t\hat{\pi}_{t+j}. \quad (69)$$

Using equation (68) to eliminate $\hat{s}_{t,t+j}(x)$ in equation (69) and manipulating the resulting equation yields

$$\hat{p}_t(x) = (1 - \alpha\beta)\hat{\zeta}\sum_{j=0}^{\infty}(\alpha\beta)^jE_t[\omega\hat{x}_{t+j} - \hat{\lambda}_{xt+j}] + \alpha\beta\sum_{j=1}^{\infty}(\alpha\beta)^{j-1}E_t\hat{\pi}_{t+j} - \alpha\beta\sum_{j=0}^{\infty}(\alpha\beta)^jE_t\hat{\pi}_{t+j}, \quad (70)$$

where $\hat{\lambda}_{xt} = \hat{\lambda}_t - \hat{\lambda}_t^n$ and $\hat{\zeta} = 1/(1 + \omega\theta)$.

A linear approximation of the expression for the price index—equation (31)—in the case with indexation between price changes yields

$$\hat{\pi}_t - \hat{\pi}_{t-1} = \frac{1 - \alpha}{\alpha}\hat{p}_t(x). \quad (71)$$

Using this last equation to replace $\hat{p}_t(x)$ in equation (70) yields

$$\hat{\pi}_t - \hat{\pi}_{t-1} = \kappa\hat{\zeta}\sum_{j=0}^{\infty}(\alpha\beta)^jE_t[\omega\hat{x}_{t+j} - \hat{\lambda}_{xt+j}] + (1 - \alpha)\beta\sum_{j=1}^{\infty}(\alpha\beta)^{j-1}E_t\hat{\pi}_{t+j} - (1 - \alpha)\beta\sum_{j=0}^{\infty}(\alpha\beta)^jE_t\hat{\pi}_{t+j}.$$

Quasi-differencing this equation yields

$$(\hat{\pi}_t - \hat{\pi}_{t-1}) - \alpha\beta(E_t\hat{\pi}_{t+1} - \hat{\pi}_t) = \kappa\hat{\zeta}(\omega\hat{x}_{t+j} - \hat{\lambda}_{xt+j}) + (1 - \alpha)\beta(E_t\hat{\pi}_{t+1} - \hat{\pi}_t),$$

which implies

$$\Delta\hat{\pi}_t = \beta E_t\Delta\hat{\pi}_{t+1} + \kappa\hat{\zeta}(\omega\hat{x}_{t+j} - \hat{\lambda}_{xt+j}). \quad (72)$$

Finally, we rewrite the household's Euler equation—equation (60) in terms of the marginal utility gap:

$$\hat{\lambda}_{xt} = E_t \hat{\lambda}_{xt+1} - \sigma(\hat{i}_t - E_t \hat{\pi}_{t+1} - r_t^n), \quad (73)$$

where r_t^n denotes the “natural rate of interest” as is given by

$$r_t^n = \frac{1}{\sigma} E_t \Delta \hat{\lambda}_{t+1}^n. \quad (74)$$

H.7 Determination of Natural Rate of Output and Productivity

Since the monetary shock affects private sector beliefs about the path of the natural rate of interest, it also affects the private sector's beliefs about the path of the natural rate of output. The solution to the following equation:

$$(1 + b\beta + b^2\beta)\hat{y}_{t+1}^n = b\beta E_t \hat{y}_{t+2}^n + (1 + b + b^2\beta)\hat{y}_t^n - b\hat{y}_{t-1}^n + \sigma_c^{-1} \psi \bar{r}_t \quad (75)$$

using our assumed initial response for the natural rate of output of $y_0^n = \psi \bar{r}_0$ yields a path for the natural rate of output that is consistent with the path of the natural rate of interest implied by our assumption about Fed information, i.e., $r_t^n = \psi \bar{r}_t$. This can be verified by using the resulting path for the natural rate of output to construct a path for the natural rate of marginal utility according to equation (62) and then plugging the resulting path for the natural rate of marginal utility into equation (74). This will yield $r_t^n = \psi \bar{r}_t$.

The logic for this construction of the path of the natural rate of output is easier to comprehend in the textbook New Keynesian model without habit. Suppose $r_t^n = \psi \bar{r}_t$ and $y_0^n = \psi \bar{r}_0$ in that model and we are interested in constructing the path for the natural rate of output that is consistent with these assumptions. The consumption Euler equation in that model implies that $\hat{y}_t^n = E_t \hat{y}_{t+1}^n - \sigma \psi \bar{r}_t$. For this equation to hold, it must be that $\hat{y}_{t+1}^n = \hat{y}_t^n + \sigma \psi \bar{r}_t$. One can thus construct a path for the natural rate of output that is consistent with the desired path for the natural rate of interest by iterating forward $\hat{y}_{t+1}^n = \hat{y}_t^n + \sigma \psi \bar{r}_t$ with the initial condition $y_0^n = \psi \bar{r}_0$. The argument above, is the equivalent argument when households have internal habit.

Given the path for the natural rate of output that we construct above, one can construct a path for the response of private sector beliefs about productivity (the exogenous shock that we assume is driving variation in the natural rate of output and the natural rate of interest) by using equation (67). In the counterfactual, we assume that agents believe productivity is a random walk and then feed in a shock process for productivity that makes productivity follow the same path as in the

actual case of the monetary shock.

Table A.1: Response of Interest Rates to Monetary Shocks for Different Sample Periods

	Baseline Sample		Pre-Crisis (2000-2007)		Full Sample		Baseline w/ Unsched.	
	Nominal	Real	Nominal	Real	Nominal	Real	Nominal	Real
3M Treasury Yield	0.67 (0.14)		0.76 (0.13)		0.73 (0.15)		0.76 (0.11)	
6M Treasury Yield	0.85 (0.11)		0.85 (0.12)		0.90 (0.12)		0.91 (0.10)	
1Y Treasury Yield	1.00 (0.14)		1.00 (0.14)		1.00 (0.13)		1.00 (0.13)	
2Y Treasury Yield	1.10 (0.33)	1.06 (0.24)	1.11 (0.36)	1.04 (0.24)	1.19 (0.29)	1.46 (0.39)	1.30 (0.37)	1.21 (0.26)
3Y Treasury Yield	1.06 (0.36)	1.02 (0.25)	1.03 (0.39)	0.97 (0.25)	1.21 (0.31)	1.34 (0.33)	1.26 (0.40)	1.18 (0.28)
5Y Treasury Yield	0.73 (0.20)	0.64 (0.15)	0.67 (0.20)	0.58 (0.15)	0.78 (0.18)	0.81 (0.16)	0.69 (0.16)	0.68 (0.11)
10Y Treasury Yield	0.38 (0.17)	0.44 (0.13)	0.36 (0.18)	0.44 (0.13)	0.50 (0.17)	0.57 (0.16)	0.38 (0.13)	0.43 (0.10)
2Y Tr. Inst. Forward Rate	1.14 (0.46)	0.99 (0.29)	1.07 (0.48)	0.90 (0.27)	1.31 (0.38)	0.97 (0.30)	1.34 (0.49)	1.15 (0.31)
3Y Tr. Inst. Forward Rate	0.82 (0.43)	0.88 (0.32)	0.66 (0.43)	0.76 (0.29)	1.14 (0.41)	1.09 (0.35)	1.00 (0.46)	1.03 (0.34)
5Y Tr. Inst. Forward Rate	0.26 (0.19)	0.47 (0.17)	0.20 (0.19)	0.47 (0.16)	0.44 (0.21)	0.61 (0.21)	0.27 (0.13)	0.45 (0.12)
10Y Tr. Inst. Forward Rate	-0.08 (0.18)	0.12 (0.12)	-0.01 (0.19)	0.21 (0.13)	0.05 (0.17)	0.10 (0.13)	-0.07 (0.12)	0.04 (0.11)

Each estimate comes from a separate OLS regression. The dependent variable in each regression is the one day change in the variable stated in the left-most column. The independent variable is a change in the policy news shock over a 30 minute window around regularly scheduled FOMC announcements, except the last two columns where we include unscheduled FOMC announcements. The baseline sample period is 1/1/2000 to 3/19/2014, except that we drop July 2008 through June 2009. The "Pre-Crisis" sample is January 2000 through December 2007. The "Full Sample" is 1/1/2000 to 3/19/2014. In the last two columns, we exclude a 10 day period after 9/11/2001. For 2Y and 3Y yields and real forwards, the sample starts in 2004. For each sample period, we construct the policy new shocks from the same sample of observations as the regressions are run on—that is, the results from the different sample periods use slightly different policy news shock series. Robust standard errors are in parentheses.

Table A.2: Response to a Fed Funds Rate Shock

	Nominal	Real	Inflation
3M Treasury Yield	0.50 (0.16)		
6M Treasury Yield	0.59 (0.10)		
1Y Treasury Yield	0.41 (0.16)		
2Y Treasury Yield	0.48 (0.32)	0.50 (0.20)	-0.02 (0.15)
3Y Treasury Yield	0.38 (0.34)	0.41 (0.19)	-0.03 (0.18)
5Y Treasury Yield	0.11 (0.16)	0.21 (0.12)	-0.10 (0.09)
10Y Treasury Yield	-0.00 (0.12)	0.10 (0.09)	-0.10 (0.07)
2Y Treasury Inst. Forward Rate	0.29 (0.40)	0.30 (0.20)	-0.01 (0.25)
3Y Treasury Inst. Forward Rate	0.07 (0.34)	0.13 (0.19)	-0.06 (0.22)
5Y Treasury Inst. Forward Rate	-0.09 (0.13)	0.07 (0.12)	-0.16 (0.07)
10Y Treasury Inst. Forward Rate	-0.11 (0.16)	-0.02 (0.11)	-0.08 (0.09)

Each estimate comes from a separate OLS regression. The dependent variable in each regression is the one day change in the variable stated in the left-most column. The independent variable is a change in the Fed Funds future over the remainder of the month over a 30 minute window around the time of FOMC announcements. The sample period is all regularly scheduled meetings from 1/1/2000 to 3/19/2014, except that we drop July 2008 through June 2009. For 2Y and 3Y yields and real forwards, the sample starts in January 2004. The sample size for the 2Y and 3Y yields and forwards is 74. The sample size for all other regressions is 106. In all regressions, the policy news shock is computed from these same 106 observations. Robust standard errors are in parentheses.

Table A.3: Responses to Policy News Shock Using Rigobon Estimator

	Nominal	Real	Inflation
3M Treasury Yield	0.69 (0.15)		
6M Treasury Yield	0.85 (0.12)		
1Y Treasury Yield	0.98 (0.15)		
2Y Treasury Yield	1.07 (0.37)	1.03 (0.29)	0.05 (0.20)
3Y Treasury Yield	1.03 (0.42)	0.99 (0.30)	0.04 (0.19)
5Y Treasury Yield	0.69 (0.22)	0.62 (0.16)	0.07 (0.12)
10Y Treasury Yield	0.34 (0.19)	0.42 (0.14)	-0.08 (0.09)
2Y Treasury Inst. Forward Rate	1.10 (0.51)	0.96 (0.34)	0.14 (0.25)
3Y Treasury Inst. Forward Rate	0.78 (0.49)	0.86 (0.37)	-0.08 (0.17)
5Y Treasury Inst. Forward Rate	0.22 (0.20)	0.46 (0.18)	-0.24 (0.09)
10Y Treasury Inst. Forward Rate	-0.12 (0.19)	0.11 (0.13)	-0.22 (0.10)

Each estimate comes from a separate "regression." The dependent variable in each regression is the one day change in the variable stated in the left-most column. The independent variable is a change in the policy news shock over a 30 minute window around the time of FOMC announcements. All results are based on Rigobon's (2003) method of identification by heteroskedasticity. The sample of "treatment" days for the Rigobon method is all regularly scheduled FOMC meeting days from 1/1/2000 to 3/19/2014—this is also the period for which the policy news shock is constructed in all "regressions." The sample of "control" days for the Rigobon analysis is all Tuesdays and Wednesdays that are not FOMC meeting days over the same period of time. In both the treatment and control samples, we drop July 2008 through June 2009 and 9/11/2001-9/21/2001. For 2Y forwards, the sample starts in January 2004. Standard errors are calculated using a non-parametric bootstrap with 5000 iterations.

Table A.4: Breakeven Inflation versus Inflation Swaps

	Breakeven	Swaps
Inflation Over Next 2 Years	-0.02 (0.18)	0.37 (0.35)
Inflation Over Next 3 Years	-0.03 (0.17)	0.41 (0.32)
Inflation Over Next 5 Years	-0.13 (0.14)	-0.02 (0.15)
Inflation Over Next 10 Years	-0.22 (0.12)	-0.17 (0.16)

Each estimate comes from a separate OLS regression. The dependent variable in each regression is the one day change in expected inflation measured either by breakeven inflation from the difference between nominal Treasuries and TIPS (first column) or from inflation swaps (second column) for the period stated in the left-most column. The independent variable is a change in the policy news shock over a 30 minute window around the time of FOMC announcements, where the policy news shocks are constructed on the 2000-2014 sample used in Table 1. The sample is all regularly scheduled FOMC meeting day from 1/1/2005 to 11/14/2012, except that we drop July 2008 through June 2009. Robust standard errors are in parentheses.

Table A.5: Response of Expected Output Growth

Exp. Output Growth in Current Qr	1.38 (0.72)
Exp. Output Growth 1 Qr Ahead	1.56 (0.54)
Exp. Output Growth 2 Qr Ahead	0.66 (0.37)
Exp. Output Growth 3 Qr Ahead	0.82 (0.27)
Exp. Output Growth 4 Qr Ahead	0.51 (0.25)
Exp. Output Growth 5 Qr Ahead	0.54 (0.28)
Exp. Output Growth 6 Qr Ahead	0.48 (0.25)
Exp. Output Growth 7 Qr Ahead	0.90 (0.57)

Each estimate comes from a separate OLS regression. We regress changes in survey expectations from the Blue Chip Economic Indicators on the policy news shock. Since the Blue Chip survey expectations are available at a monthly frequency, we construct a corresponding monthly measure of our policy news shock. In particular, we use any policy news shock that occurs over the month except for those that occur in the first week (because we do not know whether these occurred before or after the survey response). The dependent variable is the change in the forecasted value of output growth N quarters ahead, between this month's survey and last month's survey. See Appendix F for details. The sample period is all regularly scheduled FOMC meetings between January 1995 to April 2014, except that we drop July 2008 through June 2009 and the aforementioned first-week meetings. The policy news shock is constructed on the same sample period. Sample sizes are 120 for the first five rows, then 75, 45, and 13. Robust standard errors are in parentheses.

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