

Perceptions about Monetary Policy *

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Abstract

We estimate perceptions about the Fed's monetary policy rule from panel data on professional forecasts of interest rates and macroeconomic conditions. The perceived dependence of the federal funds rate on economic conditions is highly time-varying. Forecasters update their perceptions about the policy rule in response to monetary policy actions, measured by high-frequency interest rate surprises, suggesting that forecasters have imperfect information about the rule. The perceived rule is priced into financial markets crucial for monetary policy transmission, affecting how interest rates respond to macroeconomic news and term premia in long-term interest rates.

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1 Introduction

Over the last 30 years, the Federal Reserve and other central banks have increasingly focused on communicating monetary policy strategy to the public. Underlying this trend are two propositions: First, monetary policy strategy is complex, depending on a wide range of considerations that vary across time and states of the world (Woodford, 2005). Second, the public’s perceptions of monetary policy—including its goals, framework, and future course—play a crucial role in determining policy effectiveness (Bernanke, 2010).¹ But what monetary policy strategy does the public perceive? How do these perceptions vary over time? And how is the perceived strategy linked to actual policy rates?

Empirical progress on these questions requires a measure of forward-looking perceptions of the monetary policy framework, which may differ from historical monetary policy rules. Since the seminal work of Taylor (1993), the monetary economics literature has commonly described the monetary policy framework using simple monetary policy rules that link policy rates to macroeconomic conditions. This approach has been the foundation of extensive positive and normative analyses of monetary policy (e.g., Clarida et al., 2000; Smets and Wouters, 2007). However, the estimation of policy rules—and thus empirical descriptions of policy frameworks—is traditionally focused on the actual historical rule followed by the Fed from macroeconomic time series data. Such estimates cannot speak to public perceptions of monetary policy strategy, learning about the monetary policy rule, or the time-varying transmission to interest rates.²

In this paper, we estimate perceived monetary policy rules *each month* from January 1985 until April 2023 using rich survey data from the Blue Chip Financial Forecasts (BCFF). We characterize time variation in the estimated rules and their relationship to actual monetary policy decisions, as well as their influence on financial markets. For each month, we form a forecaster-by-horizon panel, which consists of fed funds rate, output gap, and inflation forecasts across 30-50 forecasters and horizons from zero to five quarters. Analogous to the simple monetary policy rules typically estimated with historical macroeconomic data we then

¹The classic New Keynesian model of monetary policy suggests that the public’s perceptions about the conduct of monetary policy determine the trade-offs faced by policy-makers, the anchoring of long-run expectations, and the stability of macroeconomic equilibria (e.g., Clarida et al. (2000), Orphanides and Williams (2005), Eggertsson and Woodford (2003), Cogley et al. (2015)). Perceptions of the monetary policy framework are also crucial for financial market reactions to monetary policy surprises and macroeconomic announcements (e.g., Piazzesi (2001), Ang and Piazzesi (2003), Cieslak (2018), Bauer and Swanson (2021), Law et al. (2020), and Bianchi et al. (2022a)).

²Studies estimating low-frequency changes in the monetary policy rule using historical data include Clarida et al. (2000); Kim and Nelson (2006); Boivin (2006); Orphanides (2003); Cogley and Sargent (2005). Notable exceptions to this approach are Bianchi et al. (2022a) and Bianchi et al. (2022b), who use models linking asset prices to the monetary policy rule.

estimate a simple forward-looking monetary policy rule—relating fed funds rate forecasts to inflation forecasts and output gap forecasts in that month’s panel. In line with how historical monetary policy rules are often estimated in practice, we also estimate an inertial rule that controls for the lagged fed funds rate and thereby isolates the perceived short-term monetary policy response to economic conditions. We conduct all our analyses on both estimated rules, and characterize differences based on their interpretation as perceived long-run vs. short-run monetary policy responses.

In our empirical analysis, the coefficient on the output gap in the perceived rule, $\hat{\gamma}_t$, summarizes the Fed’s overall responsiveness to economic conditions for two reasons related to our sample period. First, inflation was relatively stable and close to the Fed’s now-explicit two percent target, which renders the coefficient on inflation less meaningful.³ Second, supply shocks were largely absent until the end of the period. When demand shocks are the dominant drivers of economic fluctuations, the output gap also captures anticipated inflationary pressures, and thus serves as a summary statistic for both parts of the Fed’s dual mandate.

Our first key finding is that the perceived monetary policy rule exhibits substantial variation over time. The Fed’s perceived responsiveness to the output gap, as measured by $\hat{\gamma}_t$, varies between about 0 and 1.5. Variation in the perceived monetary policy rule generally lines up with rolling estimates of the Fed’s historical behavior from time series macroeconomic data. However, it diverges during periods such as the zero-lower-bound and lift-off, when policy in the future is expected to differ significantly from the recent past.

We then show that variation in the perceived policy rule is correlated with the monetary policy cycle and financial conditions, but not with the business cycle. We show that over our sample $\hat{\gamma}_t$ is positively correlated with the slope of the yield curve, a measure of anticipated monetary tightening. Perceived $\hat{\gamma}_t$ tends to be high in the early stages of tightening cycles, indicating that the Fed is perceived to be highly data-dependent at these times. Conversely, when the yield curve is flat or downward-sloping, $\hat{\gamma}_t$ tends to be low—the Fed tries to “get ahead of the curve”—and the policy rate is therefore viewed to be less dependent on the macroeconomic outlook going forward. The Fed’s responsiveness is also perceived to be lower at times of high financial uncertainty, consistent with forecasters perceiving a time-varying monetary policy rule that reflects the Fed’s shifting concerns with current economic data versus financial and other risks. The perceived responsiveness $\hat{\gamma}_t$ does not drop immediately to zero during the first zero-lower-bound (ZLB) period, but instead falls to zero only in

³As noted by [Clarida et al. \(2000\)](#), estimation of the response coefficient on inflation requires a sample with sufficient variation in inflation; otherwise “one might mistakenly conclude that the Fed is not aggressive in fighting inflation” (p. 143).

2011, when the Fed publicly announced its commitment to near-zero policy rates through 2013 (see also [Swanson and Williams \(2014\)](#) and [Campbell et al. \(2019\)](#)).

We next show in Section 3 that perceptions about the monetary policy rule respond to high-frequency monetary policy surprises on Federal Open Market Committee (FOMC) announcement dates in a state-contingent manner. This updating suggests that forecasters have imperfect information about the policy rule prior to announcements of monetary policy decisions. Intuitively, a surprise interest rate increase in a strong economy should signal to forecasters that the Fed’s response to the output gap is strong, whereas a surprise interest rate increase in a weak economy should signal the opposite. We confirm this prediction in the data, showing that the perceived monetary policy output weight $\hat{\gamma}_t$ increases following a positive high-frequency monetary policy surprise conditional on a strong economy, but declines following the same type of surprise conditional on a weak economy. The empirical response peaks about six months after the monetary policy surprise, and its magnitude suggests that monetary policy surprises on FOMC dates would be 50% less volatile if the monetary policy rule were fully known.

Having characterized how the perceived monetary policy rule varies over time and in response to actual monetary policy decisions, we next show that it matters for the key asset prices that transmit monetary policy to the real economy: short- and long-term interest rates. Section 4.1 documents that market interest rates react more strongly during narrow intervals around macroeconomic news surprises when the Fed’s perceived responsiveness from survey data is high. These results link our survey-based estimates of the perceived policy rule to the high-frequency analysis of [Swanson and Williams \(2014\)](#), which documents changes in the market’s sensitivity to macro news. Our high-frequency analysis also validates our estimates of $\hat{\gamma}_t$ using a data source that is completely different than our Blue Chip survey data. Economically, these findings show that the perceived monetary policy rule can “do the central bank’s work for it” ([Woodford, 2005](#)), moving the expected path of rates in response to economic developments before the Fed changes the actual policy rate.

Shifts in the perceived monetary policy rule also have a pronounced impact on long-term interest rates, as we document in Section 4.2. Long-term rates are particularly important for the transmission of monetary policy because they affect mortgages and other borrowing in the economy. We show that policy rule perceptions affect the term premium that investors require for holding long-term bonds, driving a wedge between long-term rates and the expected path of short-term policy rates. Classic finance theory suggests that the higher is $\hat{\gamma}_t$, the more investors expect interest rates to fall, and hence bond prices to rise, in bad economic states. Thus, a higher $\hat{\gamma}_t$ means that investors perceive Treasury bonds to be better hedges, lowering the risk premium they demand. We document precisely this pattern: subjective

risk premia, calculated from survey expectations of future yields as in Piazzesi et al. (2015) and Nagel and Xu (2022) move inversely with $\hat{\gamma}_t$. Consistent with the intuition that risk of long-term bonds should depend more strongly on the perceived long-term monetary policy response to economic conditions, we show that term premia depend most strongly on the perceived $\hat{\gamma}_t$ from the basic rule rather than $\hat{\gamma}_t$ from the inertial rule. Taken together, we provide evidence that term premia in long-term bonds are not disconnected from monetary policy, but instead are linked to monetary policy through the perceived rule.

In Section 5 we present a simple model with imperfect information about the policy rule and forecaster heterogeneity that synthesizes and motivates our empirical findings. The true unobserved monetary policy output gap coefficient follows a random walk, and forecasters learn about it using a Kalman filter. Forecasters receive different signals about the output gap and form policy rate forecasts according to their perceived rule. A key lesson from the model is that regressions of policy rate forecasts onto output gap forecasts in a forecaster-horizon panel recover a consistent estimate of the perceived monetary policy output gap coefficient. Further, the model predicts that forecasters update their perceived monetary policy output weight upwards following a surprise monetary policy tightening that occurs in a strong economy, but their perceived weight downwards following a surprise tightening when the output gap is low. It also predicts that fed funds futures should respond more strongly to macro news when the perceived output weight is high and that bond risk premia are inversely related to the perceived output weight. Adding overconfidence in the precision of one’s own estimate of $\hat{\gamma}_t$ similarly to Angeletos and Lian (2022) generates hump-shaped state-contingent impulse responses for the perceived monetary policy rule, as in the data.

Finally, Section 6 shows two types of robustness exercises. First, we show that our estimates are robust to various alternative specifications, including allowing for heterogeneous beliefs about the Fed’s responsiveness and the inclusion of expected financial conditions in the estimating regressions. Second, we address the well-known concern that policy rule regressions can yield biased estimates because macroeconomic variables endogenously depend on all shocks in the economy, including the monetary policy shock. A simple bias adjustment from a New Keynesian model building on Carvalho et al. (2021) suggests that this bias is unlikely to affect the time-series variation in $\hat{\gamma}_t$ and hence our main results. In addition, our two empirical strategies using high-frequency identified shocks favor an interpretation of $\hat{\gamma}_t$ as a perceived policy rule coefficient, finding that it responds to monetary policy surprises and explains high-frequency interest responses to macro news. Nevertheless, an alternative, more general interpretation of $\hat{\gamma}_t$ as simply the perceived comovement between the short-term policy rate and macroeconomic variables is possible. Under this broader interpretation, many of the take-aways from our empirical analysis remain valid. For example, we show that

this perceived comovement is priced in financial markets and determines bond risk premia.

In summary, using a novel methodology for estimating perceptions of the monetary policy rule from professional forecasts, we establish three key results. First, the perceived monetary policy rule varies significantly over time. Second, forecasters' information about the policy rule updates following monetary policy surprises. Third, variation in the perceived rule impacts financial markets even before Fed policy decisions are actually made, explaining how interest rates respond to macro news over time and the term premium on long-term bonds.

By providing estimates of the perceived monetary policy rule, our paper contributes to the growing literature on incomplete information and monetary policy (e.g., [Mankiw and Reis, 2002](#); [Primiceri, 2006](#); [Coibion and Gorodnichenko, 2015](#); [García-Schmidt and Woodford, 2019](#); [Gabaix, 2020](#); [Angeletos and Lian, 2022](#); [Angeletos and Sastry, 2021](#); [Afrouzi and Yang, 2021](#); [Bordalo et al., 2020](#)). We document that investors learn about the rule from policy decisions, and document that their perceptions of the rule are transmitted into financial market prices like short- and long-term interest rates. [Cogley et al. \(2015\)](#) and [Orphanides and Williams \(2005\)](#) argue that the real cost of a disinflation is substantially higher when agents learn about the monetary policy rule, as our empirical evidence suggests. Our findings are complementary to [Caballero and Simsek \(2022\)](#), who have studied disagreement between the public and the Federal Reserve and its implications for monetary policy surprises as viewed by the public, and [Stein and Sunderam \(2018\)](#), who examine strategic communication between the central bank and market participants. We take a step back and focus on the cross-section of professional forecasters to document that the perceived monetary policy rule indeed varies over time and exhibits interesting and plausible updating properties, consistent with perceptions about the monetary policy framework not being necessarily full information rational. Our evidence is also complementary to evidence on the gap between market and household expectations ([Reis \(2020\)](#)) and the differences across short-term vs. long-term financial institutions ([Bahaj et al. \(2023\)](#)). Our data set represents a set of agents that are plausibly relevant for how perceptions about monetary policy transmit to financial markets, as a typical forecaster in our data is a chief economist at a large broker-dealer. In addition, our work connects to the debate on rules versus discretion in monetary policy going back to [Kydland and Prescott \(1977\)](#) and [Taylor \(1993\)](#). While our results do not speak directly to the optimal conduct of monetary policy, they suggest that in practice monetary policy strategy varies significantly over time, consistent with the arguments of advocates for discretion.

Our paper contributes to an evolving empirical literature on the estimation of monetary policy rules from financial and survey data. [Hamilton et al. \(2011\)](#) estimate a market-

perceived rule using high-frequency responses to macroeconomic news; We build on the methodologies of [Kim and Pruitt \(2017\)](#), who estimate the perceived rule using consensus survey and [Andrade et al. \(2016\)](#) and [Carvalho and Nechio \(2014\)](#), who use individual survey forecasts with constant parameter rules, with at most one single parameter break. We go beyond these prior studies by studying higher-frequency variation in the perceived monetary policy framework, which allows us to characterize the perceived rule’s response to high-frequency monetary policy surprises, and its pricing in short- and long-term rates. Our methodology for estimating monetary policy rules takes the idea of using linear regressions for monetary policy rules—in the manner of [Taylor \(1999\)](#)—and applies it to forward-looking multidimensional panel data from survey forecasts. The advantages of this approach include its simplicity and comparability to the prior literature.

Finally, we contribute to a large and growing macro-finance literature on the financial market impacts of monetary policy (e.g., [Cochrane and Piazzesi, 2002](#); [Gürkaynak et al., 2005](#); [Hanson and Stein, 2015](#); [Nakamura and Steinsson, 2018](#)). Some recent studies connect this issue to perceptions about monetary policy, as we do: [Bianchi et al. \(2022b\)](#) study FOMC announcements and perceptions of regime-switching policy rules in a New Keynesian asset pricing model, and [Haddad et al. \(2021\)](#) estimate the option-implied state-contingency of the Fed’s corporate bond purchases during the pandemic. Our empirical approach is different as we directly estimate policy rule perceptions from survey data. It has the added advantage of covering a long sample period, which allows us to study time-variation in the perceived monetary policy rule, and test directly for its transmission to financial markets.

2 Data and estimation

This section describes the details of our survey data set and the main regression specifications. It then provides some simple descriptive statistics describing the time variation in the estimated perceived monetary policy rule parameters.

2.1 Blue chip survey data

Our main data source is the Blue Chip Financial Forecasts (BCFF) survey, a monthly survey of professional forecasters going back to 1982. The survey asks for forecasts of interest rates, including the federal funds rate and Treasury yields of different maturities. The BCFF is ideal for recovering a perceived rule because it asks forecasters about their *assumptions* about real GDP growth and CPI inflation used to make interest rate forecasts, and individual forecasts are recorded with forecaster institution information. The number of participants

each month ranges from 30 to 50 different institutions. We start in 1985 because the data quality is poor in the first few years of the survey. Our survey data ends in April 2023 for a total of 460 monthly surveys.

The timing of the surveys is such that calendar time is monthly but forecasts are made for the current quarter and each quarter up to five quarters ahead.⁴ To simplify the notation, we measure time t in months, unless otherwise stated. For example, for the current-quarter forecast in the January 2000 survey, $t + h$ corresponds to March 2000 and $h = 2$. We denote individual j 's forecast of the federal funds rate made at t for the funds rate at $t + h$ by $E_t^{(j)}i_{t+h}$.

Our rules are specified in terms of forecasts of federal funds rate – the policy rate of the Federal Reserve – the output gap, and 4-quarter CPI inflation. We transform macroeconomic forecasts, since empirical monetary policy rules are usually specified in terms of year-over-year inflation and activity gap measures, such as the output gap (e.g., Taylor, 1999). We use CPI inflation forecasts, and we calculate year-over-year inflation forecasts $E_t^{(j)}\pi_{t+h}$. Output gap forecasts are calculated as the deviation of the GDP forecasts from the potential GDP projections in percentage points:

$$E_t^{(j)}x_{t+h} = 100 \frac{E_t^{(j)}Y_{t+h} - E_t Y_{t+h}^*}{E_t^{(j)}Y_{t+h}^*},$$

where x_t is the output gap and Y_t^* is potential GDP in the quarter ending in t . We use real-time vintages from ALFRED for the level of real GDP and potential GDP projections from immediately before the survey with a small number of exceptions. It is worth emphasizing that our output gap projections assume that all forecasters share the same potential output forecasts, equal to the CBO projection. Across surveys, horizons, and forecasters, there are over 115,000 individual forecasts. All the forecasts we use exhibit significant within-month variation, across both forecasters and horizons. For detailed descriptions of the BCFF data and summary statistics see Appendix A.

2.2 Baseline policy rule specification

We now turn to the estimation of a perceived policy rule from monthly forecaster-horizon panels of forecasts for the fed funds rate, inflation, and the output gap. Our starting point is a standard simple policy rule (e.g., Taylor, 1999; Orphanides, 2003; Taylor and Williams, 2010):

$$i_t = r_t^* + \pi_t^* + \gamma_t x_t + \beta_t (\pi_t - \pi_t^*) + u_t, \tag{1}$$

⁴Before 1997, the forecast horizon extends out only four quarters.

where π_t^* is the inflation target, r_t^* is the equilibrium real interest rate, and the equilibrium nominal short-term interest rate is $i_t^* = r_t^* + \pi_t^*$. The key parameters are β_t and γ_t , the coefficients on the inflation gap and the output gap.⁵ Finally, u_t is a monetary policy shock that is exogenous to the policy rule.

Our estimation of the time- t perceived monetary policy coefficients $\hat{\gamma}_t$ and $\hat{\beta}_t$ then relies on a forecaster-horizon panel regression of the form:

$$E_t^{(j)} i_{t+h} = \underbrace{c_t^{(j)}}_{E_t^{(j)} r_t^* + (1-\hat{\beta}_t) E_t^{(j)} \pi_t^*} + \hat{\gamma}_t E_t^{(j)} x_{t+h} + \hat{\beta}_t E_t^{(j)} \pi_{t+h} + e_{th}^{(j)}, \quad (2)$$

where $c_t^{(j)}$ is a forecaster fixed effect. Figure 1 shows the estimated output gap coefficients $\hat{\gamma}_t$ in the top panel and estimated inflation coefficients $\hat{\beta}_t$ in the bottom panel.

The central assumption under which a regression of this form allows us to recover the time-varying perceived monetary policy rule is that forecasters “agree to disagree” about the economy, and form their interest rate forecasts according to the perceived rule. This is the same assumption as in Caballero and Simsek (2022), and we discuss it in more detail in the motivating model in Section 5. We hereby build on the large literature that has documented that expectations differ across different financial institutions and across households (e.g. Mankiw, Reis and Wolfers (2003)) and link differences in economic forecasts to different forecasted policy rates. On average, the regression (2) has an R^2 of 70% (including forecaster fixed effects), indicating that a simple monetary policy rule fits the forecast data well. The same regression without forecaster fixed effects has an R^2 of 33%, indicating a strong relationship between funds rate, output gap, and inflation forecasts.

In our analysis, we focus on the estimates with forecaster fixed effects because estimates without these fixed effects are consistent only if the forecaster specific intercept $c_t^{(j)}$ is uncorrelated with the macro forecasts for all h . By contrast, the fixed effects estimates will be consistent if $c_t^{(j)}$ is correlated with the macro forecasts, which likely is the more relevant case. We consider extensive robustness to this specification in Section 6, and show that the time-variation in $\hat{\gamma}_t$ is fundamentally unchanged if we drop the fixed effects, allow for heterogeneous perceived rule parameters across forecasters, include forecasts of financial conditions in the rule, and adjust for the endogeneity of output to monetary policy using a simple New Keynesian model.

⁵In contrast to Andrade et al. (2016), we specify the perceived monetary policy rule in terms of the output gap rather than GDP growth and estimate time-varying monetary policy coefficients. Our specification is consistent with the literature and matches variation in interest rate disagreement across different forecast horizons, see Appendix A.2.

2.3 Inertial policy rule specification

Our baseline monetary policy rule (1) does not include an inertial term on the lagged fed funds rate forecast because the regression intercept already absorbs the time- t level of the policy rate. However, much theoretical and empirical research has documented the relevance of interest-rate smoothing and policy inertia (e.g., Brainard (1967), Taylor (1999), Woodford (2003), Bernanke (2004), Taylor and Williams (2010)). Therefore we also consider an inertial policy rule of the following form:

$$i_t = r_t^* + \pi_t^* + \gamma_t x_t + \beta_t(\pi_t - \pi_t^*) + \rho_t i_{t-1} + u_t, \quad (3)$$

which leads us to estimate the time-varying perceived inertial rule at time t using a forecaster-horizon panel:

$$E_t^{(j)} i_{t+h} = \underbrace{c_t^{(j)}}_{E_t^{(j)} r_t^* + (1-\hat{\beta}_t) E_t^{(j)} \pi_t^*} + \hat{\gamma}_t E_t^{(j)} x_{t+h} + \hat{\beta}_t E_t^{(j)} \pi_{t+h} + \hat{\rho}_t E_t^{(j)} i_{t+h-1} + e_{th}^{(j)}. \quad (4)$$

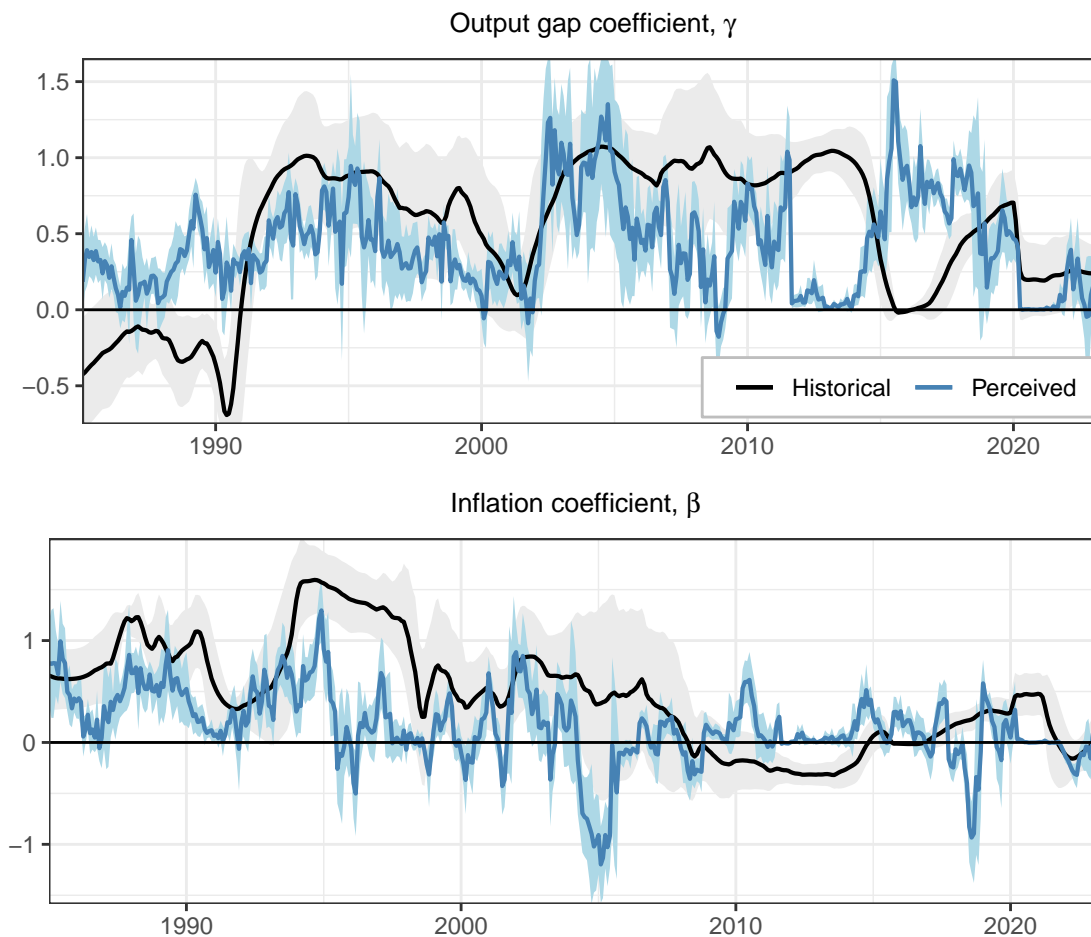
Figure 2 shows the estimated output gap coefficients $\hat{\gamma}_t$ in the top panel and estimated inflation coefficients $\hat{\beta}_t$ in the bottom panel. Like our baseline rule, the perceived inertial rule is estimated with forecaster fixed effects. The coefficients β_t and γ_t from the inertial rule (3) are the perceived *short-run responses* of monetary policy to inflation and the output gap, with long-run responses given by $\beta_t/(1 - \rho_t)$ and $\gamma_t/(1 - \rho_t)$ provided that $|\rho_t| < 1$. Economically, the perceived inertial rule estimate $\hat{\gamma}_t$ therefore captures the perceived short-run monetary policy response to the economy, whereas the baseline perceived $\hat{\gamma}_t$ captures the perceived long-run response.

2.4 Perceived vs. historical rules

To show that our estimates of the perceived rules are reasonable, we superimpose rolling estimates of the historical rule followed by the Fed. Specifically, we regress the federal funds rate on inflation, measured as the annual percentage change in the CPI index, and the output gap, measured as percent deviation of real GDP from CBO potential output, and report the estimated time-varying coefficients. The rolling inertial rule additionally includes the one-quarter lagged federal funds rate as in (3). We choose a seven-year rolling window to strike a balance between allowing for sufficient variation in the parameters and mimicking the forecast horizons available in BCFF (requiring a shorter window) and obtaining sufficiently

precise estimates (requiring a longer window).⁶

Figure 1: Estimated time-varying perceived baseline policy rule



Estimated policy-rule parameters $\hat{\gamma}_t$ and $\hat{\beta}_t$ from month-by-month panel regressions (2), using Pooled OLS (OLS) and forecaster Fixed Effects (FE). FE estimates include 95% confidence intervals based on standard errors with two-way clustering (by forecasters and horizon). The sample consists of monthly Blue Chip Financial Forecast surveys from January 1985 to April 2023.

The baseline $\hat{\gamma}_t$ estimate varies in a range from zero to about 1.5. As expected, the estimates of the output gap coefficient $\hat{\gamma}_t$ are generally positive, and usually statistically significant. The average level of the baseline estimate is 0.43, in line with policy rules in the literature. For example, the original Taylor (1993) rule used an output gap coefficient of 0.5, while Clarida et al. (2000) estimate a coefficient of 0.3 for the pre-Volcker period and 0.9 for the post-Volcker period. Prior to 2010, the correlation between the estimated output

⁶The upward-shift in the historical output gap weight post-2000 in the historical rule is similar to the historical estimates in Bauer and Swanson (2022), which use a much longer estimation window and therefore isolate longer-term movements. We find a lower historical inflation weight because our shorter rolling windows feature relatively little variation in inflation.

gap coefficients $\hat{\gamma}_t$ for the perceived and historical rules is 0.45. The average levels are also similar.

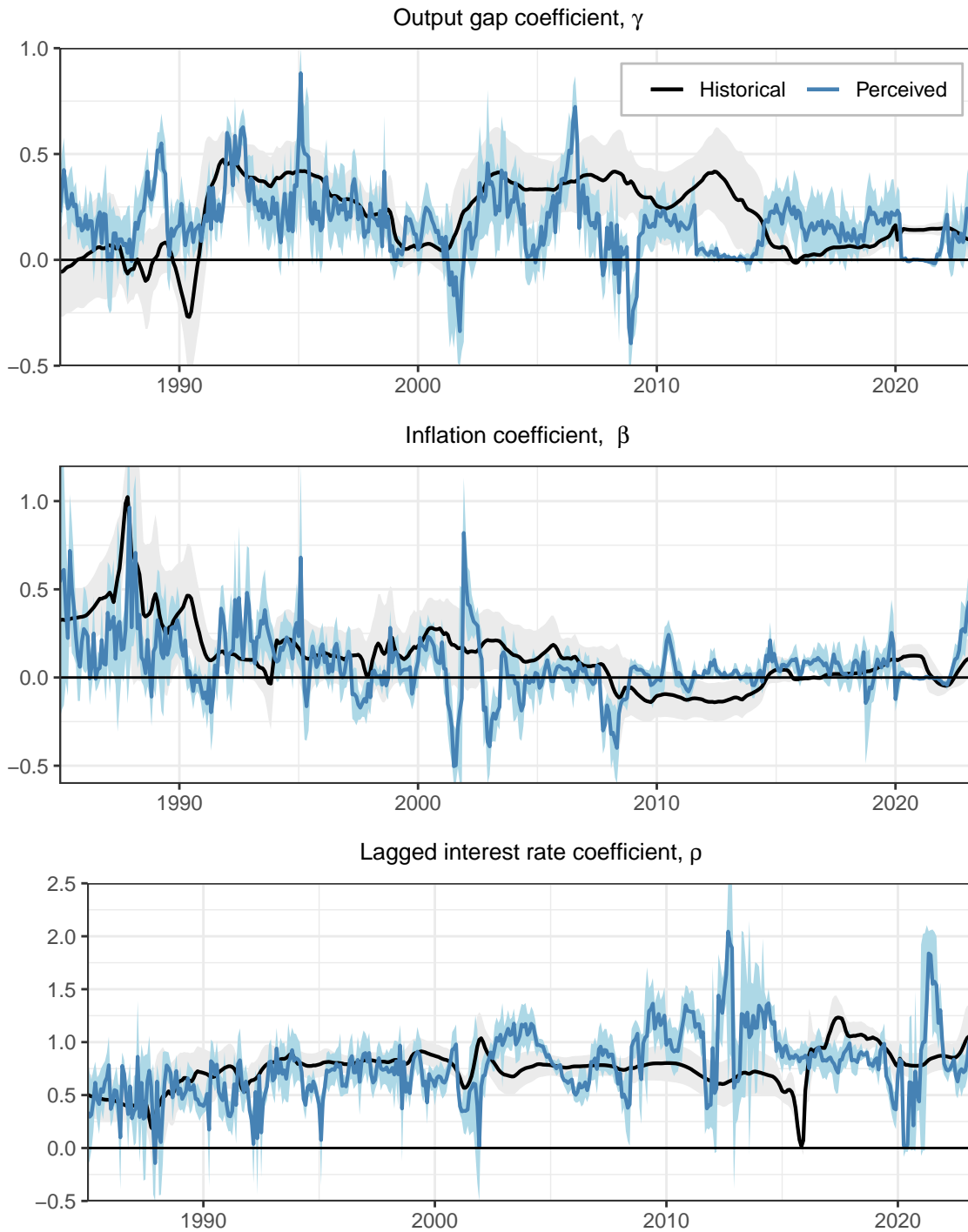
In the post-2010 period, the historical and perceived rules differ, illustrating the value of our approach. The difference is driven by the fact that our perceived rule is estimated using forward-looking survey expectations, while the historical rule is estimated using backward-looking historical data. For instance, the perceived sensitivity to the output gap, $\hat{\gamma}_t$ plummets to zero in September 2011 after the Federal Reserve’s announcement that it would maintain “exceptionally low levels for the federal funds rate at least through mid-2013.”⁷ The historical rule captures this change with significant delay, dropping to zero only in 2015. However, by this time the Fed was already engaged in “data-dependent” tightening, as correctly captured by the rise in perceived $\hat{\gamma}_t$.⁸ Appendix Figure A.3 provides a plot of baseline $\hat{\gamma}_t$ with key event dates.

The perceived inflation coefficient $\hat{\beta}_t$ generally fluctuates around zero. It is persistently positive only over the first few years of our sample, rising again sharply at the very end of the sample. The level and time-variation of the perceived $\hat{\beta}_t$ are similar to the rolling historical rule. While this pattern contrasts with typical empirical and optimal policy rules, which feature an inflation coefficient exceeding unity in line with the “Taylor principle” (Taylor, 1993), it simply reflects the fact that our sample period featured mostly low and stable inflation, and it was arguably dominated by demand shocks. As noted by Clarida et al. (2000), with limited variability in inflation the estimated coefficient in policy rules should be expected to be low, even if the central bank was in fact committed to stable inflation. Consistent with this interpretation, we see that the estimated $\hat{\beta}_t$ rises substantially at the end of the sample, the first time in the sample where the Fed faced persistent inflationary pressures in part due to supply shocks. When inflation is expected to move up and down a stable Phillips curve, as it was over most of our sample, the perceived output gap coefficient $\hat{\gamma}_t$ serves as a summary statistic of the Fed’s overall responsiveness to economic conditions. We therefore focus on the time-variation in $\hat{\gamma}_t$ in the remainder of our analysis.

⁷See the FOMC statement of September 21, 2011 available at <https://www.federalreserve.gov/newsevents/pressreleases/monetary20110921a.htm>. Campbell et al. (2012) also discuss the significance of this announcement for the switch from “Delphic” to “Odyssean” forward guidance.

⁸Among many mentions of “data-dependence” around this period, see, Janet Yellen’s 12/2/2015 speech “The Economic Outlook and Monetary Policy”. Our interpretation of the tightening cycle 2003-2006 differs from Lunsford (2020). While he interprets this as a period of relatively data-independent commitment to future interest rates, we estimate the perceived data dependency $\hat{\gamma}$ to be high. Our estimates are backed up by a strong response of interest rates to output gap relevant macroeconomic news during this period, noted at the time by then-Governor Ben Bernanke: “Because of the FOMC’s communication strategy, which has linked future rate changes to the levels of inflation and resource utilization (...), markets have responded to recent data on payrolls, spending, and inflation by bringing forward a considerable amount of future policy tightening into current financial conditions.” (May 20, 2004, Remarks by Governor Ben S. Bernanke).

Figure 2: Estimated time-varying perceived inertial policy rule



Estimated policy-rule parameters $\hat{\rho}_t$, $\hat{\gamma}_t$ and $\hat{\beta}_t$ from month-by-month panel regressions (4), using Pooled OLS (OLS) and forecaster Fixed Effects (FE). FE estimates include 95% confidence intervals based on standard errors with two-way clustering (by forecasters and horizon). The sample consists of monthly Blue Chip Financial Forecast surveys from January 1985 to April 2023.

Finally, the inertial coefficient $\hat{\rho}_t$ shown in Figure 2 also exhibits significant and intuitive time variation. At low frequencies, it has trended up over time. Its average value is 0.6 prior to 2000 and 0.89 after, consistent with other evidence that the Fed has become more gradual over time (Coibion and Gorodnichenko (2012), Campbell et al. (2020)). $\hat{\rho}_t$ is also estimated to be very close to one during the two periods in our sample where policy was at the zero lower bound. Since the Fed tends to follow monetary policy cycles, where small increases tend to be followed by more small increases in the future, our estimated $\hat{\rho}_t$ sometimes even exceeds one. To the extent that monetary policy cycles tend induce a constant upward bias in $\hat{\rho}_t$, time variation in $\hat{\rho}_t$ should still be captured by our estimates.

2.5 Correlations with cyclical variables

Table 1 shows that the time-varying perceived monetary output gap coefficient $\hat{\gamma}_t$ is significantly correlated with the monetary policy cycle and financial conditions, but its correlation with the business cycle is ambiguous. Column (1) shows that $\hat{\gamma}_t$ is positively correlated with the slope of the yield curve. In Table 1, we think of the slope of the yield curve as primarily capturing the expected path of short-term rates and the stance of monetary policy (Rudebusch and Wu, 2008), even though it also includes a risk premium (Campbell and Shiller, 1991). We have found that lagged values of the slope are more strongly correlated with $\hat{\gamma}_t$, so the slope is lagged by one year in these regressions. Column (2) reiterates the empirical relationship with the monetary policy cycle using a dummy for monetary policy tightening cycles. Column (4) shows that the direct association with the ZLB (defined as September 2008 through November 2015) is weak because it mixes two types of ZLB periods. During the first half of the ZLB prior to September 2011, perceived $\hat{\gamma}_t$ was quite elevated, as the Fed was expected to lift off from the ZLB soon.⁹

The association between perceived $\hat{\gamma}_t$ with monetary policy tightening vs. easing episodes is consistent with anecdotal evidence. For instance, the FOMC meeting minutes from January 29-30, 2001 described the sequence of large interest rate cuts in that month as “front-loaded easing policy”, while the New York Times noted that “investors and analysts do not expect the Fed to be as fast in cutting rates in the months ahead”. Similarly, the FOMC committee conference call on January 9, 2008 described interest rate cuts as “taking out insurance against (...) downside risks.” On the other hand, rate increases are often publicly characterized as “data-dependent”, including communication by all three recent Fed Chairs Bernanke, Yellen and Powell.

Columns (3) and (5) of Table 1 show that the perceived monetary policy output gap

⁹This mixed evidence on the ZLB is consistent with the evidence from Swanson and Williams (2014), who find that long-term rates remained sensitive to macroeconomic news through 2011.

Table 1: The perceived monetary policy rule and cyclical variables

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A: Baseline $\hat{\gamma}$</i>						
Slope (12m lag)	0.12*** (0.03)					0.13*** (0.03)
Tightening		0.21** (0.08)				
Easing		0.04 (0.08)				
Unemployment			-0.02 (0.02)			
ZLB				-0.12 (0.11)		-0.18** (0.09)
VIX					-0.01*** (0.004)	-0.01*** (0.004)
Constant	0.20*** (0.06)	0.35*** (0.05)	0.54*** (0.14)	0.46*** (0.05)	0.72*** (0.09)	0.45*** (0.09)
R ²	0.18	0.08	0.01	0.03	0.12	0.32
<i>Panel B: Inertial $\hat{\gamma}$</i>						
Slope (12m lag)	0.04** (0.01)					0.04*** (0.01)
Tightening		0.03 (0.03)				
Easing		-0.04 (0.04)				
Unemployment			-0.01 (0.01)			
ZLB				-0.10*** (0.03)		-0.11*** (0.03)
VIX					-0.01*** (0.002)	-0.01*** (0.002)
Constant	0.10*** (0.03)	0.18*** (0.02)	0.20*** (0.05)	0.20*** (0.02)	0.32*** (0.05)	0.25*** (0.05)
R ²	0.07	0.03	0.003	0.08	0.14	0.28
<i>N</i>	460	460	460	460	448	448

Regressions for $\hat{\gamma}_t$ in monthly data from January 1985 to April 2023. Top panel shows results for the baseline estimate of $\hat{\gamma}_t$, bottom panel for the inertial-rule estimate of $\hat{\gamma}_t$. *Slope*: slope of the yield curve measured as the second principal component of Treasury yields from [Gürkaynak et al. \(2007\)](#), lagged by twelve months; *Tightening* and *Easing*: indicator variables for the months from the first to the last change in the fed funds rate of monetary tightening or easing cycles; *Unemployment* is the unemployment rate; *ZLB* is an indicator variable for zero lower bound periods; *VIX*: CBOE Volatility Index from 1990 onwards, and S&P 100 Volatility Index 1985–1989. Regressions use a one-month lead of $\hat{\gamma}_t$ to account for the publication lag. Newey-West standard errors using 12 lags in parentheses.

coefficient $\hat{\gamma}_t$ is lower when financial uncertainty, measured by the VIX, is high, but is not strongly related with the unemployment rate. When financial uncertainty is high, the Fed has tended to ease in our sample, so this provides additional color on the relationship between the perceived monetary policy output coefficient and the monetary policy cycle. In a related paper, [Cieslak et al. \(2022\)](#) study how policymakers’ uncertainty impacts the level of the policy rate, whereas our analysis suggests that greater economic and financial uncertainty can also impact how the policy rate responds to the output gap. One interpretation is that news of financial stress has tended to lower the Fed’s concern with the real economy, consistent with a “Fed put” ([Cieslak and Vissing-Jorgensen, 2021](#)).¹⁰ The multivariate regression in column (6) shows that both the slope of the yield curve and the VIX remain economically and statistically significant.

Taken together, we find an association between the perceived output gap coefficient $\hat{\gamma}_t$ with the slope of the yield curve and financial conditions, but no significant relationship with the business cycle. While this evidence may partly arise from a more complicated perceived monetary policy rule that changes systematically with financial conditions, a dependence on financial conditions may also have been unanticipated and a result of monetary policy “discretion” within our specific sample. Further, the explanatory power of cyclical variables for $\hat{\gamma}_t$ is far from perfect, leaving room for forecasters to update about unpredictable shifts in the actual monetary policy rule.

3 Responses to high-frequency monetary policy surprises

Do forecasters revise their perceived monetary policy rule in response to actual decisions taken by the Fed? We next show that the perceived rule responds to high-frequency monetary policy surprises on FOMC announcement dates, consistent with the idea that forecasters have imperfect information and update their views based on policy decisions. Under the assumption that changes in market rates around FOMC announcements are mainly due to the monetary policy announcement itself, they reflect the surprise component of the monetary policy actions. This surprise component combines pure monetary policy shocks and—to the extent that the markets do not have full information about the monetary policy rule—news about the Fed’s response to economic data (see also [Romer and Romer, 1989](#);

¹⁰Table 4 shows that including forecasters’ expectations of financial conditions directly in our perceived monetary policy rule estimation does not qualitatively change our estimates of the perceived output gap response $\hat{\gamma}_t$, while the results here show that the estimated $\hat{\gamma}_t$ itself tends to vary with realized financial conditions.

Bauer and Swanson, 2021, 2022).¹¹

The idea that economic agents do not have full information about the Fed’s monetary policy rule has testable implications for how forecasters should update their perceptions about monetary policy. In particular, the perceived rule should update in a state-contingent manner after monetary policy surprises. Intuitively, a tightening surprise in an economic boom suggests that the Fed is even more committed to reigning in an overheating economy than previously believed. Therefore, this kind of surprise should lead to an increase in $\hat{\gamma}_t$. By contrast, a tightening surprise during a recession would signal less Fed concern with output stabilization, so forecasters would tend to revise downward $\hat{\gamma}_t$. This logic is formalized in our model in Section 5 below.

We empirically investigate belief updating by studying the evolution of $\hat{\gamma}_t$ in response to monetary policy surprises, calculated from changes in high-frequency money market futures rates around FOMC announcements (following [Gürkaynak et al., 2005](#); [Nakamura and Steinsson, 2018](#), and many others). We follow [Bauer and Swanson \(2022\)](#) and measure the monetary policy surprise, mps_t , as the first principal component of 30-minute changes in several Eurodollar futures rates around the FOMC announcement. This measure, which is available from 1988 to 2023, captures changes in policy rate expectations over a horizon of about a year, and thus includes changes in forward guidance. We normalize the surprise to have a unit effect on the four-quarter-ahead Eurodollar futures rate, measured in percentage points. We convert the announcement-frequency surprises to a monthly series by summing them if there is more than one announcement during a month, and setting $mps_t = 0$ if there are no announcements during month t , following [Gertler and Karadi \(2015\)](#) and others.

We estimate the following state-dependent local projection regressions:

$$\hat{\gamma}_{t+h} = a^{(h)} + b_1^{(h)}mps_t(1 - weak_t) + b_2^{(h)}mps_tweak_t + c^{(h)}weak_t + d^{(h)}\hat{\gamma}_{t-1} + \varepsilon_{t+h}, \quad (5)$$

and calculate Newey-West standard errors with $1.5h$ lags.¹² To capture episodes when the economy is growing slowly and economic slack is high, we define an indicator variable $weak_t$, which equals one when the output gap is below its median and zero otherwise.¹³ The regressions control for lagged $\hat{\gamma}_t$ to account for serial correlation in the perceived policy rule coefficient. We estimate these local projections for horizons h from zero to twelve months.

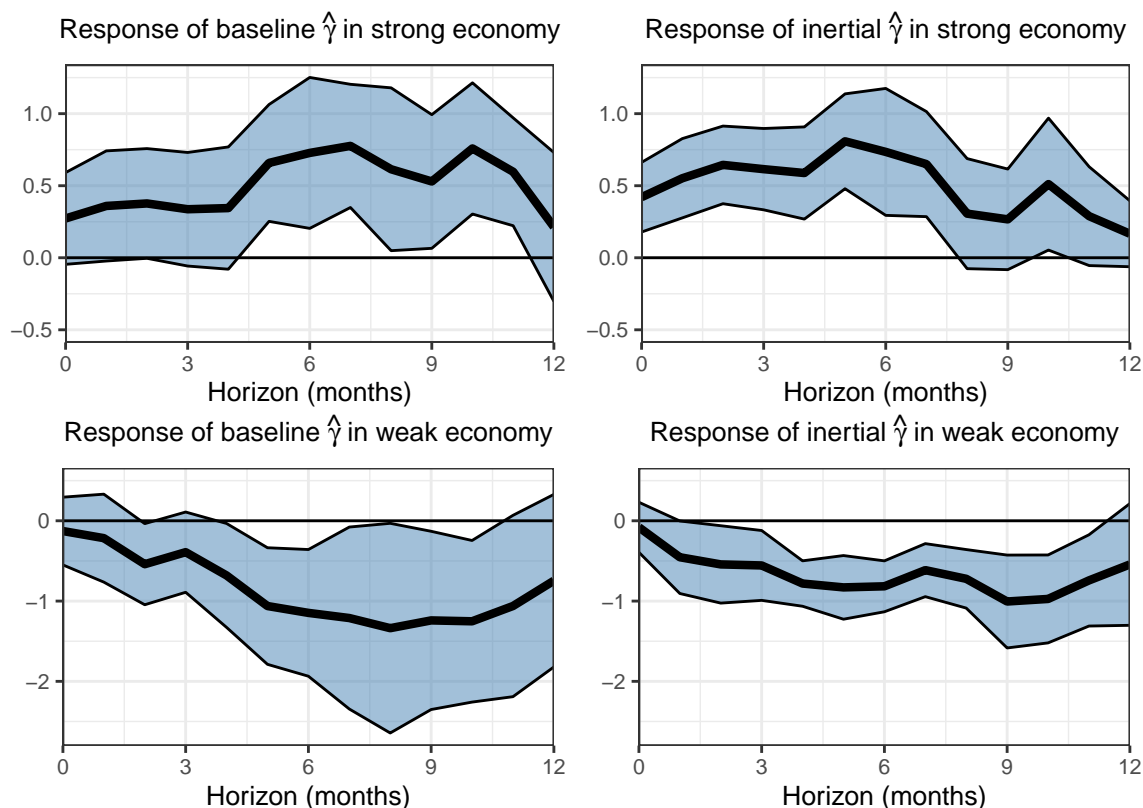
¹¹High-frequency monetary policy surprises may in addition contain information about output when there is a Fed information effect ([Nakamura and Steinsson \(2018\)](#)). However, such an effect would be unlikely to move $\hat{\gamma}_t$, given that it has little correlation with standard business cycle variables in Table 1.

¹²Our estimation method for state-dependent local projections using identified shocks follows [Ramey and Zubairy \(2018\)](#).

¹³For this classification, we calculate the output gap using the real GDP data and CBO potential output estimates from FRED.

The sample period is from January 1988 to April 2023.

Figure 3: Response to high-frequency monetary policy surprise



State-dependent local projections for $\hat{\gamma}_t$, using regressions $\hat{\gamma}_{t+h} = a^{(h)} + b_1^{(h)} mps_t(1 - weak_t) + b_2^{(h)} mps_t weak_t + c^{(h)} weak_t + d^{(h)} \hat{\gamma}_{t-1} + \varepsilon_{t+h}$, where mps_t is the monetary policy surprise, and $weak_t$ is an indicator for whether the output gap during month t was below the sample median. The top panels show estimates of $b_1^{(h)}$, and the bottom panels show estimates of $b_2^{(h)}$. Estimates in the left panels use the baseline estimate of $\hat{\gamma}_t$, and the estimates in the right panels use the inertial rule estimate. Shaded areas are 95% confidence bands based on Newey-West standard errors with $1.5 \times h$ lags. Sample: monthly data January 1988–April 2023.

The impulse responses of the perceived monetary policy coefficient are shown in Figure 3, and they strongly support the prediction of a state-dependent response of $\hat{\gamma}_t$ to monetary policy surprises. The left two panels show responses for the baseline estimate of $\hat{\gamma}_t$, while the right two panels show them for the inertial rule estimate. The top panels plot estimates of $b_1^{(h)}$ against h and show that there is a pronounced and persistent positive response of $\hat{\gamma}_t$ to monetary policy surprises when the economy is strong. The responses peak between six and nine months, and are statistically significant for several horizons, judging by the 95%-confidence bands shown in the plots. In line with our hypothesis, the picture reverses in the bottom panels, which show persistently negative responses when the economy is weak. These responses are roughly symmetric. The responses for the inertial rule parameter, shown in the top right and bottom right panels, are similar and estimated somewhat more precisely.

A one percentage point monetary policy surprise leads to an increase in $\hat{\gamma}_t$ of roughly 0.7 conditional on a strong economy. The same monetary policy surprise is estimated to lead to a similar size decrease in $\hat{\gamma}_t$ conditional on a weak economy. The magnitudes in Figure 3 are economically meaningful relative to the standard deviation of the baseline $\hat{\gamma}_t$ (0.3) and inertial $\hat{\gamma}_t$ (0.15). Consistent with the pronounced differences in the estimated responses in the top and bottom panels, Appendix B shows that the interaction effect $mps_t \times weak_t$ is statistically significant.

Overall, the evidence in this section suggests that the actual monetary policy rule is time-varying and at least partly unknown, as forecasters learn about it from monetary policy surprises. Their updating about the rule depends on the state of the economy, as predicted by the simple learning model if monetary policy surprises are informative about the Fed’s response to economic data. In addition, the perceived responsiveness $\hat{\gamma}_t$ appears to update somewhat gradually over the six months following monetary policy surprises.

4 Transmission to financial markets

Having examined the drivers of variation in the perceived monetary policy rule, we next show that the perceived monetary policy rule affects the key asset prices that transmit monetary policy to the real economy: short- and long-term interest rates.

4.1 Interest rate responses to macroeconomic news surprises

This section examines interest rate responses to macroeconomic news surprises in narrow announcement windows. In particular, we show that interest rates respond more strongly to macroeconomic news, such as nonfarm payroll surprises, when the estimated $\hat{\gamma}_t$ is high. We estimate event-study regressions of the form

$$\Delta y_t = b_0 + b_1 \hat{\gamma}_t + b_2 Z_t + b_3 \hat{\gamma}_t Z_t + \varepsilon_t, \quad (6)$$

where Δy_t is change in yield y on announcement date t and Z_t is a macroeconomic announcement surprise (i.e., the realized announcement value relative to survey expectations of the announcement the day before). Macroeconomic announcement surprises have been used extensively to identify the effects of monetary policy on financial markets, including Hamilton et al. (2011), Law et al. (2020) and Swanson and Williams (2014).

Our regression specification in equation (6) is closely related to the empirical setup of Swanson and Williams (2014), who also document time variation in the high-frequency responses of financial market variables to macroeconomic news announcements. Like them, we

rely on the identification assumption that the information released during narrow intervals around macroeconomic announcements is primarily about the macroeconomy, and that interest rates responses reflect the anticipated Fed response to this macroeconomic news. The key difference is that [Swanson and Williams \(2014\)](#) allow the magnitude of the response to vary over time in an unrestricted fashion, while we directly tie it to our estimates of the perceived monetary policy rule.¹⁴ Specifically, a positive interaction coefficient b_3 reveals that our estimates of $\hat{\gamma}_t$ are consistent with the perceived monetary policy rule in financial markets.

We study the responses of four different interest rates: 3-month and 6-month federal funds futures rates, and 2-year and 10-year Treasury yields. Fed funds futures provide the closest match to the policy rate used in the estimation of $\hat{\gamma}_t$ from survey data, and we include results for medium-term and long-term Treasury bond yields for comparability with [Swanson and Williams \(2014\)](#). The left four columns in [Table 2](#) use the single most influential macroeconomic announcement, nonfarm payroll surprises, as Z_t . The right four columns use a linear combination of all macroeconomic surprises. Following [Swanson and Williams \(2014\)](#), this linear combination is simply the fitted value of the regression of the high-frequency interest rate change on all macroeconomic news. In [Table 2](#), panel A reports results for baseline estimate of $\hat{\gamma}_t$, while panel B uses the inertial estimate.

[Table 2](#) shows that our coefficient of interest, b_3 , is uniformly estimated to be positive and is statistically significant across almost all combinations of interest rates, macroeconomic news, and estimates of $\hat{\gamma}_t$.¹⁵ The interaction between macroeconomic surprises with inertial $\hat{\gamma}_t$ enters even more strongly, especially for shorter-term interest rate changes, confirming the economic interpretation of inertial $\hat{\gamma}_t$ as a perceived short-term monetary policy response that adjusts for the perceived lag in monetary policy. The magnitudes for both versions of $\hat{\gamma}_t$ are economically meaningful. For instance, the estimates in [Table 2](#) suggest that interest rates do not respond to nonfarm payroll surprises when $\hat{\gamma}_t$ is zero and strongly respond when it is positive. Similarly, the estimates for all macroeconomic announcements suggest that the sensitivity of interest rates to macro news is two to four-times higher when $\hat{\gamma}_t = 1$ than it is when $\hat{\gamma}_t = 0$.

Overall, the evidence in [Table 2](#) suggests that the perceived monetary policy rule is priced in financial markets. It seems plausible that there is no information about monetary policy shocks in narrow time intervals around nonfarm payroll and other macroeconomic

¹⁴Because there are many more Bluechip forecasts in a given month than macro news announcements, our methodology allows us to measure time variation in the perceived policy rule at higher frequencies than [Swanson and Williams \(2014\)](#).

¹⁵The only exceptions are 3- and 6-month fed funds futures, for all macro announcements and the baseline rule. This is potentially because the Fed sometimes acts with a significant lag, as in 2021 and 2022.

Table 2: Sensitivity of interest rates to macroeconomic news announcements

Panel A: Baseline $\hat{\gamma}_t$								
	Z=Nonfarm Payroll				Z=All Announcements			
	3m FF	6m FF	2y Tsy	10y Tsy	3m FF	6m FF	2y Tsy	10y Tsy
$\hat{\gamma}$	0.3 (0.18)	0.4* (0.22)	0.07 (0.28)	-0.02 (0.31)	0.3 (0.18)	0.3 (0.23)	0.3 (0.30)	0.07 (0.32)
Z	0.000 (0.0003)	0.000 (0.0003)	0.000 (0.0003)	0.001*** (0.0002)	0.8*** (0.22)	0.8*** (0.17)	0.7*** (0.13)	0.8*** (0.13)
$\hat{\gamma} \times Z$	0.04*** (0.006)	0.07*** (0.007)	0.09*** (0.009)	0.07*** (0.009)	0.5 (0.40)	0.5 (0.32)	0.8*** (0.26)	0.6** (0.25)
Const.	-0.1 (0.11)	-0.1 (0.13)	-0.3 (0.16)	-0.2 (0.17)	-0.1 (0.11)	-0.2 (0.13)	-0.09 (0.17)	-0.02 (0.18)
N	3999	3999	3999	3999	3999	3999	3999	3999
R^2	0.03	0.05	0.06	0.03	0.02	0.04	0.05	0.04

Panel B: Inertial $\hat{\gamma}_t$								
	Z=Nonfarm Payroll				Z=All Announcements			
	3m FF	6m FF	2y Tsy	10y Tsy	3m FF	6m FF	2y Tsy	10y Tsy
$\hat{\gamma}$	0.7 (0.43)	0.3 (0.55)	-0.2 (0.67)	0.05 (0.71)	0.5 (0.46)	0.01 (0.59)	0.2 (0.73)	0.3 (0.75)
Z	-0.000 (0.0004)	-0.001 (0.0005)	-0.000 (0.0007)	0.000 (0.0005)	0.6*** (0.19)	0.6*** (0.14)	0.6*** (0.12)	0.7*** (0.13)
$\hat{\gamma} \times Z$	0.09*** (0.016)	0.1*** (0.016)	0.2*** (0.019)	0.1*** (0.019)	2.7*** (0.91)	2.6*** (0.80)	2.7*** (0.56)	2.2*** (0.60)
Const.	-0.1 (0.10)	-0.02 (0.11)	-0.2 (0.14)	-0.2 (0.16)	-0.09 (0.10)	0.005 (0.11)	-0.003 (0.15)	-0.03 (0.17)
N	3999	3999	3999	3999	3999	3999	3999	3999
R^2	0.03	0.05	0.05	0.03	0.03	0.04	0.05	0.04

Estimates of the regression $\Delta y_t = b_0 + b_1 \hat{\gamma}_t + b_2 Z_t + b_3 \hat{\gamma}_t Z_t + \varepsilon_t$. The dependent variables are daily changes in yields on macroeconomic announcement dates, expressed in basis points. The independent variable Z is either the surprise in nonfarm payrolls, normalized to have mean zero and standard deviation 1, or an aggregate variable that captures all surprises. We compute the aggregate variable as the fitted value of a regression of the change in yields on all announcements following [Swanson and Williams \(2014\)](#) normalized such that the coefficient of the change in yields onto Z without interaction terms equals 1. Robust standard errors are reported in parentheses.

news announcements. If one were concerned that our estimated $\hat{\gamma}_t$ primarily captures the perceived endogenous economic response to monetary policy shocks, interest rate movements

during these narrow intervals should therefore be unrelated to $\hat{\gamma}_t$. By contrast, in the data high-frequency interest rate responses to macroeconomic news scale up with $\hat{\gamma}_t$. These high-frequency responses therefore help address concerns that our estimated $\hat{\gamma}_t$ might reflect the endogenous economic response to monetary policy, and validate our estimates in completely separate high-frequency data.

4.2 Term premia in long-term interest rates

In this section, we show that term premia in long-term bonds vary with perceptions about the monetary policy rule. Term premia are a key component of monetary policy transmission because they drive a wedge between the expected path of short-term policy rates and long-term rates, which matter for much of the borrowing in the economy. Whereas term premia are often viewed as outside the reach of traditional monetary policy, an alternative view is that an increasing output coefficient in the monetary policy rule has been responsible for a decline in term premia (Smith and Taylor (2009), Bianchi et al. (2022a)). Our empirical measure of the time-varying perceived monetary policy rule provides direct empirical evidence for this link between term premia and perceptions of the monetary policy rule.

The intuition that $\hat{\gamma}_t$ should be inversely related to expected bond excess comes from basic asset pricing logic: Assets that pay out in bad states of the world should require lower expected returns. A higher perceived monetary policy coefficient $\hat{\gamma}_t$ means that interest rates are expected to fall more—and bond prices are expected to rise more—during recessions. Thus, when $\hat{\gamma}_t$ is high, bonds are better hedges and should have lower expected returns.¹⁶

We construct subjective expected one-year excess returns on 6- and 11-year Treasury bonds similarly to Cieslak (2018), Piazzesi et al. (2015), and Nagel and Xu (2022). Our preferred measure of expected bond excess returns is the subjective expected excess return inferred from Blue Chip surveys because realized returns are a noisy realization of expected returns. We proxy for the expected 6-year Treasury bond par yield $\bar{E}_t y_{t+12}^{(6),par}$ using the average Blue Chip survey forecast of the 5-year Treasury bond yield at the 4-quarter forecast horizon. Because Blue Chip forecasters forecast par yields, we use the par yield on a 6-year Treasury bond from Gürkaynak et al. (2007), $y_t^{(6),par}$, to compute expected returns. Blue Chip forecasters are required to submit their responses at the end of the previous month, so to make sure the information sets are consistent we pair the March survey with the end-of-month par yield at the end of February. Letting $y_t^{(1)}$ denote the one-year zero-coupon yield,

¹⁶These predictions are worked out in detail in Campbell et al. (2017), Campbell et al. (2020), and Pflueger (2022), for example. The link between $\hat{\gamma}_t$ and subjective term premia does not rely on the interpretation of $\hat{\gamma}_t$ as a perceived monetary policy rule coefficient, and remains valid if $\hat{\gamma}_t$ simply captures the perceived comovement of interest rates and the economy.

Table 3: Term premia

	$\bar{E}_t x r_{t+12}^{(6)}$			$\bar{E}_t x r_{t+12}^{(11)}$		
Baseline $\hat{\gamma}_t$	-0.61*** (0.17)	-0.70*** (0.19)	-0.82*** (0.12)	-0.95** (0.39)	-1.09*** (0.41)	-1.19*** (0.17)
TERM		0.32* (0.19)			0.51 (0.34)	
R^2	0.12	0.16	0.61	0.09	0.12	0.61
Inertial $\hat{\gamma}_t$	0.16 (0.18)	0.17 (0.17)	-0.38*** (0.11)	0.26 (0.36)	0.27 (0.34)	-0.71*** (0.23)
TERM		0.18 (0.19)			0.28 (0.33)	
R^2	0.01	0.02	0.46	0.01	0.02	0.52
PCs	No	No	Yes	No	No	Yes

Regressions for subjective expected log bond excess return on six-year and 11-year nominal Treasury bonds over twelve-month (four-quarter) holding periods on baseline $\hat{\gamma}_t$ (top panel) and $\hat{\gamma}_t$ from the inertial rule (bottom panel) of $\hat{\gamma}_t$ and yield curve variables. $\hat{\gamma}_t$ is standardized to have unit standard deviation. Term spread $TERM_t$ is the difference between the 10-year and one-year zero-coupon nominal Treasury yields from [Gürkaynak et al. \(2007\)](#). If indicated, regressions control for the first three principal components (PCs) of zero-coupon yields with maturities one, two, five, seven, ten, fifteen, and twenty years. Coefficients on the constant and the three principal components are omitted. Sample: 425 monthly observations from January 1988–April 2023. Newey-West standard errors with automatic lag selection (between 19 and 28 months) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

we then compute the one-year expected excess return on the 6-year Treasury bond as

$$\bar{E}_t x r_{t+12}^{(6)} = Dur^{(6)} y_t^{(6),par} - (Dur^{(6)} - 1) \bar{E}_t y_{t+12}^{(5),par} - y_t^{(1)}. \quad (7)$$

The duration of the 6-year par bond, $Dur^{(6)}$, is estimated from bond yields, assuming that bonds sell at par ([Campbell et al., 1996](#), p. 408). The expected one-year excess return on a 11-year Treasury bond is computed analogously. We then run regressions of the form

$$\bar{E}_t x r_{t+12}^{(n)} = b_0 + b_1 \hat{\gamma}_t + b_2 TERM_t + \varepsilon_t, \quad (8)$$

where the term spread $TERM_t$ is defined as the difference between 10-year and one-year zero-coupon Treasury bond yields.

Table 3 reports the results. Starting with the first column in panel A, we see that the coefficient on the baseline $\hat{\gamma}_t$ is negative and statistically significant, as would be expected if higher values of $\hat{\gamma}_t$ mean that investors perceive bonds to be better hedges. The magnitudes

are economically meaningful. A one-standard deviation increase in $\hat{\gamma}_t$ is associated with a 0.6 percentage point decline in the expected excess return on a six-year Treasury bond over the next year. Since we have found the term spread to be correlated with $\hat{\gamma}_t$ it is important to control for the term spread. Column (2) shows that the term spread enters only marginally significantly, consistent with the findings in Nagel and Xu (2022). This finding supports our interpretation in Table 1 of the relationship between $\hat{\gamma}_t$ and the slope of the term structure in terms of the expected path of interest rates and the monetary policy cycle. In the third column, we control for the first three principal components of the term structure, which increases the R^2 substantially but leaves the coefficient on $\hat{\gamma}_t$ unchanged. The right three columns in panel A show analogous results for the expected one-year returns on 11-year Treasuries, finding similar results with larger point estimates.

Panel B shows similar results for the inertial estimate of $\hat{\gamma}_t$, which however are only significant when controlling for the first three principal components of the term structure of interest rates. The larger magnitudes for the baseline $\hat{\gamma}_t$ support the economic interpretation that inertial $\hat{\gamma}_t$ captures the perceived short-run response of interest rates to the economy, whereas long-term bond risk premia depend on the longer-term behavior of interest rates.¹⁷ In Appendix Table D.3, we also find that subjective expected bond excess returns decline with perceived monetary policy inertia, as predicted if a higher $\hat{\rho}_t$ increases the perceived cyclicity of long-term interest rates for a given perceived short-term monetary policy response.

A simple back-of-the-envelope calculation illustrates the quantitative importance of this channel for long-term yields. Conditional on a weak economy, the bottom-left panel in Figure 3 shows that a 10 bps positive monetary policy shock leads to a decrease in baseline $\hat{\gamma}_t$ of 0.1—or 0.3 standard deviations—with a peak response six months after the shock. The first column in panel A of Table 3 shows that an decrease in $\hat{\gamma}_t$ of this magnitude is associated with a $-0.3 \times -0.61 = 0.18$ percentage point increase in the subjective risk premium for a 6-year Treasury. A 10 bps surprise *increase* in the policy shock during good times could therefore lead to an even larger *increase* in the term premium of the 6-year Treasury. Thus, this channel suggests a new explanation for why long-term bond yields were excessively sensitive to monetary policy surprises during the post-2000 period (Hanson and Stein (2015)), but may also decouple from short-term rates during other tightening cycles.

¹⁷Appendix D.1 shows that the relationship between expected bond excess returns and $\hat{\gamma}_t$ is unchanged when we control for interest rate disagreement following Giacoletti et al. (2021).

5 Motivating model with learning and heterogeneity

We now present a simple model where agents have imperfect knowledge and not-necessarily-rational beliefs about the time-varying monetary policy framework. Forecasters “agree to disagree” and have heterogeneous signals about the state of the economy, leading to heterogeneous policy rate forecasts. We establish key lessons from the model for the relationship between interest rate and output gap forecasts across forecasters and forecast horizons at a given point in time, how perceptions about the monetary policy rule update after monetary policy surprises, the response of fed funds futures to macroeconomic news announcements, and term premia in long-term bonds. The model also provides a way to quantitatively assess the importance of uncertainty about the monetary policy rule for high-frequency monetary policy surprises.

We assume that the policy rate is described by a simple monetary policy rule

$$i_t = \gamma_t x_t + \rho i_{t-1} + u_t, \quad (9)$$

where (as in [Bauer and Swanson \(2022\)](#)) the actual monetary policy rule γ_t is unobserved and follows a random walk

$$\gamma_{t+1} = \gamma_t + \xi_{t+1}. \quad (10)$$

For simplicity monetary policy inertia ρ is known and constant. We assume that the output gap x_t follows an exogenous AR(1) process, abstracting from the effect of monetary policy on the economy

$$x_t = \phi x_{t-1} + \varepsilon_t. \quad (11)$$

Forecaster j 's prior of the monetary policy rule is given by

$$E^j(\gamma_1 | \mathcal{Y}_0) = \hat{\gamma}_0, \quad Var^j(\gamma_1 | \mathcal{Y}_0) = \sigma_1^2, \quad (12)$$

where \mathcal{Y}_t denotes the filtration based on observing the output gap and interest rates up to and including time t .¹⁸ We use \bar{E} to denote average expectations across all forecasters j , $\hat{\gamma}_t \equiv \bar{E}(\gamma_{t+1} | \mathcal{Y}_t)$, $\sigma_{t+1}^2 = \bar{V}ar(\gamma_{t+1} | \mathcal{Y}_t)$.

¹⁸To capture persistent model differences across forecasters ([Patton and Timmermann \(2010\)](#)) one could additionally assume that forecasters have heterogeneous priors about the unobserved monetary policy rule. However, as long as such heterogeneous priors are uncorrelated with heterogeneous output gap signals, the key model implications would remain unchanged. We therefore abstract from heterogeneous priors for simplicity.

We introduce heterogeneity following [Caballero and Simsek \(2022\)](#) by assuming that forecasters “agree to disagree”, and use their perceived rule to make heterogeneous interest rate forecasts. We model disagreement very simply through incomplete information, assuming that in each period forecasters first observe a noisy signal about the output gap $\nu_t^j = x_t + \eta_t^j$, where $\eta_t^j \sim N(0, \sigma_\eta^2)$.¹⁹ To model the possibility that forecasters’ updating process may not be fully rational, we build on the model of belief misspecifications of [Angeletos et al. \(2021\)](#). Specifically, we assume that forecasters perceive a monetary policy shock variance $\frac{\sigma_u^2}{\kappa}$ when it actually equals σ_u^2 . If $\kappa < 1$ this implies that forecasters overweight their own private prior relative to the public signal contained in the policy rate, in the spirit of [Bordalo et al. \(2020\)](#)’s model of overreaction to private signals and aggregate underreaction to public signals. [Angeletos et al. \(2021\)](#) study the implications of such “overconfidence”, and argue that it is crucial to explain hump-shaped overreaction in output and inflation survey forecasts.²⁰

The timing within the period is as follows. Forecasters first observe their output gap signals, and policy rate and output gap forecasts are reported in a cross-forecaster and cross-forecast horizon panel. All forecasters then observe the actual the period- t output gap, similar to a macroeconomic announcement in the data. Finally, the Fed sets the policy rate i_t based on the policy rule, similar to an FOMC announcement. Forecasters then update their beliefs about γ_t based on the observed period t output gap and interest rate.

Lemma 1 describes how forecasters update their perceptions of the monetary policy rule at the end of period t .

Lemma 1: Denoting the monetary policy surprise by

$$mps_t \equiv i_t - \bar{E}(i_t | \mathcal{Y}_{t-1}, x_t) \tag{13}$$

¹⁹While [Caballero and Simsek \(2022\)](#) model different opinions for the market vs. the Fed as a driver of interest rate forecasts, we further allow for different opinions across forecasters. Their key insight that disagreement between the market and the Fed about the output gap leads to monetary policy shocks is a microfoundation for the monetary policy shock u_t in equation (9). We use the assumption of incomplete information as the simplest way to generate the relationship between interest rate and output gap forecasts. However, the model implications are not dependent on rational output gap forecasts and a similar perceived policy rate-output gap relationship would obtain if output gap forecasts were subject to rational inattention or slow learning as in [Reis \(2020\)](#).

²⁰A large literature in behavioral economics provides empirical support for overconfidence and slow information diffusion. See, for example, [Mankiw and Reis \(2002\)](#), [Barberis and Thaler \(2003\)](#) and [Coibion and Gorodnichenko \(2015\)](#). While [Angeletos et al. \(2021\)](#) assume that agents overstate the precision of their own signal, we assume that agents understate the precision of the public signal. Because only the signal-to-noise ratio of the public to private signal matters these two specifications are isomorphic, except that in our model it is slightly simpler to write the model in terms of the variance of the public signal.

each forecaster j updates his perceived monetary policy coefficient according to:

$$\hat{\gamma}_t - \hat{\gamma}_{t-1} = \omega_t \frac{mps_t}{x_t}, \quad \omega_t \equiv \frac{\sigma_t^2 x_t^2}{\sigma_t^2 x_t^2 + \frac{\sigma_u^2}{\kappa}}, \quad \sigma_{t+1}^2 = \sigma_t^2(1 - \omega_t) + \sigma_\xi^2. \quad (14)$$

Sketch of Proof: The key economic insight is that the monetary policy surprise equals $mps_t = (\gamma_t - \hat{\gamma}_t)x_t + u_t$. In the absence of monetary policy shocks it follows that $\gamma_t - \hat{\gamma}_t = \frac{mps_t}{x_t}$ and the period t monetary policy rule coefficient can be learned perfectly. With monetary policy shocks, forecasters scale their posterior towards their prior according to the perceived signal-to-noise ratio ω_t . The Kalman filter completes the proof.

The model gives rise to a number of corollaries. Corollary 1 predicts how the perceived time-varying monetary policy rule can be recovered from a forecaster-horizon panel of forecasts.

Corollary 1 (Period-by-Period Panel Regression): In a panel regression of policy rate forecasts on output gap forecasts:

$$E^j(i_{t+h} | \mathcal{Y}_{t-1}, \nu_t^j) = \alpha_j^0 + g_t E^j(x_{t+h} | \mathcal{Y}_{t-1}, \nu_t^j) + b_t E^j(i_{t+h-1} | \mathcal{Y}_{t-1}, \nu_t^j) + \varepsilon_{jht} \quad (15)$$

the estimated g_t is a consistent estimate of $\hat{\gamma}_t$.

Corollary 2 says that the time-varying perceived monetary policy rule should also influence how strongly interest rates respond to macroeconomic news announcements.

Corollary 2 (Macro Surprises): Define a macroeconomic surprise as $\Delta x_t = x_t - \bar{E}(x_t | \mathcal{Y}_{t-1}, \nu_t^j)$ and the contemporaneous change in interest rate forecasts as $\Delta i_t = \bar{E}(i_t | \mathcal{Y}_{t-1}, x_t) - \bar{E}(i_t | \mathcal{Y}_{t-1}, \nu_t^j)$. The interaction coefficient in the following regression is predicted to be positive:

$$\Delta i_t = b_0 + b_1 \hat{\gamma}_t + b_2 \Delta x_t + b_3 \hat{\gamma}_t \Delta x_t + \varepsilon_t. \quad (16)$$

Corollary 3 traces out the implications of the time-varying perceived monetary policy rule for long-term bond premia. It is natural to assume a simple stochastic discount factor where marginal utility is inversely related to the output gap. As one concrete microfoundation, CRRA consumption utility with consumption equal to output and constant potential generates such a correlation. Similar assumptions for the stochastic discount factor are also

common in structural and more reduced form asset pricing models, e.g. [Lettau and Wachter \(2007\)](#).

Corollary 3 (Bond Risk Premia): Assuming a log stochastic discount factor $m_{t+1} = -i_t - \psi\varepsilon_{t+1} - \frac{1}{2}\psi^2\sigma_\varepsilon^2$, the model implies that expected excess bond returns depend negatively on the perceived monetary policy coefficient $\hat{\gamma}_t$.

5.1 Learning about the Time-Varying Monetary Policy Rule: Empirical Implications

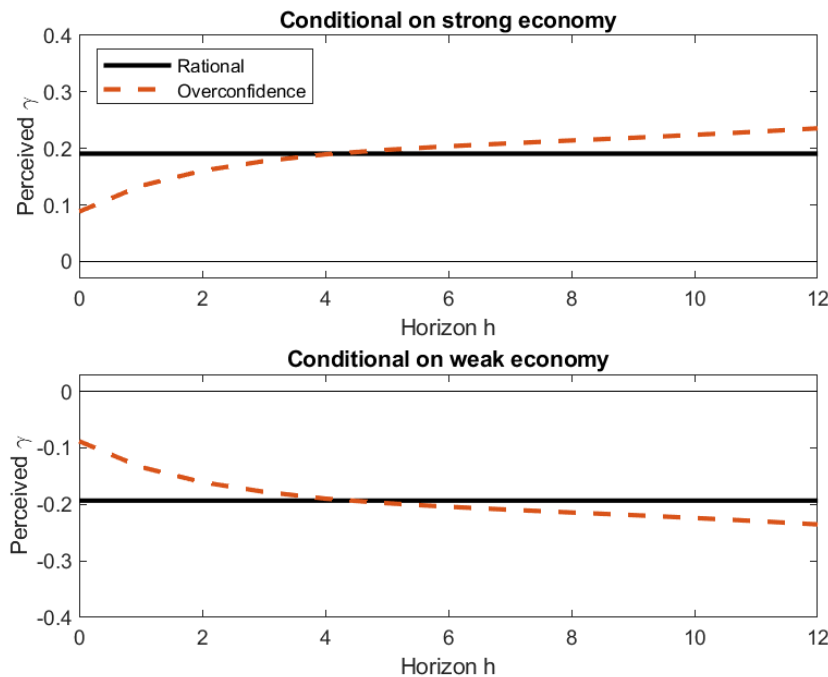
Our empirical strategy in Section 2 builds on the insight from Corollary 1 that the time-varying perceived rule coefficient $\hat{\gamma}_t$ can be recovered by estimating a simple monetary policy rule period-by-period on forecaster-horizon panels. This is the basis for our estimation of the time-varying perceived monetary policy rule.

Having a consistent estimate for the time-varying perceived monetary policy rule coefficient, $\hat{\gamma}_t$, Lemma 1 then provides testable implications for how the perceived monetary policy rule should change in response to high-frequency monetary policy surprises, which reflect both news about the rule and pure uncorrelated monetary policy shocks. Because a positive monetary policy surprise tends to reflect either an above-average output gap and higher-than-expected monetary policy coefficient, or a below-average output gap and lower-than-expected monetary policy coefficient, the predicted response coefficient is positive conditional on a strong economy but negative conditional on a weak economy. The magnitude of the perceived monetary policy response to a normalized surprise, $\frac{mps_t}{x_t}$, can be used to estimate the share of uncertainty about the monetary policy surprise because the monetary policy rule is uncertain. A simple back-of-the-envelope calculation comparing the peak response in the top-left-panel in Figure 3 of 0.7 with an average output gap of 1.4 pp suggests that forecasters attribute about $0.7/1.4 \approx 50\%$ of the variation in monetary policy surprises to uncertainty about the policy rule.

As in [Angeletos et al. \(2021\)](#) the speed of the predicted response depends on agents' misperceptions about the precision of their own prior versus the public signal. The perceived monetary policy rule is predicted to respond immediately if forecasters are perfectly rational. But the predicted model response can be slower and gradual if forecasters believe that idiosyncratic monetary policy shocks are too volatile, and hence update their prior too little in response to monetary policy surprises. These model predictions are depicted in Figure 4. The black line shows the immediate, state-contingent responses for $\hat{\gamma}_t$ with rational updating. The blue dashed line shows that with overconfidence ($\kappa < 1$) the impulse responses are similar

in sign and magnitude, but emerge more gradually.

Figure 4: Model impulse responses of perceived monetary policy coefficient



Regression on model-simulated data: $\hat{\gamma}_{t+h|t+h-1} = a^{(h)} + b_1^{(h)} mps_t(1 - weak_t) + b_2^{(h)} mps_t weak_t + c^{(h)} weak_t + d^{(h)} \hat{\gamma}_{t-1} + \varepsilon_{t+h}$, where $weak_t$ is an indicator for whether the output gap during period t was negative. We report the average across 2000 simulations of length 3000.

It is important to note that the model predicts no updating following actual monetary policy decisions in two special cases: (i) an alternative full-information model where forecasters observe γ_t at the beginning of each period; and (ii) the limiting case in which the volatility of the monetary policy shock is very large relative to the uncertainty about the monetary policy coefficient (i.e., $\sigma_u^2 \rightarrow \infty$). These restrictions are therefore inconsistent with the empirical evidence in Section 3.

Corollaries 2 and 3 have implications for the transmission of the time-varying perceived monetary policy rule to short-term and long-term interest rates that we confirm in the data. In Table 2, we proxy for changes in interest rate forecasts around macroeconomic news with changes in fed funds futures and confirm that macroeconomic news indeed transmit into interest rates according to the time-varying perceived monetary policy rule, as predicted by Corollary 2. Because macroeconomic news announcements are plausibly exogenous to the change in fed funds futures within short announcement windows these empirical results also alleviate concerns that our baseline estimates might be driven by the endogenous output response to monetary policy, and validate our baseline estimates in high-frequency data.

Corollary 3 predicts that the time-varying perceived monetary policy rule should percolate to long-term interest rates even beyond its impact on expected future policy rates. We confirm these predictions for expected bond excess returns in Section 4.2. When the perceived monetary policy coefficient, $\hat{\gamma}_t$, is high, interest rates are expected to fall and bond prices are expected to rise in recessions, which are states of high marginal utility. This perceived comovement turns long-term bonds into desirable hedges, so investors are willing to hold long-term bonds at yields below the average expected policy rate over the lifetime of the bond. Even though Corollary 3 formally only considers two-period bonds, it extends in a simple manner to longer-term bonds if we make the auxiliary assumption that bonds are priced as if the monetary policy rule is perceived to be known and constant. An increase in the monetary policy inertia parameter, ρ , then also lowers long-term bond risk premia, as for a given value of $\hat{\gamma}_t$ long-term interest rates then are even more pro-cyclical and longer-term bonds even better hedges.

In sum, a simple model of heterogeneous forecasters who learn about an unobserved, time-varying monetary policy rule motivates our empirical measure of the time-varying perceived monetary policy rule, and predicts how this measure responds to high-frequency monetary policy surprises, the transmission of time-varying perceived monetary policy rules to short-term interest rates to macroeconomic news surprises, and their pricing in long-term bond premia.

6 Robustness of estimated perceived policy rules

This section demonstrates robustness of our key variable—the estimated perceived monetary policy output gap weight $\hat{\gamma}_t$. We start by considering variations in our baseline specification that address heterogeneity in the perceived rule across forecasters and control for expected financial conditions. Table 4 shows correlations with our baseline $\hat{\gamma}_t$ and a version that does not include forecaster fixed effects (OLS). Appendix C describes the details of the alternative estimates and shows plots.

We account for heterogeneity across forecasters in several ways. First, we estimate a version of $\hat{\gamma}_t$ that gives each forecaster equal weight in the regressions, as one might be concerned that in our baseline estimation some forecasters might receive higher weight in some periods simply because they have more extreme output gap forecasts. Estimating a regression of the form (2) each month at the forecaster level (i.e., only utilizing the cross-horizon variation) and then taking an equal-weighted average across forecasters addresses this concern. The high correlation of 81% with our baseline $\hat{\gamma}_t$ confirms that those estimates resemble closely the average perceived coefficient over time and are not driven by shifting weights of different

forecasters in the estimation. Appendix C.1 characterizes the equal-weighted estimator as a multidimensional panel regression with appropriate fixed effects and interactions. This estimator also makes clear that variation of fed funds rate and macroeconomic forecasts across forecast horizons is important for our estimation. The cross-section matters because the regression for each individual forecaster is bound to be very noisy, but averaging slope coefficients across forecasters gives precise estimates that vary smoothly over time.

Table 4: Robustness: Correlation of alternative $\hat{\gamma}_t$ estimates

	Equal OLS	Hetero-Weighted	Hetero-geneous	Infl. 1	Terciles 2	Terciles 3	Credit spread	Bias adjust	Inertial $\hat{\gamma}$	Inertia $\hat{\rho}$
Baseline $\hat{\gamma}_t$	0.84	0.81	0.88	0.85	0.81	0.85	0.94	0.92	0.48	0.11
OLS	.	0.54	0.95	0.76	0.68	0.63	0.86	0.73	0.51	-0.07

Correlations between different estimates for the perceived output gap weight in the policy rule, $\hat{\gamma}_t$. Sample period ends in April 2023, and starts in January 1985 for baseline, OLS, equal-weighted, inflation tercile 1, 2, 3, inertial $\hat{\gamma}_t$, and inertial $\hat{\rho}_t$ estimates, in January 1993 for *Heterogeneous*, and in January 2001 for *Credit spread* estimates. *Terciles* split forecasters into terciles by the four-quarter horizon CPI inflation forecast residualized with respect to monthly fixed effects, and re-estimates the baseline estimate of $\hat{\gamma}_t$ on these terciles. Inertial $\hat{\gamma}_t$ is from an estimation of the inertial rule of the form (4). For details on alternative estimates, see Appendix C.1.

Next, we impose additional structure on forecaster heterogeneity motivated by our information model in Section 5. The “heterogeneous” estimate includes forecaster fixed effects interacted with the output gap and inflation, i.e., it estimates a multidimensional panel regression of the form

$$E_t^{(j)} i_{t+h} = a_t + \alpha_j + (b_j + \beta_t) E_t^{(j)} \pi_{t+h} + (g_j + \gamma_t) E_t^{(j)} x_{t+h} E_t^{(j)} \pi_{t+h} + \gamma_t E_t^{(j)} x_{t+h} + e_{t,j,h} \quad (17)$$

Note that this estimate does not contain forecaster-by-month fixed effects, so it should be expected to be closer to the “pooled OLS” estimate than the baseline estimate (which contains forecaster fixed effects), which is indeed what we see in Table 4. Because forecaster ID’s were reshuffled in 1993, this regression necessarily starts in January 1993.

We then account for forecaster heterogeneity in a less parametric way, splitting forecasters by characteristics and estimating different policy rules for each forecaster group. In particular, one might wonder whether inflation hawks and doves perceive different monetary policy rules. We split forecasters into terciles by their four-quarter horizon CPI inflation forecast residualized with respect to monthly fixed effects. We then estimate baseline regressions separately for each of the three terciles, with *Tercile 1* corresponding to the forecasters with low inflation expectations and *Tercile 3* corresponding to the forecasters with the highest

inflation expectations. The estimates of $\hat{\gamma}_t$ naturally become noisier due to the smaller sample sizes, but the correlations with our baseline estimate of $\hat{\gamma}_t$ remain high, exceeding 80% for all three terciles. While hawks versus doves may therefore perceive different levels for the monetary policy output weight (the average $\hat{\gamma}_t$ equals 0.42 for the doves in *Tercile 1* vs. 0.52 for the hawks *Tercile 3*), the time-variation in $\hat{\gamma}_t$ is very similar. Splitting forecasters by inflation hence again confirms that our baseline estimator $\hat{\gamma}_t$ captures common time-variation in the perceived monetary policy rule shared by all forecasters.

A separate concern about our estimates is that a high value for $\hat{\gamma}_t$ might partly reflect the perceived monetary policy response to financial conditions, which are likely to be correlated with the economy. We investigate this possibility by including in our baseline estimation each forecaster’s expectation of the spread between Baa corporate bond yields and the ten-year Treasury yield, as a proxy for expected financial conditions. Forecasts of the Baa yield are available in the Blue Chip data starting in 2001. Our estimates suggest an important perceived role for financial conditions in determining the policy rate—expected credit spreads enter with a coefficient that is often substantially negative and statistically significant (see Appendix Figure C.1). However, as Table 4 shows, incorporating credit spread forecasts into the perceived policy rule has little effect on the estimated response to output gap forecasts. The correlation is 94% between the $\hat{\gamma}_t$ coefficients estimated in our baseline specification and the specification including expected credit spreads.

Finally, we compare our estimates of the baseline and inertial policy rules. The correlation between the estimates of $\hat{\gamma}_t$ from the simple rule and the inertial rule is 0.48. This is lower than the other correlations we report, but is quite high considering that the two estimates capture conceptually different objects—the estimates of $\hat{\gamma}_t$ in the inertial rule capture the short-run response of monetary policy to the output gap, while the estimates of $\hat{\gamma}_t$ in the simple rule capture the medium-run response. Finally, the last column of Table 4 shows that our estimates of $\hat{\gamma}_t$ are essentially uncorrelated with the estimate of the inertia parameter $\hat{\rho}$ in the inertial rule. We therefore conclude that our estimate of $\hat{\gamma}_t$ captures the time-varying perceived monetary policy weight on the economy, and not time-variation in the perceived inertia of the monetary policy rule. Additional robustness checks, including estimates using forecaster-level data from the Survey of Professional Forecasters (SPF) and the Fed’ Survey of Economic Projections, are reported in the Appendix. In Appendix D.1 we show that our baseline estimates of $\hat{\gamma}_t$ are only slightly positively correlated with the measures of forecaster interest rate disagreement from Giacoletti et al. (2021), suggesting that the Fed’s ability to eliminate disagreement about future policy rates is not driving our estimates.

Overall, we find that these various alternative estimates of $\hat{\gamma}_t$ are all highly correlated with our baseline estimates.

6.1 Endogeneity and estimation bias

We next turn to the concern that our estimates of monetary policy rules are potentially biased due to the endogeneity of the macroeconomic variables. After all, inflation and output are endogenously determined by all structural shocks in the economy, including the monetary policy shock.²¹ Recent work by [Carvalho et al. \(2021\)](#) analyzing different types of New Keynesian models suggests that OLS estimates of policy rules may not be affected much by this bias. Nevertheless, one might worry that our estimates of $\hat{\gamma}_t$ might be biased by the *perceived* endogenous response of inflation and output to monetary policy, and therefore do not capture the perceived responsiveness of monetary policy to economic conditions.

One way to address this concern is to try to quantify the bias and adjust for it. We adapt the approach of [Carvalho et al. \(2021\)](#) to our cross-sectional setting to do this; Appendix [C.2](#) shows the details. As expected, we find that the bias-adjusted $\hat{\gamma}_t$ is somewhat higher than the baseline estimate, with a sample mean of 0.57 vs. 0.43. This sign is consistent with the idea that forecasters expect exogenous monetary policy shocks to cause output to contract, biasing down $\hat{\gamma}_t$. However, the bias adjustment leaves the time-series variation in $\hat{\gamma}_t$, our main object of interest, largely unchanged. The last column of [Table 4](#) shows the correlation of the bias-adjusted estimate with our other estimates. The correlation of the baseline estimates with and without bias adjustment is 92%.

A structural interpretation of our estimates as coefficients in a perceived policy rule is also supported by our additional evidence, showing that $\hat{\gamma}_t$ responds to monetary policy surprises in a state-dependent, theory-consistent manner ([Section 3](#)), and that it explains interest rate responses during narrow intervals around macroeconomic news surprises ([Section 4.1](#)). That said, an alternative interpretation of $\hat{\gamma}_t$ as simply the perceived comovement between the policy rate and the macroeconomy is possible, sidestepping the endogeneity concern. Under this interpretation, our results help understand how forecasters learn about this comovement, and how their perceptions are reflected in financial markets.

7 Conclusion

This paper presents new time-varying estimates of the monetary policy rule perceived by professional forecasters, using the rich panel data on forecasts available each month. With our new estimates of the perceived monetary policy rule, we document a number of new facts that are relevant for monetary policy and asset pricing. First, the perceived responsiveness

²¹[Cochrane \(2011\)](#) shows that under certain conditions monetary policy rules cannot be identified at all from observed data, due to the endogenous response of long-run inflation to long-run nominal rates. [Sims \(2008\)](#), however, shows that the identification problem is mitigated when the natural interest rate is unknown.

of monetary policy to the economy varies substantially over time. It tends to be high during monetary tightening cycles when Fed policy is perceived to be data-dependent, but low during easing cycles and times of elevated economic and financial uncertainty. However, the perceived monetary policy rule is not strongly correlated with the business cycle. Second, following high-frequency monetary policy surprises on FOMC announcement dates forecasters update their estimates of the monetary policy rule, indicating that they perceive monetary policy surprises to be informative in this regard. The way forecasters update depends on the state of the economy, as the same surprise tightening indicates higher responsiveness to the economy in a strong economy and weaker responsiveness in a weak economy. Third, the perceived monetary policy rule affects the transmission of monetary policy to financial markets, explaining the sensitivity of interest rates to macroeconomic news as well as variation in subjective term premia in long-term interest rates.

Taken together, our evidence suggests that forecasters perceive a highly time-varying monetary policy rule that reflects the Fed’s shifting concerns about current economic data versus financial and other risks. Our evidence suggests that forecasters learn about the monetary policy rule from observed interest rate decisions, as if the monetary policy rule follows a partly unobserved process subject to monetary policy “discretion”. Our results illustrate the promise of further research into how changes in the monetary policy framework affect beliefs about monetary policy and the macroeconomy.

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Appendix for Online Publication

A Data construction

We start in 1985 because the data quality is poor in the first few years of the survey. Our survey data ends in April 2023 for a total of 460 monthly surveys. Every month, each forecaster provides forecasts for horizons from the current quarter out to five quarters ahead.²² The deadline for the survey responses is the 26th of the previous month, with the exception of December, when the deadline is the 21st.

We focus our analysis on the federal funds rate, the policy rate of the Federal Reserve. The precise variable being forecast is the quarterly average of the daily effective funds rate, in annualized percent, as reported in the Federal Reserve’s H.15 statistical release. We denote individual j ’s forecast made at t for the funds rate at $t + h$ by $E_t^{(j)}i_{t+h}$. Throughout the paper, time t is measured in months, unless otherwise stated. The monthly horizon h depends on both the survey month and the quarterly forecast horizon. For example, for the one-quarter-ahead forecast in the January 2000 survey, $t + h$ corresponds to June 2000 and $h = 5$.

Macroeconomic forecasts for output growth and inflation are reported as quarter-over-quarter forecasts in annualized percent. We transform these variables, since empirical monetary policy rules are usually specified in terms of year-over-year inflation and activity gap measures, such as the output gap (e.g., Taylor, 1999). We use CPI inflation forecasts, and we calculate predicted year-over-year inflation. For forecasts with horizons of three to five quarters, we simply calculate annual inflation forecasts from the quarterly forecasts for the four longest horizons. For forecasts with horizons of less than three quarters, we combine the forecasts with actual CPI inflation over recent quarters. We denote resulting four-quarter CPI inflation forecasts as $E_t^{(j)}\pi_{t+h}$.

We derive output gap forecasts from real GDP growth forecasts from 1992 onwards and from real GNP growth forecasts before. Conceptually, the calculation is straightforward: Using the current level of real output and the quarterly growth forecasts, we calculate the forecasted future level of real output, which we then combine with CBO projections of potential output to calculate implied output gap forecasts. In practice, the calculations are slightly involved, since careful account needs to be taken of the timing of the surveys and the available real-time GDP data and potential output projections. First, we need real-time GDP for the quarter before the survey. We obtain real-time data vintages for GDP from ALFRED, and use the most recently observed vintage before the deadline of each survey. Second, we calculate forecasts for the *level* of real GDP, denoted as $E_t^{(j)}Y_{t+h}$ using the level in the quarter before the survey and the growth rate forecasts. Third, we obtain real-time vintages for the CBO’s projections of future potential GDP, also from ALFRED, and again use the most recent vintage that was available to survey participants at the time.²³ Fourth

²²Before 1997, the forecast horizon extends out only four quarters.

²³In some cases, we use vintages of real GDP or potential GDP released shortly after the survey deadline. We do this either to obtain real GDP in the quarter immediately before the survey (in case this was released after the deadline), or to obtain consistent units for actual and potential real GDP (in case the dollar base

and finally, output gap forecasts are calculated as the deviation of the GDP forecasts from the potential GDP projections in percentage points:

$$E_t^{(j)}x_{t+h} = 100 \frac{E_t^{(j)}Y_{t+h} - E_t Y_{t+h}^*}{E_t^{(j)}Y_{t+h}^*},$$

where x_t is the output gap and Y_t^* is potential GDP in the quarter ending in t . It is worth emphasizing that our output gap projections assume that all forecasters share the same potential output forecasts, equal to the CBO projection. Across surveys, horizons, and forecasters, there are over 115,000 individual forecasts. Summary statistics are reported in Appendix Table A.1.

A.1 Summary statistics

Table A.1: Summary statistics for survey forecasts

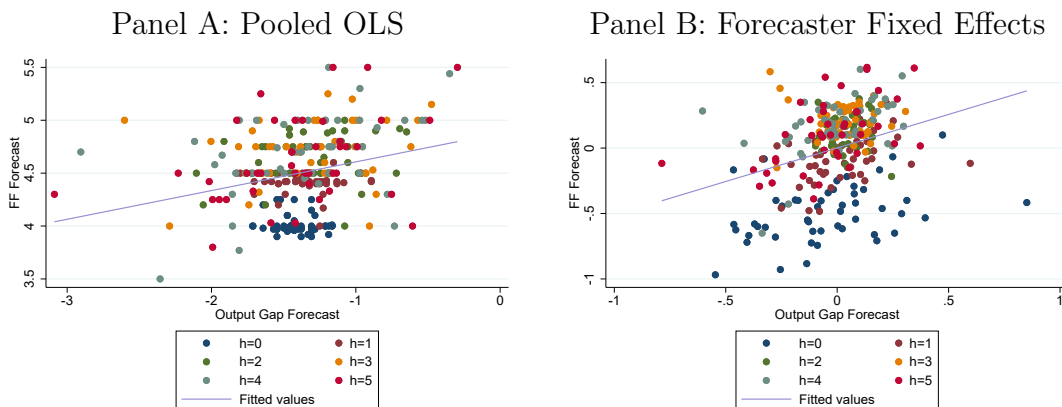
	N	Mean	Standard Deviations			
			SD	Within-Month	Within-Month-ID	Within-Month-Horizon
Fed funds rate	120,152	3.5	2.6	0.46	0.33	0.33
CPI inflation	118,929	2.7	1.2	0.61	0.48	0.40
Output growth	119,317	2.6	1.8	1.04	0.80	0.83
Output gap	119,305	-1.4	2.6	0.65	0.40	0.52

Summary statistics for individual survey forecasts in the Blue Chip Financial Forecasts from January 1985 to April 2023 (460 monthly surveys). Horizons are from current quarter to five quarters ahead (before 1997, four quarters ahead). Number of forecasters in each survey is between 28 and 50. Interest rate forecasts are in percentage points. CPI inflation forecasts are for four-quarter inflation, calculated from the reported quarterly inflation rates and, for short horizons, past realized inflation, in percent. Output growth forecasts are for quarterly real GDP growth (before 1992, real GNP growth) in annualized percent. Output gap forecasts are calculated from growth forecasts, real-time output, and CBO potential output projections as described in the text, in percent. The within-month standard deviation reports the average of the standard deviation of forecasts conditional on month t . The within-month-id standard deviation is the average standard deviation within each month-forecaster (t, j) cell. The within-month-horizon standard deviation is the average standard deviation within each month-horizon (t, h) cell.

In Table A.1 we report summary statistics for our survey data. Output gap forecasts are negative on average, in line with the fact that both real-time and revised estimates of the output gap were negative for the majority of our sample period. Forecasted CPI inflation averages around 2.7% and the average fed funds rate forecast equals 3.5%, in line with realized inflation and interest rates over our sample. All variables exhibit substantial within-month variation. This within-month variation reflects variation across both forecasters and forecast horizons.

Figure A.1 illustrates the variation in the data driving our estimated perceived monetary policy rule for December 2005. At this time, economic uncertainty was dominated by a year changed for the actual GDP but not for the potential GDP numbers). Furthermore, since the real-time vintages start in 1991, we use the earliest vintages for the surveys before that time.

Figure A.1: Federal funds rate and output gap forecasts in December 2005



Output gap and federal funds rate forecasts used to estimate regression (2) without (left) and with (right) residualizing with respect to forecaster fixed effects. Each dot corresponds to one forecaster-horizon pair (j, h) in the December 2005 survey. Forecast horizons (in quarters) h are color-coded. Output gap forecasts are constructed from individual forecasters' real GDP growth forecasts and the real-time vintages for the CBO's projections of future potential GDP from ALFRED. For a detailed description of the data construction see Section 2.1.

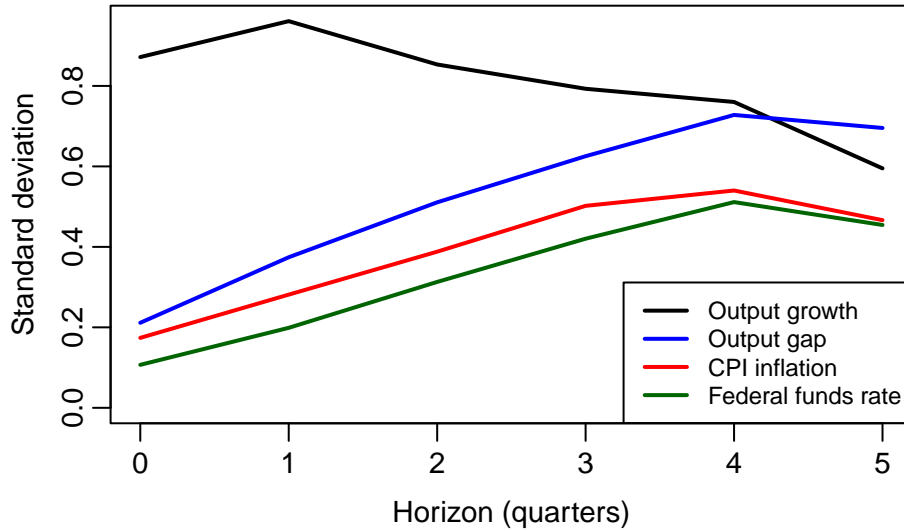
well-defined event: the recovery from Hurricane Katrina, which devastated New Orleans in August 2005. Thus, disagreement across forecasters about future output gaps and fed funds rates was likely driven by disagreement about the short-term recovery, as opposed to confounding factors like long-term growth expectations or financial conditions. Each dot shows the output gap forecast on the x-axis and the federal funds rate forecast on the y-axis for a specific forecaster at a specific forecast horizon. Different colors are used to denote different forecast horizons of one through five quarters. There is significant variation in the output gap at all forecast horizons, and we see a clear relationship between output gap forecasts and fed funds rate forecasts. The slope in the left panel equals 0.27 and the slope in the right panel equals 0.51. The R^2 in an OLS regression of fed funds rate forecasts onto output gap and inflation forecasts in this survey equals 20%. While this is only a specific month, it is representative of the sample overall.

A.2 Term structure of disagreement

Figure A.2 plots the term structure of disagreement, i.e., the average cross-sectional standard deviation across forecasters, for (i) forecasts of output growth, (ii) implied forecasts for the output gap, $E_t^{(j)} x_{t+h}$, (iii) four-quarter CPI inflation forecasts, $E_t^{(j)} \pi_{t+h}$, and (iv) fed funds rate forecasts, $E_t^{(j)} i_{t+h}$. Cross-sectional disagreement for output growth declines with horizon. By contrast, disagreement in fed funds rate forecasts, inflation forecasts, and output gap forecasts increases with the forecast horizon. Intuitively, cross-sectional dispersion in output gap forecasts increases with forecast horizon because the output gap cumulates output growth forecasts.

These consistent patterns in the term structure of disagreement support our specification

Figure A.2: Term structure of disagreement



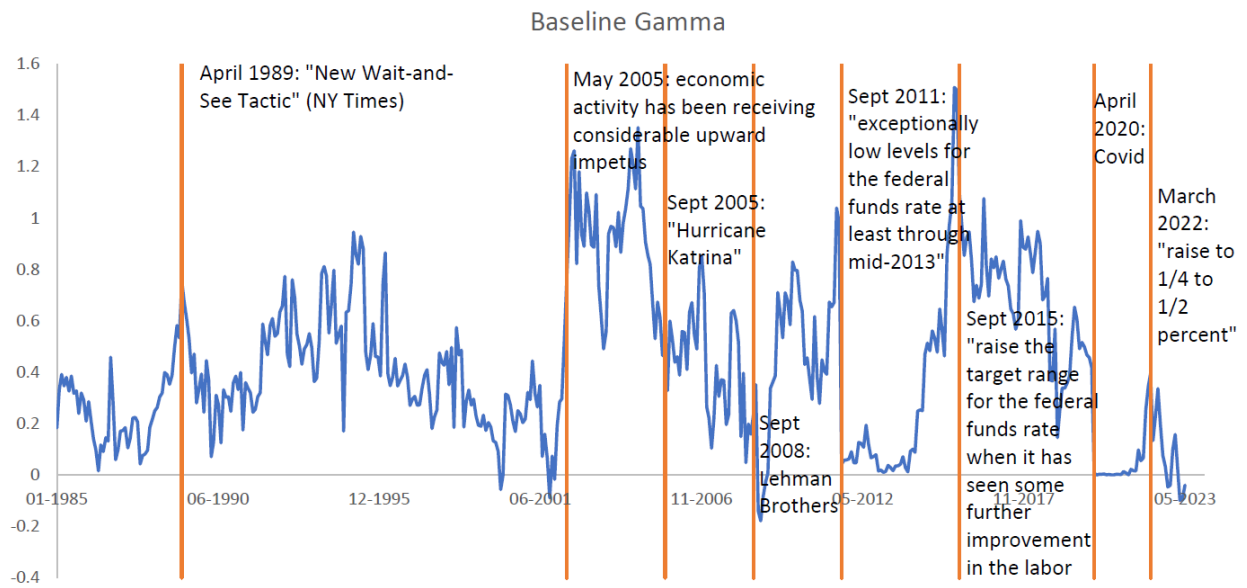
Sample average of cross-sectional standard deviation in the BCFF survey for each forecast horizon for quarter-over-quarter real GDP growth, implied output gap projections, the four-quarter CPI inflation rate, and the federal funds rate. Sample: monthly surveys from Jan-1992 to Jan-2021.

of policy rules for the fed funds rate forecasts in terms of inflation forecasts and output gap forecasts. By contrast, [Andrade et al. \(2016\)](#) estimate a model that specifies a policy rule with output growth, which makes it necessary to generate additional disagreement for policy rate forecasts at longer horizons using, for example, policy inertia in the interest rate rule.

A.3 Policy Rule and Event Dates

Figure [A.3](#) plots our baseline estimate of $\hat{\gamma}_t$ with event dates for key movements. All quotes are taken from FOMC statements from the corresponding months, with the exception of the April 1989 quote, which is from “Interest Rates Being Held Steady Amid Signs of Slowing Economy”, *New York Times* (April 27, 1989).

Figure A.3: Baseline $\hat{\gamma}_t$ and event dates



B Additional results for local projections (Section 3)

Here we report regression estimates for the local projections shown in Figure 3 and discussed in Section 3. The regressors include mps_t instead of $mps_t(1 - weak_t)$ so that the coefficient on the interaction term $mps_t weak_t$ measures the difference between the two state-dependent impulse responses, and we can easily report the test statistic for the null hypothesis that there is no state dependence. That is, we estimate the regression

$$\hat{\gamma}_{t+h} = a^{(h)} + b_1^{(h)} mps_t + \tilde{b}^{(h)} mps_t weak_t + c^{(h)} weak_t + d^{(h)} \hat{\gamma}_{t-1} + \varepsilon_{t+h},$$

where all variables are as defined in 3. Note that the impulse responses shown in the top panels of Figure 3 correspond to estimates of $b_1^{(h)}$, and the responses shown in the bottom panels correspond to $b_1^{(h)} + \tilde{b}^{(h)}$.

Table B.1 shows the estimation results for horizons of three, six, nine and twelve months. Most importantly, the interaction coefficient on is consistently negative and highly statistically significant. This evidence confirms the visual impression from Figure 3 that $\hat{\gamma}$ responds positively to a hawkish policy surprise when the economy is strong, but negatively when the economy is weak.

Table B.1: Local Projection Regressions

<i>Horizon:</i>	FE $\hat{\gamma}_{t+h}$				SSM $\hat{\gamma}_{t+h}$			
	$h = 3$	$h = 6$	$h = 9$	$h = 12$	$h = 3$	$h = 6$	$h = 9$	$h = 12$
mps_t	0.26 (1.00)	0.73** (2.28)	0.39** (2.03)	-0.02 (-0.06)	-0.07 (-0.56)	0.30** (2.51)	0.30*** (2.70)	0.27** (2.02)
$mps_t \times weak_t$	-0.45 (-1.17)	-1.63*** (-2.79)	-1.33** (-1.98)	-0.36 (-0.57)	-0.05 (-0.25)	-0.75*** (-2.71)	-0.86*** (-2.75)	-0.78** (-2.30)
$weak_t$	0.06 (1.46)	0.12* (1.88)	0.18** (2.37)	0.22*** (2.63)	0.03 (1.62)	0.06* (1.89)	0.09** (2.10)	0.11** (2.19)
$\hat{\gamma}_{t-1}$	0.67*** (10.18)	0.52*** (5.65)	0.40*** (3.80)	0.33*** (3.01)	0.78*** (15.14)	0.61*** (7.22)	0.49*** (4.71)	0.40*** (3.53)
Constant	0.14*** (4.12)	0.18*** (3.97)	0.21*** (4.17)	0.23*** (3.83)	0.06*** (2.96)	0.11*** (3.06)	0.14*** (3.23)	0.16*** (3.49)
N	356	353	350	347	356	353	350	347
R^2	0.46	0.32	0.25	0.22	0.61	0.4	0.31	0.26

Local projection estimates of the state-dependent response of $\hat{\gamma}_t$ —measured as the FE estimate of $\hat{\gamma}_t$ in the first four columns and as the SSM estimate in the last four columns—to high-frequency monetary surprises of Nakamura and Steinsson (2018), mps_t . The estimated regression is $\hat{\gamma}_{t+h} = a^{(h)} + b_1^{(h)} mps_t + \tilde{b}^{(h)} mps_t weak_t + c^{(h)} weak_t + d^{(h)} \hat{\gamma}_{t-1} + \varepsilon_{t+h}$, where $weak_t$ is an indicator for whether the output gap during month t was below the sample median. Newey-West t -statistics, using $1.5 \times h$ lags, are reported in parentheses. Sample period: Jan-1992 to Jan-2021.

C Robustness: Details and plots

C.1 Robustness: Heterogeneity and controlling for credit spread forecasts

Here we provide details for the alternative estimates discussed in Section 6.

We stack all our observations in a survey-forecaster-horizon panel, so each observation is identified by (t, j, h) . In this panel, we first estimate the following regression:

$$E_t^{(j)} i_{t+h} = a_t + \beta_t E_t^{(j)} \pi_{t+h} + \gamma_t E_t^{(j)} x_{t+h} + e_{t,j,h}. \quad (\text{C.1})$$

That is, we include time fixed effects and, of course, allow for the coefficients on the macro forecasts to vary over time. The estimates of γ_t and β_t from regression (C.1) exactly replicate the OLS estimates from the separate survey panel regressions described in Section 2.2.

The “equal-weighted” estimator is obtained by running

$$E_t^{(j)} i_{t+h} = a_{j,t} + \beta_{j,t} E_t^{(j)} \pi_{t+h} + \gamma_{t,j} E_t^{(j)} x_{t+h} + e_{t,j,h} \quad (\text{C.2})$$

separately for each forecaster j utilizing only the variation across forecast horizons h , and taking the average of $\gamma_{t,j}$ over j . Figure C.1, Panel A reports the estimated equal-weighted average of $\hat{\gamma}_{t,j}$.

To further explore heterogeneity, we allow for forecaster fixed effects in the time-varying perceived monetary policy coefficients. That is, we estimate the regression

$$E_t^{(j)} i_{t+h} = a_t + \alpha_j + b_j E_t^{(j)} \pi_{t+h} + g_j E_t^{(j)} x_{t+h} + \beta_t E_t^{(j)} \pi_{t+h} + \gamma_t E_t^{(j)} x_{t+h} + e_{t,j,h}. \quad (\text{C.3})$$

We denote the estimates of γ_t and β_t from this regression, which represent the forecaster-average time- t perceived monetary policy coefficients, as “Heterogeneous”. The estimates of b_j and g_j represent the forecaster-specific time-invariant shifters to these perceived monetary policy coefficients, and we do not report them. Note that this estimate does not contain forecaster-by-month fixed effects, so it should be expected to be closer to the Pooled OLS estimate than the baseline estimate with forecaster fixed effects, which is indeed what we see in Table 4. Because forecaster ID’s were reshuffled in 1993, this regression starts in January 1993.

Next, we split forecasters by the level of their inflation forecast. One might think that hawks vs. doves might perceive different monetary policy rules. The level of the inflation forecast might therefore serve as a signal of whether a particular forecaster or forecasting institution is a hawk or dove, where hawks would typically be expected to be more pessimistic on inflation. We do a very simple split based on forecasters’ four-quarter CPI inflation forecast. We first de-mean the inflation forecast every month to make sure that our split captures forecasters who are relatively more hawkish than their peers in a way that is not sensitive to forecasters dropping in and out of the sample. We then compute terciles for this demeaned inflation forecast. Each month, each forecaster is sorted into a tercile depending on his de-meaned four quarter horizon CPI inflation forecast. We then run the estimation with forecaster FE on each of the terciles separately. Because we include the same fixed effects as the baseline estimator, only using a different sample, estimates to be most closely

correlated with the baseline estimate, which is indeed what we see in Table 4.

Finally, we estimate (2) while controlling for forecaster j 's period $t + h$ forecast of the Baa-Treasury credit spread, $E_t^{(j)} credit_{t+h}$ in a regression that also includes forecaster fixed effects.

Figure C.1 plots the ‘‘Heterogeneity’’, ‘‘Credit Spread’’, and ‘‘Tercile’’ series underlying the correlations in Table 4. The level of the ‘‘Heterogeneous’’ estimate is different because of the forecaster fixed effect, so we plot it on a second axis for comparability.

C.2 Bias adjustment

We use a simple New Keynesian (NK) framework to quantify potential estimation bias from the endogenous response of the economy to monetary policy. Our analysis suggests that our estimates of $\hat{\gamma}_t$ may contain a modest downward bias relative to the true perceived monetary policy coefficient $\hat{\gamma}_t$, but that this estimation bias appears to be constant over time. Thus, our primary object of interest, time-series variation in our estimated $\hat{\gamma}_t$, is unaffected.

In our theoretical analysis of estimation bias, we use $\tilde{\gamma}$ to denote the estimated perceived monetary policy coefficient on the output gap, which may include a bias. We contrast this with forecasters’ perceived coefficient $\hat{\gamma}$. Recall that the perceived coefficient $\hat{\gamma}$ need not be equal to the true monetary policy coefficient γ .

We use the following version of the canonical three-equation NK model:

$$x_t = E_t x_{t+1} - (i_t - E_t \pi_{t+1}) + v_t \tag{C.4}$$

$$\pi_t = E_t \pi_{t+1} + \kappa x_t \tag{C.5}$$

$$i_t = \hat{\beta} \pi_t + \hat{\gamma} x_t + u_t. \tag{C.6}$$

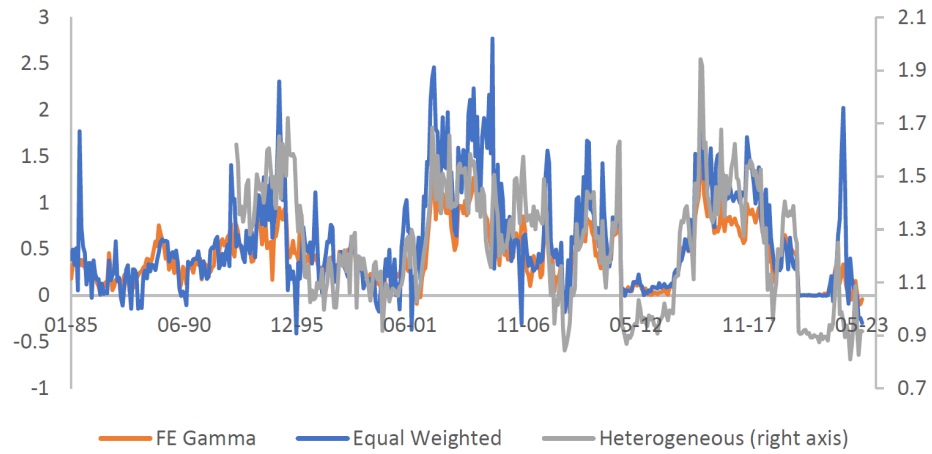
This model is completely standard; details and derivations can be found in textbook treatments such as Galí (2015). For simplicity we take the rate of time preference to be zero. The Euler equation, (C.4), assumes log-utility and includes a reduced-form demand shock v_t . Equation (C.5) is the Phillips curve. Our monetary policy rule, equation (C.6), includes a monetary policy shock u_t that is uncorrelated with v_t . The rule has constant parameters, and we will analyze shifts using comparative statics. We abstract from the intercepts in equations (C.4) through (C.6) since they do not affect the second moments that we are interested in.

As in our empirical analysis, the focus is on the monetary policy rule’s coefficient on the output gap, $\hat{\gamma}$. We can therefore shut down any effects from inflation by setting $\kappa = 0$ so that prices are fixed, following Caballero and Simsek (2022). That is, inflation is zero in equilibrium and $\hat{\beta} \pi_t$ drops out of the monetary policy rule.

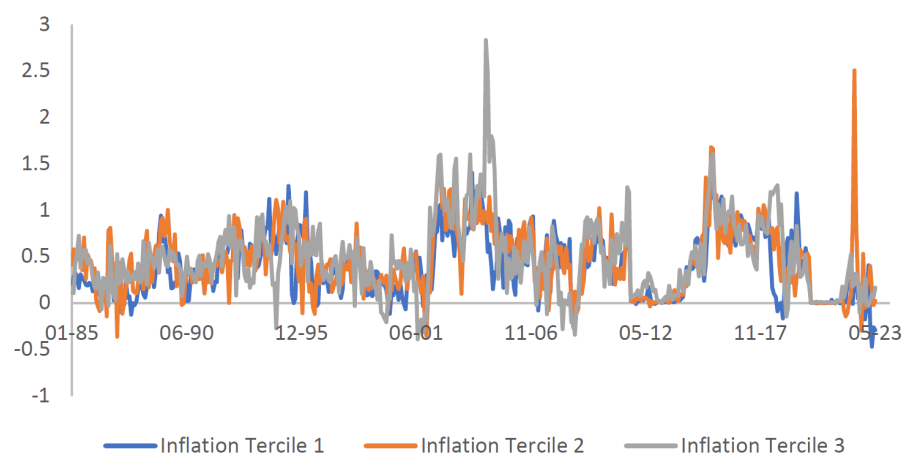
For the sake of simplicity, and to focus on the cross-sectional regression of forecasted fed funds rates onto forecasted output gaps across forecasters, we assume in this analysis that forecasters disagree over future demand and monetary policy shocks but that they agree on the monetary policy rule. In addition, we assume that forecaster j believes that his perceived monetary policy rule parameter $\hat{\gamma}_t$ is the true rule followed by the Fed, that he does not expect this rule to change in the future, and that all agents in the economy share his beliefs about demand and monetary policy shocks $E_t^{(j)} v_{t+h}$ and $E_t^{(j)} u_{t+h}$ at all

Figure C.1: Robustness: Alternative $\hat{\gamma}$ estimates

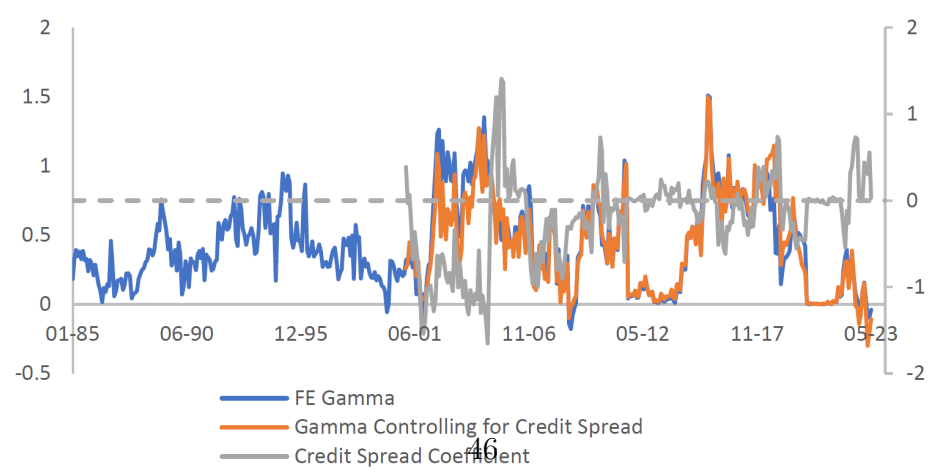
Panel A: Heterogeneity
Equal Weighted and Heterogeneous



Panel B: Inflation Terciles
Inflation Hawks vs. Doves



Panel C: Controlling for Credit Spread Forecasts
Controlling for Credit Spreads



forecast horizons h . We further impose that expectations for shocks $E_t^{(j)}v_{t+h}$ and $E_t^{(j)}u_{t+h}$ are bounded as $h \rightarrow \infty$. We do not take a stand on where differences in expectations about demand shocks and monetary policy shocks come from, which could be either rational or irrational.

With these assumptions, we can simply substitute the perceived monetary policy rule (C.6) into the Euler equation (C.4) and iterate forward to obtain forecaster j 's conditional expectations for the equilibrium policy rate and output gap at horizon $t + h$ as:

$$E_t^{(j)}x_{t+h} = \sum_{\tau=0}^{\infty} (1 + \hat{\gamma}_t)^{-(\tau+1)} (E_t^{(j)}v_{t+\tau+h} - E_t^{(j)}u_{t+\tau+h}), \quad \text{and} \quad (\text{C.7})$$

$$E_t^{(j)}i_{t+h} = \hat{\gamma}_t \sum_{\tau=0}^{\infty} (1 + \hat{\gamma}_t)^{-(\tau+1)} (E_t^{(j)}v_{t+\tau+h} - E_t^{(j)}u_{t+\tau+h}) + E_t^{(j)}u_{t+h}. \quad (\text{C.8})$$

We use the notation Cov_t and Var_t to denote covariances and variances of forecasts across forecasters and forecast horizons at a given time t . In order to say something about these cross-forecaster covariances and variances, we need to make further assumptions about the distribution of expected shocks across forecasters. Since demand and monetary policy shocks are thought to reflect structural shocks, we assume that expected demand shocks $E_t^{(j)}v_{t+h_1}$ are orthogonal to expected monetary policy shocks $E_t^{(j)}u_{t+h_2}$ at all forecast horizons h_1 and h_2 . For simplicity, we assume that $E_t^{(j)}(v_{t+h})$ and $E_t^{(j)}(u_{t+h})$ are perceived to be serially uncorrelated over forecast horizons. Even if these perceived serial correlations across forecast horizons may not be truly zero in the BCFF data, the inclusion of forecaster fixed effects in our estimation absorbs much of the correlation across forecast horizons within each forecaster. Finally, we assume that the sample means, variances and autocovariances of $E_t^{(j)}(v_{t+h})$ and $E_t^{(j)}(u_{t+h})$ converge to their population moments as the number of forecasters becomes large, i.e. that a law of large numbers holds.

We can then derive the time- t panel regression coefficient of interest rate forecasts onto output gap forecasts:

$$\begin{aligned} Cov_t \left(E_t^{(j)}i_{t+h}, E_t^{(j)}x_{t+h} \right) &= Cov_t \left(\hat{\gamma}_t E_t^{(j)}x_{t+h} + E_t^{(j)}u_{t+h}, E_t^{(j)}x_{t+h} \right), \quad (\text{C.9}) \\ &= \hat{\gamma}_t Var_t \left(E_t^{(j)}x_{t+h} \right) - Var_t \left(E_t^{(j)}u_{t+h} \right). \end{aligned}$$

The panel regression uses only time t expectations as input, which is why the perceived output gap coefficient at time t , $\hat{\gamma}_t$, enters. The simple regression coefficient from regressing interest rate forecasts onto output gap forecasts in the forecaster-horizon panel then equals

$$\tilde{\gamma}_t = \hat{\gamma}_t - (1 + \hat{\gamma}_t)^{-1} \frac{Var_t \left(E_t^{(j)}u_{t+h} \right)}{Var_t \left(E_t^{(j)}x_{t+h} \right)}$$

The term $-(1 + \hat{\gamma}_t)^{-1} \frac{Var_t \left(E_t^{(j)}u_{t+h} \right)}{Var_t \left(E_t^{(j)}x_{t+h} \right)}$ reflects the downward estimation bias due to the endogenous macroeconomic response to monetary policy, which we want to correct.

From now on we make the normalization $Var_t \left(E_t^{(j)} x_{t+h} \right) = 1$ to save on notation. This is without loss of generality as long as all other variances and covariances are interpreted as relative to the variance of output forecasts. Then the perceived monetary policy coefficient $\hat{\gamma}_t$ and the cross-forecaster and cross-horizon variance of monetary policy shocks $Var_t \left(E_t^{(j)} u_{t+h} \right)$ can be solved for exactly as two unknowns from the following two nonlinear equations:

$$\tilde{\gamma}_t = Cov_t \left(E_t^{(j)} i_{t+h}, E_t^{(j)} x_{t+h} \right) \quad (C.10)$$

$$= \hat{\gamma}_t - (1 + \hat{\gamma}_t)^{-1} Var_t \left(E_t^{(j)} u_{t+h} \right), \quad (C.11)$$

$$Var_t \left(E_t^{(j)} i_{t+h} \right) = \hat{\gamma}_t^2 + 2\hat{\gamma}_t Cov_t \left(E_t^{(j)} i_{t+h}, E_t^{(j)} x_{t+h} \right) + Var_t \left(E_t^{(j)} u_{t+h} \right) \quad (C.12)$$

We use these two equations solve for $\hat{\gamma}_t$ and $Var_t \left(E_t^{(j)} u_{t+h} \right)$, where $Var_t \left(E_t^{(j)} i_{t+h} \right)$ and $Cov_t \left(E_t^{(j)} i_{t+h}, E_t^{(j)} x_{t+h} \right)$ are estimated from the data.

In order to derive the panel regression coefficient on the panel of time t forecasts with fixed effects, we make the additional assumption that forecaster j believes that the long-run natural rate equals $E_t^{(j)} r_t^*$. The equilibrium for the output gap (C.7) then is unchanged, and the equilibrium for the policy rate C.8 is shifted up by a constant $E_t^{(j)} r_t^*$. After projecting onto forecaster-level fixed effects, the expression for $\tilde{\gamma}_t$ is therefore exactly as before and all derivations go through, provided that we replace the OLS coefficient with the regression coefficient with forecaster fixed effects.

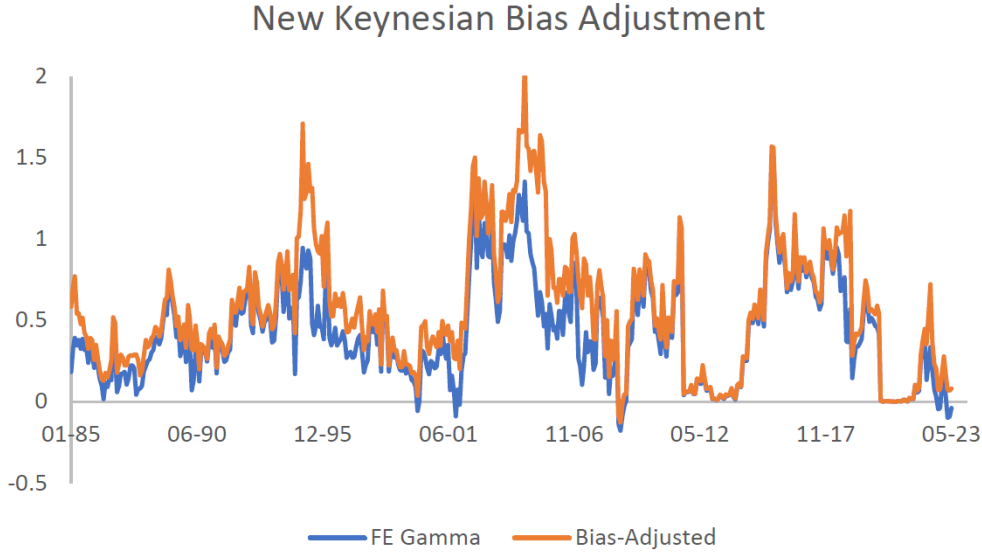
The bias adjusted $\hat{\gamma}_t$ in Table 4 is obtained by solving the two equations (C.11) and (C.12) numerically for $\hat{\gamma}_t$ after residualizing everything with respect to forecaster fixed effects.

C.3 Robustness: Survey of Professional Forecasters

The Philadelphia Fed’s quarterly Survey of Professional Forecasters includes individual forecasts of various macroeconomic variables and interest rates. We estimate a policy rule for the three-month T-bill rate, the interest rate with the shortest maturity, which is highly correlated with the federal funds rate. For inflation we use the CPI forecasts, as before. As a measure of economic activity we use the unemployment rate forecasts, since we are mainly interested how the use of a different variable than the output gap affects our estimates. The SPF includes forecasts for the current quarter and the next four quarters. The data starts in 1981:Q3, and each quarter there are generally around 30-35 individual forecasters.

We estimate FE regressions for each quarterly SPF forecaster panel. The estimated coefficient on the unemployment rate forecasts has a correlation of -0.77 with the $\hat{\gamma}_t$ estimates from the BCFF over the period where they are both available. The former is generally about -2 times as large as the latter, consistent with Okun’s law. Figure C.3 shows a visual comparison of the two estimates. For the BCFF, it shows the FE point estimates and 95% confidence intervals, as in the top panel of Figure 1. For the SPF, it shows the fitted values from a regression of the BCFF on the SPF estimate, in order to rescale the latter and make the two series comparable. While there is more volatility in the month-to-month BCFF

Figure C.2: Estimation Bias Adjusted $\hat{\gamma}_t$



Endogeneity bias-adjusted FE estimate of $\hat{\gamma}_t$ versus the baseline FE estimate of $\hat{\gamma}_t$.

estimates, the cyclical patterns of the two series are generally very similar.

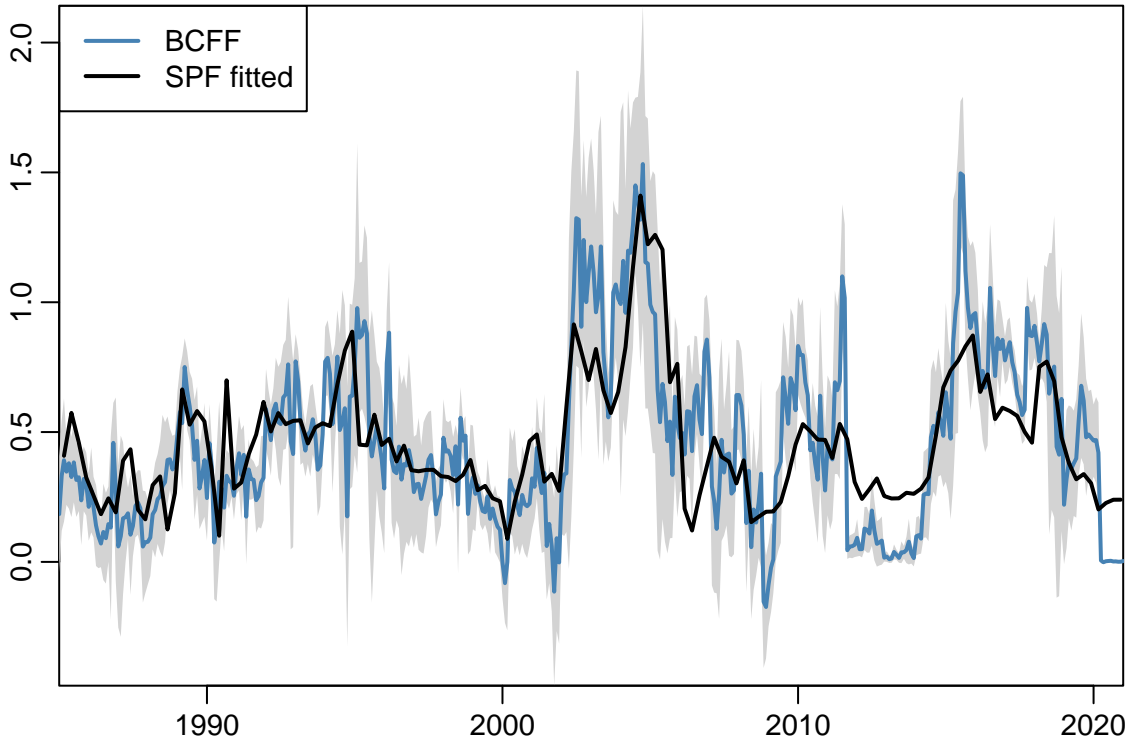
C.4 Comparison with the Fed’s rule: A case study

In this section, we compare our estimates of the perceived monetary policy rule from Blue Chip forecasts to direct estimates of the Fed’s actual monetary policy rule, which we construct from the cross-section of Fed forecasts in the “Summary of Economic Projections” (SEP). This descriptive comparison supports our findings elsewhere in the paper that the perceived rule behaves reasonably, but also that there are important differences, i.e., that FIRE is violated.

To obtain monetary policy coefficients from the Fed’s own forecasts, we use the same panel regression approach as for the Blue Chip data, described in Section 2.2. We construct output gap projections by combining CBO projections for potential output with the those for the level of real GDP implied by the growth forecasts. While there are some differences in the forecast data—such as the sample period, the forecast horizons, and the inflation measure (PCE instead of CPI)—the estimation method remains the same, which allows for a meaningful comparison of the estimates. For comparability with the Blue Chip forecasts, we use only the forecasts for the current and next years. The macro forecasts pertain to the last quarter of each year, and for the inflation and real GDP growth rates are four-quarter percentage changes. For the fed funds rate, the projections are for the end of each year. Due to data availability, we study the years 2012-2016, a period covering the first liftoff from the ZLB and thus including rapid changes in the stance of monetary policy and a strong Fed focus on communicating those changes.²⁴ For each of 21 forecast releases over the period

²⁴Individual projections of each FOMC participant are made public with a publication lag of five years, and

Figure C.3: Comparison with estimates for Survey of Professional Forecasters



Comparison of perceived policy rule coefficients for real activity in Blue Chip Financial Forecasts (BCFF) and Survey of Professional Forecasters (SPF). Estimation method is FE in both cases, as described in 2.2. Estimate for BCFF corresponds to the output gap forecasts, while the estimate for SPF corresponds to unemployment rate forecasts. SPF estimate is scaled using a regression of BCFF on SPF estimates, taking the fitted values. Sample is quarterly from 1985:Q1 to 2020:Q4.

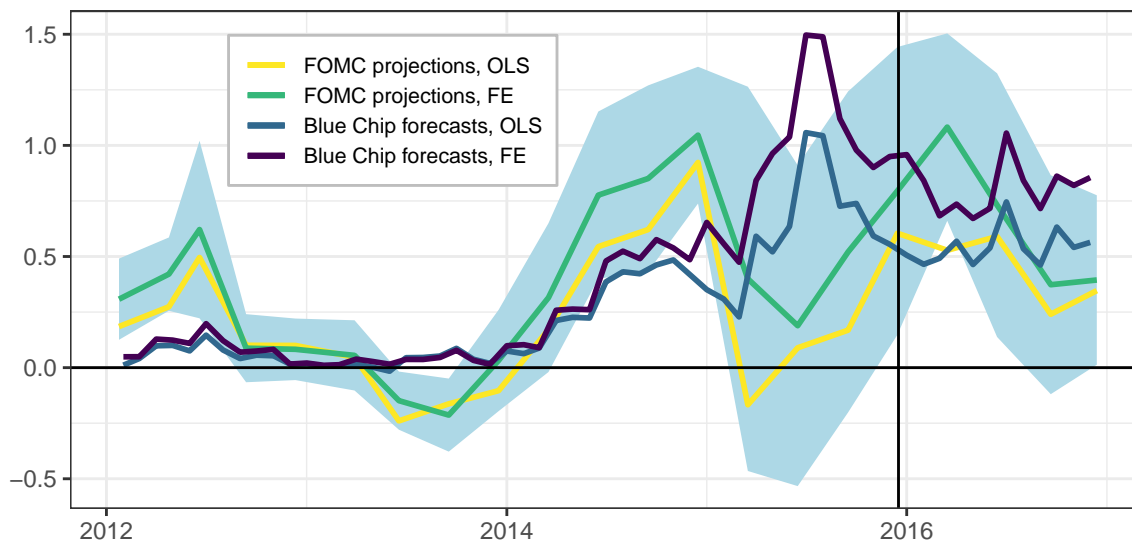
from 2012 to 2016, we have a panel of 16 to 19 Fed forecasters in the SEP.

As shown in Figure 1, there were significant fluctuations in the perceived output gap coefficient $\hat{\gamma}$ in the time period around the first ZLB. After both the funds rate and $\hat{\gamma}_t$ decreased to zero in 2008, the $\hat{\gamma}$ quickly rose again and remained at a high level until August 2011. During this period, forecasters generally expected the Fed to lift the policy rate off the ZLB within the next year or so, resulting in a high estimated perceived output gap weight $\hat{\gamma}$. On August 9, 2011, however, the Fed introduced calendar-based forward guidance, predicting a near-zero policy rate “at least through mid-2013.” In response, the estimated $\hat{\gamma}$ dropped sharply and stayed near zero until lift-off started to come into view again in spring 2014, suggesting that our estimates pick up on “Odyssean” forward guidance where the Fed

since 2012 these projections have include the forecasted path of the federal funds rate. Detailed information about FOMC meetings, including the staff (“Greenbook”) forecasts, the transcripts of the meetings, and individual economic projections, are made public with a delay of five years and can be found at https://www.federalreserve.gov/monetarypolicy/fomc_historical.htm. In these forecasts, each participant projects a corresponding path for the federal funds rate “under appropriate monetary policy”. That is, the projections reflect what the participants think the policy rate *should* be, not what it is most likely to be. It is therefore natural to view these projections as reflecting each participant’s implicit monetary policy rule.

predicts and essentially commits to a certain path for the future policy rate (Campbell et al., 2012).

Figure C.4: Output gap policy rule coefficients implied by FOMC economic projections



Estimated policy-rule parameters γ_t from repeated panel regressions (2), using Pooled OLS (OLS) and forecaster Fixed Effects (FE). FE estimates include 95% confidence intervals based on robust standard errors. Estimates for the FOMC are based on the individual projections of FOMC participants for the “Summary of Economic Projections” (SEP) between 2012 and 2016 (21 meetings, 16-19 individual projections, forecasts for the current year and the following year). Also shown are the OLS and FE estimates of the perceived coefficients from the Blue Chip Financial Forecasts. The vertical line indicates the Federal Reserve’s actual liftoff date from the ZLB.

Figure C.4 shows the OLS and FE estimates of γ_t obtained from the FOMC projections (SEP), together with 95% confidence intervals for the FE estimates. It also includes the estimates of the perceived coefficients $\hat{\gamma}_t$ based on the Blue Chip data for the time period where both are available. The date of actual liftoff is indicated with a vertical line. We see that the perceived output gap coefficient as estimated from Blue Chip forecasts captures well the change in the Fed’s own monetary policy rule around liftoff. It rises from around zero to around 0.5 shortly before actual liftoff. The magnitude of the Blue Chip private forecaster coefficient is similar to the Fed’s, though the private forecaster coefficient appears to lag somewhat behind. Overall, the episode around the first lift-off from the ZLB suggests that private forecasters updated their perceived output gap coefficient $\hat{\gamma}_t$ in the right direction but more slowly than the true response coefficient γ_t , consistent with the evidence of broadly rational but sluggish updating elsewhere in the paper.

D Robustness expected bond excess returns

D.1 Robustness: Controlling for interest rate disagreement

We next compare our estimates of $\hat{\gamma}_t$ to the measures of forecaster disagreement from [Giacoletti et al. \(2021\)](#). [Giacoletti et al. \(2021\)](#) use the 90-10 spread for the 2-year and 10-year Treasury forecasts and show that these measures of forecaster disagreement predict future bond excess returns. One might naturally expect that the 90-10 spread in policy rate forecasts should be correlated with our measures of $\hat{\gamma}_t$, because a high perceived $\hat{\gamma}_t$ mechanically leads to a larger spread in policy rate forecasts, holding constant disagreement about the future output gap and disagreement about future monetary policy shocks. However, we find that the perceived monetary policy output weight $\hat{\gamma}_t$ shows distinct time-series variation from interest rate disagreement in the data. We replicate the measures of interest rate disagreement by [Giacoletti et al. \(2021\)](#). In addition, we consider the 90-10 forecaster spread for the 4-quarter fed funds rate forecast. We consider this measure of fed funds rate disagreement because this matches most closely our estimation of the perceived monetary policy rule and therefore might be expected to be more strongly correlated with $\hat{\gamma}_t$ than the other measures of interest rate disagreement.

Table [D.1](#) shows correlations of our benchmark estimate of $\hat{\gamma}_t$ with these three measures of interest rate disagreement. As expected, the correlations between interest rate disagreement and $\hat{\gamma}_t$ are positive, but they are not large in magnitude, ranging from 0.14 to 0.42. These results therefore underscore that the perceived monetary policy response to the output gap is correlated with, but distinct from, disagreement about future interest rates across forecasters.

Table D.1: Robustness: Correlation with interest rate disagreement

	Disagreement		
	FFR	2y	10y
Baseline $\hat{\gamma}_t$	0.27	0.42	0.14
Inertial $\hat{\gamma}_t$	0.29	0.34	0.23

Correlations between different estimates for the perceived output gap weight in the policy rule, $\hat{\gamma}_t$ with measures of interest rate disagreement in the cross-section of forecasters. Disagreement is measured as the difference between the 90th and 10th percentiles of 4-quarter horizon forecasts across forecasters for the fed funds rate (FFR), 2-year Treasury rate, and 10-year Treasury rate. Sample period ends in January 2021, and starts in January 1985 for fed funds rate disagreement. The sample period starts in January 1988 for 2-year Treasury rate and 10-year Treasury rate disagreement.

We can also control for these three measures of interest rate disagreement in our regressions of subjective bond risk premia onto $\hat{\gamma}_t$. Table [D.2](#) estimates regressions analogous to those in Table [3](#), including $\hat{\gamma}_t$ as well as the level, slope and curvature of the yield curve. Adding different measures of cross-sectional interest disagreement does not materially affect the coefficient on $\hat{\gamma}_t$, which remains highly statistically significant. This evidence confirms that the perceived monetary policy rule plays a role for bond risk premia that is distinct from forecaster disagreement about interest rates.

Table D.2: Subjective bond risk premia: Controlling for forecaster interest rate disagreement

Panel A: Baseline $\hat{\gamma}$						
		$\bar{E}_t x r_{t+1}^{(6)}$			$\bar{E}_t x r_{t+1}^{(11)}$	
$\hat{\gamma}$	-0.56***	-0.67***	-0.78***	-0.84***	-0.97***	-1.11***
	(-4.90)	(-5.44)	(-8.24)	(-3.50)	(-3.89)	(-5.75)
FFR disagreement	-1.33***			-1.82***		
	(-3.90)			(-2.60)		
2y disagreement		-1.23**			-1.79*	
		(-2.57)			(-1.88)	
10y disagreement			-1.35**			-3.01***
			(-2.47)			(-2.76)
N	425	424	425	425	424	425
R-sq	0.67	0.65	0.64	0.64	0.64	0.65
Panel B: Inertial $\hat{\gamma}$						
		$\bar{E}_t x r_{t+1}^{(6)}$			$\bar{E}_t x r_{t+1}^{(11)}$	
$\hat{\gamma}$	-0.28***	-0.27***	-0.36***	-0.57***	-0.56***	-0.67***
	(-3.41)	(-2.88)	(-3.60)	(-2.94)	(-2.62)	(-3.31)
FFR disagreement	-1.97***			-2.73***		
	(-4.59)			(-3.73)		
2y disagreement		-1.91***			-2.68**	
		(-2.75)			(-2.36)	
10y disagreement			-1.69**			-3.48***
			(-2.38)			(-2.59)
N	425	424	425	425	424	425
R-sq	0.62	0.57	0.50	0.62	0.59	0.58

Regressions for subjective expected excess returns on six-year and 11-year Treasury bonds over one-year holding period, controlling for interest rate disagreement. All regressions also include a constant and the first three principal components of Treasury bond yields. The sample is the same as in Table 3. Newey-West t -statistics with automatic lag selection in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.2 Multivariate term structure regressions for time-varying perceived inertial rule

Table D.3 shows multivariate regressions of expected subjective bond excess returns onto perceived $\hat{\gamma}_t$, $\hat{\beta}_t$ and $\hat{\rho}_t$ from the inertial rule. It shows that expected bond excess return declines with perceived inertia $\hat{\rho}_t$. Expected bond risk premia also weakly increase with the time-varying perceived inflation weight $\hat{\beta}_t$ in columns (1) and (2). However, when controlling for the first three principal components of bond yields, only the time-varying perceived output gap weight $\hat{\gamma}_t$ enters, as predicted by the model and shown in Table 3 in the main paper. To the extent that a higher weight on inflation fluctuations in the monetary policy rule is similar to a lower weight on output fluctuations, all these signs are as expected by theory. The significance of the time-varying perceived inertia parameter in particular indicates that fluctuations in the *long-term* perceived cyclicalness of interest rates are priced in term premia of long-term bonds. This is in line with the model predictions in Appendix E.

Table D.3: Term premia

	$\bar{E}_t x r_{t+12}^{(6)}$			$\bar{E}_t x r_{t+12}^{(11)}$		
Inertial $\hat{\gamma}_t$	-0.00021 (0.15)	-0.017 (0.13)	-0.39*** (0.12)	-0.015 (0.29)	-0.043 (0.25)	-0.72*** (0.22)
Inertial $\hat{\beta}_t$	0.25* (0.14)	0.25* (0.14)	0.10 (0.13)	0.25 (0.22)	0.26 (0.23)	0.068 (0.25)
$\hat{\rho}_t$	-0.44** (0.22)	-0.56*** (0.21)	-0.014 (0.12)	-0.92*** (0.33)	-1.12*** (0.33)	-0.20 (0.17)
TERM		0.32** (0.15)			0.55** (0.27)	
N	425	425	425	425	425	425
R^2	0.09	0.13	0.46	0.09	0.13	0.53
PCs	No	No	Yes	No	No	Yes

This table is analogous to Panel B of Table 3 in the main paper, but controls for time-varying $\hat{\rho}_t$ and $\hat{\beta}_t$ estimated from the time-varying perceived rule with inertia. Sample: 425 monthly observations from January 1988–April 2023. Newey-West standard errors with automatic lag selection (between 19 and 28 months) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

E Details for learning model

Within-period timing:

		Period t		
Signal ν_t^j	\Rightarrow	Make forecasts	\Rightarrow	Observe $x_t \Rightarrow$ Observe $i_t \Rightarrow$ Update $\hat{\gamma}_t^j$

E.1 Proofs

Proof of Corollary 1: Forecaster j 's optimal forecast of the time- t output gap after observing his signal is

$$E^j(x_t | \mathcal{Y}_{t-1}, \nu_t^j) = \phi x_{t-1} + \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_\eta^2} (\varepsilon_t + \eta_t^j). \quad (\text{E.1})$$

Because the monetary policy shock u_t is uncorrelated with ξ_t , ε_t and ν_t^j and all these shocks are independent of the filtration \mathcal{Y}_{t-1} , agent j 's optimal forecast of the monetary policy rate at horizon h conditional on the macroeconomic signal equals

$$E^j(i_{t+h} | \mathcal{Y}_{t-1}, \nu_t^j) = \hat{\gamma}_t E^j(x_{t+h} | \mathcal{Y}_{t-1}, \nu_t^j) + \rho E^j(i_{t+h-1} | \mathcal{Y}_{t-1}, \nu_t^j). \quad (\text{E.2})$$

Corollary 1 then follows. While the forecaster fixed effect, α_j^0 , is zero under the assumptions of the model, a straightforward extension with disagreement about the natural rate implies non-zero forecaster intercepts as in our empirical estimation.

Proof of Corollary 2: Taking the forecaster average of (E.1) shows that the consensus forecast after observing the signals equals

$$\bar{E}(x_t | \mathcal{Y}_{t-1}, \nu_t^j) = \phi x_{t-1} + \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_\eta^2} \varepsilon_t. \quad (\text{E.3})$$

The revision in the consensus output gap forecast around the macroeconomic announcement therefore equals

$$x_t - \bar{E}(x_t | \mathcal{Y}_{t-1}, \nu_t^j) = \frac{\sigma_\eta^2}{\sigma_\varepsilon^2 + \sigma_\eta^2} \varepsilon_t \quad (\text{E.4})$$

Because the macroeconomic announcement leads to no updating about the perceived monetary policy coefficient, the change in the expected fed funds rate around the macroeconomic announcement equals

$$\bar{E}(i_t | \mathcal{Y}_{t-1}, x_t) - \bar{E}(i_t | \mathcal{Y}_{t-1}, \nu_t^j) = \hat{\gamma}_t (x_t - \bar{E}(x_t | \mathcal{Y}_{t-1}, \nu_t^j)). \quad (\text{E.5})$$

Corollary 2 follows immediately from (E.5).

Proof of Corollary 3: Let $B_{n,t}$ denote the end-of-period t price of a bond with n periods remaining to maturity. Here, we use the subscript t to denote an expectation conditional on

the filtration \mathcal{Y}_t . The two-period bond price is given by

$$B_{2,t} = \exp(-i_t) E_t \left[\exp \left(-\psi \varepsilon_{t+1} - \frac{1}{2} \psi^2 \sigma_\varepsilon^2 - i_{t+1} \right) \right], \quad (\text{E.6})$$

$$= \exp(-i_t) E_t \left[\exp \left(-\rho i_t - \psi \varepsilon_{t+1} - \frac{1}{2} \psi^2 \sigma_\varepsilon^2 - \gamma_{t+1} ((\phi x_t + \varepsilon_{t+1})) - u_{t+1} \right) \right], \quad (\text{E.7})$$

$$= \exp \left(-i_t - E_t i_{t+1} + \psi \hat{\gamma}_{t+1} \sigma_\varepsilon^2 + \frac{1}{2} \hat{\gamma}_{t+1}^2 \sigma_\varepsilon^2 + \frac{1}{2} \sigma_{t+1}^2 (\phi x_t)^2 + \frac{1}{2} \sigma_u^2 \right) \quad (\text{E.8})$$

The term $\psi \hat{\gamma}_{t+1} \sigma_\varepsilon^2$ is the risk premium, $\frac{1}{2} \hat{\gamma}_{t+1}^2 \sigma_\varepsilon^2$ is a Jensen's inequality adjustment, and $\frac{1}{2} \sigma_{t+1}^2 (\phi x_t)^2$ is a Jensen's inequality adjustment for uncertainty about the monetary policy rule.

The expected log excess return on a two-period bond adjusted for a Jensen's inequality term then equals

$$E_t x r_{2,t+1} + \frac{1}{2} \text{Var}_t x r_{2,t+1} \equiv E_t (b_{1,t+1} - b_{2,t} - i_t) + \frac{1}{2} \text{Var}_t (b_{1,t+1}), \quad (\text{E.9})$$

$$= -\psi \hat{\gamma}_{t+1} \sigma_\varepsilon^2. \quad (\text{E.10})$$

Equation (E.10) shows that the expected excess return on a long-term bond decreases with the perceived monetary policy coefficient $\hat{\gamma}_{t+1}$.

To solve for the three-period bond, we simplify to the case with constant $\hat{\gamma}_t = \gamma$. Then the two-period bond price simplifies to

$$B_{3,t} = \exp \left(-i_t (1 + \rho) - \gamma \phi x_t + \psi \gamma \sigma_\varepsilon^2 + \frac{1}{2} \gamma^2 \sigma_\varepsilon^2 + \frac{1}{2} \sigma_u^2 \right). \quad (\text{E.11})$$

The three-period bond price then equals

$$B_{3,t} = \exp(-i_t) E_t \left[\exp \left(-\psi \varepsilon_{t+1} - \frac{1}{2} \psi^2 \sigma_\varepsilon^2 \right) B_{2,t+1} \right], \quad (\text{E.12})$$

$$= \exp \left(-i_t (1 + \rho + \rho^2) - x_t \gamma \phi (1 + \rho + \phi) \right)$$

$$\times E_t \left[\exp \left(-\psi \varepsilon_{t+1} - \frac{1}{2} \psi^2 \sigma_\varepsilon^2 - \varepsilon_{t+1} \gamma (1 + \rho + \phi) + \psi \gamma \sigma_\varepsilon^2 + \frac{1}{2} \gamma^2 \sigma_\varepsilon^2 + \frac{1}{2} (1 + \rho)^2 \sigma_u^2 \right) \right],$$

$$= \exp \left(-i_t - E_t (i_{t+1} + i_{t+2}) \right)$$

$$\times \exp \left(\gamma \psi \sigma_\varepsilon^2 (2 + \rho + \phi) + \frac{1}{2} \gamma^2 \sigma_\varepsilon^2 (1 + (1 + \rho + \phi)^2) + \frac{1}{2} (1 + \rho)^2 \sigma_u^2 \right), \quad (\text{E.13})$$

and the expected log excess return on the three-period bond equals

$$E_t x r_{3,t+1} + \frac{1}{2} \text{Var}_t x r_{3,t+1} \equiv E_t (b_{2,t+1} - b_{3,t} - i_t) + \frac{1}{2} \text{Var}_t (b_{2,t+1}), \quad (\text{E.14})$$

$$= -\psi \gamma (1 + \rho + \phi) \sigma_\varepsilon^2, \quad (\text{E.15})$$

Expression (E.15) shows that the expected excess return for very long-term bonds declines

with the short-term monetary policy rule coefficient, γ , similarly to the expected excess return for two-period bonds in equation (E.11). In addition, the expected excess return on very long-term bonds in equation (E.15) also declines with monetary policy inertia, ρ , provided that $\gamma > 0$.

E.2 Numerical simulation details

Table E.1 provides the numerical values used in the model simulations in Section 5.

Table E.1: Simulation Parameter Values

Persistence output gap	ρ	0.95
Std. output gap shock	σ_ε	1.2
Std. MP shock	σ_u	0.05
Std. MP rule innovations	σ_ξ	0.1
Overconfidence	κ	0.1
Overextrapolation	b	0.95