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Perceptions about Monetary Policy *

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Abstract

We estimate perceptions about the Federal Reserve'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 varies substantially over time, including over the monetary policy cycle. Forecasters update their perceptions about the Fed's policy rule in response to monetary policy actions, measured by high-frequency interest rate surprises, suggesting that they have imperfect information about this rule. Monetary policy perceptions matter for monetary transmission, as they affect the sensitivity of interest rates to macroeconomic news, term premia in long-term bonds, and the response of the stock market to monetary policy surprises. A simple learning model with forecaster heterogeneity and incomplete information about the policy rule motivates and explains our empirical findings.

Keywords: FOMC, monetary policy rule, survey forecasts, beliefs
JEL Classifications: E43, E52, E58

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1 Introduction

Over the past 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 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 the effectiveness of policy (Bernanke, 2010).[1] But what monetary policy strategy does the public perceive? How do these perceptions vary over the cycle and in response to actual policy rates? And what role do they play in the transmission of monetary policy to financial markets?

Empirical progress on these questions requires a measure that captures the public's forward-looking perceptions of how the Fed will respond to future economic data at each point in time. Perceptions of the monetary policy framework may differ from the actual historical behavior of the Fed, which has been the focus of much empirical work since Taylor (1993). This type of empirical analysis typically describes the monetary policy framework by estimating simple rules that link policy rates to macroeconomic conditions in time series data, sometimes allowing for shifts in the policy rule.[2] But such estimates cannot speak to the role of public perceptions about the monetary policy framework because they are based on historical data and thus inherently backward-looking.

In this paper, we estimate perceived, forward-looking monetary policy rules *each month* using rich survey data from the Blue Chip Financial Forecasts (BCFF) spanning almost four decades of U.S. monetary policy. We characterize time variation in the estimated rules, their relationship to actual monetary policy decisions, and their influence on financial markets.

For each monthly survey from January 1985 to April 2023, we form a forecaster-by-horizon panel, which consists of forecasts for the federal funds rate, output gap, and inflation across 30–50 forecasters and horizons from zero to five quarters. We then estimate a simple *forward-looking* monetary policy rule that relates fed funds rate forecasts to macroeconomic

[1]The 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 (2023b), Elenev et al. (2022), and Bianchi et al. (2022a)).

[2]Studies 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 structural models linking asset prices to the monetary policy rule.

forecasts in each month's panel. In addition, we estimate a forward-looking inertial rule that includes lagged funds rate forecasts and thereby captures the perceived short-run response of monetary policy to economic conditions. We conduct all our subsequent analyses on both types of estimated rules and find broadly similar results.

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. Over our sample period, inflation was relatively stable and close to the Fed's now-explicit 2 percent target, which renders the inflation coefficient less meaningful. Furthermore, demand shocks were the dominant drivers of economic fluctuations, and the output gap thus also captured anticipated inflationary pressures. In our sample, the Fed's response to economic slack therefore captures both parts of its dual mandate, and we focus on $\hat{\gamma}_t$ as an approximate summary statistic for perceptions about monetary policy strategy.

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 0 and about 1.5. The perceived monetary policy rule often lines up with rolling estimates of the Fed's historical behavior from time series macroeconomic data. However, during several episodes, our forward-looking perceived rule diverges from the historical, backward-looking rule. This divergence is particularly pronounced during episodes with strong forward guidance, including zero lower bound (ZLB) periods and around liftoff.

The perceived policy rule is correlated with the monetary policy cycle and financial conditions, but not with the business cycle. The coefficient $\hat{\gamma}_t$ tends to be high in the early stages of monetary tightening cycles, when the slope of the yield curve is high, indicating that the Fed is perceived to be strongly data-dependent at these times. Conversely, $\hat{\gamma}_t$ tends to be low in monetary easing episodes and when financial market uncertainty is high. At these times, the Fed is viewed to be less responsive to standard indicators of economic slack such as the output gap, perhaps because it is putting more weight on risks not captured by these indicators.

Section 3 shows that policy perceptions respond to high-frequency monetary policy surprises around Federal Open Market Committee (FOMC) announcements in a state-contingent manner. The way forecasters update their beliefs suggests that they have imperfect information about the policy rule and learn from observed policy decisions. Intuitively, a surprise tightening in a strong economy signals to forecasters that the Fed's response to economic slack is stronger than expected, while a surprise tightening in a weak economy signals the opposite. We confirm this prediction in the data: $\hat{\gamma}_t$ increases following a positive high-frequency monetary policy surprise when the economy is strong, but declines following the same type of surprise when the economy is weak. The magnitude of the empirical response suggests that monetary policy surprises on FOMC dates would be 50% less volatile if the monetary policy rule were fully known.

Having characterized variation in the perceived monetary policy rule over time and in response to monetary policy decisions, we next show that these shifting perceptions matter for the key asset prices that transmit monetary policy to the real economy: short- and long-term interest rates, as well as stock prices.

Section 4.1 documents that market interest rates react more strongly to macroeconomic news when the Fed's perceived responsiveness $\hat{\gamma}_t$ is high. This high-frequency analysis validates our survey-based estimates of $\hat{\gamma}_t$ using financial market data, showing they are tightly linked to the "market-perceived policy rule" (Hamilton et al., 2011). It also connects our perceived policy rule to the results of Swanson and Williams (2014), who document changes in the market's sensitivity to macroeconomic news at the ZLB. Economically, our results show that monetary policy perceptions 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, which are particularly important for the transmission of monetary policy. Section 4.2 shows that policy rule perceptions affect the term premium in long-term bond yields, driving a wedge between long-term rates and expected short-term rates. Classic finance theory suggests that when $\hat{\gamma}_t$ is higher, investors expect interest rates to fall more, and hence bond prices to rise more, in bad economic states, i.e., when the output gap is low. Thus, they believe Treasury bonds are better hedges and require a lower term premium for holding them. We document precisely this pattern: both subjective term premia, calculated from survey expectations of future yields, and statistical term premia, estimated with predictive regressions, move inversely with $\hat{\gamma}_t$.

These results can help explain the reaction of long-term bond yields to monetary policy decisions (e.g., Hanson and Stein, 2015; Nakamura and Steinsson, 2018). In particular, they highlight a mechanism for monetary policy to strongly impact long-term yields: policy decisions affect perceptions of the monetary policy rule, which in turn impact term premia. Our mechanism predicts that the impact of policy surprises on term premia should be most pronounced when the economy is weak, i.e. the impact should be state-contingent. A surprise tightening in a weak economy leads investors to revise $\hat{\gamma}_t$ downwards, raising term premia. Thus, long-term yields should rise more than they would following the same surprise in a strong economy, when $\hat{\gamma}_t$ and term premia move in the other direction. In Section 4.3, we find strong evidence for such state-dependence, extending commonly used event-study regressions to document a stronger response of long-term rates to policy surprises in a weak economy than in a strong economy. These results provide additional evidence of updating about the perceived rule, and its effect on term premia, without relying on our survey-based estimate $\hat{\gamma}_t$.

We next show in Section 4.4 that the stock market's response to monetary policy also depends strongly on the perceived monetary policy rule. Using high-frequency regressions of stock returns on interest rate surprises around FOMC announcements (as in Bernanke and Kuttner, 2005), we document that the market response to a tightening surprise is significantly more negative when $\hat{\gamma}_t$ is low. This result suggests that investors anticipate more pronounced economic consequences from a monetary policy shock when the Fed is perceived to be less responsive to economic conditions, consistent with standard New Keynesian theory.

In Section 5 we present a simple model with forecaster heterogeneity and imperfect information about the policy rule that motivates and explains our empirical findings. The true policy rule is time-varying and unobserved by forecasters, who learn about it from policy rate decisions. Forecasters receive different signals about the output gap and form policy rate forecasts according to their perceived rule. According to the model, regressions of policy rate forecasts onto output gap forecasts in a forecaster-horizon panel recover the policy rule coefficient perceived by forecasters. The model predicts that forecasters update their perceived coefficient upwards following a surprise tightening in a strong economy, but update downwards following a surprise tightening in a weak economy. It also predicts that fed funds futures respond more strongly to macro news when the perceived coefficient is high, that term premia are inversely related to the perceived coefficient, and that long-term yields respond more strongly to monetary policy surprises when the economy is weak. All these predictions are confirmed in the data.

Finally, Section 6 shows that our estimates are robust to several concerns. First, we extend the policy rule specification so that the Fed is perceived to respond directly to financial conditions, measured by expected credit spreads. These estimates yield very similar estimates of $\hat{\gamma}_t$ as in our baseline specification. Second, we explore heterogeneous beliefs across forecasters about the coefficients in the policy rule. Our estimated $\hat{\gamma}_t$ essentially captures the average belief across forecasters and variation in that average belief over time. The average belief is likely what matters for asset prices, so we focus on it for our key results. Third, 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. Building on Carvalho et al. (2021), we use a model that captures this endogeneity bias and show that such bias is unlikely to affect the time-series variation in $\hat{\gamma}_t$ and hence our main results. In addition, our results in Sections 3 and 4 strongly support an interpretation of $\hat{\gamma}_t$ as a perceived policy rule coefficient. Nevertheless, many of the takeaways from our empirical analysis remain valid under a more general, noncausal interpretation of $\hat{\gamma}_t$ as the perceived endogenous comovement between the short-term policy rate and macroeconomic variables. For example, under this broader interpretation, our results show that perceived comovement is priced in financial markets and influences term premia.

In summary, using a novel methodology for estimating perceptions of the monetary policy rule from professional forecasts, we establish three key empirical results: First, the perceived monetary policy rule varies significantly over time. Second, the way forecasters update their beliefs suggests that they have incomplete information about the policy rule and learn about it from policy actions. Third, variation in the perceived rule impacts the transmission of monetary policy to financial markets, affecting the sensitivity of interest rates to macro news, the term premium in long-term bond yields, and the reactions of yields and stock prices to FOMC announcements.

By providing estimates of the perceived monetary policy rule, our paper contributes to the growing literature on incomplete information and monetary policy.[3] We document that investors learn about the rule from policy decisions and that their perceptions are transmitted to financial markets. Our findings are complementary to Caballero and Simsek (2022b), who study disagreement between the public and the Federal Reserve and its implications for monetary policy surprises, and Stein and Sunderam (2018), who examine strategic communication between the central bank and market participants. Our evidence is also complementary to evidence on the gap between market and household expectations studied by Reis (2020). Our data cover a set of agents who are highly relevant for the transmission of policy perceptions to financial markets; the typical forecaster in our data is a chief economist at a large bank or broker-dealer. 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 they do. 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) because time variation in the perceived monetary policy rule is potentially consistent with the Fed exercising significant discretion.

Methodologically, our paper is closely related to previous work that estimates monetary policy rules from financial market and survey data. The main idea in this literature is to take the concept of empirical monetary policy rules—in the manner of Taylor (1999)—and apply it to forward-looking data. Some papers have estimated perceived policy rules using consensus survey forecasts (e.g., Bundick et al., 2015; Kim and Pruitt, 2017; Jia et al., 2023),

[3]See, for example, Mankiw and Reis (2002); Primiceri (2006); Coibion and Gorodnichenko (2015); Gabaix (2020); Angeletos and Lian (2023); Angeletos and Sastry (2021); Afrouzi and Yang (2021); Bordalo et al. (2020); Cieslak et al. (2022).

while others have used individual forecasts to estimate constant-parameter rules, potentially allowing for a single parameter break (Carvalho and Nechio, 2014; Andrade et al., 2016, 2019).[4] We make two related contributions to this literature: First, in contrast to prior work we estimate the perceived rule in each monthly survey, using variation across both forecasters and horizons to pin down the rule's parameters. Second, we relate month-to-month shifts in the perceived rule to monetary policy actions and the key asset prices responsible for monetary policy transmission. Our results suggest that the perceived monetary policy rule is an important determinant of risk premia and that FOMC announcements influence asset prices in part by changing perceptions of the policy rule.

We also contribute to a large macro-finance literature on the financial market effects of monetary policy.[5] Some recent studies connect 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. (2023) estimate the option-implied state-contingency of the Fed's corporate bond purchases during the COVID pandemic. Our empirical approach is different and complementary. We directly estimate policy rule perceptions from survey data, study time variation in the perceived monetary policy rule, and directly test for its transmission to financial markets.

2 The perceived monetary policy rule

This section describes how we estimate the perceived monetary policy rule from survey data and characterizes its cyclical patterns.

2.1 Blue chip survey data

Blue Chip Financial Forecasts (BCFF) is a monthly survey of professional forecasters going back to 1982. The survey asks for forecasts of interest rates, including the federal funds rate, various Treasury yields, and corporate bond yields. In addition, forecasters are queried about the macroeconomic *assumptions* underlying their rate forecasts, specifically, their growth and inflation forecasts. The number of participating institutions, each identified by name, ranges between 30 and 50 across surveys. We start our sample in January 1985, because the quality of the data is poor in earlier years, and end in April 2023 for a total of 460 monthly surveys.

Forecasts are made for quarterly horizons from the current quarter out to five quarters

[4]Other related work studies the cross-section of survey forecasts through the lens of a policy rules; see Dräger et al. (2016), Dräger and Lamla (2017) and Czudaj (2023).

[5]See, for example, Bernanke and Kuttner (2005); Gürkaynak et al. (2005); Hanson and Stein (2015); Nakamura and Steinsson (2018); Bauer et al. (2023).

ahead.[6] We denote the forecast of institution j made at t for a generic variable y by $E_t^{(j)} y_{t+h}$. We measure time t in months as the survey is monthly. Since forecasts are for end-of-quarter observations, the monthly horizon h depends on both the survey month and the forecast horizon. For example, for the one-quarter-ahead forecast in the January 2000 survey, $t+h$ corresponds to June 2000 and $h = 5$.

We specify policy rules for the federal funds rate, the Fed's policy rate, denoted by i_t. Since empirical monetary policy rules are usually specified in terms of year-over-year inflation, π_t, and the output gap, x_t, we compute these measures from the macroeconomic forecasts in the BCFF. Year-over-year CPI inflation forecasts, denoted as $E_t^{(j)} \pi_{t+h}$, are calculated from quarterly forecasts and, for short horizons, observed CPI inflation. To calculate output gap forecasts, $E_t^{(j)} x_{t+h}$, we impute forecasts for the level of real GDP from GDP growth forecasts, and take projections of potential GDP from the Congressional Budget Office (CBO), using real-time data at the time of the survey for most of our sample. These output gap projections assume that all forecasters share the same potential output forecast, equal to the CBO projection, but Appendix C.4 shows that using unemployment rate projections in the Survey of Professional Forecasters (SPF) leads to similar results.

Across surveys, horizons, and institutions, our data contain about 120,000 individual forecasts. There is substantial variation across both forecasters and horizons. For detailed descriptions of the BCFF data, calculations, and summary statistics, see Appendix A.1.

2.2 Estimation of perceived rules from survey panels

We now describe how we estimate perceived monetary policy rules from survey data. The basic procedure is as follows: In each monthly BCFF survey, we regress forecasts for the federal funds rate on forecasts for the output gap and inflation. As we formalize in the model in Section 5, if survey respondents first form views on future output and inflation and then use a policy rule to translate these views into funds rate forecasts, this procedure will recover the perceived monetary policy rule.

In each month of the BCFF survey, there is variation across both forecasters and forecast horizons. In principle, either dimension of variation would be sufficient for our procedure. To see the intuition, suppose for simplicity that forecasters believe that the Fed follows a rule according to which it sets the federal funds rate to 0.5 times the output gap. Further suppose that two forecasters have one-year-ahead output gap forecasts of 2% and 4%. Then their one-year-ahead funds rate forecasts are 1% and 2% respectively, and a regression of funds rate forecasts on output gap forecasts correctly recovers a coefficient on the output gap of 0.5.

[6]Before 1997, the forecast horizon extends out only four quarters.

Alternatively, suppose there is only one forecaster, who forecasts that the output gap will be 2% next year and 0% two years from now. Then her funds rate forecasts are 1% for next year and 0% for the year after that. Again, a regression of funds rate forecasts on output gap forecasts correctly recovers the perceived output gap coefficient. Our estimation procedure exploits variation across both forecasters and forecast horizons, which adds precision to our estimates.

Formally, we start by assuming that the monetary policy rule takes a simple form standard in the literature (e.g., Taylor, 1993, 1999):

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

where π_t^* is the inflation target and r_t^* is the equilibrium real interest rate. Importantly, the coefficients on the inflation gap and the output gap, β_t and γ_t, are allowed to vary over time. u_t is an exogenous monetary policy shock.

To estimate the perceived monetary policy coefficients $\hat{\gamma}_t$ and $\hat{\beta}_t$, we regress federal funds rate forecasts on output gap and inflation forecasts in the forecaster-horizon panel at time t. Specifically, we estimate the regression:

$$E_t^{(j)} i_{t+h} = a_t^{(j)} + \hat{\gamma}_t E_t^{(j)} x_{t+h} + \hat{\beta}_t E_t^{(j)} \pi_{t+h} + e_{th}^{(j)}, \tag{2}$$

where the error term $e_{th}^{(j)}$ contains forecaster j's expectation of the future monetary policy shock at $t+h$, $E_t^{(j)} u_{t+h}$, as well as any measurement and specification errors affecting forecasts of the policy rate. The forecaster fixed effects $a_t^{(j)} = E_t^{(j)} r_t^* + (1 - \hat{\beta}_t) E_t^{(j)} \pi_t^*$ allow for the possibility that forecasters have different beliefs about the natural rate of interest r_t^* and long-run inflation π_t^*. In a simple OLS regression, the estimated coefficient on the output gap, for instance, would reflect both the policy rule—forecasters' perception of how the Fed will react to *news* about output—and the correlation across forecasters in long-run expectations about output and interest rates. Forecaster fixed effects eliminate this estimation problem.[7]

Three assumptions are sufficient for regression (2) to recover the perceived monetary policy rule, and they are satisfied in both our illustrative example above and in our model in Section 5. First, forecasters disagree about the economic outlook, i.e., there is some heterogeneity in $E_t^{(j)} x_{t+h}$ and $E_t^{(j)} \pi_{t+h}$ across forecasters j. This assumption builds on a large body of evidence for disagreement in economic expectations (e.g., Mankiw et al., 2003; Andrade et al., 2016; Caballero and Simsek, 2022b). In our BCFF data, there is a substantial variation across both forecasters and horizons, as documented in Appendix Table A.1.

[7]In addition, forecaster fixed effects mitigate the influence on our estimates of forecaster-level biases, a potentially important feature of survey forecasts (Angeletos et al., 2021; Juodis and Kučinskas, 2023).

The second assumption is that economic forecasts are determined independently of any expected future monetary policy shock, $E_t^{(j)} u_{t+h}$. This assumption is unlikely to hold exactly, and some endogeneity bias, arising from the perceived effects of monetary policy shocks on output, could affect our estimates. This potential problem afflicts most empirical work on monetary policy rules.[8] Endogeneity bias may be less severe in our context since the framing of the BCFF explicitly asks forecasters about the macroeconomic *assumptions* underlying their rate forecasts. Consistent with this view, the empirical results in Sections 3 and 4.1 suggest that our estimates indeed capture a perceived policy rule and that endogeneity bias is likely small or at least stable over time. To the extent that any bias is stable over time, it will not affect our main results, which concern time variation in the perceived rule. In Section 6 we explore this issue further, estimating a bias correction using a standard New Keynesian model. We find very similar results.

The third assumption is that policy rate forecasts are made according to the policy rule in (1). This assumption imposes two separate restrictions. First, the perceived policy rule could depend on factors beyond the output gap and inflation. Second, there may be heterogeneity across forecasters in the perceived coefficients $\hat{\gamma}_t$ and $\hat{\beta}_t$. These restrictions are standard in the literature, so imposing them makes our estimates more comparable to both existing work on survey-based policy rules (Carvalho and Nechio, 2014; Kim and Pruitt, 2017) and the broader literature on empirical policy rules. Moreover, we show in Section 6 that both restrictions can be relaxed. The estimated perceived rule exhibits very similar time variation if we allow for heterogeneous perceptions or include credit spread forecasts in the specification of the policy rule. These findings are consistent with the fact that the simple policy rule fits the data well: The average R^2 of regression (2) across months is 70% with forecaster fixed effects and 33% without fixed effects.[9]

Our approach of estimating perceived policy rules using the rich panel structure of forecasts at each time t contrasts with previous work that relies primarily on time series (Kim and Pruitt, 2017; Jia et al., 2023) or cross sections (Carvalho and Nechio, 2014; Dräger et al., 2016) of survey forecasts. Section 6 demonstrates that our policy-rule estimates are highly robust to a number of variations on our estimation procedure and regression specification.

[8]Some studies attempt to circumvent this problem using instrumental variables (e.g. Clarida et al., 2000).

[9]Our derivation of (2) relies on the assumption that forecasters view the parameters of the monetary policy rule as highly persistent, or formally as time-varying martingale parameters and orthogonal to other shocks, e.g., $E_t^{(j)} \beta_{t+h} = \hat{\beta}_t$ and $E_t^{(j)} \beta_{t+h} z_{t+h} = \hat{\beta}_t E_t^{(j)} z_{t+h}$ for any macro variable z_t. This is a standard assumption in the literature on time-varying parameter models (e.g. Primiceri, 2005). In 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. Using the output gap is consistent with the literature (e.g. Taylor, 1993; Clarida et al., 2000). In addition, forecaster disagreement about interest rates is more similar to disagreement about the output gap in our data than to disagreement about GDP growth, supporting this choice. See Appendix A.2.

Much theoretical and empirical research has documented the relevance of interest-rate smoothing and policy inertia (e.g. Woodford, 2003b; Bernanke, 2004; Taylor and Williams, 2010). We therefore also consider the possibility that policy follows an inertial rule:

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

where ρ_t is the time-varying "inertia parameter" that determines the extent to which last quarter's policy rate affects the current policy rate, and the coefficients β_t and γ_t are the short-run responses of monetary policy to inflation and the output gap. Long-run policy responses are given by $\beta_t/(1-\rho_t)$ and $\gamma_t/(1-\rho_t)$, provided that $|\rho_t| < 1$. To estimate the perceived parameters of this rule, including $\hat{\rho}_t$, we simply augment regression (2) with the funds rate forecast for the preceding quarter:

$$E_t^{(j)} i_{t+h} = a_t^{(j)} + \hat{\rho}_t E_t^{(j)} i_{t+h-3} + \hat{\gamma}_t E_t^{(j)} x_{t+h} + \hat{\beta}_t E_t^{(j)} \pi_{t+h} + e_{th}^{(j)}. \tag{4}$$

In this case, the forecaster fixed effect still absorbs disagreement about long-run real rates and long-run inflation.

2.3 Perceived baseline policy rule

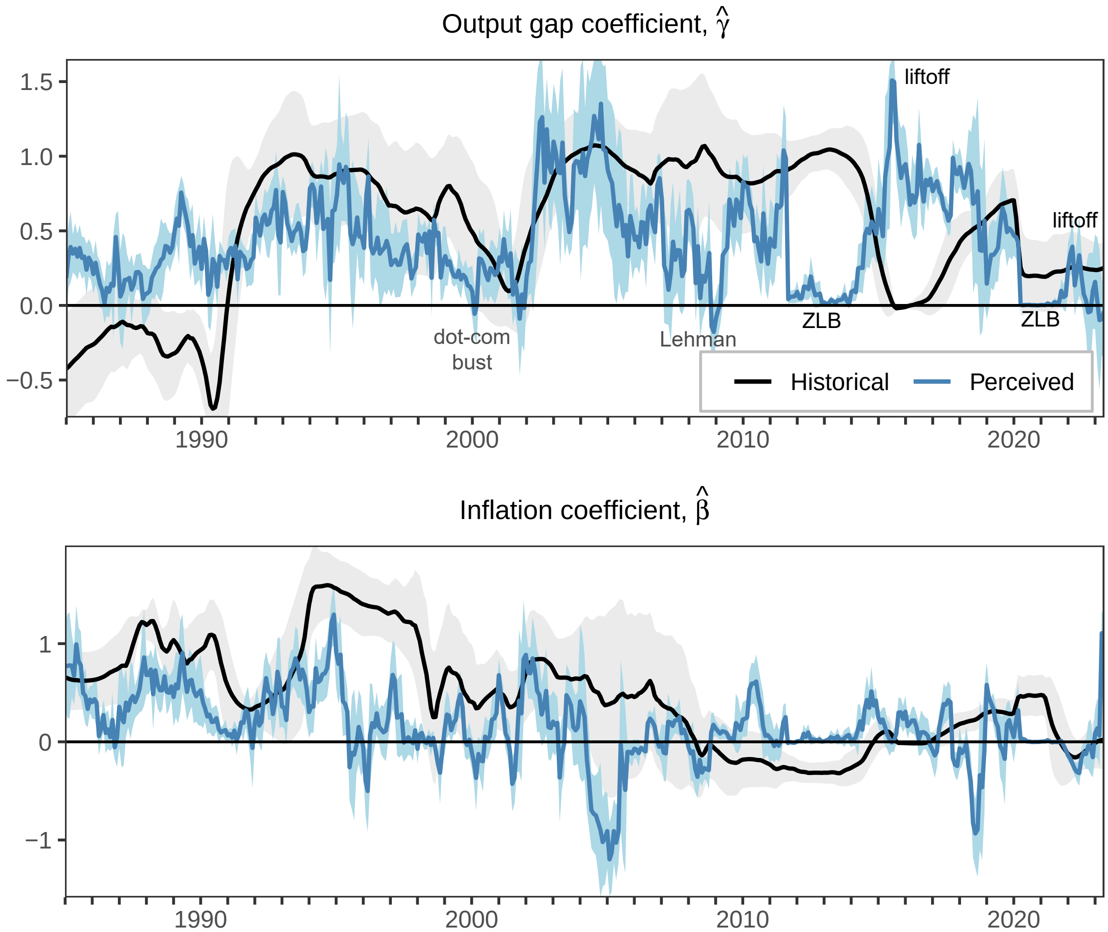
Figure 1 plots the time series of the estimated perceived policy rule from our baseline specification (2). The top panel shows the perceived output gap coefficient, $\hat{\gamma}_t$, which has a sample average around 0.5, in line with conventional empirical estimates of policy rules (Taylor, 1993; Clarida et al., 2000). The estimated coefficient $\hat{\gamma}_t$ exhibits a striking amount of variation, ranging between 0 and 1.5, that can be linked to the monetary policy cycle.

Before and during monetary tightenings—for instance, in the mid-1990s, between 2003 and 2005, and around liftoff from the ZLB in 2015 and in 2022—$\hat{\gamma}_t$ tends to be high, indicating that the rate outlook is perceived to be strongly related to the economic outlook. During these episodes the Fed is viewed as highly data-dependent, consistent with Fed communication at the time. Examples include speeches from all three recent Fed Chairs Bernanke, Yellen, and Powell, such as Yellen (2015), where the Chair emphasized that "policy will depend on [...] incoming data." The Fed also provided explicit forward guidance that led forecasters to expect rate hikes, for example in 2004 and before each liftoff.[10]

By contrast, before and during monetary easings, $\hat{\gamma}_t$ is typically low, as forecasters see little connection between the rate outlook and the economic outlook. These episodes are often marked by elevated financial stress, as in the dot-com bust in 2001 and the failure of

[10] See Lunsford (2020) for an extensive discussion of forward guidance in the 2000s.

Figure 1: Parameter estimates for baseline policy rule



Estimated policy-rule coefficients for the output gap, $\hat{\gamma}_t$, and inflation, $\hat{\beta}_t$. Blue lines show estimates of perceived policy rules from month-by-month panel regressions (2) with forecaster fixed effects, estimated from Blue Chip Financial Forecast surveys from January 1985 to April 2023, with shaded areas for 95% confidence intervals based on standard errors with two-way clustering (by forecasters and horizon). Black lines show estimated historical policy rules using a seven-year estimation window of monthly observations for the federal funds rate, the output gap, and four-quarter CPI inflation.

Lehman Brothers in 2008. At such times, the Fed likely pays attention to a broader set of indicators, including financial conditions, that are informative about economic risks in real time. As a result, the Fed's decisions may appear more discretionary and less rules-based during these periods. In addition, the Fed may take a "risk management approach," cutting rates before the economic outlook deteriorates too much.[11] Strong forward guidance at the ZLB, such as the announcement in September 2011 that the Fed would keep rates near zero

[11] Anecdotal evidence includes FOMC meeting minutes from January 29-30, 2001, describing the sequence of large interest rate cuts in that month as "front-loaded easing policy," and an FOMC conference call on January 9, 2008, characterizing interest rate cuts as "taking out insurance against (...) downside risks."

"at least through mid-2013," led to a particularly sharp disconnect between expectations of rates and economic conditions, essentially pinning $\hat{\gamma}_t$ at zero.[12] Our results show that there is an asymmetry between easing and tightening episodes, consistent with financial market evidence that rate cuts are more often surprising than rate hikes (Cieslak, 2018; Schmeling et al., 2022).

Figure 1 also compares the perceived rule to an estimate of the historical policy rule, obtained by estimating rolling regressions of the fed funds rate on inflation (annual percent change in the CPI) and the output gap (percent deviation of real GDP from CBO potential output). We use a seven-year rolling window so that each window is long enough to allow for relatively precise estimates but short enough to uncover time variation.[13] Until 2008, the output gap coefficients in the perceived and historical rules exhibit broadly similar patterns, and their correlation is 0.5. But after 2008, the historical and perceived rules diverge, illustrating the value of our approach. For instance, the perceived coefficient, $\hat{\gamma}_t$ immediately captures the Fed's forward guidance in 2011 and plummets to zero, while the output gap coefficient in the historical policy rule barely budges. It only drops to zero several years later in 2015. However, by this time the Fed was already engaged in "data-dependent" tightening, as captured by the rise in $\hat{\gamma}_t$. While the historical rule is necessarily backward-looking, our survey-based perceived rule is forward-looking.

The perceived inflation coefficient $\hat{\beta}_t$ generally fluctuates around zero and is persistently positive only over the first few years of our sample. This pattern contrasts with typical empirical and optimal policy rules, which feature an inflation coefficient exceeding one, and is explained by two features of our sample period: First, over most of this period, inflation was low and stable, hovering near the Fed's inflation target. As noted by Clarida et al. (2000), with limited variability in inflation, the estimated policy rule coefficient may well be low even if the central bank is in fact committed to stable inflation.[14] Second, in the pre-COVID period, the first 35 years of our sample, the U.S. economy was affected mainly by demand instead of supply shocks. When inflation is expected to move up and down a stable Phillips curve, as for most of our sample, the perceived output gap coefficient $\hat{\gamma}_t$ serves as a sufficient statistic for the Fed's overall responsiveness to economic conditions. Intuitively, the Fed is expected to react to changes in the output gap partly because it also summarizes inflationary pressures. For these reasons, we focus on $\hat{\gamma}_t$ as a measure of "perceived Fed

[12] See Campbell et al. (2012) and Swanson and Williams (2014) for a discussion of this "Odyssean" forward guidance.

[13] Similarly to Bauer and Swanson (2023a), we find an upward-shift in the estimated historical output gap coefficient post-2000. We find a lower inflation coefficient than they do because our shorter rolling windows feature less variation in inflation.

[14] Clarida et al. (2000) caution that in a sample with insufficient variation in inflation "one might mistakenly conclude that the Fed is not aggressive in fighting inflation" (p. 143).

responsiveness" in the remainder of our analysis.

2.4 Perceived inertial policy rule

Figure 2 shows the estimated coefficients for the perceived inertial policy rule. Because the estimated perceived inertia, $\hat{\rho}_t$, sometimes exceeds one and the long-run perceived responses are undefined in those instances, we focus our analysis on the short-run perceived responses $\hat{\beta}_t$ and $\hat{\gamma}_t$. We again superimpose historical policy rule coefficients from rolling-window regressions, in this case including a three-month lag of the funds rate as in equation (3).

The coefficients of the perceived inertial rule, shown in Figure 2, show broadly similar patterns as those for the baseline rule in Figure 1. The inertial rule coefficients are naturally smaller in magnitude because they capture the perceived short-run policy response, while the baseline rule captures the perceived long-run response.[15] Similar to our results above, there are cyclical shifts in the perceived output gap coefficient $\hat{\gamma}_t$ that are generally consistent with those in the historical policy rule before 2008, but important differences thereafter due to the forward-looking nature of our survey-based estimates.

The bottom panel of Figure 2 shows that $\hat{\rho}_t$ trends up over our sample period: the average is 0.6 prior to 2000 and 0.9 thereafter. This pattern is consistent with other evidence that the Fed has become more gradual and forward guidance more important (Coibion and Gorodnichenko, 2012; Pflueger, 2023; Bianchi et al., 2022b). At the same time, the inertial $\hat{\gamma}_t$ becomes more compressed relative to the baseline $\hat{\gamma}_t$, indicating that there is less variation in the perceived short-run responses of monetary policy than in the perceived long-run responses in the second half of the sample. In light of this wedge, one might expect baseline $\hat{\gamma}_t$ to be more relevant for long-term asset prices.

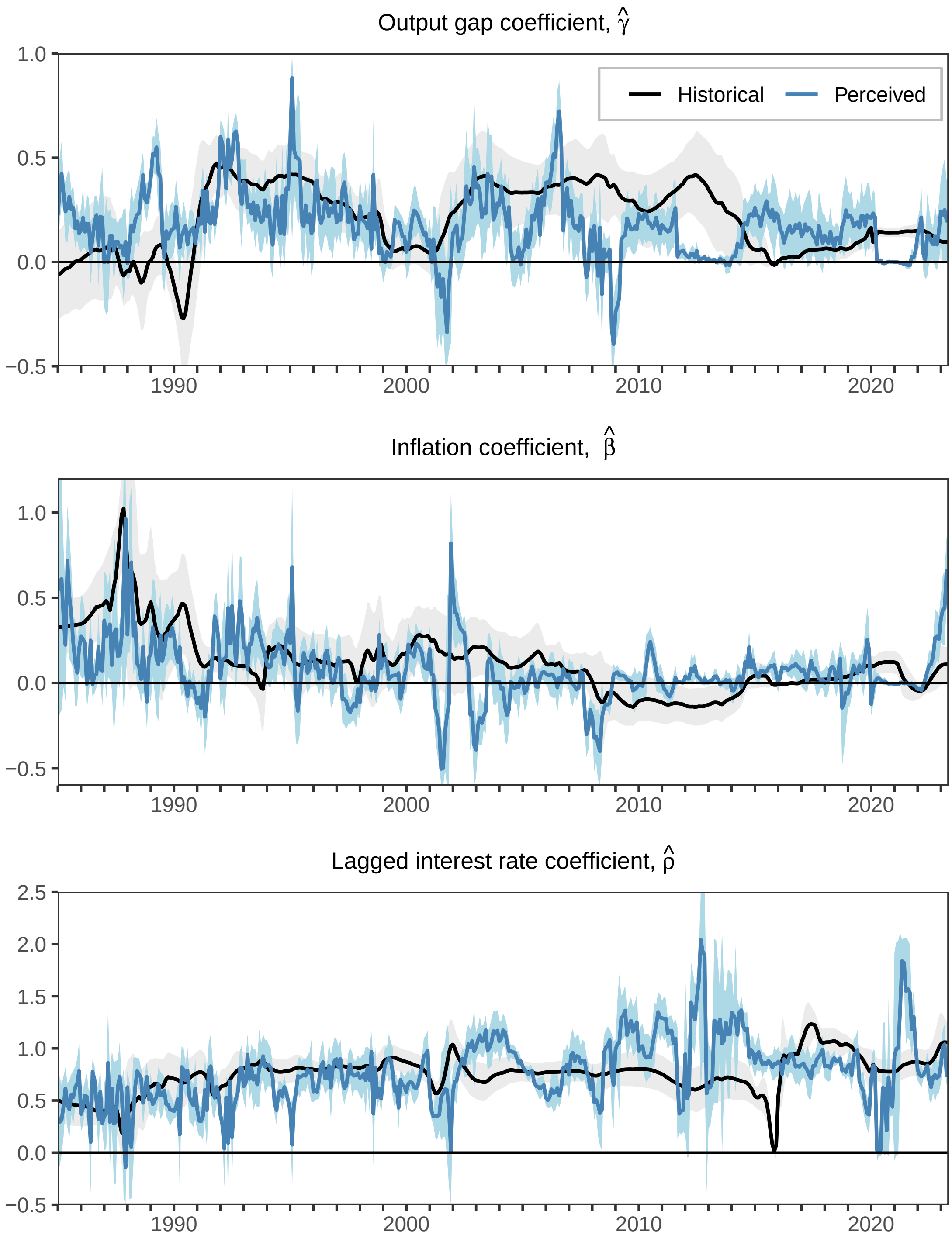
The inflation coefficient $\hat{\beta}_t$ again varies mostly around zero, with an important exception: Over the last year of our sample, $\hat{\beta}_t$ rose sharply, due to the recent surge in inflation and the corresponding monetary policy response. This pattern is more evident in the inertial estimates than the baseline estimates because inflation was expected to gradually decline, so that the perceived long-run response of policy is somewhat muted.

2.5 Cyclical variation

To document systematic variation in the Fed's perceived responsiveness, Table 1 reports univariate regressions of $\hat{\gamma}_t$ on cyclical variables. Results for the baseline rule are in the top panel, and results for the inertial rule are in the bottom panel. While these regressions do

[15] As we show in Appendix E.1, if the Fed is actually following an inertial rule (3) and we estimate our baseline rule (2), the estimates $\hat{\beta}_t$ and $\hat{\gamma}_t$ will capture the long-run response of policy to output and inflation.

Figure 2: Parameter estimates for inertial policy rule



Estimated policy-rule coefficients for the output gap, $\hat{\gamma}_t$, inflation, $\hat{\beta}_t$, and the one-quarter lagged interest rate, $\hat{\rho}_t$. Blue lines show estimates of perceived policy rules from month-by-month panel regressions (4) with forecaster fixed effects, estimated from Blue Chip Financial Forecast surveys from January 1985 to April 2023, with shaded areas for 95% confidence intervals based on standard errors with two-way clustering (by forecasters and horizon). Black lines show estimated historical policy rules using a seven-year estimation window of monthly observations for the federal funds rate, the output gap, and four-quarter CPI inflation.

not speak to causality, they provide suggestive evidence on factors that could drive variation in the perceived monetary policy rule.

The first two columns show that $\hat{\gamma}_t$ tends to be high during the tightening portion of a monetary policy cycle. The slope of the yield curve reflects the expected path of future policy rates, and a positive slope anticipates monetary tightening, while a flat or inverted yield curve predicts monetary easing and typically a recession.[16] We find a strong positive correlation between $\hat{\gamma}_t$ and the slope. The correlation is even stronger for the lagged slope—which is intuitive since the yield curve is often upward-sloping well before the onset of the tightening cycle—thus the slope is lagged by one year in the regression in Table 1. The second column uses a dummy variable for monetary tightening cycles, which is equal to one from the first to the last month with an increase in the fed funds rate during the cycle. Although the coefficient is statistically significant only for the baseline rule, the estimates confirm that $\hat{\gamma}_t$ tends to be elevated during tightening cycles.

While the perceived policy rule shifts with monetary policy, it has no clear relationship with the business cycle. Table 1 shows that $\hat{\gamma}_t$ is unrelated to the unemployment rate, and we have found similar results for various other indicators of economic activity, including NBER recession dummies.

The fourth column shows that the Fed is perceived to be somewhat less responsive to economic conditions during ZLB periods than non-ZLB periods. ZLB periods mix two kinds of episodes. During episodes of strong, Odyssean forward guidance, for instance from September 2011 until 2013, funds rate forecasts are near zero for all horizons in the BCFF data, so $\hat{\gamma}_t$ is near zero as well. However, between 2009 and September 2011, the Fed was mistakenly expected to lift off from the ZLB soon, so $\hat{\gamma}_t$ is elevated.[17]

The last column of Table 1 shows that the Fed's perceived responsiveness to economic data is lower when financial market uncertainty, measured by the VIX, is high.[18] In additional analysis we find similar patterns for various other measures of financial and macroeconomic uncertainty, including the uncertainty measures of Jurado et al. (2015). These findings further support the idea that the Fed is viewed as less data-dependent during monetary easing episodes because elevated uncertainty and financial stress render standard economic data less informative about the underlying economic conditions that the Fed cares about.[19]

[16]See Rudebusch and Wu (2008) on the slope as a measure of the monetary policy stance, and Bauer and Mertens (2018) on its predictive power for recessions.

[17]Swanson and Williams (2014) also find that long-term rates remained sensitive to macro news until 2011.

[18]Section 6 shows that including forecasts of credit spreads directly in our estimation of the perceived monetary policy rule does not qualitatively change our $\hat{\gamma}_t$ estimates.

[19]This interpretation is consistent with theories showing that the optimal monetary policy response to economic indicators should depend on economic uncertainty and financial conditions (e.g., Sack, 2000; Aoki, 2003; Svensson and Woodford, 2003), as well as with evidence for a Fed put, i.e., that the Fed pays more

Table 1: Cyclical variables and the perceived monetary policy rule

	Slope (12m lag)	Tightening dummy	Unemployment rate	ZLB dummy	VIX
Panel A: Baseline $\hat{\gamma}_t$					
Coefficient	0.12***	0.14*	-0.02	-0.12	-0.01***
	(0.03)	(0.08)	(0.02)	(0.11)	(0.00)
Intercept	0.20***	0.37***	0.54***	0.46***	0.72***
	(0.06)	(0.04)	(0.14)	(0.05)	(0.09)
R^2	0.18	0.04	0.01	0.03	0.12
Panel B: Inertial $\hat{\gamma}_t$					
Coefficient	0.04**	0.05	-0.01	-0.10***	-0.01***
	(0.01)	(0.04)	(0.01)	(0.03)	(0.00)
Intercept	0.10***	0.16***	0.20***	0.20***	0.32***
	(0.03)	(0.02)	(0.05)	(0.02)	(0.05)
R^2	0.07	0.02	0.00	0.08	0.14
N	460	460	460	460	448

Regressions of $\hat{\gamma}_t$ on cyclical variables in monthly data from January 1985 to April 2023. The top panel shows results for the baseline rule (2), and the bottom panel for the inertial rule (4). Regressors are the slope of the yield curve measured as the second principal component of Treasury yields from Gürkaynak et al. (2007), lagged by 12 months; a tightening dummy for the months from the first to the last change in the fed funds rate of monetary tightening cycles; the unemployment rate; a ZLB dummy for zero lower bound periods; and the VIX, i.e., CBOE Volatility Index from 1990 onwards and S&P 100 Volatility Index 1986–1989. 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, * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

One might be concerned that misspecification of the policy rule is driving some of the time variation we document. Perhaps a more comprehensive perceived rule—including many more factors potentially important to Fed decisions—would lead to more stable perceived coefficients. Empirical policy rules prominent in the literature tend to be simple and parsimonious. They provide a natural benchmark for our estimation of forward-looking rules and to assess how monetary policy perceptions vary over time. For robustness, we analyze both our baseline and inertial rule estimates throughout the paper. As mentioned above, in Section 6 we consider alternative specifications, for example including credit spread forecasts.

In sum, perceptions about monetary policy exhibit substantial time variation related to easing and tightening cycles, forward guidance, and economic and financial uncertainty. Taken together, the cyclical variables in Table 1 explain a meaningful fraction of the variation in $\hat{\gamma}_t$, with an R^2 of 0.35 in a multivariate regression. But a large share of the variation remains unexplained, and we next turn to understanding unexpected shifts in the perceived

attention to financial markets during times of financial stress (Cieslak and Vissing-Jorgensen, 2021).

monetary policy rule in response to new information.

3 The perceived rule and monetary policy surprises

Do forecasters revise their perceived monetary policy rule in response to actual Fed decisions? We next show that they do. Perceptions respond to monetary policy surprises in a manner consistent with the idea that forecasters have imperfect information about the policy rule and learn from observed policy decisions.

Following common practice we measure monetary policy surprises as high-frequency rate changes around FOMC announcements, based on the assumption that these rate changes are mainly due to the policy action (e.g. Gürkaynak et al., 2005; Nakamura and Steinsson, 2018). If market participants do not have full information about the policy rule, these surprises can arise not only from monetary policy shocks, but also from differences between the perceived and actual Fed response to macroeconomic data (Bauer and Swanson, 2023b,a).[20] In this case, beliefs about the policy rule should respond to surprises in a state-contingent manner: A tightening surprise in an economic boom suggests that the Fed cares even more about output than previously believed, so 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 should 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 using state-dependent local projections (Jordà and Taylor, 2016; Ramey and Zubairy, 2018). We use the high-frequency surprise measure of Bauer and Swanson (2023a), the first principal component of 30-minute changes in Eurodollar futures rates around FOMC announcements, which captures changes in policy rate expectations, and thus forward guidance, over a horizon of about a year. The surprise is normalized to have a unit effect on the four-quarter-ahead Eurodollar futures rate, measured in percentage points. The monthly monetary policy surprise, mps_t, sums up announcement surprises and equals zero in months without announcements. We estimate local projections

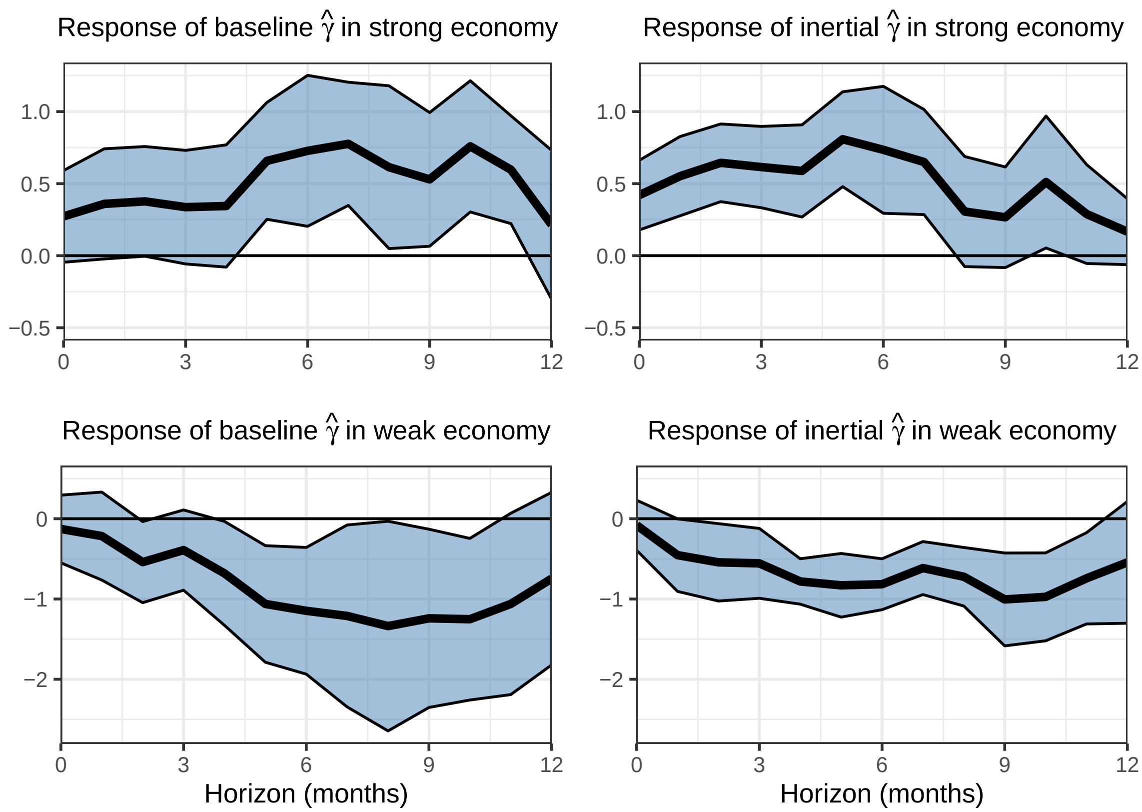
$$\hat{\gamma}_{t+h} = a^{(h)} + b_1^{(h)} mps_t(1 - weak_t) + b_2^{(h)} mps_t weak_t + c^{(h)} weak_t + d^{(h)} \hat{\gamma}_{t-1} + \varepsilon_{t+h}, \qquad (5)$$

where the indicator variable $weak_t$ equals one when the output gap is below its median and zero otherwise, capturing episodes when the economy is growing slowly and economic slack

[20] High-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.

is high. The regressions control for lagged $\hat{\gamma}_t$ to account for serial correlation in the perceived policy rule coefficient. We estimate equation (5) over the entire sample for $\hat{\gamma}_t$, from January 1985 to April 2023. There are 323 announcement surprises from February 1988 to December 2019, and we set mps_t to zero when no policy surprises are available.

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 from January 1985 to April 2023.

The impulse responses in Figure 3 show that $\hat{\gamma}_t$ responds to monetary policy surprises in a state-contingent manner, consistent with the idea that forecasters learn about the monetary policy rule from actual Fed decisions. The top panels plot estimates of $b_1^{(h)}$ against h and document 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. In line with our hypothesis, the picture reverses in the bottom panels, which show persistently negative responses when the economy is weak. The responses for the inertial rule parameter, shown in the top right and bottom right panels, are similar and estimated somewhat more precisely.

The magnitudes in Figure 3 are economically meaningful relative to the standard deviations of baseline $\hat{\gamma}_t$ (0.3) and inertial $\hat{\gamma}_t$ (0.15). A one percentage point monetary policy surprise leads to an increase in $\hat{\gamma}_t$ of roughly 0.7 in a strong economy. The same monetary policy surprise is estimated to lead to a somewhat larger decline in $\hat{\gamma}_t$ in a weak economy. A simple back-of-the-envelope calculation in Section 5, based on the model presented there and the magnitudes of these impulse responses, suggests that about 50% of the variation in monetary policy surprises is due to incomplete information about the policy rule. Appendix B shows that the differences between the estimated responses in the top and bottom panels of Figure 3 are strongly statistically significant.[21]

Overall, the evidence in this section suggests that the actual monetary policy rule is time-varying and at least partly unknown. Forecasters learn from monetary policy surprises, which are informative about the Fed's actual rule. They update their perceived policy rule differently in expansions than in recessions, as predicted by a simple rational learning argument. In addition, they appear to update somewhat gradually over the six months following monetary policy surprises.

4 Transmission to financial markets

Having characterized time variation in the perceived monetary policy rule, we next show that it affects the key asset prices that transmit monetary policy to the real economy: short- and long-term interest rates, as well as stock prices.

4.1 Interest rate responses to macroeconomic news surprises

This section examines the sensitivity of interest rates to macroeconomic news. Event studies using narrow windows around macroeconomic announcements have previously been used to identify the effects of monetary policy on financial markets by Hamilton et al. (2011) and Swanson and Williams (2014). Our contribution is to document a connection between the sensitivity of financial markets to macroeconomic news and the perceived monetary policy rule, as captured by $\hat{\gamma}_t$.

[21]One concern might be that policy rule perceptions would mechanically respond to a monetary policy shock even if agents had complete information about the policy rule, simply because of the expected comovement of interest rates and macroeconomic aggregates after a policy shock. However, such comovement would not generate *state-contingent* impulse responses, as we find in the data. See Appendix C.3 for simulated impulse responses in a standard full information rational New Keynesian model.

To investigate this connection, we estimate event-study regressions

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

where Δy_t is the change in an interest rate on announcement date t and Z_t is a macroeconomic announcement surprise, that is, the value of the macroeconomic data release minus the consensus expectations for this data release before the day of the announcement. A positive interaction coefficient b_3 indicates that interest rates are more sensitive to macro news at times when the Fed is perceived to be more responsive to economic conditions.

Regression (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 in a narrow interval around a macro announcement is primarily about the macroeconomy, and that the interest rate response reflects the anticipated monetary policy reaction. Swanson and Williams (2014) allow the magnitude of the response to vary over time in an unrestricted fashion, investigating shifts during the ZLB period. By contrast, we directly tie variation in the sensitivity of interest rates to news to our estimates of the perceived monetary policy rule with the interaction effect $\hat{\gamma}_t \times Z_t$. In this way, we assess whether our survey-based estimates of the perceived policy rule, $\hat{\gamma}_t$, are consistent with changes in the sensitivity of financial market prices to macroeconomic news.

Table 2 reports estimates of equation (6) for four different interest rates: Three-month and six-month federal funds futures rates and two-year and ten-year Treasury yields. Fed funds futures measure policy rate expectations over the near term, and Treasury yields capture longer-term expectations. The left four columns in Table 2 use the single most influential macroeconomic announcement, nonfarm payrolls 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 the fitted value from a regression of high-frequency interest rate changes on all macroeconomic news. In Table 2, Panel A reports results for the baseline estimate of $\hat{\gamma}_t$, while Panel B uses the inertial estimate. The sample starts in 1990, when our macro news data begins, and ends in April 2023.

The results in Table 2 show that our coefficient of interest, b_3, is uniformly positive and statistically significant across almost all combinations of interest rates, macroeconomic news, and estimates of $\hat{\gamma}_t$. That is, interest rates respond more strongly to macroeconomic news when the Fed is perceived to be more responsive to macro data. This result conforms with intuition: the same news about output leads markets to expect a larger change in future policy rates when the Fed is perceived to be more sensitive to output. The model in Section

Table 2: Sensitivity of interest rates to macroeconomic news

	News: Nonfarm payrolls				News: All announcements			
	3m FF	6m FF	2y Tsy	10y Tsy	3m FF	6m FF	2y Tsy	10y Tsy
Panel A: Baseline $\hat{\gamma}_t$								
$\hat{\gamma}$	0.00	0.00*	0.00	-0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Z	0.00	0.00	0.00	0.00***	0.84***	0.83***	0.75***	0.79***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.21)	(0.17)	(0.13)	(0.14)
$\hat{\gamma} \times Z$	0.21***	0.35***	0.45***	0.33***	0.46	0.49	0.70***	0.58**
	(0.03)	(0.04)	(0.05)	(0.05)	(0.39)	(0.32)	(0.25)	(0.27)
Intercept	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.03	0.05	0.06	0.03	0.03	0.04	0.05	0.03
Panel B: Inertial $\hat{\gamma}_t$								
$\hat{\gamma}$	0.01	0.00	0.00	-0.00	0.01	0.00	0.00	0.00
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Z	-0.00	-0.00	-0.00	0.00	0.59***	0.61***	0.64***	0.72***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.19)	(0.13)	(0.12)	(0.14)
$\hat{\gamma} \times Z$	0.48***	0.72***	0.85***	0.58***	2.89***	2.84***	2.62***	2.04***
	(0.08)	(0.08)	(0.09)	(0.10)	(0.91)	(0.78)	(0.54)	(0.64)
Intercept	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.03	0.05	0.05	0.02	0.03	0.05	0.05	0.03

Estimates of the regression $\Delta y_t = b_0 + b_1\hat{\gamma}_t + b_2 Z_t + b_3\hat{\gamma}_t Z_t + \varepsilon_t$, where Δy_t is the interest rate change on days with macroeconomic announcements, expressed in percentage points, and Z_t is either the (standardized) surprise in nonfarm payrolls or a macro news aggregate that captures all announcements. Following Swanson and Williams (2014), we compute the news aggregate as the fitted value of a regression of the interest rate change on all macro news. Robust standard errors are reported in parentheses. The sample consists of all 3984 days with macro announcements between January 1990 and April 2023.

5 formalizes this argument.[22]

The magnitudes of the interaction effects are also economically significant. Note that the 95th percentile of baseline $\hat{\gamma}_t$ is about one, and the 95th percentile of inertial $\hat{\gamma}_t$ is about 0.5; the 5th percentiles of both series are about zero. The estimates in Table 2 suggest that interest rates do not respond to nonfarm payrolls surprises when $\hat{\gamma}_t$ is zero,

[22]The finding that changes in the shortest-term fed funds futures are more significantly related to the interaction with the inertial $\hat{\gamma}_t$ (Panel B) than the interaction with the baseline $\hat{\gamma}_t$ (Panel A) is also intuitive: Inertial $\hat{\gamma}_t$ captures the short-run response of monetary policy, and thus it should determine the response of short-term interest rates to macro news surprises. In contrast, baseline $\hat{\gamma}_t$ should determine the response of long-term interest rates. Appendix E.1 makes this point explicit in the context of our model.

and respond strongly when $\hat{\gamma}_t$ is positive. Panel A shows that when baseline $\hat{\gamma}_t$ equals one, a one-standard deviation nonfarm payrolls surprise raises interest rates by 20 to 45 basis points. The estimates for all macroeconomic announcements show that the sensitivity of interest rates to macro news doubles and sometimes triples as $\hat{\gamma}_t$ changes from its 5th to 95th percentiles.

Overall, Table 2 provides clear evidence of a connection between $\hat{\gamma}_t$ and the sensitivity of interest rates to macro news, showing that our survey-based perceived policy rule is consistent with the "market-perceived monetary policy rule" (Hamilton et al., 2011). This evidence also alleviates endogeneity concerns that our estimates of $\hat{\gamma}_t$ might be influenced by the perceived endogenous response of output to monetary policy shocks. If our estimates of $\hat{\gamma}_t$ were primarily driven by this endogenous response, the sensitivity of interest rates to macro news should be unrelated to $\hat{\gamma}_t$ because macroeconomic data cannot respond to policy rates within narrow announcement windows. The finding that the impact of macro news on interest rates scales up with $\hat{\gamma}_t$ validates the idea that we are capturing the perceived monetary policy rule.

4.2 Term premia in long-term interest rates

In this section, we show that term premia in long-term bonds vary with monetary policy perceptions. This finding has important implications for monetary policy transmission because longer-term interest rates significantly influence aggregate spending and output. Term premia are often viewed as independent of conventional monetary policy, but recent work in macro-finance has questioned this view. For example, changes in the monetary policy rule have been proposed as an explanation for the decline in term premia (Smith and Taylor, 2009; Bianchi et al., 2022a). Our empirical measure of the perceived monetary policy rule provides direct evidence for such a link between term premia and monetary policy.

Standard asset pricing logic suggests that $\hat{\gamma}_t$ should be inversely related to term premia in long-term bonds. Assets that have higher payoffs in bad states of the world—when agents have higher marginal utility—should be more valuable and therefore command lower expected returns. With a higher perceived monetary policy coefficient $\hat{\gamma}_t$, interest rates are expected to fall more during a recession, and bond prices are expected to rise more. Thus, when $\hat{\gamma}_t$ is high, bonds are perceived to be better hedges and should have lower expected returns and term premia.[23] The model in Section 5 formalizes this prediction.[24]

[23]These predictions are worked out in detail in Campbell et al. (2017), Campbell et al. (2020), and Pflueger (2023), 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.

[24]Caballero and Simsek (2022a) make the distinct prediction that when the Fed and financial markets

To investigate this prediction, we use survey expectations of future interest rates to construct subjective expected excess returns on long-term bonds. We prefer this measure over realized bond returns for two reasons: First, realized returns are a noisy realization of expected returns. Second, because our focus is on subjective perceptions we want to allow for discrepancies between full information rational expectations and subjective expectations, which recent work has documented to be empirically important (e.g. Greenwood and Shleifer, 2014; Cieslak, 2018; Piazzesi et al., 2015; Nagel and Xu, 2022).[25]

We construct subjective expected one-year excess returns for par Treasury bonds following Piazzesi et al. (2015). The expected twelve-month-ahead par yield on an n-year Treasury bond, $\bar{E}_t y_{t+12}^{(n),par}$, is approximated using the consensus BCFF forecast at the 4-quarter forecast horizon. The log excess return on a par bond is:

$$\bar{E}_t xr_{t+12}^{(n+1)} = Dur_t^{(n+1)} y_t^{(n+1),par} - (Dur_t^{(n+1)} - 1)\bar{E}_t y_{t+12}^{(n),par} - y_t^{(1)}, \quad (7)$$

where $y_t^{(1)}$ denotes the one-year zero-coupon yield and $Dur_t^{(n+1)}$ is the duration of a par bond with maturity $n+1$ years (Campbell, 2017, pp. 236–237). Since BCFF includes forecasts for five- and ten-year yields, we can calculate expected excess returns for bonds with maturities of 6 and 11 years. Blue Chip forecasters are required to submit their responses at the end of the previous month, so for consistency we use observed yields from the last trading day of that month. We regress these subjective risk premia on contemporaneous $\hat{\gamma}_t$ and controls,

$$\bar{E}_t xr_{t+12}^{(n+1)} = b_0 + b_1\hat{\gamma}_t + b_2 TERM_t + \varepsilon_t, \quad (8)$$

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

Table 3 Panel A reports results for the baseline estimate of $\hat{\gamma}_t$. The first column shows a negative and statistically significant relationship with the subjective term premium on the six-year bond. This result is consistent with basic asset pricing logic: investors perceive bonds to be better hedges when they view the Fed as being more responsive to economic conditions. The estimated coefficient is economically large: When baseline $\hat{\gamma}_t = 1$, the expected bond excess return is almost 2 percentage points lower than when $\hat{\gamma}_t = 0$.

Since the slope of the yield curve is correlated with $\hat{\gamma}_t$ (see Section 2.5), we control

disagree about the future state of the economy, markets charge a policy risk premium for perceived monetary policy 'mistakes'. We provide evidence for a complementary but distinct source of risk premia because the Fed response coefficient to the state of the economy is perceived to vary over time.

[25] Consistent with this prior literature, our analysis studies subjective expectations of returns on nominal bonds due to survey data availability. The difference between term premia on nominal and real bonds should be relatively small in our sample period, which was largely characterized by low and stable inflation.

Table 3: Term premia

	$\bar{E}_t xr^{(6)}_{t+12}$			$\bar{E}_t xr^{(11)}_{t+12}$		
Panel A: Baseline $\hat{\gamma}_t$						
$\hat{\gamma}$	-1.93***	-2.24***	-2.61***	-3.02**	-3.49***	-3.79***
	(0.55)	(0.61)	(0.37)	(1.24)	(1.31)	(0.55)
TERM		0.32*			0.51	
		(0.19)			(0.34)	
R^2	0.12	0.16	0.61	0.09	0.12	0.61
Panel B: Inertial $\hat{\gamma}_t$						
$\hat{\gamma}$	1.06	1.10	-2.49***	1.69	1.76	-4.64***
	(1.24)	(1.14)	(0.74)	(2.37)	(2.21)	(1.50)
TERM		0.18			0.28	
		(0.19)			(0.33)	
R^2	0.01	0.02	0.46	0.01	0.02	0.52
PCs	No	No	Yes	No	No	Yes

Regressions of subjective expected log excess returns on six-year and 11-year nominal Treasury bonds over twelve-month holding periods on baseline $\hat{\gamma}_t$ (Panel A) and inertial $\hat{\gamma}_t$ (Panel B) and yield curve variables. $TERM$ is the spread between the ten-year and one-year zero-coupon nominal Treasury yields. If indicated, regressions control for the first three principal components (PCs) of Treasury yields. Coefficients on the constant and the three PCs are omitted. Sample: 425 monthly observations from December 1987 to 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.

for information in the yield curve in columns (2) and (3). The term spread enters only marginally significantly in column (2), consistent with the findings in Nagel and Xu (2022). In the third column, we control for the first three principal components of Treasury yields with maturities one, two, five, seven, ten, fifteen, and twenty years. Naturally, including this yield curve information increases the R^2, but leaves the coefficient on $\hat{\gamma}_t$ largely unchanged. The remaining three columns in Panel A report similar results for the expected one-year excess returns on 11-year Treasuries.

Table 3 Panel B shows results for the inertial estimate of $\hat{\gamma}_t$. In the specifications that include the first three principal components of yields, the coefficient of interest is also negative and statistically significant at the one percent level, as in Panel A. For the other two specifications, however, the coefficient on $\hat{\gamma}_t$ is not statistically significant. This is consistent with the idea that the inertial $\hat{\gamma}_t$ captures the perceived *short-run* response of interest rates to the economy, whereas term premia depend on the longer-term behavior of interest rates, which is better captured by baseline $\hat{\gamma}_t$.[26]

[26] In line with this intuition, Appendix Table D.4 shows that subjective term premia decline with perceived

Although we focus on subjective term premia, there is of course a long tradition of estimating statistical term premia using predictive regressions for excess bond returns (e.g., Campbell and Shiller, 1991; Cochrane and Piazzesi, 2005; Bauer and Hamilton, 2018). Appendix D.1 shows that the perceived monetary policy output gap coefficient, $\hat{\gamma}_t$, predicts realized bond excess returns with a negative sign, controlling for the usual predictors including the shape of the yield curve. The perceived policy rule is therefore related to both subjective and statistical bond term premia, as predicted by standard asset pricing theory.

4.3 Bond market responses to monetary policy surprises

The link we document in Section 4.2 between the perceived monetary policy rule and term premia has additional implications when combined with our results on belief updating from monetary policy actions in Section 3: Monetary policy actions can affect term premia by changing beliefs about the policy rule.

The "Greenspan conundrum" is an illustrative example. During the monetary tightening of 2004–2005, the Fed raised the policy rate, but long-term yields stayed flat or even decreased. The Greenspan conundrum is often attributed to a decline in term premia (e.g., Backus and Wright, 2007), and our results suggest that shifting perceptions of the policy rule may have driven this decline. In particular, our results show that tightening episodes shift beliefs about the policy rule, raising the Fed's perceived responsiveness, $\hat{\gamma}_t$. As a consequence, term premia tend to fall, mitigating or even reversing the rise in long-term yields.

More broadly, since updating about the monetary policy rule from policy rates depends on the state of the economy, our results suggest that the response of long-term bond yields to FOMC announcements should too. Specifically, long-term bond yields should respond more strongly to monetary policy surprises around FOMC announcements when the economy is weak, since term premia move inversely with $\hat{\gamma}_t$. We test this hypothesis directly, using event-study regressions similar to Hanson and Stein (2015) and Nakamura and Steinsson (2018), who document that long-term nominal and real interest rates respond strongly to high-frequency monetary policy surprises.

We generalize the regression specification of Hanson and Stein (2015) as follows:

$$\Delta y_t = b_0 + b_1 \Delta y_t^{(2)} + b_2 weak_t + b_3 \Delta y_t^{(2)} weak_t + \varepsilon_t, \tag{9}$$

where each observation is an FOMC announcement. Following Hanson and Stein (2015), the monetary policy surprise proxy, $\Delta y_t^{(2)}$, is the two-day change in the two-year nominal

monetary policy inertia $\hat{\rho}_t$: holding fixed the perceived short-term monetary policy response, more policy inertia increases the perceived long-term response and hence the effect on term premia.

Treasury yield. The dependent variable is the change in either nominal or real long-term Treasury yields or (instantaneous) forward rates, and the sample starts in 1999, when data on real interest rates becomes reliable. We add an interaction with the indicator variable $weak_t$, defined to equal one when the output gap is below its median as in Section 3. Our main interest is in b_3, the coefficient on the interaction $\Delta y_t^{(2)} \times weak_t$, which captures state-dependence and is predicted to be positive.

Table 4: Sensitivity of long-term rates to monetary policy surprises

	Nominal yield		Nominal forward		TIPS yield		TIPS forward	
Panel A: Five-year maturity								
$\Delta y_t^{(2)}$	1.07***	0.86***	0.92***	0.48***	0.85***	0.61***	0.89***	0.51***
	(0.06)	(0.04)	(0.12)	(0.09)	(0.10)	(0.08)	(0.15)	(0.08)
$weak_t$		0.00		0.01		-0.01		0.00
		(0.01)		(0.02)		(0.01)		(0.02)
$\Delta y_t^{(2)} \times weak_t$		0.52***		1.06***		0.60***		0.93***
		(0.12)		(0.24)		(0.22)		(0.29)
Intercept	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.00	-0.00
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.74	0.79	0.32	0.42	0.33	0.37	0.25	0.31
Panel B: Ten-year maturity								
$\Delta y_t^{(2)}$	0.85***	0.56***	0.41***	0.14	0.71***	0.49***	0.33**	0.25**
	(0.09)	(0.07)	(0.11)	(0.11)	(0.09)	(0.07)	(0.14)	(0.10)
$weak_t$		0.01		0.02		0.00		0.01
		(0.01)		(0.02)		(0.01)		(0.02)
$\Delta y_t^{(2)} \times weak_t$		0.71***		0.65***		0.54***		0.19
		(0.16)		(0.19)		(0.19)		(0.34)
Intercept	0.00	-0.00	-0.00	-0.01	-0.00	-0.01	-0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.43	0.50	0.09	0.14	0.32	0.37	0.07	0.07

Estimates of regressions $\Delta y_t = b_0 + b_1 \Delta y_t^{(2)} + b_2 weak_t + b_3 \Delta y_t^{(2)} weak_t + \varepsilon_t$, where the dependent variable is the two-day change in a nominal/TIPS yield or instantaneous forward rate with maturity five years (Panel A) or ten years (Panel B), $\Delta y_t^{(2)}$ is the two-day change in the two-year nominal Treasury yield, and $weak_t$ is an indicator of whether the output gap is below the median. The sample consists of 168 FOMC announcement dates between January 1999 and April 2023. Robust standard errors are reported in parentheses.

Table 4 shows our regression estimates, with results for five-year bonds in Panel A and ten-year bonds in Panel B. For each dependent variable, we present estimates of the univariate regression with only the policy surprise, for comparability with Hanson and Stein (2015), and for the multivariate regression (9). The first column of Panel A shows that the five-year nominal Treasury yield rises about one-for-one with the two-year yield around FOMC announcements, but the second column shows that this unconditional estimate masks pronounced state dependence. In a strong economy, a one percentage point tightening surprise raises the five-year yield only 86 basis points, whereas in a weak economy, the effect rises to 138 basis points. That is, the effect is about 60 percent larger in a weak economy. The difference is even larger for the five-year forward rate, where the effect roughly triples (from 48 to 155 basis points). The stronger state dependence of forward rates is consistent with the idea that movements in term premia play an important role. The last four columns of Table 4 Panel A report results for five-year TIPS yields, where the effect of policy surprises on real rates doubles in a weak economy, and for five-year TIPS forward rates, where the effect roughly triples.

For ten-year bonds, the findings are similar, as shown in Panel B. The interaction coefficient is positive in all four multivariate regressions, and, with the exception of only the ten-year real forward rate, statistically significant at the one-percent level and large in magnitude. For both nominal and real ten-year yields, the effect of policy surprises on long-term rates more than doubles in a weak economy.

Our evidence clearly shows that a tightening monetary policy surprise increases long-term rates more in a weak economy than in a strong economy. These patterns can be explained by updating about the policy rule, coupled with a connection between the perceived policy rule and term premia. In a weak economy, a tightening surprise indicates to the public that the Fed is *less* sensitive to output than previously thought, making long-term bonds worse hedges. This in turn causes term premia to rise, which amplifies the response of long-term yields to the surprise. Conversely, in a strong economy, a tightening surprise decreases term premia because the public learns that the Fed is *more* sensitive to the economy than expected and that long-term bonds are better hedges, dampening the impact on long-term rates.

These results may help explain why long-term bond yields have responded only weakly to interest rate hikes during expansions (the Greenspan conundrum), while they have responded strongly on average over the post-1999 period (Hanson and Stein (2015), Nakamura and Steinsson (2018), Hanson et al. (2021)), which has been dominated by economic weakness and severe recessions. On the whole, our evidence supports the conclusion that perceptions about monetary policy influence term premia in long-term interest rates.

4.4 Stock market responses to monetary policy surprises

Finally, the perceived monetary policy rule should impact how stock prices respond to monetary policy surprises around FOMC announcements. If the Fed is perceived to better stabilize the output gap—and hence equity cash flows—then stocks should respond less to any well-identified shock, including a high-frequency monetary policy surprise.

Bernanke and Kuttner (2005) documented that tightening surprises are associated with large declines in the aggregate stock market, while easing surprises lead to sizable increases. To examine how this relationship varies with the perceived policy rule we estimate event-study regressions

$$R_t^M = b_0 + b_1\hat{\gamma}_t + b_2 mps_t + b_3\hat{\gamma}_t mps_t + \varepsilon_t, \tag{10}$$

where mps_t is the monetary policy surprise of Bauer and Swanson (2023a), as in Section 3. We estimate (10) with the stock returns R_t^M measured as either the CRSP value-weighted market return on the day of an FOMC announcement, or the intraday return on S&P500 futures from 10 minutes before to 20 minutes after the announcement. The sample starts in February 1988 and ends in December 2019.[27]

Table 5 shows the results. In the first three columns, the dependent variable is the CRSP value-weighted return on the day of the announcement. The first column reports the benchmark result without interaction effect: stock returns are strongly negatively related to monetary policy surprises around FOMC announcements. The magnitudes are similar to those reported by Bernanke and Kuttner (2005), with a monetary policy surprise of 100 basis points causing a decline in the aggregate stock market index of seven percentage points.

The next two columns of Table 5 report estimates of regression (10) for the baseline estimate of $\hat{\gamma}_t$ and the inertial rule $\hat{\gamma}_t$, respectively. In both regressions, the coefficient on the interaction effect is statistically significant at least at the five percent level. The positive coefficient indicates that at times with high values for $\hat{\gamma}_t$, when the Fed is perceived to be highly responsive to economic conditions, the stock market reaction to policy surprises is less pronounced or even absent. To get a sense of the magnitudes, note that when baseline $\hat{\gamma}_t$ is one the implied response coefficient $b_2 + b_3\hat{\gamma}_t$ would be zero, meaning that the stock market does not respond to policy surprises at all. In other words, the negative market response to policy surprises is driven by times when the Fed's responsiveness to output is perceived to be low. The last three columns show similar, but more precisely estimated, coefficients for the return on S&P500 futures in a 30-minute window around the announcement as the dependent variable, following Gürkaynak et al. (2005) and Bauer and Swanson (2023a).

These results are consistent with the standard New Keynesian model, where a more responsive monetary policy rule dampens the volatility of the output gap in response to

[27] In the case of intraday stock returns, t indexes FOMC announcements, of which there are 323 in the announcement data of Bauer and Swanson (2023a). With daily stock returns, t indexes days with FOMC announcements, of which there are 316 in the sample, since there are seven days with two announcements. Note that in equation (10), mps_t denotes the surprise around announcement (day) t, whereas in equation (5) it denotes the surprise in month t.

Table 5: Stock market responses to monetary policy surprises

	CRSP Daily			S&P500 30-min		
	Benchmark	Baseline $\hat{\gamma}$	Inertial $\hat{\gamma}$	Benchmark	Baseline $\hat{\gamma}$	Inertial $\hat{\gamma}$
mps_t	-6.90***	-11.1***	-8.76***	-3.92***	-6.17***	-5.45***
	(1.46)	(2.47)	(1.61)	(0.89)	(1.21)	(1.00)
$\hat{\gamma}_t$		-0.073	-0.24		-0.0029	0.24
		(0.25)	(0.51)		(0.12)	(0.37)
$mps_t \times \hat{\gamma}_t$		10.0**	13.4***		5.41***	9.96***
		(4.76)	(5.02)		(1.74)	(3.01)
Intercept	0.20***	0.23*	0.23*	-0.018	-0.019	-0.072
	(0.06)	(0.14)	(0.14)	(0.03)	(0.08)	(0.10)
R^2	0.13	0.15	0.15	0.14	0.16	0.17

Regressions of stock market returns on monetary policy surprises, mps_t, the estimated output gap coefficient in the perceived policy rule, $\hat{\gamma}_t$, and the interaction of the two. In the first three columns, the dependent variable is the daily return on the CRSP value-weighted index. In the last three columns, the dependent variable is the return on S&P500 futures in the 30-minute window around the monetary policy announcement. The sample includes 323 FOMC announcements between February 1988 and December 2019. Robust standard errors in parentheses, * p <0.10, ** p <0.05, *** p <0.01.

shocks (Clarida et al., 2000). Intuitively, following a tightening surprise or contractionary monetary policy shock, the market anticipates that output and corporate cash flows will fall, driving down stock prices.[28] If $\hat{\gamma}_t$ is high, markets perceive the Fed to be more sensitive to output and thus believe that the Fed will lower interest rates more strongly to undo the negative effects on the output gap. In this case, a tightening surprise is perceived to have smaller effects on future output, and the impact on stock prices today will be less severe. On the other hand, when the Fed is perceived to be less sensitive to output and $\hat{\gamma}_t$ is low, the same tightening surprise is expected to have more severe macroeconomic consequences, leading to a larger negative response of the stock market.

The stock market's response to FOMC announcements is often interpreted as high-frequency evidence of the real effects of monetary policy, given that stock prices reflect expectations of future macroeconomic conditions (Bernanke and Kuttner, 2005). Under this interpretation, the results in this section suggest that shifting perceptions about the monetary policy rule also matter for real economic outcomes. In particular, investors expect monetary policy shocks to more strongly affect economic outcomes at times when the Fed is

[28] In addition, risk-bearing capacity and risk appetite may fall as well (Pflueger and Rinaldi, 2022; Bauer et al., 2023).

perceived to be less responsive to the economy.

5 A simple model with learning and heterogeneity

We now present a simple model that rationalizes our estimation of the perceived monetary policy rule and explains most of our empirical findings. The model features incomplete information about both the state of the economy (as in noisy information models, e.g., Woodford, 2003a) and about the Fed's policy rule (similar to Eusepi and Preston, 2010; Bauer and Swanson, 2023a). Forecasters receive heterogeneous signals about the economy, leading to heterogeneous policy rate forecasts. The Fed's interest rate decisions provide signals about its policy rule and lead to changes in policy perceptions. We characterize in the model connections between the key variables in our empirical work: the relationship between interest rate and output gap forecasts across forecasters and horizons, the updating of policy perceptions in response to monetary policy surprises, the response of fed funds futures to macroeconomic news announcements, and the properties of 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:

$$i_t \quad = \quad \gamma_t x_t + \rho i_{t-1} + u_t, \tag{11}$$

where the actual monetary policy rule γ_t is unobserved and follows a random walk as in Bauer and Swanson (2023a):

$$\gamma_{t+1} \quad = \quad \gamma_t + \xi_{t+1}. \tag{12}$$

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:

$$x_t \quad = \quad \phi x_{t-1} + v_t. \tag{13}$$

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

$$E^j\left(\gamma_1 \,|\mathcal{Y}_0\right) \quad = \quad \hat{\gamma}_0, \qquad Var^j\left(\gamma_1 \,|\mathcal{Y}_0\right) = \sigma_1^2, \tag{14}$$

where $\mathcal{Y}_t$ denotes the filtration based on observing the output gap and interest rates up to and including time t. We use $\bar{E}$ to denote average expectations across all forecasters j, $\hat{\gamma}_t \equiv \bar{E}\left(\gamma_{t+1} \left| \mathcal{Y}_t\right.\right)$, $\sigma^2_{t+1} = \bar{V}ar\left(\gamma_{t+1} \left| \mathcal{Y}_t\right.\right)$. To capture persistent differences across forecasters (Patton and Timmermann, 2010), one could additionally assume they 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 introduce heterogeneity following Caballero and Simsek (2022b) by assuming that forecasters "agree to disagree" and use their perceived rule to make heterogeneous interest rate forecasts. We generate disagreement through incomplete information, assuming that in each period, forecasters first observe a noisy signal about the output gap $\nu^j_t = x_t + \eta^j_t$, where $\eta^j_t \sim N(0, \sigma^2_\eta)$.[29] To model the possibility that forecasters may not be fully rational, we build on the model of belief misspecifications of Angeletos et al. (2021) and assume that forecasters perceive the variance of the monetary policy shock to be $\frac{\sigma^2_u}{\kappa}$ when it is actually σ^2_u. If $\kappa < 1$, forecasters overweight their own private prior relative to the public signal contained in the policy rate in the spirit of Bordalo et al. (2020).[30]

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

$$mps_t \equiv i_t - \bar{E}\left(i_t \left| \mathcal{Y}_{t-1}, x_t\right.\right), \tag{15}$$

[29]While Caballero and Simsek (2022b) model differences of opinions between the market and the Fed, we further allow for differences of 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 (11). We use the assumption of incomplete information as the simplest way to generate variation across forecasters in interest rate and output gap forecasts. However, our model's implications are not dependent on rational output gap forecasts, and a similar relationship between policy rate and output gap forecasts would be obtained if output gap forecasts were subject to rational inattention or slow learning as in Reis (2020).

[30]A 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.

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

$$\hat{\gamma}_t - \hat{\gamma}_{t-1} = \omega_t \frac{mps_t}{x_t}, \qquad \omega_t \equiv \frac{\sigma_t^2 x_t^2}{\sigma_t^2 x_t^2 + \frac{\sigma_u^2}{\kappa}}, \qquad \sigma_{t+1}^2 = \sigma_t^2(1-\omega_t) + \sigma_\xi^2. \tag{16}$$

All proofs are given in Appendix E.1. The key economic insight is that the monetary policy surprise, $mps_t = (\gamma_t - \hat{\gamma}_t)x_t + u_t$, conveys information about γ_t. In the absence of monetary policy shocks, we would have $\gamma_t - \hat{\gamma}_t = \frac{mps_t}{x_t}$ and thus γ_t could 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 model gives rise to a number of corollaries. Corollary 1 shows that the perceived monetary policy rule can be recovered from a forecaster-horizon panel.

Corollary 1 (Period-by-Period Panel Regression): In a panel regression of time-t policy rate forecasts on time-t output gap forecasts with forecaster fixed effects:

$$E^j\left(i_{t+h}\left|\mathcal{Y}_{t-1}, \nu_t^j\right.\right) = \alpha_j^0 + g_t E^j\left(x_{t+h}\left|\mathcal{Y}_{t-1}, \nu_t^j\right.\right) + b_t E^j\left(i_{t+h-1}\left|\mathcal{Y}_{t-1}, \nu_t^j\right.\right) + \varepsilon_{jht} \tag{17}$$

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

Corollary 2 states that the perceived monetary policy rule should also influence how strongly interest rates respond macroeconomic news announcements.

Corollary 2 (Macro Surprises): Define a macroeconomic surprise as $\Delta x_t = x_t - \bar{E}\left(x_t\left|\mathcal{Y}_{t-1}, \nu_t^j\right.\right)$ and the contemporaneous change in interest rate forecasts as $\Delta i_t = \bar{E}\left(i_t\left|\mathcal{Y}_{t-1}, x_t\right.\right) - \bar{E}\left(i_t\left|\mathcal{Y}_{t-1}, \nu_t^j\right.\right)$. The interaction coefficient b_3 in the following regression is positive:

$$\Delta i_t = b_0 + b_1\hat{\gamma}_t + b_2\Delta x_t + b_3\hat{\gamma}_t\Delta x_t + \varepsilon_t. \tag{18}$$

Corollary 3 traces out the implications of the perceived monetary policy rule for term premia in long-term bonds. We assume a simple stochastic discount factor where marginal utility is inversely related to the output gap. One microfoundation for this assumption would be constant relative risk aversion (CRRA) utility over consumption with consumption equal to output and constant potential output. Similar assumptions for the stochastic discount factor are common in reduced form asset pricing models, e.g., Lettau and Wachter (2007).

Corollary 3 (Bond Risk Premia): Assuming a log stochastic discount factor $m_{t+1} =$

$-i_t - \psi v_{t+1} - \frac{1}{2}\psi^2\sigma_v^2$, the expected excess return on a two-period bond declines with the perceived monetary policy coefficient $\hat{\gamma}_t$.

Combining Lemma 1 and Corollary 3 then gives the following implications for the responses of long-term bonds to monetary policy announcements.

Corollary 4 (State-Contingent Long-Term Bond Responses): Denote the interest rate on a two-period bond by $i_{2,t}$ and let $I_{x_t<0}$ be an indicator variable equal to when the output gap is negative and zero otherwise. In the regression

$$i_{2,t} \;=\; b_0 + b_1 mps_t + b_2 I_{x_t<0} + b_3 mps_t I_{x_t<0} + \varepsilon_t, \tag{19}$$

the coefficient b_3 is positive.

We now turn to the empirical implications of this framework. Our empirical strategy in Section 2 builds on the insight from Corollary 1 that the time t perceived rule coefficient $\hat{\gamma}_t$ can be recovered by estimating a simple monetary policy rule regression in the forecaster-horizon panel at time t. This is the basis for our estimation of the time-varying perceived monetary policy rule.

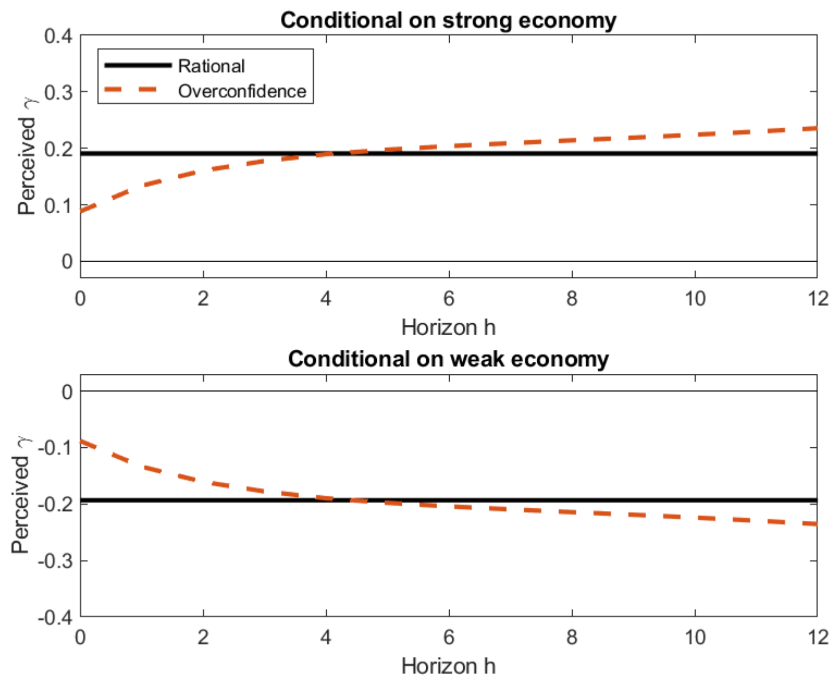
Lemma 1 then provides testable implications for how the perceived policy rule $\hat{\gamma}_t$ should respond to high-frequency monetary policy surprises. Because a positive monetary policy surprise tends to reflect either an above-average output gap and higher-than-expected monetary policy coefficient, or a below-average output gap and lower-than-expected monetary policy coefficient, forecasters update in a state-contingent way. They revise their estimates of $\hat{\gamma}_t$ up following a positive policy surprise in a strong economy, but revise them down following a positive surprise in a weak economy.

The expression for ω_t in Lemma 1 links the magnitude of the response of $\hat{\gamma}_t$ to the ratio of policy surprise and output gap, $\frac{mps_t}{x_t}$, to the share of uncertainty about the monetary policy surprise that is due to uncertainty about the policy rule. We can use this link to conduct 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% percent suggests that about $0.7/1.4 = 50\%$ of the variation in monetary policy surprises are due to the uncertainty of forecasters about the policy rule.[31]

[31]Equation (16) shows that the amount forecasters update their perceived rule $\hat{\gamma}_t$ following a surprise depends on their uncertainty about the rule (σ_t^2), the volatility of the policy shock (σ_u^2), and the output gap. The output gap is on average 1.4 percentage points above its median during the strong economic times. Substituting $\hat{\gamma}_t - \hat{\gamma}_{t-1} \approx 0.7$ and $x_t \approx 1.4$ into equation (16) and solving for ω_t suggests that forecasters attribute about 50% of the variation in monetary policy surprises to uncertainty about the policy rule.

The speed at which forecasters update their beliefs $\hat{\gamma}_t$ depends on agents' misperceptions about the precision of their own prior versus the public signal (Angeletos et al., 2021). The perceived monetary policy rule should respond immediately if forecasters are perfectly rational. But if forecasters put too much weight on their priors about the policy rule, they will respond more slowly. 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.

The model predicts no updating following 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., $\sigma_u^2 \to \infty$). These conditions are inconsistent with the empirical evidence on learning updates presented in Section 3.

Corollaries 2–4 have implications for the transmission of the perceived monetary policy rule to short-term and long-term interest rates that we confirm in the data. In Section 4.1, we confirm the prediction of Corollary 2 that the perceived monetary policy rule influences the sensitivity of interest rates to macroeconomic news. Corollary 3 predicts that the perceived monetary policy rule should influence long-term interest rates beyond its impact on expected future policy rates, i.e., through term premia. We confirm these predictions for expected excess returns on long-term bonds 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 makes long-term bonds desirable hedges, decreasing the term premia investors demand to hold them. Corollary 4 uses a two-period bond to understand the behavior of long-term bond yields around monetary policy announcements. It shows that long-term bond yields should display excess sensitivity to monetary policy surprises when the economy is weak, i.e., x_t is below average. Conversely, long-term bond rates should be relatively insensitive to monetary policy surprises if the economy is strong and x_t is above average. We confirm this prediction in Section 4.3.

6 Robustness of estimated perceived policy rules

This section demonstrates robustness of our key variable—the estimated perceived monetary policy output gap weight $\hat{\gamma}_t$—to alternative specifications of the perceived rule and different estimation methods. As Table 6 shows, we find that these various alternative estimates of $\hat{\gamma}_t$ are highly correlated with our baseline estimates. For details and plots, see Appendix C.

We first consider an estimate of the baseline rule without forecaster fixed effects, labeled "OLS" in Table 6. This estimate is 84% correlated with our baseline estimate.

We then consider heterogeneity in the perceived rule across forecasters. 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 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 it closely tracks the average perceived coefficient over time and is not driven by shifting weights put on different forecasters by the estimation procedure. 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 in fed funds rate and macroeconomic forecasts across forecast horizons is important for our estimation. The cross-section of forecasters matters because the regression for each individual forecaster is noisy, but averaging slope coefficients across forecasters gives more precise estimates that vary smoothly over time.

Table 6: Robustness: Correlation of alternative $\hat{\gamma}_t$ estimates

	OLS	Equal Weighted	Hetero-geneous	Infl. Terciles 1	2	3	Credit spread	Bias adjust
Baseline $\hat{\gamma}_t$	0.84	0.81	0.88	0.85	0.81	0.85	0.94	0.92

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. For details on alternative estimates, see Appendix C.1.

Next, we impose additional structure on forecaster heterogeneity. The "heterogeneous" estimate includes forecaster fixed effects interacted with the output gap and inflation, i.e., it estimates the multidimensional panel regression

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

This estimator allows individual forecasters to persistently perceive the Fed to be more or less responsive to output and inflation than the average forecaster. Because forecaster ID's were reshuffled in 1993, we estimate this specification starting in January 1993. It is 88% correlated with our baseline $\hat{\gamma}_t$ estimate.

We next split forecasters by their inflation forecasts and estimate different policy rules for each forecaster group, addressing the concern that 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 the lowest 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 their inflation expectations again confirms that our baseline estimator $\hat{\gamma}_t$ captures common time variation in the perceived monetary policy rule shared by all forecasters.

We next address concerns 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 credit spreads—the difference 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 BCFF 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 6 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.

Additional robustness checks, including estimates using forecaster-level data from the Survey of Professional Forecasters (SPF) and the Fed's Survey of Economic Projections, are reported in Appendix C. In Appendix D.2 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.

Finally, we address the concern that our estimates of monetary policy rules might be 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.[32] 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 quantify the bias and adjust for it. We adapt the approach of Carvalho et al. (2021) to our cross-sectional setting. 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 versus 0.43. This difference 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. Table 6 shows that the correlation of the

[32] 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.

baseline estimates with and without bias adjustment equals 92%.

A structural interpretation of our estimates as coefficients in a perceived policy rule is also supported by our empirical results, which show 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, one could also simply interpret $\hat{\gamma}_t$ as the perceived endogenous comovement between the policy rate and the macroeconomy, sidestepping these causality concerns. 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 rich panel data of monthly survey forecasts. With our 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 of monetary policy to the economy varies substantially over time, reflecting the Fed's shifting concerns about economic data versus financial and other risks. It tends to be high during monetary tightening cycles when Fed policy is perceived to be data-dependent, and low during easing cycles and times of elevated economic and financial uncertainty. 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 about the rule followed by the Fed. 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, the variation in term premia on long-term bonds both month-to-month and around monetary policy surprises, and time variation in the response of the stock market to FOMC announcements.

These conclusions have broader implications for monetary economics and the practice of monetary policy. In particular, they imply that the impact of monetary policy on financial markets—the first stage of the monetary transmission mechanism—cannot be understood without taking into account that the public has incomplete information about the Fed's monetary policy strategy and learns about it over time. This opens the door for important additional research, addressing such questions as how central bank communication shapes perceptions about the monetary policy strategy and how optimal monetary policy should account for shifting perceptions in seeking to stabilize inflation and employment.

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Appendix for Online Publication

A Survey data and perceived policy rule

A.1 BCFF data and summary statistics

The professional forecasters are queried near the end of the month preceding the release of the survey. Specifically, the deadline for the survey responses is the 26th of the previous month, with the exception of December, when the deadline is the 21st.

The BCFF contains quarterly forecasts. For the federal funds rate, the forecast target is the quarterly average of the daily effective funds rate, in annualized percent, as reported in the Federal Reserve's H.15 statistical release. The macroeconomic forecasts for output growth and inflation are reported as quarter-over-quarter forecasts in annualized percent.

We calculate year-over-year inflation forecasts as follows: 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, observed CPI inflation over recent quarters.

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

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

where x_t is the output gap and Y_t^* is potential GDP in the quarter ending in t.

In Table A.1 we report summary statistics for our survey data. Across surveys, horizons,

[33] In 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 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.

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.

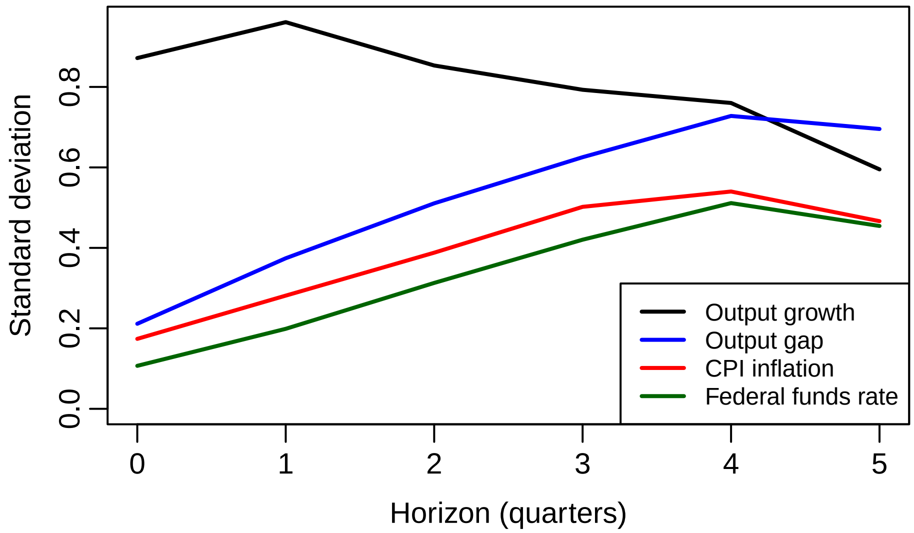
and forecasters, there are about 120,000 individual forecasts. Output gap forecasts are negative on average, in line with the fact that both real-time and revised estimates of the output gap were negative for the majority of our sample period. Forecasted CPI inflation averages around 2.7% and the average 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.

A.2 Term structure of disagreement

Figure A.1 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 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.

Figure A.1: 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.

B Additional results for local projections

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 the null hypothesis of no state dependence is easily tested. 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 is consistently negative and, for horizons shorter than $h = 12$ months, strongly 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, and that there is strong statistical evidence for state dependence.

Table B.1: Local Projection Regressions

	Baseline $\hat{\gamma}_{t+h}$				Inertial $\hat{\gamma}_{t+h}$			
Horizon:	$h=3$	$h=6$	$h=9$	$h=12$	$h=3$	$h=6$	$h=9$	$h=12$
mps_t	0.34*	0.73***	0.53**	0.21	0.61***	0.73***	0.27	0.17
	(1.67)	(2.72)	(2.24)	(0.81)	(4.27)	(3.27)	(1.50)	(1.43)
$mps_t \times weak_t$	-0.73**	-1.87***	-1.77***	-0.96*	-1.17***	-1.55***	-1.27***	-0.71*
	(-2.21)	(-3.72)	(-2.83)	(-1.68)	(-4.15)	(-5.39)	(-3.67)	(-1.81)
$weak_t$	0.03	0.07	0.12**	0.16**	-0.01	-0.01	0.00	0.02
	(0.94)	(1.46)	(2.06)	(2.47)	(-0.84)	(-0.20)	(0.06)	(0.46)
$\hat{\gamma}_{t-1}$	0.70***	0.56***	0.45***	0.39***	0.57***	0.42***	0.23***	0.12
	(13.31)	(7.66)	(5.21)	(4.32)	(8.76)	(5.52)	(3.82)	(1.60)
Constant	0.11***	0.15***	0.17***	0.18***	0.08***	0.10***	0.13***	0.14***
	(4.30)	(4.10)	(4.11)	(3.57)	(4.58)	(3.73)	(3.90)	(4.11)
N	457	454	451	448	457	454	451	448
R^2	0.48	0.33	0.25	0.21	0.36	0.22	0.1	0.03

Local projection estimates of the state-dependent response of $\hat{\gamma}_t$—measured using the baseline rule in the first four columns and using an inertial rule in the last four columns—to high-frequency monetary surprises of Bauer and Swanson (2023a), 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, * p <0.10, ** p <0.05, *** p <0.01. Sample period: January 1988–April 2023.

C Robustness of policy rule estimates

C.1 Heterogeneity and 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:

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

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 2.3.

The "equal-weighted" estimator is obtained by running

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

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

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

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".[34] The estimates of b_j and g_j represent the forecaster-specific time-invariant coefficient shifters. Note that this estimate does not contain forecaster-by-month fixed effects, thus it is closer to the Pooled OLS estimate than our baseline FE estimate, as evident from Table 6.

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 6.

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 6. 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

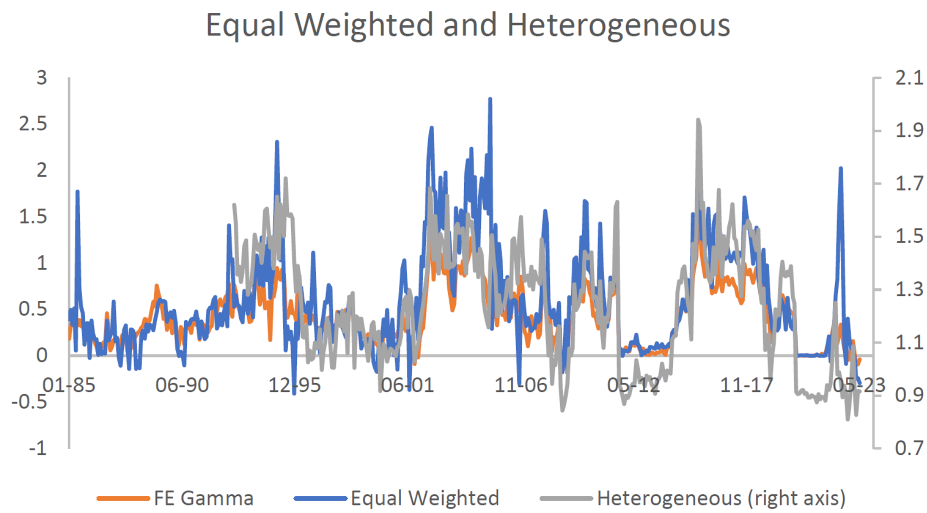
We use a simple New Keynesian (NK) framework to quantify potential estimation bias from the endogenous response of the economy to monetary policy. Our analysis suggests that our estimates of $\hat{\gamma}_t$ may contain a modest downward bias relative to the true perceived monetary policy coefficient $\hat{\gamma}_t$, 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.

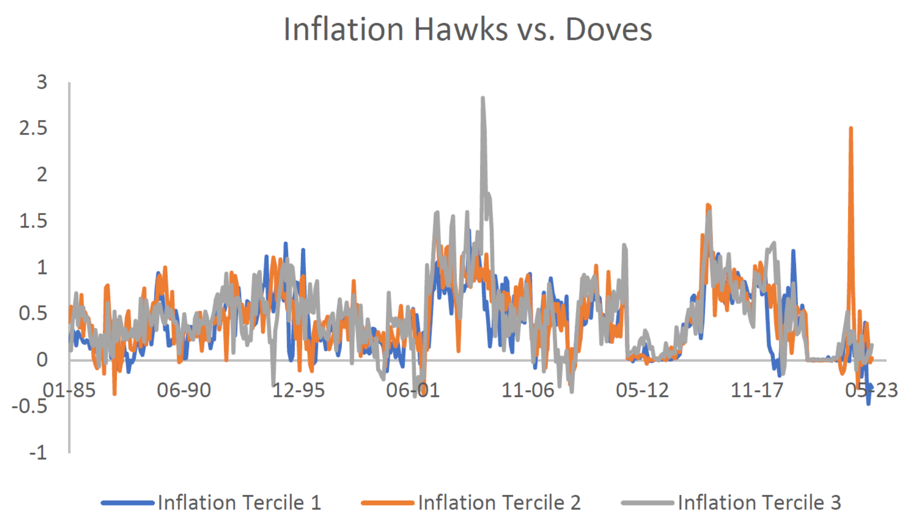
[34] Because forecaster ID's were reshuffled in 1993, this regression starts in January 1993.

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

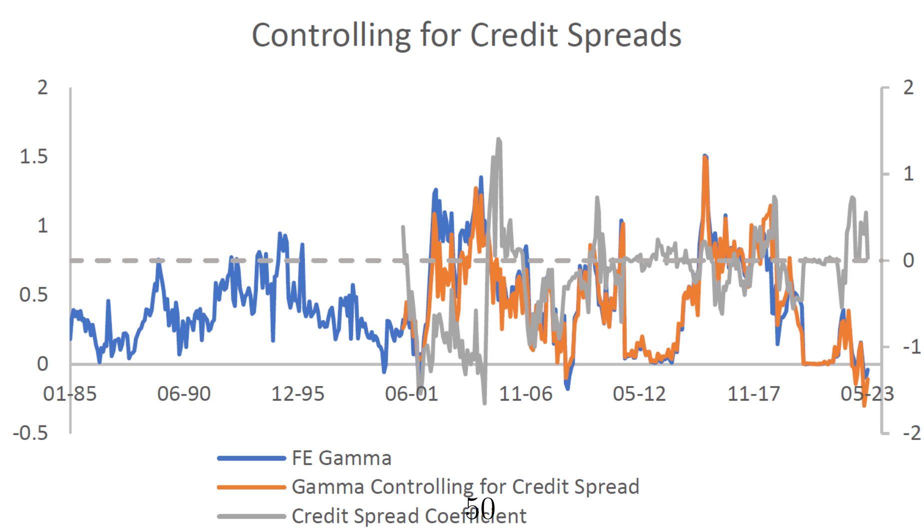
Panel A: Heterogeneity



Panel B: Inflation Terciles



Panel C: Controlling for Credit Spread Forecasts



Alternative estimates of $\hat{\gamma}_t$ used in Table 6

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

$$x_t = E_t x_{t+1} - (i_t - E_t \pi_{t+1}) + v_t \tag{C.3}$$
$$\pi_t = E_t \pi_{t+1} + \kappa x_t \tag{C.4}$$
$$i_t = \hat{\beta}\pi_t + \hat{\gamma} x_t + u_t. \tag{C.5}$$

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.3), assumes log-utility and includes a reduced-form demand shock v_t. Equation (C.4) is the Phillips curve. Our monetary policy rule, equation (C.5), 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.3) through (C.5) 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 (2022b). 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 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 $h \to \infty$. 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.5) into the Euler equation (C.3) and iterate forward to obtain forecaster j's conditional expectations for the equilibrium policy rate and output gap at horizon $t+h$ as:

$$E_t^{(j)} x_{t+h} = \sum_{\tau=0}^{\infty} (1+\hat{\gamma}_t)^{-(\tau+1)} (E_t^{(j)} v_{t+\tau+h} - E_t^{(j)} u_{t+\tau+h}), \quad \text{and} \tag{C.6}$$

$$E_t^{(j)} i_{t+h} = \hat{\gamma}_t \sum_{\tau=0}^{\infty} (1+\hat{\gamma}_t)^{-(\tau+1)} (E_t^{(j)} v_{t+\tau+h} - E_t^{(j)} u_{t+\tau+h}) + E_t^{(j)} u_{t+h}. \tag{C.7}$$

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:

$$\begin{aligned} Cov_t\left(E_t^{(j)} i_{t+h}, E_t^{(j)} x_{t+h}\right) &= Cov_t\left(\hat{\gamma}_t E_t^{(j)} x_{t+h} + E_t^{(j)} u_{t+h}, E_t^{(j)} x_{t+h}\right), \\ &= \hat{\gamma}_t Var_t\left(E_t^{(j)} x_{t+h}\right) - Var_t\left(E_t^{(j)} u_{t+h}\right). \end{aligned} \tag{C.8}$$

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:

$$\tilde{\gamma}_t = Cov_t\left(E_t^{(j)} i_{t+h}, E_t^{(j)} x_{t+h}\right) \tag{C.9}$$

$$= \hat{\gamma}_t - (1+\hat{\gamma}_t)^{-1} Var_t\left(E_t^{(j)} u_{t+h}\right), \tag{C.10}$$

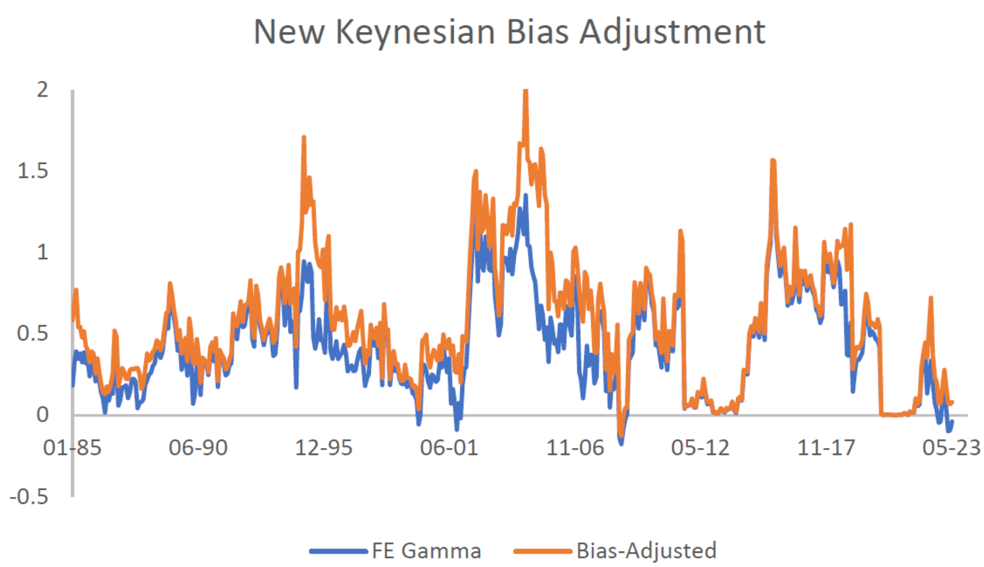
$$Var_t\left(E_t^{(j)} i_{t+h}\right) = \hat{\gamma}_t^2 + 2\hat{\gamma}_t Cov_t\left(E_t^{(j)} i_{t+h}, E_t^{(j)} x_{t+h}\right) + Var_t\left(E_t^{(j)} u_{t+h}\right) \tag{C.11}$$

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.6) then is unchanged, and the equilibrium for the policy rate C.7 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 6 is obtained by solving the two equations (C.10) and (C.11) numerically for $\hat{\gamma}_t$ after residualizing everything with respect to forecaster fixed effects.

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



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

C.3 State-contingent impulse responses in standard New Keynesian Model with full information

One might be concerned that the state-contingent impulse responses to a high-frequency monetary policy surprise in Section 3 could arise from time-varying estimation bias, because monetary policy surprises induce comovements between the policy rate, the output gap and inflation.[35]

We address this issue by considering a textbook New Keynesian model, building on the model in Section C.2. To isolate the role of potentially time-varying estimation bias, we assume in this Section that all parameters are fixed and known, i.e. $\hat{\gamma} = \gamma$, thereby switching off any learning channel. The model is given by the following three equations (see e.g. Galí

[35] We thank Ricardo Reis for raising this concern.

(2015))

$$\textbf{Euler Equation:} \quad x_t = (1-\rho^x)E_t x_{t+1} + \rho^x x_{t-1} - \psi(i_t - E_t\pi_{t+1}) + v_{x,t}, \tag{C.12}$$

$$\textbf{Phillips Curve:} \quad \pi_t = \kappa x_t + (1-\rho^\pi)\, E_t\pi_{t+1} + \rho^\pi \pi_{t-1} + v_{\pi,t}, \tag{C.13}$$

$$\textbf{Monetary Policy Rule:} \quad i_t = \gamma^x x_t + \gamma^\pi \pi_t, , \tag{C.14}$$

$$\textbf{Monetary Shock Dynamics:} \quad v_{i,t} = \rho^i v_{i,t-1} + \eta_t \tag{C.15}$$

Because we are interested in comovements between inflation and output, a constant risk premium is suppressed along with all other constants without loss of generality. The calibration uses conventional values from the literature and follows Cieslak and Pflueger (2023), setting $\rho^x = 0.45$, and $\psi = 0.27$, $\rho^\pi = 0.8$, $\kappa = 0.019$, $\gamma^x = 0.5$, $\gamma^\pi = 1.5$, and $\rho^i = 0.7$. Because model has monetary policy inertia the analogue to our empirical analysis is the short-run output gap response, which in this calibration equals $\gamma = (1-\rho^i) \times \gamma^x = 0.3 \times 0.5 = 0.15$. We assume that the monetary policy shock is serially correlated as in Galí (2015) to stack the deck against ourselves as much as possible. An alternative would be to assume an inertia parameter ρ^i in the monetary policy rule and that the monetary policy shock itself is serially uncorrelated, in which case the expected policy rate would always be exactly described by the rule in the post-shock periods, so the impulse responses for $\tilde{\gamma}$ would be exactly zero.

Figure C.3 shows the properties of this calibrated New Keynesian model, and confirms that it indeed generates standard impulse responses. In particular, a positive monetary policy shock drives up the policy rate, and generates a hump-shaped decline in the output gap. We then run regressions of the form

$$E_h i_{h+\tau} = \alpha_h + b_h E_h \pi_{h+\tau} + \gamma_h E_h x_{h+\tau} + \rho_h E_h i_{h+\tau-1} + e_{h+\tau} \tag{C.16}$$

on the impulse responses to a monetary policy shock, where the forecast horizon ranges from $\tau = 0$ to $\tau = 5$ quarters. This is designed to mimic our empirical setup in Section 3. The estimated $\tilde{\gamma}_h$ therefore uses variation across forecast horizons, similarly to our empirical specification. We denote the estimated output gap coefficient from this regression by $\tilde{\gamma}_h$. Figure C.4 plots the estimated $\tilde{\gamma}_h$ normalized by the true γ against the number of quarters after the shock, h. We see that the impulse responses for $\tilde{\gamma}_h$ jump down, but are identical across strong and weak states of the economy, in contrast to our empirical results. The model impulse responses for $\tilde{\gamma}$ are persistent because we do not simulate any shocks after the initial monetary policy shock period. If we were to simulate background noise, i.e. supply, demand and monetary policy shocks, there would be mean-reversion. Either way, the impulse responses in $\tilde{\gamma}$ from the standard New Keynesian model with full information rational expectations are not state-contingent. We therefore conclude that under the specified conditions, the standard New Keynesian model with full information do not lead to estimation bias that could rationalize the empirical findings in Section 3.

C.4 Survey of Professional Forecasters

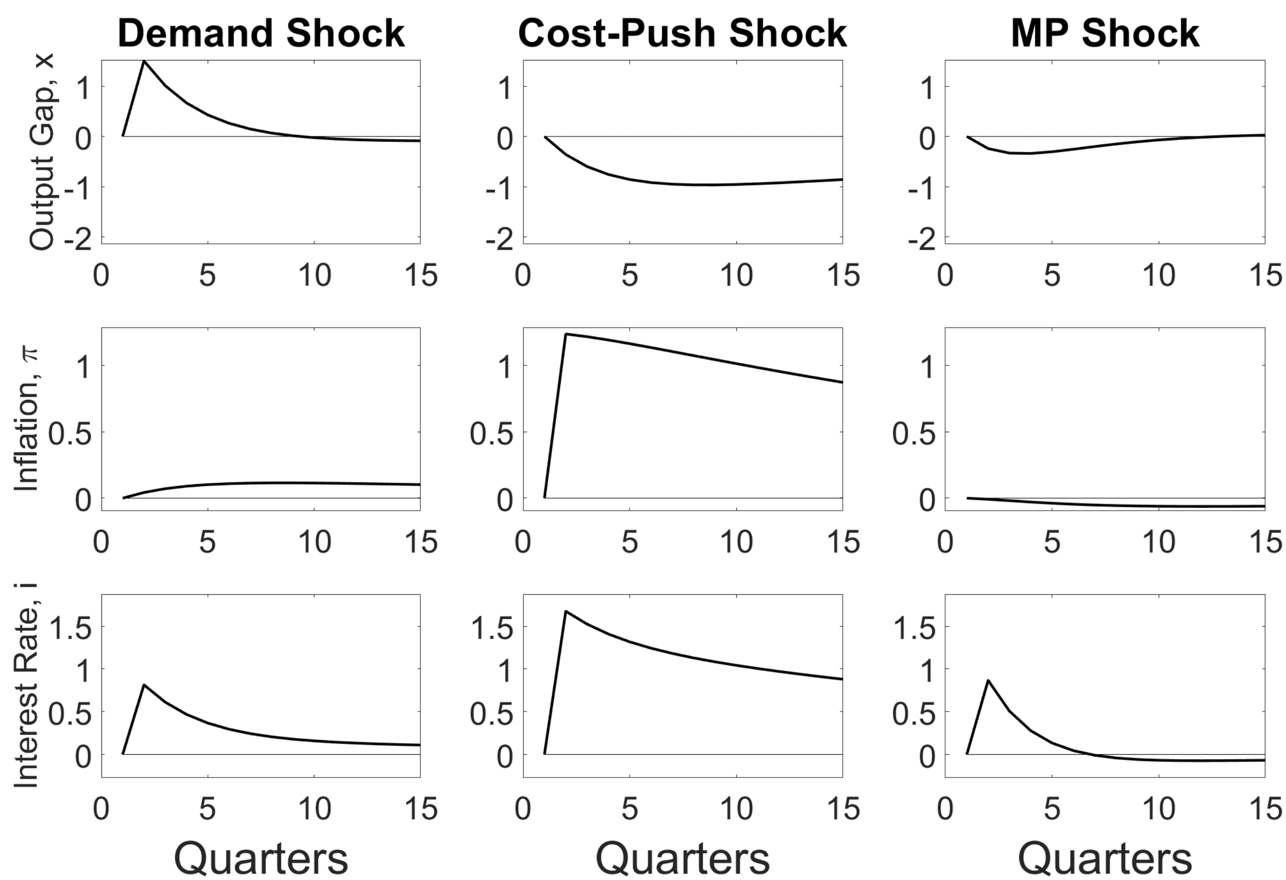
The Philadelphia Fed's quarterly Survey of Professional Forecasters (SPF) includes individual forecasts of various macroeconomic variables and interest rates. We estimate a policy rule for the three-month T-bill rate, the interest rate with the shortest maturity, which is highly correlated with the federal funds rate. For inflation we use the CPI forecasts, as before. The advantage of the SPF is that unemployment rate forecasts can be used to measure expected future economic activity. Our main interest here lies in the question how our results change if we use other types of economic forecasts instead of the imputed output gap forecasts in the BCFF. forecasts. Instead of imputing unemployment gap forecasts, we use the unemployment rate forecasts themselves in our regressions. Under the reasonable assumption that the natural rate of unemployment changes only slowly, these regressions will pick up correlations of the forecasts for the T-bill rate with forecasts for economic slack, since heterogeneity about the natural rate will be subsumed in the forecaster fixed effects.

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 both a simple baseline rule, similar to the specification in equation (2), as well as an inertial rule as in equation (4), in both cases using fixed effects as for the BCFF rules.

For the baseline rule estimates the estimated coefficient on the unemployment rate forecasts has a correlation of -0.74 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. Similarly for the inertial rule estimates, there is a high negative correlation, in this case -0.62.

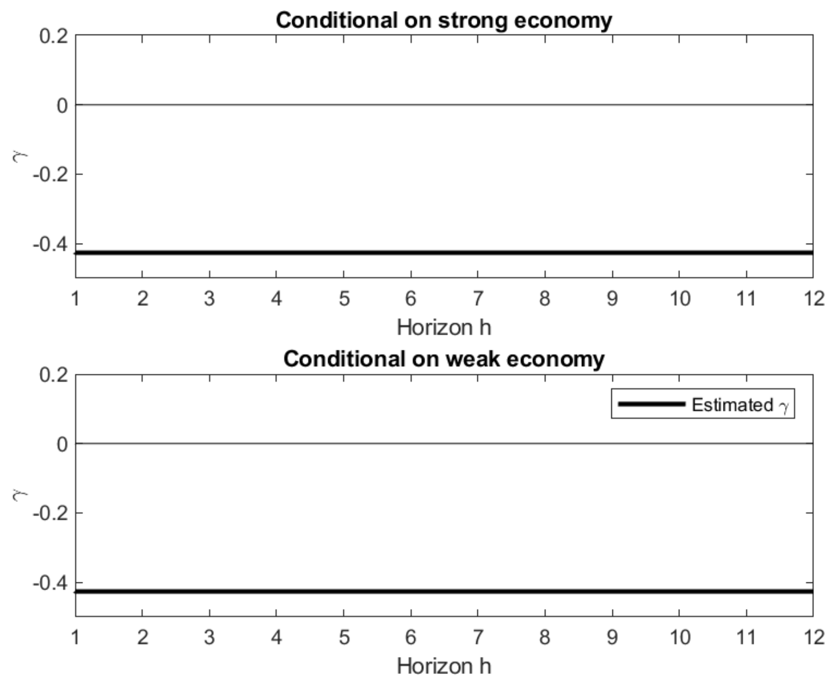
Figure C.5 provides a visual comparison. For the monthly BCFF, it plots the points estimates of $\hat{\gamma}_t$, and for the quarterly SPF, it shows the point estimates and 95% confidence intervals each multiplied by -1/2. The cyclical patterns of the SPF and BCFF series are strikingly similar, despite the different measures of economic slack being forecasted in each of these surveys. This similarity is comforting and suggests that the imputation of output gap forecasts does not introduce any spurious patterns into our policy rule estimates for the BCFF.

Figure C.3: Macroeconomic impulse responses in standard New Keynesian model



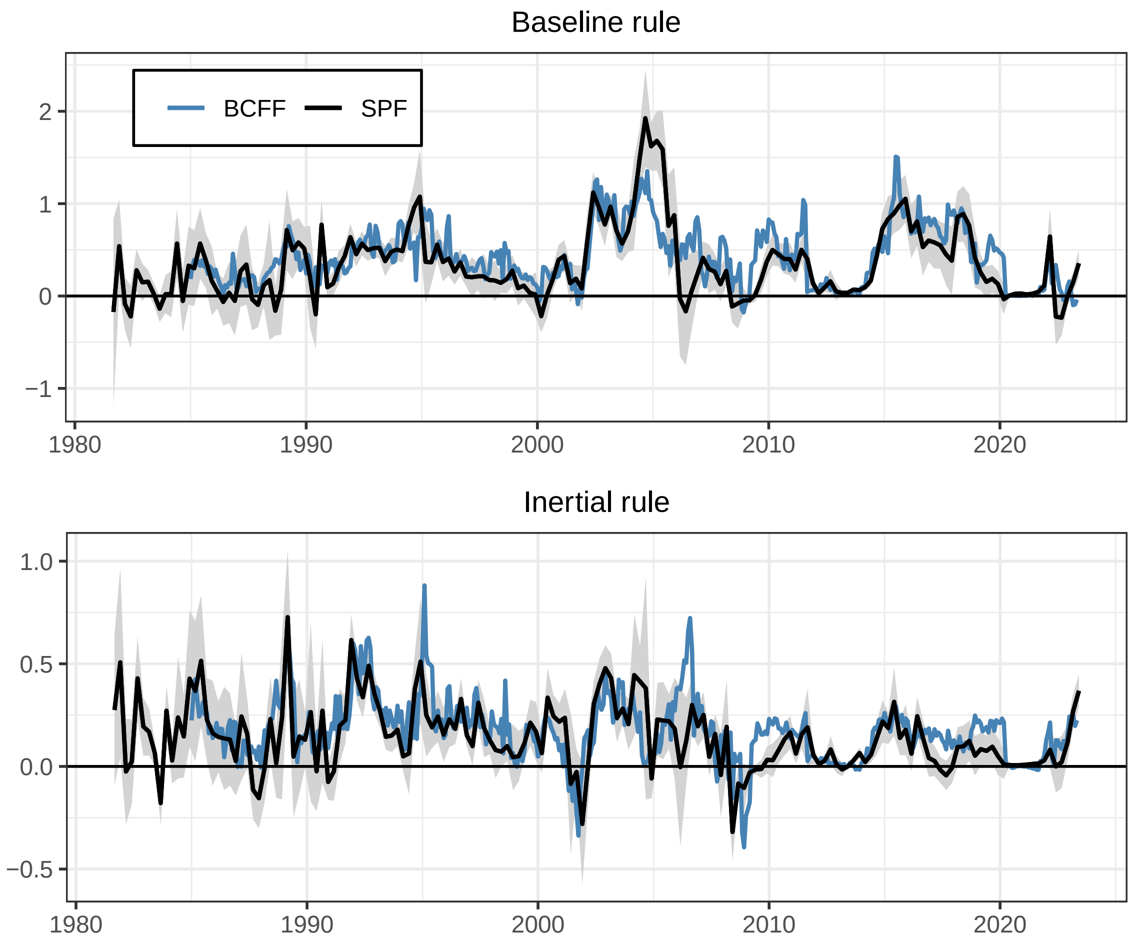
This figure shows impulse responses to demand, cost-push shock, and monetary policy shocks for the three-equation New Keynesian model. The output gap is in percent and inflation and interest rates are in annualized percent units. We show responses to a one percentage point demand shock, a one percentage point (in annualized units) cost-psush shock, and a one-percentage point (in annualized units) monetary policy shock. Quarter 1 is when the shock happens, with quarters after the shock shown on the x-axis.

Figure C.4: Model impulse responses of estimated $\tilde{\gamma}$ in standard New Keynesian model with full information



This figure shows impulse responses for estimated minus true $\tilde{\gamma}_h - \gamma$ after a one percentage point monetary policy shock. The coefficient $\tilde{\gamma}_h$ is estimated from a cross-horizon regression $E_h i_{h+\tau} = \alpha_h + b_h E_h \pi_{h+\tau} + \gamma_h E_h x_{h+\tau} + \rho_h E_h i_{h+\tau-1} + e_{h+\tau}$, where $\tau = 0, 1, 2, 3, 4, 5$. The top panel is conditional on the output gap being equal to 1% in the pre-shock period. The top panel is conditional on the output gap being equal to -1% in the per-shock period. Period 0 is when the shock happens, with quarters after the shock shown on the x-axis.

Figure C.5: 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 2.3. Estimate for BCFF is the coefficient on output gap forecasts in the BCFF perceived rule, while the estimate for SPF corresponds to -1/2 times the coefficient on the unemployment rate forecasts in the SPF perceived rule. Top panel shows estimates for the baseline rule specification; bottom panel shows estimates for inertial rules that include the interest rate forecast for the preceding quarter. The sample for SPF is quarterly from 1981:Q3 to 2023:Q2; the sample for BCFF is monthly from 1985:01 to 2023:05.

D Additional results for bond risk premia

D.1 Predictability of excess bond returns

Here we report results on the predictability of realized excess returns on long-term Treasury bonds, which complement the regressions in Section 4.2 for survey-based/subjective expected excess bond returns. Because realized bond excess returns may partly reflect lower- or higher-than-expected interest rates in addition to the expected bond excess returns, that we are interested in, we include additional controls. In particular, we control for the Chicago Fed National Activity Index (CFNAI) and its interaction with $\hat{\gamma}_t$, because Cieslak (2018) has shown that the CFNAI is related to repeated interest rate forecast errors. We end our estimation sample in February 2020 inclusive to avoid the noise from wild and unexpected swings in interest rates during the pandemic and post-pandemic period. For comparability, we use the same start date as for subjective expected returns in Table 3 in the main paper.

Using Treasury yield data from Gürkaynak et al. (2007), we estimate the following predictive regressions:

$$xr^{(n)}_{t\to t+h} = b_0 + b_1\hat{\gamma}_t + b_2 CFNAI_t + b_3\hat{\gamma}_t CFNAI_t + b_4' X_t + \varepsilon_{t+h}, \tag{D.1}$$

where $xr^{(n)}_{t\to t+h}$ is the log excess return on a zero-coupon n-year nominal Treasury bond from month t to month $t+h$, and X_t contains the first three principal components of Treasury yields with maturities one, two, five, seven, ten, fifteen, and twenty years. We compute the h-month excess return on a zero-coupon bond with n years to maturity as $rx^{(n)}_{t+h} = ny^{(n)}_t - \left(n - \frac{h}{12}\right) y^{\left(n-\frac{h}{12}\right)}_{t+h} - \frac{h}{12} y^{(n)}_t$, where $y^{(n)}_t$ is the zero-coupon yield with maturity n years. We estimate equation (D.1) using both the baseline and the inertial rule estimate for $\hat{\gamma}_t$, and we consider holding periods of both $h = 12$ and $h = 24$ months. We focus on nominal Treasury bond excess returns as opposed to inflation-indexed (Treasury Inflation Protected Securities, TIPS) because of the longer time-series in nominal Treasury bonds and liquidity concerns in TIPS during the financial crisis of 2008-2009. We report results only for the five-year bond for the sake of brevity, but other bond maturities yield qualitatively similar findings.

Table D.1 shows that baseline $\hat{\gamma}_t$ predicts realized bond excess returns negatively and significantly with magnitudes that are similar to those for subjective expected excess returns in Table 3. The magnitude and significance of $\hat{\gamma}_t$ as a predictor of future bond excess returns increases further over longer return forecasting horizons, which were not available for subjective expected excess returns. This holds whether or not we control for the CFNAI. Similar to Table 3, the return predictability regressions are stronger for baseline $\hat{\gamma}_t$ than for inertial $\hat{\gamma}_t$, consistent with the interpretation of baseline $\hat{\gamma}_t$ as the perceived long-run monetary policy response, and inertial $\hat{\gamma}_t$ as a perceived short-run response. We therefore conclude that the link between the perceived monetary policy rule and bond risk premia is similar for statistical and subjective risk premia.

Table D.1: Predictability of excess bond returns

	$xr^{(5)}_{t\to t+12}$			$xr^{(5)}_{t\to t+24}$		
Panel A: Baseline $\hat{\gamma}_t$						
$\hat{\gamma}$	-2.76***	-2.25**	-2.47***	-4.81***	-3.67***	-3.93***
	(-2.92)	(-2.53)	(-2.98)	(-4.13)	(-3.91)	(-4.65)
$CFNAI$		-0.88	-1.58***		-1.96**	-2.77***
		(-1.28)	(-2.64)		(-2.49)	(-4.74)
$\hat{\gamma} \times CFNAI$			-1.09***			-1.24**
			(-2.66)			(-2.27)
R^2	0.20	0.21	0.24	0.22	0.30	0.32
Panel B: Inertial $\hat{\gamma}_t$						
$\hat{\gamma}$	-0.21	1.52	0.89	-5.28*	-2.20	-3.48
	(-0.10)	(0.75)	(0.39)	(-1.71)	(-0.72)	(-1.04)
$CFNAI$		-1.32*	-1.31**		-2.30***	-2.27***
		(-1.91)	(-2.09)		(-2.79)	(-3.42)
$\hat{\gamma} \times CFNAI$			-2.34			-4.73**
			(-0.99)			(-2.22)
R^2	0.16	0.19	0.20	0.13	0.24	0.26
N	375	375	375	363	363	363

Predictive regressions for excess returns on five-year nominal Treasury bonds over one-year and two-year holding periods: $xr^{(n)}_{t\to t+h} = b_0 + b_1\hat{\gamma}_t + b_2 CFNAI_t + b_3\hat{\gamma}_t CFNAI_t + \varepsilon_{t+h},$. The top panel uses the baseline estimate and the bottom panel uses the inertial estimate of $\hat{\gamma}_t$. All regressions control for the first three principal components of the yield curve. Coefficients on the three principal components and the constant are suppressed. CFNAI, the Chicago Fed National Activity Index, is standardized to have unit standard deviation. The estimation sample starts in December 1987 and ends in February 2019 for the one-year holding period ($h = 12$) and in February 2018 for the two-year holding period ($h = 24$). Newey-West t-statistics using $1.5h$ lags in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

D.2 Interest rate disagreement

To investigate potential links with interest rate disagreement, we compare our estimates of $\hat{\gamma}_t$ to the measures of forecaster disagreement from Giacoletti et al. (2021). We first establish that the relationship between expected bond excess returns and $\hat{\gamma}_t$ documented above is unchanged when we control for interest rate disagreement.

Giacoletti et al. (2021) use the 90-10 spread for the two-year and ten-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 $\hat{\gamma}$, 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.2 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.2: 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), two-year Treasury rate, and ten-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 two-year Treasury rate and ten-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.3 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.

D.3 Policy inertia

Table D.4 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

Table D.3: Term premia controlling for forecaster interest rate disagreement

	Panel A: Baseline $\hat{\gamma}_t$					
	$\bar{E}_t xr_{t+1}^{(6)}$			$\bar{E}_t xr_{t+1}^{(11)}$		
$\hat{\gamma}$	-1.80***	-2.13***	-2.49***	-2.68***	-3.11***	-3.53***
	(-4.90)	(-5.44)	(-7.19)	(-3.53)	(-3.91)	(-5.86)
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^2	0.67	0.65	0.64	0.64	0.64	0.65
	Panel B: Inertial $\hat{\gamma}_t$					
	$\bar{E}_t xr_{t+1}^{(6)}$			$\bar{E}_t xr_{t+1}^{(11)}$		
$\hat{\gamma}$	-1.82***	-1.78***	-2.36***	-3.73***	-3.72***	-4.39***
	(-3.53)	(-2.99)	(-3.59)	(-2.93)	(-2.61)	(-3.35)
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^2	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.

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 cyclicality 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.4: Term premia onto components of perceived inertial rule

	$\bar{E}_t xr^{(6)}_{t+12}$			$\bar{E}_t xr^{(11)}_{t+12}$		
Inertial $\hat{\gamma}_t$	0.00	-0.02	-0.39***	-0.015	-0.043	-0.72***
	(0.15)	(0.13)	(0.12)	(0.29)	(0.25)	(0.22)
Inertial $\hat{\beta}_t$	0.25*	0.25*	0.10	0.25	0.26	0.068
	(0.14)	(0.14)	(0.13)	(0.22)	(0.23)	(0.25)
$\hat{\rho}_t$	-0.44**	-0.56***	-0.014	-0.92***	-1.12***	-0.20
	(0.22)	(0.21)	(0.12)	(0.33)	(0.33)	(0.17)
TERM		0.32**			0.55**	
		(0.15)			(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

$$E^j\left(x_t \left| \mathcal{Y}_{t-1}, \nu_t^j\right.\right) = \phi x_{t-1} + \frac{\sigma_v^2}{\sigma_v^2 + \sigma_\eta^2}\left(v_t + \eta_t^j\right). \tag{E.1}$$

Because the monetary policy shock u_t is uncorrelated with ξ_t, v_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

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

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

$$\bar{E}\left(x_t \left| \mathcal{Y}_{t-1}, \nu_t^j\right.\right) = \phi x_{t-1} + \frac{\sigma_v^2}{\sigma_v^2 + \sigma_\eta^2} v_t. \tag{E.3}$$

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

$$x_t - \bar{E}\left(x_t \left| \mathcal{Y}_{t-1}, \nu_t^j\right.\right) = \frac{\sigma_\eta^2}{\sigma_v^2 + \sigma_\eta^2} v_t \tag{E.4}$$

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

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

Corollary 2 follows immediately from (E.5).

We can also derive some simple expressions for long-term interest rate responses to macroeconomic news in the model. To keep things simple, consider a long-term fed funds future. Because this model has constant risk premia, the change in a long-term bond yield is simply the average of the changes in the fed funds futures over the lifetime of the bond. The change in the consensus forecast for the fed funds rate h periods in the future around the macroeconomic announcement equals

$$\bar{E}\left(i_{t+h}\left|\mathcal{Y}_{t-1},x_t\right.\right)-\bar{E}\left(i_{t+h}\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right) = \hat{\gamma}_t\phi^h\frac{1-(\rho/\phi)^{h+1}}{1-(\rho/\phi)}\left(x_t-\bar{E}\left(x_t\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right)\right). \tag{E.6}$$

The response coefficient of long-term interest rates, $\hat{\gamma}_t\phi^h\frac{1-(\rho/\phi)^{h+1}}{1-(\rho/\phi)}$ is therefore not identical to $\hat{\gamma}_t$ from the inertial rule if ρ also varies over time.

To see how the long-term rate response to macro news relates to the regression coefficient from the baseline regression, consider the univariate cross-sectional relationship between long-term fed funds rate forecasts and output gap forecasts. Iterating on equation (E.2) to substitute out for $E^j\left(i_{t+h-1}\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right)$ and plugging in the perceived AR(1) process for the output gap, agent j's optimal forecast of the monetary policy rate at horizon h can be expressed in terms of the output gap forecast at horizon h

$$E^j\left(i_{t+h}\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right) = \hat{\gamma}_t\frac{1-(\rho/\phi)^{h+1}}{1-(\rho/\phi)}E^j\left(x_{t+h}\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right). \tag{E.7}$$

The coefficient in equation (E.7) can be viewed as the model equivalent of the baseline regression (2) estimating the perceived long-run monetary policy response. Comparing (E.7) with (E.6) shows that the response of long-term interest rates to macroeconomic news surprises is proportional to the baseline estimated perceived monetary policy rule as long as the persistence of the output gap, ϕ, is known and constant. The model therefore predicts that the inertial $\hat{\gamma}_t$ is linked to the response of short-term fed funds futures to macroeconomic news surprises, while the baseline $\hat{\gamma}_t$ is linked to the response of long-term interest rates to macroeconomic news surprises.

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

$$\begin{aligned} B_{2,t} &= exp(-i_t)E_t\left[exp\left(-\psi v_{t+1}-\frac{1}{2}\psi^2\sigma_v^2-i_{t+1}\right)\right], && \text{(E.8)}\\ &= exp(-i_t)E_t\left[exp\left(-\rho i_t-\psi v_{t+1}-\frac{1}{2}\psi^2\sigma_v^2-\gamma_{t+1}\left((\phi x_t+v_{t+1})\right)-u_{t+1}\right)\right], && \text{(E.9)}\\ &= exp\left(-i_t-E_t i_{t+1}+\psi\hat{\gamma}_t\sigma_v^2+\frac{1}{2}\hat{\gamma}_t^2\sigma_v^2+\frac{1}{2}\sigma_{t+1}^2\left(\phi x_t\right)^2+\frac{1}{2}\sigma_u^2\right) && \text{(E.10)}\end{aligned}$$

The term $\psi\hat{\gamma}_{t+1}\sigma_v^2$ is the risk premium, $\frac{1}{2}\hat{\gamma}_{t+1}^2\sigma_v^2$ is a standard Jensen's inequality adjustment, and $\frac{1}{2}\sigma_{t+1}^2\left(\rho x_t\right)^2$ 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

$$E_t xr_{2,t+1} + \frac{1}{2} Var_t xr_{2,t+1} \equiv E_t\left(b_{1,t+1} - b_{2,t} - i_t\right) + \frac{1}{2} Var_t\left(b_{1,t+1}\right), \tag{E.11}$$

$$= -\psi \hat{\gamma}_t \sigma_v^2. \tag{E.12}$$

Equation (E.12) shows that the expected excess return on a two-period 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 and known $\hat{\gamma}_t = \gamma$. Then the two-period bond price simplifies to

$$B_{3,t} = exp\left(-i_t(1+\rho) - \gamma\phi x_t + \psi\gamma\sigma_v^2 + \frac{1}{2}\gamma^2\sigma_v^2 + \frac{1}{2}\sigma_u^2\right). \tag{E.13}$$

The three-period bond price then equals

$$\begin{aligned} B_{3,t} &= exp(-i_t) E_t\left[exp\left(-\psi v_{t+1} - \frac{1}{2}\psi^2\sigma_v^2\right) B_{2,t+1}\right], \quad &(E.14) \\ &= exp\left(-i_t(1+\rho+\rho^2) - x_t\gamma\phi(1+\rho+\phi)\right) \\ &\quad \times E_t\left[exp\left(-\psi v_{t+1} - \frac{1}{2}\psi^2\sigma_v^2 - v_{t+1}\gamma(1+\rho+\phi) + \psi\gamma\sigma_v^2 + \frac{1}{2}\gamma^2\sigma_v^2 + \frac{1}{2}(1+\rho)^2\sigma_u^2\right)\right], \\ &= exp\left(-i_t - E_t\left(i_{t+1} + i_{t+2}\right)\right) \\ &\quad \times exp\left(\gamma\psi\sigma_v^2(2+\rho+\phi) + \frac{1}{2}\gamma^2\sigma_v^2\left(1 + (1+\rho+\phi)^2\right) + \frac{1}{2}(1+\rho)^2\sigma_u^2\right), \quad &(E.15) \end{aligned}$$

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

$$E_t xr_{3,t+1} + \frac{1}{2} Var_t xr_{3,t+1} \equiv E_t\left(b_{2,t+1} - b_{3,t} - i_t\right) + \frac{1}{2} Var_t\left(b_{2,t+1}\right), \tag{E.16}$$

$$= -\psi\gamma\left(1+\rho+\phi\right)\sigma_v^2, \tag{E.17}$$

Expression (E.17) shows that the expected excess return for very long-term bonds declines with the inertial rule, γ, similarly to the expected excess return for two-period bonds in equation (E.13). In addition, the expected excess return on very long-term bonds in equation (E.17) also declines with monetary policy inertia, ρ, provided that $\gamma > 0$.

Proof of Corollary 4: The change in the two-year bond yield in response to learning the current-period policy rate then equals

$$\begin{aligned} i_{2,t} - E\left(i_{2,t} \,|\mathcal{Y}_{t-1}, x_t\right) &= \frac{1}{2}\Big(mps_t + E_t i_{t+1} - E\left(i_{t+1} \,|\mathcal{Y}_{t-1}, x_t\right) - \psi(\hat{\gamma}_t - \hat{\gamma}_{t-1})\sigma_v^2 \\ &\quad - \frac{1}{2}\left(\hat{\gamma}_t^2 - \hat{\gamma}_{t-1}^2\right)\sigma_v^2\Big), \quad &(E.18) \\ &= \frac{1}{2}\left(mps_t(1+\phi\omega_t) - \psi\sigma_v^2\omega_t\frac{mps_t}{x_t} - \frac{1}{2}\omega_t\frac{mps_t}{x_t}\left(\hat{\gamma}_t + \hat{\gamma}_{t-1}\right)\sigma_v^2\right). \quad &(E.19) \end{aligned}$$

The σ_{t+1}^2 term from (E.10) drops out because σ_{t+1} only depends on x_t and σ_t, but not on i_t. Further, $mps_t\omega_t$ and $\omega_t\frac{mps_t}{x_t}(\hat{\gamma}_t + \hat{\gamma}_{t-1})$ are unconditionally uncorrelated with $mps_t 1_{x_t<0}$, but of course $\frac{mps_t}{x_t}$ is, proving Corollary 4.

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_v	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