Categorical Thinking about Interest Rates

(PRELIMINARY AND INCOMPLETE, COMMENTS WELCOME)*

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March 22, 2024

Abstract

Rational expectations imply that the current long-term interest rate should already incorporate public knowledge of anticipated increases in short rates. Yet, there is a widespread misconception that expected future shifts in the short rate forecast corresponding future movements in the long rate. We hypothesize that people lump short- and long-term interest rates into the coarse category of "interest rates," leading to overestimation of their comovement. We show that categorical thinking about interest rates is evident even among professional forecasters and distorts the real behavior of borrowers and investors. Expectations of rising short rates prompt homebuyers and firms to rush to lock in long-term debt before further increases in long rates, reducing the effectiveness of monetary policy. Investors are also less willing to hold long-term bonds because they anticipate future increases in long rates. The increase in supply and decrease in demand for long-term debt cause long rates to overreact to changes in short rates, and can help explain the excess volatility puzzle in long rates.

*We thank Nick Barberis, Stefano Giglio, and seminar participants at Notre Dame and Yale for helpful comments. Chen Wang acknowledges financial support from the International Center for Finance at Yale School of Management.

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> *Jerome Powell indicated that he wants to move quicker when it comes to increasing interest rates…When the Federal Reserve raises its interest rates, interest rates across the board are affected. Meaning, rates for mortgages, credit cards and personal loans will likely rise due to the Fed's actions. So if you've been thinking about taking on a personal loan for a home renovation, a much-needed car repair, or even to consolidate your debt, now might be the time to submit your application before interest rates increase.* –CNBC

If investors have rational expectations, the current long-term interest rate should already incorporate all public knowledge about anticipated changes in short-term interest rates. By an accounting identity, the long rate equals the average of expected future short rates over the life of the long bond plus a term premium component. This accounting identity implies that, absent changes in the term premium, expected future changes in the short rate should not forecast corresponding future changes in the long rate. Indeed, expected increases in the short rate do not predict future increases in the long rate in the historical data.

In this paper, we show that there is a widespread misconception that expected future shifts in the short-rate forecast corresponding future movements in the long rate. The CNBC advice quoted above is wrong: knowledge that the Federal Reserve plans to gradually increase short rates does not mean that long rates will move in parallel, and there is no reason to rush to lock in long-term debt now before long rates rise. Instead, the long rate should jump immediately in response to news about expected changes in short rates, and future changes in the long rate should be unpredictable.

We hypothesize that this misconception occurs because of a categorical thinking error in which people lump short- and long-term interest rates into the same coarse category of "interest rates." Categorical thinking is a cognitive shortcut in which people organize similar concepts, objects, and events into a category, and apply the same rule or judgment to all items within a category, thereby reducing cognitive load (Smith, 1998; Fiske, 1998; Kruschke, 1996). Common examples of categories used to simplify our thinking include Ivy

League universities, S&P500 firms, and Morningstar investment style categories. Research in behavioral economics has argued that categorical thinking can cause people to overlook differences within categories, leading to errors in judgment and decision-making (Mullainathan, 2002; Barberis and Shleifer, 2003; Mullainathan, Schwartzstein, and Shleifer, 2008).

It is natural to think about short and long term interest rates in the same category because they indeed share many characteristics. The contemporaneous levels of short and long term rates are strongly correlated. It is also true that Federal Reserve announcements of surprise changes to the Federal Funds rate simultaneously affects short and long rates in the same direction. However, people fail to recognize that long and short rates are correlated precisely because long rates are an average of expected future short rates. Thus, long rates should not be expected to move in tandem with *expected* future changes in short rates.

We show that categorical thinking about interest rates is evident even among professional forecasters and distorts the real behavior of borrowers and investors. Expectations of rising short rates prompt homebuyers and firms to rush to lock in long-term debt before further increases in long rates. The resulting increase in household and firm borrowing during monetary tightening cycles reduces the effectiveness of monetary policy. Expectations of rising short rates also prompt investors to be less willing to hold long-term bonds because they anticipate future increases in long rates (implying a decline the prices of long bonds). The combined increase in supply and decrease in demand for long-term debt are not immediately absorbed by risk-average arbitrageurs (Hanson, Lucca, and Wright, 2021), and cause long rates to overreact to changes in short rates, and subsequently reverse as arbitrage occurs. Thus, categorical thinking about interest rates can help explain the puzzle of excessive movement and reversals in the prices of long-maturity claims (Stein, 1989; Cochrane and Piazzesi, 2005; Gürkaynak et al., 2005; Hanson and Stein, 2015; Giglio and Kelly, 2018).

Contrary to much of the behavioral economics literature, which shows that errors in judgment and decision-making decrease with financial literacy, we find that categorical thinking errors can actually increase with education and wealth. This occurs because a minimum level of sophistication is necessary for people to tie their expectations of changes in long rates to publicly available information about the path of short rates. They must (a) be aware of expected changes in the short rate, (b) be aware of the correlation between long and short rates, and (c) have the ability to issue long term debt and the flexibility to engage in market timing (for tests relating to real behavior).

We begin by showing that there is no reason, based on the historical publicly available data, to believe that expected changes in short rates predict future changes in long rates in the same direction. We proxy for beliefs about expected changes in short rates using the consensus forecast for the Federal Funds Rate from the Blue Chip Financial Forecasts (BCFF) data. We show that expected changes in the Federal Funds Rate over the next quarter do not predict increases in long rates such as the 10-year, 30-year, Aaa, Baa, or HMR (the 30-year rate for fixed-rate mortgages) yields. Rather, expected changes in the short rate negatively predict realized changes in long rates over the next quarter. This fact is consistent with the excess volatility puzzle in which long rates overreact to expected changes in the short rate and subsequently correct.

Next, we assess how professional forecasters make errors consistent with categorical thinking. One benefit of looking at survey evidence is that anomalies can be attributed to mistaken beliefs rather than market microstructure frictions that could lead to temporary mispricing in long yields. We find that professional forecasters believe that the long rate (as proxied by HMR, which has the longest data series) will increase by 20 to 30 basis points over the next quarter when they believe that the short rate will increase by 1 percent. This belief is incorrect: an anticipated percentage point increase in the short rate actually predicts a decline in the long rate, leading to predictable forecast errors of 40 to 45 basis points.

We conduct several tests to explore potential alternative explanations. First, it could be that the long rate in month t prices in information about expected changes in short rates over the next quarter with a delay instead of instantaneously. To rule out this explanation, we allow the long rate a full month to price beliefs in month t about expected movements in the short rate over the next quarter, and find similar results. Second, individual forecasters may not be fully aware of consensus forecasts in month t of expected movements in the short rate when they make forecasts for changes in the long rate over the next quarter. However, we find similar results when we look at the relation between month $t+1$ forecasted changes in the long rate and month t expected changes in the short rate. Finally, professional forecasters may believe (possibly mistakenly) that they possess private information about future movements in short rate. This private information would not be reflected in the current long rate and should predict future movements in the long rate once the private information becomes public. We show that private information about short rates is unlikely to drive our results. We find very similar results when we proxy for short rate expectations with data from Federal Fund Futures markets, which should only reflect public information about expected movements in the short rate.

We are also able to distinguish a categorical thinking error from a more general phenomenon in which investors overreact to news. Imagine a situation in which it is known well in advance that the Fed will increase short term interest rates at time t. There is no news to overreact to at time t; thus an overreaction story would not lead people to believe that the long rate will increase at time t. On the other hand, categorical thinking leads people to believe that short and long rates comove together, regardless of whether movements in the short rate are known in advance. Therefore, categorical thinking leads people to expect that the long rate will increase along with the short rate at time t even when no new information is released at time t. We show that professional forecasters have expectations of future changes in the long rate that are much more strongly related to expected changes in short rates than *changes in expectations* about movements in short rates. We also show graphically that professional forecasters report similar expected paths for the levels of short and long rates over the next four quarters, consistent with a categorical thinking error in which people believe that short and long rates move in tandem.

Next, we examine household beliefs about interest rate movements using the Fannie

Mae National Housing Survey. Because the survey only asks households for their beliefs about expected movements in long rates, we proxy for publicly available information about expected movements in short rates using consensus forecasts from the BCFF. We find that households are 19 percentage points more likely to believe that mortgage interest rates will go up over the next year when short rates are expected to increase over the same interval.

Household categorical thinking about interest rates is strictly increasing in education and income. Households with graduate school education are 20 percentage points more likely to believe the mortgage rates will increase over the next year when short rates are expected to increase compared to households without a high school education. Households with income above $200K are 31 percentage points more likely to believe that mortgage rates will increase compared to households with income below $10K.

In the second half of our paper, we explore how categorical thinking can distort the real behavior of borrowers and investors. If people think categorically about interest rates, expectations of rising short rates should prompt borrowers to rush to lock in long-term debt before further increases in long rates, leading to an increase in the supply of debt. On the other side, investors should be more inclined to sell long term bonds if they expect long yields to increase, leading to a decrease in demand for long term debt. In the absence of instantaneous arbitrage, these combined supply and demand shifts for long term bonds can contribute to excess movement and subsequent reversals in long rates.

We first look at long term debt issuance by firms. Using data from Compustat, we find that a 1 percentage point expected increase in the short rate over the next quarter is associated with a 10 percent increase in the probability of any long term bond issuance and a 17 percent increase in the value of long term bond issuance. When firms believe that both short and long term rates will rise, they have an extra incentive to borrow long rather than short, because borrowing short implies they will have to keep rolling over short term loans at rising rates. Consistent with this idea, we find that the long term share of all corporate debt issuance increases by approximately 10 percent when short rates are expected to increase by

1 point. The increasing share of long term issuance shows that our results are unlikely to be driven by an alternative explanation in which firms borrow more because they want to increase investment during market booms (which may coincide with periods with expected increases in short rates). If that were the case, we would expect the issuance of short term debt to increase as well rather than an increase in the share of long term of issuance.

We see similar shifts in the borrowing behavior of relatively sophisticated households. Using data on aggregate new mortgages initiated in each month, we find that expectations of rising short rates are associated with a large increase in the volume of jumbo mortgages (typically larger loans exceeding $650K) but are not associated with significant changes in the volume of conventional mortgages (typically loans under $650K). These patterns for the household supply of long term debt are consistent with our earlier findings related to sophistication. Only households who have the flexibility to engage in market timing and are aware of publicly available information about the path of short rates would rush to lock in long term debt.

Finally, we examine the behavior of investors in long term bond funds. Categorical thinking should prompt investors to sell off long-term bond mutual funds when they anticipate rising short rates. We use data on intermediate to long term fixed income mutual funds from the CRSP mutual fund database from 1997-2021. When short rates are expected to rise by 1 percentage point, bond funds experience average outflows of 3% of AUM or $5B. We find slightly larger effects for bond funds targeted at retail investors, although we continue to find substantial outflows for institutional class shares in these bond funds.

Overall, we find evidence across multiple settings consistent with categorical thinking. People mistakenly believe that expected increases in short term interest rates predict corresponding changes in the long rate, and fail to recognize that the current long rate already reflects future expected changes in short rates. These errors in beliefs translate to errors in real borrower and investor behavior that can limit the effectiveness of monetary policy and can help explain the puzzle of excess movement and reversals in long rates.

Our research builds on related work by Hanson, Lucca, and Wright (2021, HLW), who show that the excess sensitivity of long rates can be explained by a model of rate-amplifying demand combined with a slow arbitrage response. We differ from HLW in several ways. First, HLW focuses on mortgage refinancing and extrapolative beliefs as the main drivers of shifts in demand. We focus on a categorical thinking error that leads to large shifts in the supply and demand for long term debt. Second, whereas HLW examine the correlation between contemporaneous movements in long and short rates, we show that expectations of changes in long rates are more strongly predicted by expected changes in short rates than by past changes in short rates. Third, HLW finds support for Stein (2013)'s recruitment channel in which movements in long rates increase the effectiveness of monetary tightening, whereas we show that the increase in the long rate is driven by increased corporate and household borrowing in the face of tightening monetary policy, which can limit rather than amplify the effectiveness of monetary policy.

Our research also contributes to the economics literature concerning expectational errors in financial and macroeconomic forecasts. Much of the existing research focuses on mistaken beliefs about the *persistence* of shocks (e.g., Cieslak, 2018; Bordalo, Gennaioli, Ma, and Shleifer, 2020; Wang, 2020; d'Arienzo, 2020) and over- or under-reaction to news (e.g. Daniel, Hirshleifer, and Subrahmanyam, 1998; Hong and Stein, 1999; Augenblick, Lazarus, and Thaler, 2021). In contrast, we explore a new behavioral mechanisms that can drive large belief errors and distortions in real behavior. We show that professional forecasters and investors have fairly accurate beliefs about the future path of short rates and react to news about short rates in a rational manner. However, the correct forecasts of short rates lead to incorrect forecasts of long rates due to the mistaken notion that short and long rates belong in the same category and move in tandem.

Finally, our finding that investors fail to recognize that the current long rate should already incorporate public information about expected future changes in short rates is related to the behavioral finance literature showing that some investors trade on stale news (e.g., DeMarzo, Vayanos, and Zwiebel, 2003; Tetlock, 2011; Eyster, Rabin, and Vayanos, 2019). We carry these insights, which have generally been tested in equity markets, into fixed income markets and real firm and household borrowing behavior.

1 Data

In this section, we describe various data sources that we use in our analysis to detect categorical thinking about interest rates. We divide the data sources into two categories: data on beliefs and data on real behavior of borrowers and investors.

1.1 Data on beliefs

1.1.1 Professional forecasts

The primary dataset for interest rate expectations is the Blue Chip Financial Forecasts (BCFF), which provide survey forecasts of various interest rates from professional forecasters. This monthly survey maintains a stable and large panel of professional forecasters and is the longest consistently run survey, dating back to the 1980s. Among the various datasets of professional forecasts, it is especially suitable for studying expectation formation and asset prices.

Each month, the BCFF survey collects forecasts from a panel of, on average, over 40 economists from leading financial institutions and economic consulting firms. They are asked to provide forecasts of future financial and macroeconomic variables at horizons from the current quarter ("nowcast") to four quarters ahead. The forecasts are collected over a two-day period, usually between the 23rd and 27th of each month, and published on the first day of the following month. To study the subjective expectations of short and long-term interest rates, we require that the forecasts have reasonably long and continuous time series. Specifically, we choose the Federal Funds Rate (FFR) as the short-term interest rate and the home mortgage rate (HMR) as the long-term interest rate. We also use BCFF forecasts of other long rates, including 10-year and 30-year Treasury yield ($y^{(10)}$ and $y^{(30)}$), Aaa and Baa corporate bond rates (Aaa and Baa). We use the HMR as the representative long rate in the main analysis due to its longer time series in BCFF and its relevance to mortgage borrowers.[1] A sample BCFF survey questionnaire with detailed definitions of all forecasted interest rates is provided in the Appendix.

Notation and timing. We focus on one-quarter-ahead forecasts of various interest rates, denoted as $\mathbb{E}_t(\overline{X}_{t+1Q})$. For each interest rate variable, BCFF asks forecasters to provide their forecasts of the average daily interest rate over the next quarter $\overline{X}_{t+1Q}$. Though the forecasts are published on the first day of the following month, they are formed based on information available at the time of the survey, which is close to the end of each month. Therefore, we denote t as the time of forecast (end of the month) to line up with other end-of-month variables.

Forecasters. One of the advantages of the BCFF survey is that it includes each forecaster's name and affiliated institution.[2] Studies that examine the individual level BCFF forecast mostly focus on the institutional level, while we are the first to map the institutions to the actual economists making the forecasts and are able to track one economist across time, and potentially across institutions. This feature allows us to keep track of the time series of each firm's forecasts and hence make the BCFF forecasts a panel dataset.

For each target variable, we obtain monthly forecasts of individual economists and the consensus (defined as cross-sectional mean) from 1983:04 (when FFR forecasts became available) to 2021:12 across all forecast horizons (1-4Q).

[1] As depicted in Figure A.5 in the Appendix, the realized values of these long rates are highly correlated. HMR has a correlation of at least 0.97 with the other long rates.

[2] Among 86 unique participating institutions with more than 60 monthly forecasts, 26 are banks, 15 are broker-dealers, and 17 are primary dealers of the Federal Reserve Bank of New York. Table A.1 in the Appendix provides a full list of institutions that participate in the BCFF survey, grouped by type of institution.

Realized values. We obtain the realized interest rates according to their exact definitions provided by BCFF from the Federal Reserve Economic Data (FRED) database or directly from BCFF (Aaa and Baa). We use $\overline{X}_{t+1Q}$ to denote realized average daily interest rates over quarter $t + 1Q$, which are available at the end of the quarter.

1.1.2 Households beliefs

We obtain consumer housing expectations from the Fannie Mae National Housing Survey (NHS).[3] After the housing crisis in 2007-08, Fannie Mae launched the National Housing Survey in 2010 to generate new information about consumer attitudes, intentions, and financial conditions that pertain to housing and mortgage markets. It is the only large, national, monthly survey of consumers focused primarily on housing. NHS is a nationally representative telephone survey polling 1,000 consumers a month about owning and renting a home, home and rental price changes, the economy, household finances, and overall consumer confidence. Each month, Fannie Mae elicits answers to about 100 survey questions on a wide range of housing-related topics. Among these questions, we focus on the question regarding mortgage rate expectations, which asks respondents to provide their expectations of the direction of mortgage rates over the next 12 months. The question has three possible answers: up, down, or remain about the same.[4]

We obtain detailed individual-level responses to all question at a monthly frequency since 2010. Besides information about household beliefs, NHS also provide demographic information about the respondents, including age, income, education, and location. We use this information to study how different demographic groups form their beliefs about future mortgage rates.

[3] A detailed introduction of the National Housing Survey is available on Fannie Mae's website.

[4] A screenshot of the survey question is provided in Figure A.2 in the Appendix.

1.2 Data on real behavior

1.2.1 Corporate borrowing data

We obtain firm-level borrowing data from the COMPUSTAT Quarterly Fundamentals file. The coverage begins in 1961, and we use the quarterly data from 1983 to 2021 to align with the BCFF survey. The primary variables we construct are long-term issuance and short-term issuance, which are the dollar amount of long-term and short-term debt issued by the firm during the quarter, respectively. We compute long term issuance by converting the year-to-date long-term debt issued (DLTISY) by the firm to quarterly frequency and correcting for a few apparent errors in the data. We compute short term issuance following Baker, Greenwood, and Wurgler (2003); Greenwood, Hanson, and Stein (2010) as the change in the level of short-term corporate debt outstanding (NPQ), plus one-quarter the level of short-term debt in the previous quarter. As NPQ is not available for all firms, we fill the missing values with one-quarter of the notes payable from the COMPUSTAT Annual Fundamentals file (NP). We normalize the long-term issuance by the book value of assets (AT) and lagged total debt, respectively, to control for the size and leverage of the firm. We compute the long-term issue share (LT Share) as the ratio of quarterly long-term issuance to the sum of long-term and short-term issuance.

Finally, we aggregate the firm-level issuance to the economy level by summing up issuances from all firms for each quarter, and calculate the aggregate long-term issue share accordingly.

1.2.2 Mortgage borrowing data

We obtain aggregate-level mortgage borrowing data from the National Mortgage Database Aggregate Statistics of the Federal Housing Finance Agency (FHFA). The National Mortgage Database (NMDB) is a nationally representative five percent sample of residential mortgages in the United States. It provides aggregate statistics of the quantity, dollar amount, and various characteristics of the mortgage loans covered in its sample. We use the monthly data from 1998 to 2021.

1.2.3 Bond investor data

We measure changes in investors' demand for long-term bonds using the net flows into long-term bond mutual funds. We obtain bond mutual funds data from the CRSP Survivorship-Bias Free Mutual Fund Database. Specifically, we define long-term bond funds as those with a Lipper objective code in the following categories: IUG, GUS, GUT, A, BBB, and IID. We follow the standard approach in the literature (e.g., Lou, 2012) to construct monthly flows to each bond fund as at the share class (institutional and retail) level: $flow_{i,t} = \frac{TNA_{i,t}}{TNA_{i,t-1}} - (1 + R_{i,t})$, where $TNA_{i,t}$ is the total net assets of fund i at time t, and $R_{i,t}$ is the monthly raw return of fund i at time t. Since CRSP's coverage of bond mutual funds is only comprehensive after 1997, we use the monthly data from 1997 to 2021.

1.3 Summary statistics

In order to tease out the effect of categorical thinking on interest rate expectations and real behavior, we control for a wide range of macroeconomic and financial variables that characterize the debt market conditions. We follow Baker, Greenwood, and Wurgler (2003) and additionally obtain the following variables from the FRED database at the St. Louis Fed: inflation (π); the term spread; the credit spread (Baa credit spread); and the credit term spread (Baa credit term spread).

Since categorical thinking about interest rate works through the (expected) changes in interest rate across maturities, we difference out the current level of the interest rate and construct our interest rate expectations variables as forecasted changes in interest rates (e.g., $\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$). We also include the current level of the interest rate as a control variable in all regressions.

Table 1 provides the summary statistics of our main variables and control variables used in the analysis. The forecasted changes in the Federal Funds Rate ($\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$) and in the Home Mortgage Rate ($\mathbb{E}_t(\overline{HMR}_{t+1Q}) - HMR_t$), as well as the actual changes in the HMR ($\overline{HMR}_{t+1Q} - HMR_t$) and the forecast errors of HMR ($\overline{HMR}_{t+1Q} - \mathbb{E}_t(\overline{HMR}_{t+1Q})$), are included as the main variables. The main and control variables span from 1983:04 to 2021:12, with 465 monthly observations. Table 2 in provides the correlation matrix of these variables. Additionally, we report statistics for actual changes in other long rates, the sample period of which may vary due to data availability.

2 Conceptual framework

Consider the one-period nominal short rate as i_t and the n-period nominal bond yield as $y_t^{(n)}$. The holding period excess return of an n-period bond is defined as $rx_t^{(n)} = ny_t^{(n)} - (n-1)y_{t+1}^{(n-1)} - i_t$. Rearranging the definition of $rx_t^{(n)}$ and iterating the equation forward, we obtain an accounting identity that can decompose the long rate as follows:

$$y_t^{(n)} = \underbrace{\frac{1}{n}\mathbb{E}_t\left(\sum_{i=0}^{n-1} i_{t+i}\right)}_{\text{Expectations hypothesis (EH) component}} + \underbrace{\frac{1}{n}\mathbb{E}_t\left(\sum_{i=0}^{n-2} rx_{t+i+1}^{(n-i)}\right)}_{\text{Term premium (TP) component}}, \tag{1}$$

The current n-period yield is the sum of investors' expectations about the future path of the short rate (the expectations hypothesis, or EH, component) and average expected excess returns to be earned over the life of the bond (the term premium, or TP, component). This identity is equivalent to the decomposition of Campbell and Shiller (1988) for the stock market.

If investors have rational expectations, the expectations hypothesis component implies that the current long rate already incorporates all public information about the future path of the short rate. This further implies that, absent changes in the term premium, expected future increases in the short rate should not forecast corresponding future increases in the long rate. Knowledge that the Federal Reserve plans to gradually increase short rates does not mean that long rates will move in parallel. Instead, the long rate should jump immediately in response to news about expected changes in short rates, and future changes in the long rate should be close to unpredictable (we present bounds for this relationship later in this section).

Indeed, expected changes in the short rate do not positively predict changes in the long rate in the historical data. Table 3 summarizes the results of regressions of the actual change in various long rates on the forecasted changes in the Fed Funds Rate based on consensus forecasts from the SPF. We control for debt market conditions by including the current short rate, inflation, term spread (the difference between 10-year Treasury yield and FFR), credit spreads, and credit term spread. The coefficients of the expected changes in FFR are negative across all five long rates and are statistically significant in four of them. That is, the long rate actually moves in the opposite direction of the expected changes in the short rate. This negative relationship is consistent with the notion that long rates exhibit significant "excess volatility," i.e., they overreact to the news about the future path of the short rate and subsequently reverse (e.g., Stein, 1989; Hanson and Stein, 2015; Giglio and Kelly, 2018; Hanson et al., 2021)

In this paper, we show that there is a widespread misconception that expected future shifts in the short-rate forecast corresponding future movements in the long rate. We hypothesize that this misconception occurs because of a categorical thinking error in which people lump short- and long-term interest rates into the same coarse category of "interest rates."

The intuition behind categorical thinking in the context of short-term and long-term interest rates is depicted in Figure 1, which serves as a graphical representation of how investors' expectations can diverge from rationality.

The figure plots the short rate, i, and the long rate, y, over time. We present the case in which y exceeds i, consistent with an upward sloping yield curve which is commonly featured in the historical data. At time t, news arrives that short rates will increase gradually until

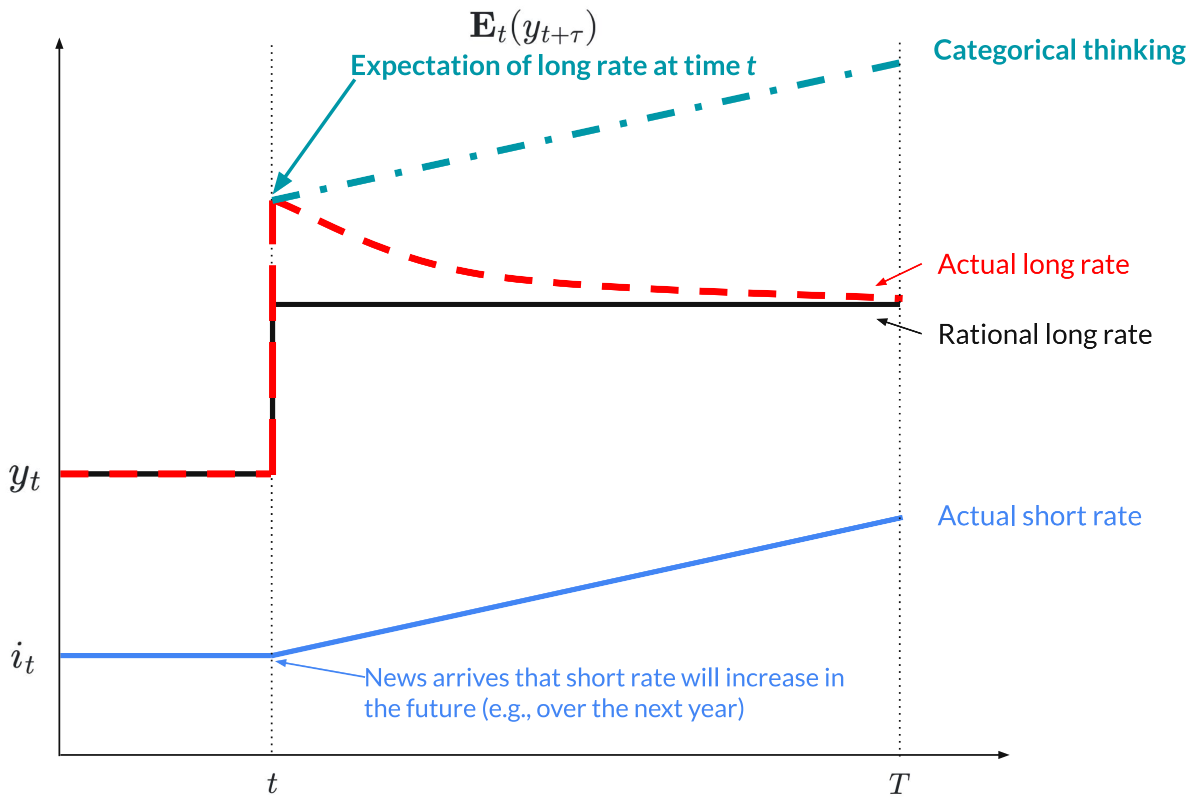

Figure 1 An illustration of categorical thinking about short and long rates

some time T, as represented by the solid blue line. This could represent, for instance, an announcement by the Federal Reserve of planned rate hikes over the coming year.

If investors are fully rational, the long rate would immediately adjust upwards to reflect the expected higher short rates and then level off with a slope that is close to zero (see discussion below for bounds on the magnitude of this slope), as depicted by the solid black line in the figure.

However, empirical observations reveal an overshooting of long-term rates in response to news of expected changes in the short rate, followed by a reversion to the level predicted by rational expectations, a phenomenon encapsulated in Table 3. This path of the actual long rate, as seen in the historical data, is illustrated by the dashed red line.

The crux of the categorical thinking error lies in how investors form beliefs $\mathbb{E}_t(y_{t+\tau})$ about the future path of long rates at time t. Rational expectations would dictate beliefs that align with the actual trajectory of the long rate. Alternatively, if investors recognize that the short rate path is already priced in the long rate but fail to account for empirical overshooting, beliefs about the future path of long rates should be level. However, investors who engage in categorical thinking would erroneously expect that short and long rates invariably move in tandem. Consequently, their forecasts for the long-term rate would erroneously track the trajectory of the short-term rate, as illustrated by the dot-dashed turquoise line.

The mistaken belief at time t that long rates will rise in the future generates an increase in the supply of long-term debt because households and firms believe they can benefit by borrowing long at time t to lock in the current long rate before it rises. The mistaken belief at time t that long rates will rise also reduces demand for long term debt, because investors reason that prices of long bonds will fall as yields are expected to rise. We explore these supply and demand implications in Section 4. The combined shifts in supply and demand due to mistaken beliefs, as illustrated in the dot-dashed turquoise line, can help explain why actual long rates overreact to news and subsequently reverse, as illustrated in the dashed red line.

Building on this conceptual framework, our empirical strategy to test for categorical thinking in the formation of interest rate expectations is delineated as follows:

$$\mathbb{E}_t(y_{t+1Q}^{(n)}) - y_t^{(n)} = \alpha_1 + \beta_1 \left[\mathbb{E}_t(i_{t+1Q}) - i_t\right] + \gamma X_t + \epsilon_t \tag{2}$$

$$\underbrace{y_{t+1Q}^{(n)} - y_t^{(n)}}_{\text{Actual changes}} = \alpha_1 + \beta_2 \left[\mathbb{E}_t(i_{t+1Q}) - i_t\right] + \gamma X_t + \epsilon_{t+1Q} \tag{3}$$

$$\underbrace{y_{t+1Q}^{(n)} - \mathbb{E}_t(y_{t+1Q}^{(n)})}_{\text{Forecast errors}} = \alpha_1 + \beta_3 \left[\mathbb{E}_t(i_{t+1Q}) - i_t\right] + \gamma X_t + \epsilon_{t+1Q} \tag{4}$$

Here, we control for the debt market conditions X_t across all three tests. Controls include the current short rate, inflation, term spread (the difference between 10-year Treasury yield and FFR), credit spreads, and credit term spread.

Our baseline specification in equation (2) simply explores the contemporaneous comovement between expected changes in the short and long rates. As discussed earlier, if forecasters are influenced by categorical thinking, we expect β_1 to be positive. If they are fully rational and understand that long rates overshoot in the data, we expect β_1 to be negative. If forecasters are aware of the long-term yield identity but do not account for overshooting of the long rate in the data, we expect β_1 to be very close to zero. To see this, we iterate the yield identity and express the expected changes in long rate as a function of the expected long-run short rate (assuming a stable term premium):

$$\mathbb{E}_t\left(y_{t+1}^{(n)}\right) - y_t^{(n)} = \frac{1}{n}\mathbb{E}_t\left(\sum_{i=0}^{n-1} i_{t+1+i} - \sum_{i=0}^{n-1} i_t\right) = \frac{1}{n}\left(\mathbb{E}_t i_{t+n} - i_t\right) \tag{5}$$

If the time series properties of expectations of the distant short rate, $\mathbb{E}_t i_{t+n}$, is close to those of $\mathbb{E}_t i_{t+1}$, then $\beta_1 \to 1/n$. In our empirical implementation, one period represents a quarter, so β_1 would be $1/120 = 0.0083$ for a 30-year bond. Alternatively, if expectations of the distant short rate, $\mathbb{E}_t i_{t+n}$, are weakly or uncorrelated with $\mathbb{E}_t i_{t+1}$, then $\beta_1 \to 0$. Under both reasonable assumptions, β_1 should be close to zero.

The second test (3) examines the predictability of the actual changes in the long rate by the expected changes in the short rate. This is a direct test of whether there is any discernible relationship between expected changes in the short rate and future realization of the long rate.

The final specification (4) investigates forecast errors of long rates. Though the results can be anticipated from the previous two specifications, a test of predictability of forecast errors reveals whether categorical thinking constitutes a systematic bias in interest rate expectations. If forecasters are influenced by categorical thinking, we expect β_3 to be negative, indicating a departure from rationality. In contrast, if forecasters are fully rational, their forecast errors should not be systematically predictable based on prior information, leading to $\beta_3 = 0$.

3 Categorical thinking in interest rate expectations

3.1 Professional forecasters

We start by implementing the baseline tests outlined in equations (2)-(4) using the consensus forecasts, focusing on the Federal Funds Rate (FFR) for short-term rates and the 30-year Home Mortgage Rate (HMR) for long-term rates. We use the 1-quarter ahead forecasts of short and long rates at the monthly frequency. In the following regressions, we incorporate a comprehensive set of control variables: the current short rate (FFR), the term spread (HMR-FFR), the current inflation rate, the Baa credit spread, and the Baa credit term spread.

$$\mathbb{E}_t(\overline{HMR}_{t+1Q}) - HMR_t = \alpha_1 + \beta_1 \left[\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t\right] + \gamma X_t + \epsilon_t$$

$$\overline{HMR}_{t+1Q} - HMR_t = \alpha_1 + \beta_2 \left[\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t\right] + \gamma X_t + \epsilon_{t+1Q}$$

$$\overline{HMR}_{t+1Q} - \mathbb{E}_t(\overline{HMR}_{t+1Q}) = \alpha_1 + \beta_3 \left[\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t\right] + \gamma X_t + \epsilon_{t+1Q}$$

The results from these regressions are summarized in Table 4. The first three columns report the results for the first equation. Across all three specifications in which we incorporate the control variables incrementally, β_1 estimates are all positive and significant at the 1% level. The coefficient is economically meaningful, with a 1% increase in the short rate forecast leading to a 0.24% increase in the long rate forecast based on the coefficient estimated with the full set of controls. Moreover, as discussed in the previous section, these results not only reject the null of $\beta_1 < 0$ due to long-rate overreacting to news about short rate but also indicate significant deviation from the $1/n$ benchmark (unreported) at 1% levels. The results suggest that the comovement between short and long rate expectations is excessive, supporting our hypothesis that forecasters bundle the short and long interest rates together in their expectations formation process and expect them to move in tandem in the future.

Columns (4)-(6) estimate the second equation. They are slightly different from those in Table 3 in that we control for the term spread using the difference between HMR and FFR, which is more relevant to the pair at hand. Despite this difference, the point estimates are all negative, albeit statistically insignificant. These results suggest that contrary to the excessive movement in beliefs, expected changes in the short rate bear almost no predictive power for future changes in the long rate.

Finally, columns (7)-(9) report the results for the third equation testing the predictability of HMR forecast errors. As expected, the coefficients across all specifications are negative and significant at the 1% level, suggesting that the forecast errors in the long rate are predictable by the short rate forecasts. The tendency for forecasters to overreact to expected hikes in the Federal Funds Rate, especially against a backdrop where consensus forecasts typically exhibit underreaction to new information (Bordalo et al., 2020), is particularly striking. This pronounced predictability underscores a clear departure from rationality, consistent with the prediction from categorical thinking in interest rate forecasts.

There are possible concerns that the documented excessive comovement and the predictability of long rate forecast errors might be specific to the choice of long rates, to certain subsamples, or only to consensus forecasts. In what follows, we present a series of robustness checks to our main results.

Alternative specifications. An immediate concern of using the HMR as the long rate is that it may take longer for the actual HMR to fully incorporate information concerning the future path of the short rate, as dictated by the yield identity. To address this concern, we allow the HMR an additional month to adjust to the anticipated changes in the future short rate. specifically, we reestimate the first equation using $\mathbb{E}_t(\overline{HMR}_{t+1Q}) - HMR_{t+1}$ as the dependent variable. The results are reported in columns (1)-(3) of Table 4. The coefficient estimates are almost identical to those in the baseline regressions and significant at the 1% level, suggesting that the excessive comovement between short and long rate expectations is not due to the short adjustment of the current HMR_t. Additionally, applying the same tests to the alternative long rates such as 10 and 30-year Treasury yield, Aaa and Baa corporate yields as the long rate, we obtain similar results.

A related concern is that the long rate expectation at time t might be stale. Had we used the long rate forecasts that sufficiently incorporate the short rate information, the comovement might have been less pronounced. We address this concern by moving the expected changes in long rate by one month forward and reestimate the first equation using $\mathbb{E}_{t+1}(\overline{HMR}_{t+1Q}) - HMR_{t+1}$ as the dependent variable. The results are reported in columns (4)-(6) of Table 4. Again, the coefficient estimates are close to those in the baseline regressions and significant at the 1% level, indicating that excessive comovement is even stronger.

Forecast revision and recent changes in short rates. The seminal work of Coibion and Gorodnichenko (2015) suggests that forecast revisions, the changes in the forecasters' beliefs about the same quantity across different periods, represent how forecasters update their beliefs in response to new information. Researchers often use the forecast revision as a proxy for news about the underlying variable.

Relatedly, ample evidence in behavioral economics and finance indicates that people have extrapolative beliefs: their estimate of the future value of a quantity is a positive function of the recent past values.[5] In the context of interest rate forecasts, HLW find that investors extrapolate recent changes in short rates, contributing to excessive movement in the long rate.

On the other hand, categorical thinking about interest rate, we posit, mainly requires that people categorize the short and long rates together and expect them to move in tandem in the future. Our proposed mechanism requires short and long rate expectations to move together. It does not rely on news or how people respond to the new information; it also does not necessarily requires forecasters have extrapolative beliefs.

To see this, we compare the time series dynamics of our main independent variable, $\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$, with forecast revisions in which the two forecasts are made 3 months

[5]See Barberis (2018) for a thorough review of the literature on extrapolative beliefs.

apart, $\mathbb{E}_t(\overline{FFR}_{t+1Q}) - \mathbb{E}_{t-1Q}(\overline{FFR}_{t+1Q})$, and with the 1-quarter changes in the short rate, $FFR_t - FFR_{t-1Q}$. The results are plotted in Figures A.6 and A.7 in the Appendix. In both cases, the correlation between the two series is positive and around 0.4, suggesting that the forecast revision and the recent changes in short rates capture all the dynamics of the expected changes in FFR. We reestimate our baseline tests by running horse races between expected changes and forecast revisions (Tables 6), and between expected changes and recent realized changes in the short rate (Tables 7), respectively.

In Table 6, adding the forecast revision barely changes the coefficient or significance of β_1. In the second and third tests, the results are even strengthened in terms of magnitude and statistical significance for β_2 and β_3. Notably, expected changes in FFR now significantly predict a reversal in the future long rate, consistent with long-rate overshoot. Forecast revisions of FFR have a coefficient of zero in the first test and positively predict future changes and the forecast errors of HMR in the other tests.

In Table 7, the incorporation of recent changes in FFR lowers β_1 estimates slightly but does not change the significance against a null of zero or $1/n$. In the other two tests, estimates for β_2 and β_2 are barely changes in the horse race and the coefficients of recent changes in short rate are never significant. The findings suggest that the extrapolative beliefs are also partially responsible for the comovement between short and long rate expectations; however, they are not the main driver of the comovement or responsible for the overreaction in long rate forecasts.

Results from the horse races verify that our documented excessive comovement and predictability of long rate forecast errors are not driven by response to news or extrapolative beliefs.

Influential dates. Bauer and Swanson (2023) find that certain FOMC dates appear more influential in shaping the relationship between monetary shock and forecasters' beliefs about the short rate. They argue that these influential dates usually feature more new information about future short rates. Short rate expectations may move significantly to incorporate this new information and can be *positively* predictive of the future long rates on these days. It is possible that these influential dates can contribute to the documented excessive comovement.

Following Bauer and Swanson (2023), we categorize months by the size of monetary policy shocks, which we obtain from Swanson (2021).[6] We label a month as influential with a large FFR shock if the shock in absolute value is greater than the median, and non-influential if it is lower or there is no monetary shock during that month. We then reestimate our second tests separately for the two subsamples. The results are reported in Table A.4 in the Appendix. Across all samples, the coefficient estimates (β_2) are always negative, refuting the possibility that short rate expectations can positively predict future long rates on these influential monetary policy dates. Moreover, on the influential dates, the coefficient estimates are even more negative and significant at the 1% level with a full set of control variables, suggesting that the long rate overshoot and the predictability of long rate forecast errors are even more pronounced on these days.

Economist-level forecasts. Bordalo et al. (2020) have highlighted the crucial differences between the individual and consensus forecasts. Most notably, as the consensus forecast is an average of individual forecasts and private information embedded in these forecasts, it can behave differently from the individual forecasts in tests of under- and overreaction. In particular, the consensus forecast is less likely to overreact to new information.

To ensure that our results are not driven by this specific feature of the consensus forecasts, we compile economist-level forecasts from BCFF. We plot the cross-sectional dispersion of the 1-quarter-ahead FFR and HMR forecasts in Figure 3. Though there is noticeable heterogeneity in short and long rate forecasts, especially in the earlier part of the sample, most of the individual forecasts are close to the consensus. We then reestimate our baseline tests using these economist-level forecasts. The results are reported in Table A.5 in the Appendix.

[6] We thank Eric Swanson for sharing the monetary policy shocks data. We focus on Swanson's shocks, instead of those from Nakamura and Steinsson (2018), because of their longer time series.

Controlling for the economist fixed effects, all the conclusions from the consensus forecasts apply to the individual forecasts. The β_1 estimates of around 0.40 are larger in magnitude and deviate even more from the rational benchmarks, suggesting that the excessive comovement between short and long rate expectations is not due to the consensus forecasts.

3.1.1 Public knowledge or private information about future short rate

Our baseline tests focus on the interplay between the short and long rate expectations, assuming that anticipated changes in short rates are public knowledge, which forecasters fail to incorporate into their long rate forecasts. An alternative explanation for the positive comovement of short and long rate expectations is that forecasters may (mistakenly) believe that they possess private information about future short rates, which is not yet reflected in the current long rate. In this case, these forecasters would expect the short rate to incorporate their private information in the future and the long rate to move in the same direction. This explanation is possible as BCFF forecasters are professional economists who might have expertise in generating private information concerning the Fed's future policy decisions.

To discriminate between the alternatives, we turn to expectations derived from Fed funds futures, which proxy for public knowledge about future short rates. We source the Fed funds futures data from Bloomberg and interpolate futures contracts with different maturities to obtain 1-quarter-ahead forecasts of FFR implied by the futures (denoted as $\mathbb{E}_t^{Fut}(FFR_{t+1Q})$). The consensus and futures-implied forecasts of FFR, plotted in Figure 4, are almost indistinguishable in levels in both levels (correlation $\rightarrow$ 1) and are highly correlated changes (correlation of 0.9). This finding is consistent with the literature that the survey and futures-implied forecasts of the Fed funds rates are very close to each other (Cieslak, 2018), suggesting that the average forecaster does not possess private information relative to the futures market.

As a second and potentially sharper test, we hone in on a subgroup of forecasters whose short-rate predictions closely align with futures-based expectations. Similarly to the consensus forecasts, these people are unlikely to believe that they possess private information about future short rates. We identify this group by restricting their short-rate forecasts to be within 50 basis points from the futures-implied forecasts. We reestimate our tests by interacting the economist-level short rate expectations with the indicator of whether the forecast is close to the futures. The results are reported in Table 8. Focusing on the "Close to Futures" subsample, the beta coefficients have the same statistical significance as in the full sample, with a slightly smaller magnitude. For instance, a 1% increase in the short rate forecast leads to a 0.26% increase in the long rate forecast, compared to 0.40% in the full sample. Categorical thinking in interest rate forecasts is well and alive among these forecasters who are unlikely to possess private information about future short rates, suggesting that the excessive comovement between short and long rate expectations is not due to the private information about future short rates.

3.1.2 Forecasts across different horizons

So far, our analysis relies on the 1-quarter-ahead forecasts of short and long rates. We now make full use of forecasts across all available horizons and examine the term structures of forecasts across horizons. Figure 5 plots term structures of FFR and HMR forecasts across time, conditioning on the current level of their respective rates at the time of the forecast. The forecast horizon ranges from 1 to 4 quarters ahead. The vertical distance between points along each term structure and the dashed line represents the corresponding forecast error.

If people suffer from categorical thinking when forming beliefs about interest rates, we expect the term structures to move in the same direction at the same point in time. This prediction stems from the notion that forecasters, affected by categorical thinking, may align their short and long rate forecasts too closely, disregarding the fact that the current long rate should intrinsically reflect anticipated future short-term rates.

The representation in Figure 5 corroborates this hypothesis: aside from instances when the actual short-term rate approached the zero lower bound, the term structures for both short and long-term rate forecasts exhibit a consistent parallel movement. This graphical analysis provides a more intuitive and direct visualization of this cognitive bias of categorical thinking from a distinct perspective.

3.2 Consumer beliefs

If professional forecasters think categorically about interest rates, it seems natural that consumers would as well. In this section, we explore whether there is evidence of a similar bias among consumers. We do this using the Fannie Mae National Housing Survey data described in Section 1.1.2. While the survey does not ask respondents to forecast future mortgage rates precisely, it does ask them whether they expect mortgage rates to increase, decrease, or remain about the same over the next 12 months.

Therefore, to test for categorical thinking about interest rates, we examine whether consumers are more likely to expect an increase in mortgage rates over the next 12 months during times when the consensus forecast is for the federal funds rate to increase over the same time period (based on the professional forecasters). Again, to the extent that there is public information suggesting that the Fed will increase the Fed funds rate over the next 12 months, that information should already be reflected in current mortgage rates. Therefore, individuals should not expect future mortgage rate increases during such times.

Following this logic, we begin by estimating equations of the form:

$$\begin{aligned}&\mathbb{1}(\text{Consumer Expected Change in Mortgage Rate} > 0)_{it} = \\ &\qquad \beta \mathbb{1}(\text{Analyst Expected Change in FF Rate} > 0)_t \ + \text{Controls} + \epsilon_{it} \quad (6)\end{aligned}$$

The results are shown in Table 9. As can be seen, we estimate β to be positive and statistically significant. The magnitudes in column (2) suggest that, on average, consumers are 19 percentage points more likely to expect increases in mortgage rates over the next 12 months during times when the consensus forecast is for the Fed funds rate to increase over the same time period.

Next, we explore whether there is heterogeneity in categorical thinking about interest rates across different types of consumers. On the one hand, one might think that more sophisticated individuals would be less subject to this type of bias. On the other hand, a certain amount of sophistication is likely necessary for one to be subject to this bias at all. In particular, one needs to have at least some knowledge about short-term interest rate expectations in order to conflate short-term interest rate expectations with long-term interest rate expectations.

In Table 10, we re-estimate Table 9 by interacting our main independent variable of interest with a series of education level indicator variables. Interestingly, the results suggest that categorical thinking about interest rates becomes monotonically stronger with education. In particular, the results in column (2) suggest that individuals without a high school degree are only 5.3 percentage points more likely to expect increases in mortgage rates over the next 12 months during times when the consensus forecast is for the Fed funds rate to increase. In contrast, those with a graduate degree are 26 percentage points more likely to expect increases in mortgage rates during such times.

Table 11 similarly explores heterogeneity by income. Interestingly, the results suggest that categorical thinking about interest rates becomes monotonically stronger with income. Thus, the bias that we document in this paper is fairly unusual relative to the literature, in that it does not diminish with education and income, but rather becomes stronger.

4 Supply and demand for long-term debt

Having established categorical thinking about interest rates in both professional and consumer settings, our next objective is to explore how these biases translate into tangible actions by different economic participants. Categorical thinking, as a cognitive bias, can manifest in systematic decision-making patterns across various contexts (Brunnermeier et al., 2021).

Our investigation delves into the dynamics of long-term debt, focusing on how categorical thinking influences the borrowing and investing decisions of firms, households, and investors. This cognitive bias about interest rates leads us to anticipate specific behavioral patterns in the supply and demand for long-term debts:

Prediction 1 (Categorical thinking and supply and demand of long-term debt) *If people suffer from categorical thinking about interest rates, expectations of rising short rates will drive:*

- *Borrowers to rush to lock in long-term debt before further increases in long rates, leading to an increase in the supply of long term debt*
- *Investors to sell long-term bonds, leading to a decrease in demand of long term debt*

These predictions set the stage for our empirical tests:

$$Z_{t+1} = \alpha + \theta \times \left[\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t\right] + \gamma X_t + \epsilon_{t+1} \tag{7}$$

where Z_{t+1} is a measure of the supply (for firms or consumers) or the demand of long-term debt (for investors), $\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$ is the expected change in short-term interest rates, and X_t is a vector of control variables. We expect θ to be positive for firms and negative for investors. A few empirical notes are in order. First, since we do not directly observe the individual beliefs of the decision-makers, we use the consensus forecasts as a proxy. This is a reasonable assumption, as the consensus forecasts are wide availabile in the economy. Though one may not have access to the BCFF consensus, other close substitutes, such as the Survey of Professional Forecasters, are freely availabile. Second, as there exist lags between the time of beliefs and the timing of borrowing and investing activities due to processing time, and actual or cognitive costs of taking an action, we forward the dependent variable Z_{t+1} by one period (depending on the frequency of the data). This choice of timing accounts for the lag, ensuring that the actions are taken based on the expectations of future interest rates and not vice versa.

4.1 Supply: Firms' long-term borrowing

For firms' long-term borrowing, we use the following measures of long-term debt supply: an indicator for long-term borrowing, $\mathbb{1}(\text{LT Issues}_t > 0)$, the ratio of long-term borrowing to total assets, $\text{LT Issues}_t/\text{AT}_{t-1}$, the ratio of long-term borrowing to total debt, $\text{LT Issues}_t/\text{Total Debt}_{t-1}$, and the long-term issuance share, LT Share_t. The data is available at the quarterly frequency, so link the consensus forecasts in the last month of each quarter to the borrowing decisions for the subsequent quarter.

We expect the coefficients on $\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$ to be positive for all measures, consistent with the prediction that firms will rush to lock in their long-term borrowing in (mistaken) anticipation of rising long-term borrowing rates. Based on detailed issue-level information from the Mergent FISD database, we find that the average maturity of the long-term borrowing is around 5 years. In the firm-level regressions, we control for the term spread as the difference between 5-year Treasury yield and FFR. We cluster the standard errors by firm and year-quarter to account for the potential correlation of the borrowing decisions within the same firm and in the same quarter.

Tables 12 to 15 report the results from the firm-level regressions. The θ coefficient is positive and statistically significant at the 1% level for all measures of long-term borrowing and for all specifications. This positive relationship confirms the prediction from categorical thinking that firms rush to lock in their long-term borrowing when they anticipate the long-term borrowing rate to rise in the future. The results are robust to the inclusion of control variables and the firm fixed effects. Notably, firms will issue fewer long-term debts when the short-term rates are high, when the yield curve is steep, and when the credit spreads are wide, consistent with the standard theories of corporate financing.

To put the economic magnitude of the findings in perspective, a one percentage point expected increase in next-quarter's short rate is associated with a 3.5% increase in the likelihood of issuing long-term debt (mean likelihood of 38%), a 0.5% increase in the ratio of long-term borrowing to total assets (mean ratio of 3%), and a 5% increase in the long-term issuance share (mean share of 60%). This is a substantial effect, given that the size of the long-term borrowing induced by categorical thinking is usually around 10% of the mean level of long-term borrowing.

Finally, we aggregate the firm-level long-term borrowing measures to the economy level and run the same regressions. The results, reported in Table 16, are consistent with the firm-level results, suggesting that the documented effect is widespread and not driven by a few smaller firms.

While firms often raise long-term capital for impending investment opportunities, we investigate whether an expected rise in the FFR aligns with an increase in such opportunities, potentially driving long-term borrowing. We find that this is not the case. In a placebo test, we replace the long-term borrowing measures with the subsequent one- to four-quarter capital expenditures (CAPX). The results reveal no significant relationship between future investments and expected short-rate changes. This implies that firms' long-term debt issuance is not primarily for financing imminent profitable projects, further underscoring the influence of categorical thinking on their borrowing decisions.

4.2 Supply: Household mortgage decisions

Our second analysis on the supply side delves into household mortgage choices, leveraging the FHFA's comprehensive mortgage data outlined in Section 1.2.2. We use the logarithmic value of the total new mortgage volume initiated in the month subsequent to the forecasts as the dependent variable. The FHFA dataset categorizes loans by type—encompassing total, refinancing, and purchasing mortgages—and by size, distinguishing between conforming and jumbo loans.

In our regressions, we incorporate data across all loan types and sizes, including fixed effects for each loan type to account for inherent differences. Furthermore, we introduce an interaction term between the expected changes in FFR and a binary indicator for jumbo mortgages, which represent larger loans typically exceeding $650K. This distinction is crucial as borrowers of jumbo mortgages may exhibit more sophistication compared to the average mortgage applicant, potentially influencing their response to expected changes in interest rates.

The results, reported in 17, indicate that expectations of rising short rates are associated with a large increase in the volume of jumbo mortgages but are not associated with significant changes in the volume of conventional mortgages. These patterns for the household supply of long term debt are consistent with our earlier findings related to sophistication. Only households who have the flexibility to engage in market timing and are aware of publicly available information about the path of short rates would rush to lock in long term debt.

4.3 Demand: Bond mutual fund investment

In the final segment of our analysis, we turn to the demand for long-term debts, specifically focusing on mutual fund investors' allocation decisions in long-term bond funds. Variable construction and fund classification are detailed in Section 1.2.3. Our dependent variables are the monthly mutual fund flows at the share class level, expressed both in billion-dollar terms ("Fund flows, $B") and as a percentage of the previous month's total net assets ("Fund flows, %"). These measures are evaluated in the month immediately following the forecasts of short rates. We run the tests separately for the full sample, institutional share classes, and retail share classes.

Categorical thinking should prompt investors to sell off long-term bond mutual funds when they anticipate rising short rates, leading to a negative sign for the coefficient θ. The findings, as outlined in Table 18, corroborate this prediction: When short rates are expected to rise by 1 percentage point, bond funds experience average outflows of 3% of AUM or

\$5B. We find slightly larger effects for bond funds targeted at retail investors, although we continue to find substantial outflows for institutional class shares in these bond funds.

Overall, the evidence across multiple settings indicates that categorical thinking in beliefs translates to errors in real borrower and investor behavior. In times when short rates are expected to rise, the demand for long-term debt decreases while the supply increases. This interplay significantly contributes to the excess volatility and subsequent reversals observed in long-term interest rates.

5 Conclusion

In this paper, we show that there is a widespread misconception that expected future shifts in the short-rate forecast corresponding future movements in the long rate. We hypothesize that this misconception occurs because of a categorical thinking error in which people lump short- and long-term interest rates into the same coarse category of "interest rates." Thus, people expect long rates to move in tandem with short rates in the future, and fail to recognize that the current long rate already reflects future expected changes in short rates.

We show that categorical thinking about interest rates is evident even among professional forecasters and distorts the real behavior of borrowers and investors. Expectations of rising short rates prompt homebuyers and firms to rush to lock in long-term debt before further increases in long rates. The resulting increase in household and firm borrowing during monetary tightening cycles reduces the effectiveness of monetary policy. Expectations of rising short rates also prompt investors to be less willing to hold long-term bonds because they anticipate future increases in long yields. The combined increase in supply and decrease in demand for long-term debt cause long rates to overreact to changes in short rates, and can help explain the puzzle of excess movement and reversals in long rates.

Our focus on categorical thinking highlights a relatively under-explored behavioral mechanism that can drive large belief errors in financial and macroeconomic forecasts and affect real borrower behavior. Whereas much of the existing behavioral finance literature has focused on mistaken beliefs about the persistent of shocks or over- and under-reaction to news, we explore a different mechanism in which people can have accurate forecasts of one variable (short term interest rates) that lead to incorrect forecasts of a related variable (long term interest rates) due to the mistaken notion that the two variables belong to the same category and thus move in tandem.

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Tables and Figures

Table 1 Summary statistics of main time-series and firm-level variables

	n	mean	sd	p5	p25	median	p75	p95	AR(1)
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$	465	0.04	0.30	-0.52	-0.06	0.03	0.20	0.52	0.82
$\mathbb{E}_t(\overline{HMR}_{t+1Q}) - HMR_t$	465	0.08	0.22	-0.31	-0.07	0.10	0.24	0.39	0.74
$\overline{HMR}_{t+1Q} - HMR_t$	465	-0.08	0.46	-0.85	-0.34	-0.12	0.21	0.74	0.74
$\overline{HMR}_{t+1Q} - \mathbb{E}_t(\overline{HMR}_{t+1Q})$	465	-0.15	0.49	-0.89	-0.48	-0.21	0.12	0.73	0.81
Control Variables									
FFR_t	465	3.71	3.06	0.09	0.41	3.30	5.82	9.10	0.99
$y_t^{(5)} - FFR_t$	465	1.03	0.96	-0.63	0.34	1.03	1.72	2.59	0.96
π_t	465	2.68	1.35	0.48	1.74	2.64	3.53	4.95	0.95
Baa credit spread$_t$	465	1.89	0.57	1.20	1.48	1.81	2.19	2.73	0.95
Baa credit term spread$_t$	465	1.54	0.64	0.68	1.08	1.47	1.96	2.53	0.95
Other Long Rates									
$\bar{y}_{t+1Q}^{(10)} - y_t^{(10)}$	417	-0.03	0.45	-0.73	-0.34	-0.03	0.24	0.72	0.71
$\bar{y}_{t+1Q}^{(30)} - y_t^{(30)}$	384	-0.04	0.45	-0.75	-0.28	0.01	0.22	0.64	0.71
$\overline{Aaa}_{t+1Q} - Aaa_t$	456	-0.14	0.46	-0.92	-0.41	-0.15	0.15	0.60	0.77
$\overline{Baa}_{t+1Q} - Baa_t$	276	-0.19	0.54	-1.18	-0.45	-0.13	0.14	0.53	0.80
Firm Variables									
$\mathbb{1}$(LT Issues$_t > 0$)	750,698	0.38	0.48	0	0	0.00	1.00	1.00	0.53
LT Issues$_t$/AT$_{t-1}$	746,807	0.03	0.08	0	0	0.00	0.01	0.17	0.34
LT Issues$_t$/Total Debt$_{t-1}$	588,700	0.16	0.53	0	0	0.00	0.07	0.84	0.26
LT Share$_t$	382,391	0.60	0.48	0	0	0.93	1.00	1.00	0.73

Table 2 Correlations between main time series variables

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$								
(2)	$\mathbb{E}_t(\overline{HMR}_{t+1Q}) - HMR_t$	.40							
(3)	$\overline{HMR}_{t+1Q} - HMR_t$	-.10	.10						
(4)	$\overline{HMR}_{t+1Q} - \mathbb{E}_t(\overline{HMR}_{t+1Q})$	-.27	-.35	.90					
(5)	FFR_t	-.20	-.44	-.10	.10				
(6)	$y_t^{(5)} - FFR_t$	.43	.10	-.14	-.17	-.20			
(7)	π_t	-.14	-.25	-.10	.02	.58	-.12		
(8)	Baa credit spread$_t$	-.18	-.14	-.05	.01	-.22	.04	-.34	
(9)	Baa credit term spread$_t$	-.06	.06	.04	.01	-.50	.15	-.52	.88

Table 3 Overreaction in long rates to expected changes in short rates

	$\bar{y}^{(10)}_{t+1Q} - y^{(10)}_t$ (1)	$\bar{y}^{(30)}_{t+1Q} - y^{(30)}_t$ (2)	$\overline{Aaa}_{t+1Q} - Aaa_t$ (3)	$\overline{Baa}_{t+1Q} - Baa_t$ (4)	$\overline{HMR}_{t+1Q} - HMR_t$ (5)
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$	-0.25**	-0.20*	-0.22*	-0.19	-0.22*
	(0.13)	(0.11)	(0.12)	(0.13)	(0.13)
FFR_t	0.01	0.01	0.02	0.11**	-0.004
	(0.02)	(0.02)	(0.02)	(0.04)	(0.02)
$y^{(10)}_t - FFR_t$	-0.04	-0.03	0.02	0.14***	-0.04
	(0.03)	(0.03)	(0.04)	(0.05)	(0.03)
π_t	-0.05	-0.09**	-0.07**	0.01	-0.02
	(0.03)	(0.04)	(0.03)	(0.07)	(0.03)
Baa credit spread$_t$	-0.20	0.004	-0.07	-0.06	-0.34**
	(0.15)	(0.14)	(0.15)	(0.25)	(0.14)
Baa credit term spread$_t$	0.25	0.10	0.02	-0.12	0.27*
	(0.16)	(0.14)	(0.16)	(0.28)	(0.16)
Standard-Errors			NW		
R^2	0.08	0.12	0.04	0.15	0.06
Observations	417	384	456	276	465

Table 4 Categorical thinking in consensus forecasts: Main specification

	$\mathbb{E}_t(\overline{HMR}_{t+1Q}) - HMR_t$			$\overline{HMR}_{t+1Q} - HMR_t$			$HMR_{t+1} - \mathbb{E}_t(\overline{HMR}_{t+1Q})$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$	0.29***	0.27***	0.24***	-0.15	-0.14	-0.19	-0.45***	-0.41***	-0.43***
	(0.05)	(0.05)	(0.05)	(0.12)	(0.12)	(0.13)	(0.12)	(0.12)	(0.12)
FFR_t		-0.03***	-0.03***		-0.03*	-0.01		0.00	0.02
		(0.00)	(0.01)		(0.02)	(0.02)		(0.02)	(0.02)
$HMR_t - FFR_t$		-0.04***	-0.03***		-0.07**	-0.07*		-0.03	-0.03
		(0.01)	(0.01)		(0.03)	(0.04)		(0.04)	(0.04)
π_t			0.00			-0.02			-0.02
			(0.01)			(0.03)			(0.03)
Baa credit spread$_t$			-0.10			-0.32**			-0.22*
			(0.06)			(0.14)			(0.13)
Baa credit term spread$_t$			0.05			0.28*			0.23
			(0.06)			(0.16)			(0.16)
Standard-Errors					NW				
R^2	0.164	0.338	0.354	0.010	0.052	0.079	0.074	0.081	0.096
Observations	465	465	465	465	465	465	465	465	465

Table 5 Categorical thinking in consensus forecasts: Alternative specifications

	$\mathbb{E}_t(\overline{HMR}_{t+1Q}) - HMR_{t+1}$			$\mathbb{E}_{t+1}(\overline{HMR}_{t+1Q}) - HMR_{t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$	0.28***	0.25***	0.24***	0.34***	0.29***	0.27***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
FFR_t		-0.03***	-0.03***		-0.02***	-0.03***
		(0.01)	(0.01)		(0.01)	(0.01)
$HMR_t - FFR_t$		-0.02	-0.02		0.01	0.02
		(0.02)	(0.02)		(0.02)	(0.02)
π_t			0.00			0.00
			(0.02)			(0.02)
Baa credit spread$_t$			0.05			0.06
			(0.07)			(0.07)
Baa credit term spread$_t$			-0.07			-0.11
			(0.07)			(0.08)
Standard-Errors	NW					
R^2	0.072	0.125	0.128	0.105	0.151	0.164
Observations	465	465	465	464	464	464

Table 6 Categorical thinking in consensus forecasts: Horse race against forecast revisions

	$\mathbb{E}_t(\overline{HMR}_{t+1Q}) - HMR_t$				$\overline{HMR}_{t+1Q} - HMR_t$				$HMR_{t+1} - \mathbb{E}_t(\overline{HMR}_{t+1Q})$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$	0.29***	0.30***	0.24***	0.24***	-0.15	-0.28**	-0.19	-0.31**	-0.45***	-0.57***	-0.43***	-0.55***
	(0.05)	(0.07)	(0.05)	(0.05)	(0.12)	(0.14)	(0.13)	(0.14)	(0.12)	(0.14)	(0.12)	(0.13)
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - \mathbb{E}_{t-1Q}(\overline{FFR}_{t+1Q})$		0.00		0.00		0.16**		0.16**		0.16**		0.15**
		(0.04)		(0.03)		(0.06)		(0.07)		(0.07)		(0.07)
FFR_t			-0.03***	-0.03***			-0.01	-0.01			0.02	0.02
			(0.01)	(0.01)			(0.02)	(0.02)			(0.02)	(0.02)
$HMR_t - FFR_t$			-0.03***	-0.03***			-0.07*	-0.06*			-0.03	-0.02
			(0.01)	(0.01)			(0.04)	(0.03)			(0.04)	(0.04)
π_t			0.00	0.00			-0.02	-0.02			-0.02	-0.02
			(0.01)	(0.01)			(0.03)	(0.03)			(0.03)	(0.03)
Baa credit spread_t			-0.10	-0.10			-0.32**	-0.30**			-0.22*	-0.20*
			(0.06)	(0.06)			(0.14)	(0.13)			(0.13)	(0.12)
Baa credit term spread_t			0.05	0.05			0.28*	0.29*			0.23	0.23
			(0.06)	(0.06)			(0.16)	(0.15)			(0.16)	(0.14)
Standard-Errors	NW											
R^2	0.16	0.16	0.35	0.35	0.01	0.03	0.08	0.10	0.07	0.10	0.10	0.11
Observations	465	465	465	465	465	465	465	465	465	465	465	465

Table 7 Categorical thinking in consensus forecasts: Horse race against recent changes in short rates

	$\mathbb{E}_t(\overline{HMR}_{t+1Q}) - HMR_t$				$\overline{HMR}_{t+1Q} - HMR_t$				$HMR_{t+1} - \mathbb{E}_t(\overline{HMR}_{t+1Q})$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$	0.29***	0.22***	0.24***	0.16***	-0.15	-0.22	-0.19	-0.24*	-0.45***	-0.44***	-0.43***	-0.39***
	(0.05)	(0.05)	(0.05)	(0.06)	(0.12)	(0.14)	(0.13)	(0.14)	(0.12)	(0.13)	(0.12)	(0.14)
$FFR_t - FFR_{t-1Q}$		0.10***		0.10***		0.09		0.07		-0.01		-0.04
		(0.03)		(0.04)		(0.07)		(0.07)		(0.06)		(0.07)
FFR_t			-0.03***	-0.03***			-0.01	-0.01			0.02	0.02
			(0.01)	(0.01)			(0.02)	(0.02)			(0.02)	(0.02)
$HMR_t - FFR_t$			-0.03***	-0.03**			-0.07*	-0.06*			-0.03	-0.04
			(0.01)	(0.01)			(0.04)	(0.04)			(0.04)	(0.04)
π_t			0.00	0.00			-0.02	-0.02			-0.02	-0.02
			(0.01)	(0.01)			(0.03)	(0.03)			(0.03)	(0.03)
Baa credit spread$_t$			-0.10	-0.08			-0.32**	-0.31**			-0.22*	-0.23*
			(0.06)	(0.05)			(0.14)	(0.14)			(0.13)	(0.13)
Baa credit term spread$_t$			0.05	0.05			0.28*	0.29*			0.23	0.23
			(0.06)	(0.06)			(0.16)	(0.16)			(0.16)	(0.16)
Standard-Errors							NW					
R^2	0.164	0.205	0.354	0.397	0.010	0.018	0.079	0.083	0.074	0.074	0.096	0.097
Observations	465	465	465	465	465	465	465	465	465	465	465	465

Table 8 Categorical thinking in economist-level forecasts: FFR forecasts close to futures

	$\overline{FFR}_{t+1Q} - FFR_t$			$\mathbb{E}_t^j(\overline{HMR}_{t+1Q}) - HMR_t$			$\overline{HMR}_{t+1Q} - HMR_t$			$HMR_{t+1} - \mathbb{E}_t^j(\overline{HMR}_{t+1Q})$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\mathbb{E}_t^j(\overline{FFR}_{t+1Q}) - FFR_t$ × Close to Futures	1.36***	1.34***	1.22***	0.29***	0.30***	0.26***	0.00	0.03	-0.04	-0.30***	-0.27**	-0.31***
	(0.09)	(0.09)	(0.09)	(0.04)	(0.03)	(0.03)	(0.11)	(0.10)	(0.11)	(0.11)	(0.11)	(0.11)
$\mathbb{E}_t^j(\overline{FFR}_{t+1Q}) - FFR_t$ × Not Close to Futures	0.73***	0.70***	0.61***	0.42***	0.41***	0.38***	-0.15*	-0.13*	-0.19**	-0.58***	-0.56***	-0.59***
	(0.10)	(0.09)	(0.08)	(0.04)	(0.03)	(0.03)	(0.08)	(0.07)	(0.07)	(0.09)	(0.08)	(0.08)
FFR_t		-0.04**	-0.01		-0.05***	-0.04***		-0.09***	-0.07***		-0.04**	-0.03
		(0.02)	(0.03)		(0.01)	(0.01)		(0.02)	(0.02)		(0.02)	(0.03)
$HMR_t - FFR_t$		-0.01	0.01		-0.06***	-0.06***		-0.15***	-0.13***		-0.08**	-0.08*
		(0.04)	(0.03)		(0.02)	(0.01)		(0.03)	(0.03)		(0.04)	(0.04)
π_t			-0.08**			0.00			-0.03			-0.03
			(0.03)			(0.01)			(0.03)			(0.03)
Baa credit spread$_t$			-0.32			-0.21***			-0.29**			-0.09
			(0.20)			(0.05)			(0.13)			(0.15)
Baa credit term spread$_t$			0.13			0.16***			0.19			0.04
			(0.24)			(0.06)			(0.16)			(0.18)
Starting Year	1989											
Standard-Errors	Driscoll-Kraay											
R^2	0.486	0.498	0.543	0.289	0.319	0.337	0.027	0.114	0.148	0.156	0.171	0.177
Observations	23,275	23,275	23,275	20,654	20,654	20,654	23,275	23,275	23,275	20,654	20,654	20,654
Economist FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 9 Categorical thinking in consumer beliefs: Baseline results

	$\mathbb{1}$(Consumer Expected Change in Mortgage Rate > 0)	
	(1)	(2)
$\mathbb{1}$(Analyst Expected Change in FF Rate > 0)	0.162***	0.190***
	(0.0104)	(0.0224)
FFR_t		0.0275**
		(0.0134)
HMR_t		0.0506***
		(0.0154)
Observations	119278	119278

Table 10 Categorical thinking in consumer beliefs: Heterogeneity by education

	$\mathbb{1}$(Consumer Expected Change in Mortgage Rate > 0)	
	(1)	(2)
$\mathbb{1}$(Analyst Expected Change in FF Rate > 0)	0.0233	0.0527*
	(0.0198)	(0.0291)
$\mathbb{1}$(Analyst Expected Change in FF Rate > 0) × High School	0.0783***	0.0774***
	(0.0225)	(0.0224)
$\mathbb{1}$(Analyst Expected Change in FF Rate > 0) × Some College	0.131***	0.131***
	(0.0183)	(0.0183)
$\mathbb{1}$(Analyst Expected Change in FF Rate > 0) × Technical School	0.133***	0.130***
	(0.0221)	(0.0219)
$\mathbb{1}$(Analyst Expected Change in FF Rate > 0) × College	0.176***	0.175***
	(0.0227)	(0.0225)
$\mathbb{1}$(Analyst Expected Change in FF Rate > 0) × Graduate School	0.208***	0.207***
	(0.0247)	(0.0244)
FFR_t		0.0276**
		(0.0134)
HMR_t		0.0508***
		(0.0155)
Observations	115252	115252

Table 11 Categorical thinking in consumer beliefs: Heterogeneity by income

	$\mathbb{1}$(Consumer Expected Change in Mortgage Rate > 0)	
	(1)	(2)
$\mathbb{1}$(Analyst Expected Change in FF Rate > 0)	-0.00936	0.0152
	(0.0255)	(0.0318)
$\mathbb{1}$(Analyst Expected Change in FF Rate > 0) × Income \$10,000-\$14,999	0.0920***	0.0947***
	(0.0311)	(0.0307)
$\mathbb{1}$(Analyst Expected Change in FF Rate > 0) × Income \$15,000-\$24,999	0.101***	0.102***
	(0.0291)	(0.0283)
$\mathbb{1}$(Analyst Expected Change in FF Rate > 0) × Income \$25,000-\$34,999	0.151***	0.153***
	(0.0270)	(0.0268)
$\mathbb{1}$(Analyst Expected Change in FF Rate > 0) × Income \$35,000-\$49,999	0.120***	0.122***
	(0.0325)	(0.0320)
$\mathbb{1}$(Analyst Expected Change in FF Rate > 0) × Income \$50,000-\$74,999	0.189***	0.193***
	(0.0232)	(0.0224)
$\mathbb{1}$(Analyst Expected Change in FF Rate > 0) × Income \$75,000-\$99,999	0.217***	0.220***
	(0.0344)	(0.0340)
$\mathbb{1}$(Analyst Expected Change in FF Rate > 0) × Income \$100,000-\$149,999	0.248***	0.251***
	(0.0300)	(0.0292)
$\mathbb{1}$(Analyst Expected Change in FF Rate > 0) × Income \$150,000-\$199,999	0.257***	0.261***
	(0.0340)	(0.0334)
$\mathbb{1}$(Analyst Expected Change in FF Rate > 0) × Income \$200,000+	0.310***	0.313***
	(0.0386)	(0.0385)
FFR_t		0.0271**
		(0.0127)
HMR_t		0.0518***
		(0.0150)
Observations	104943	104943

Table 12 Firm long-term issuance: Likelihood of issuance

	$\mathbb{1}(\text{LT Issues}_{t+1} > 0)$			
	(1)	(2)	(3)	(4)
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$	0.0377***	0.0374***	0.0352***	0.0348***
	(0.0112)	(0.0097)	(0.0115)	(0.0096)
FFR_t	0.0011	0.0014	0.0036***	0.0040***
	(0.0011)	(0.0014)	(0.0010)	(0.0013)
$y_t^{(5)} - FFR_t$	-0.0138***	-0.0130***	-0.0130***	-0.0122***
	(0.0025)	(0.0025)	(0.0025)	(0.0024)
π_t		-0.0066***		-0.0061***
		(0.0019)		(0.0019)
Baa credit spread$_t$		0.0104		0.0102
		(0.0093)		(0.0090)
Baa credit term spread$_t$		-0.0158*		-0.0152*
		(0.0091)		(0.0089)
Standard-Errors	Firm & Year-Quarter			
R^2	0.001	0.001	0.358	0.359
Observations	750,698	750,698	750,698	750,698
Firm FE			✓	✓

Table 13 Firm long-term issuance: Issuance scaled by assets

	$\frac{\text{LT Issues}_{t+1}}{\text{AT}_t}$			
	(1)	(2)	(3)	(4)
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$	0.0047***	0.0052***	0.0043***	0.0049***
	(0.0015)	(0.0010)	(0.0011)	(0.0009)
FFR_t	-0.0005***	-0.0005***	-0.0004***	-0.0005***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$y_t^{(5)} - FFR_t$	-0.0029***	-0.0030***	-0.0026***	-0.0027***
	(0.0004)	(0.0003)	(0.0003)	(0.0003)
π_t		-0.0018***		-0.0013***
		(0.0004)		(0.0003)
Baa credit spread$_t$		-0.0033***		-0.0027***
		(0.0009)		(0.0008)
Baa credit term spread$_t$		-0.0024**		-0.0017*
		(0.0010)		(0.0009)
Standard-Errors	Firm & Year-Quarter			
R^2	0.001	0.003	0.221	0.221
Observations	746,807	746,807	746,807	746,807
Firm FE			✓	✓

Table 14 Firm long-term issuance: Issuance scaled by total debt

	$\frac{\text{LT issues}_{t+1}}{\text{Total debt}_t}$			
	(1)	(2)	(3)	(4)
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$	0.0388***	0.0420***	0.0288***	0.0315***
	(0.0109)	(0.0077)	(0.0078)	(0.0068)
FFR_t	-0.0037***	-0.0044***	-0.0003	-0.0013
	(0.0010)	(0.0013)	(0.0010)	(0.0013)
$y_t^{(5)} - FFR_t$	-0.0138***	-0.0143***	-0.0080***	-0.0086***
	(0.0026)	(0.0023)	(0.0024)	(0.0023)
π_t		-0.0087***		-0.0058**
		(0.0024)		(0.0022)
Baa credit spread$_t$		-0.0142		-0.0083
		(0.0086)		(0.0076)
Baa credit term spread$_t$		-0.0178*		-0.0160*
		(0.0092)		(0.0084)
Standard-Errors		Firm & Year-Quarter		
R^2	0.001	0.002	0.153	0.153
Observations	588,700	588,700	588,700	588,700
Firm FE			✓	✓

Table 15 Firm long-term issuance: Long-term issuance share

	LT Share_{t+1}			
	(1)	(2)	(3)	(4)
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$	0.0819***	0.0849***	0.0482***	0.0494***
	(0.0172)	(0.0174)	(0.0113)	(0.0120)
FFR_t	-0.0211***	-0.0185***	-0.0135***	-0.0123***
	(0.0018)	(0.0026)	(0.0016)	(0.0020)
$y_t^{(5)} - FFR_t$	-0.0400***	-0.0411***	-0.0261***	-0.0264***
	(0.0043)	(0.0044)	(0.0032)	(0.0033)
π_t		-0.0076**		-0.0026
		(0.0033)		(0.0022)
Baa credit spread_t		-0.0315**		-0.0098
		(0.0139)		(0.0096)
Baa credit term spread_t		0.0169		0.0076
		(0.0159)		(0.0110)
Standard-Errors	Firm & Year-Quarter			
R^2	0.022	0.022	0.483	0.483
Observations	382,391	382,391	382,391	382,391
Firm FE			✓	✓

Table 16 Firm long-term issuance: Aggregate evidence

	Log LT Issues_{t+1}	$\frac{\text{LT Issues}_{t+1}}{\text{AT}_t}$	$\frac{\text{LT Issues}_{t+1}}{\text{Total Debt}_t}$	LT Share_{t+1}
	(1)	(2)	(3)	(4)
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$	1.103***	0.0075***	0.0332***	0.1012***
	(0.2271)	(0.0026)	(0.0125)	(0.0338)
FFR_{t-1}	-0.4202***	-0.0011***	-0.0055***	-0.0272***
	(0.0451)	(0.0002)	(0.0011)	(0.0077)
$y_t^{(5)} - FFR_t$	-0.6547***	-0.0037***	-0.0167***	-0.0482***
	(0.0801)	(0.0011)	(0.0052)	(0.0119)
π_t	0.0361	-0.0002	1.81×10^{-5}	-0.0102
	(0.0446)	(0.0006)	(0.0023)	(0.0083)
Baa credit spread_t	-0.0753	-0.0024	-0.0162	0.0304
	(0.2902)	(0.0027)	(0.0118)	(0.0614)
Baa credit term spread_t	-0.2569	-0.0006	0.0062	-0.0501
	(0.3412)	(0.0028)	(0.0127)	(0.0642)
Standard-Errors	NW(4)			
R^2	0.82	0.31	0.36	0.49
Observations	155	155	155	155

Table 17 Aggregate mortgage issuance: Jumbo mortgages

	Log Total Loan_{t+1}			
	(1)	(2)	(3)	(4)
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$	-0.3059	-0.3059	-0.1687	-0.1687
	(0.2152)	(0.2152)	(0.2628)	(0.2628)
Jumbo	-0.7677**	-0.7677**	-0.7677**	-0.7677**
	(0.0787)	(0.0787)	(0.0788)	(0.0788)
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$ × Jumbo	0.7811***	0.7811***	0.7811***	0.7811***
	(0.0424)	(0.0424)	(0.0425)	(0.0425)
FFR_{t-1}	-0.1663**	-0.1663**	-0.1429*	-0.1429*
	(0.0345)	(0.0345)	(0.0357)	(0.0357)
$HMR_t - FFR_{t-1}$	-0.2169***	-0.2169***	-0.2178***	-0.2178***
	(0.0077)	(0.0077)	(0.0099)	(0.0099)
π_t			0.0329***	0.0329***
			(0.0024)	(0.0024)
Baa credit spread_t			-0.3582*	-0.3582*
			(0.1138)	(0.1138)
Baa credit term spread_t			0.3764**	0.3764**
			(0.0512)	(0.0512)
Standard-Errors	Clustered by Type			
R^2	0.152	0.267	0.158	0.273
Observations	864	864	864	864
Type FE		✓		✓

Table 18 Long-term bond mutual fund flows

Share class:	Fund flows, %	Fund flows, $B	Fund flows, %	Fund flows, $B	Fund flows, %	Fund flows, $B
	Full sample		Institutional		Retail	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$	-3.042***	-5.108**	-2.698***	-6.985*	-3.265***	-3.567***
	(0.6518)	(2.094)	(0.5547)	(4.088)	(0.8509)	(1.004)
FFR_t	1.039***	0.5374**	0.9179***	0.0374	1.119***	0.8468***
	(0.0838)	(0.2234)	(0.0903)	(0.3838)	(0.1128)	(0.2264)
$y_t^{(5)} - FFR_t$	1.417***	0.1375	1.545***	-0.8346	1.335***	0.8402**
	(0.1425)	(0.5025)	(0.1451)	(0.8959)	(0.1832)	(0.3777)
π_t	-0.0423	-0.2803**	-0.0753	-0.5832***	-0.0280	-0.1021
	(0.0865)	(0.1356)	(0.0858)	(0.1929)	(0.1104)	(0.1423)
Baa credit spread$_t$	1.069**	-0.4366	1.044**	-1.292	1.127*	0.5334
	(0.4845)	(0.7271)	(0.4544)	(1.187)	(0.6213)	(0.7098)
Baa credit term spread$_t$	-0.0387	0.6642	-0.5631	0.1709	0.2982	0.6630
	(0.5616)	(0.7661)	(0.4771)	(1.253)	(0.7481)	(0.7312)
Standard-Errors			Fund & Date			
R^2	0.06401	0.16154	0.05379	0.16991	0.07650	0.14501
Observations	324,739	324,739	147,129	147,129	177,610	177,610
Fund FE	✓	✓	✓	✓	✓	✓

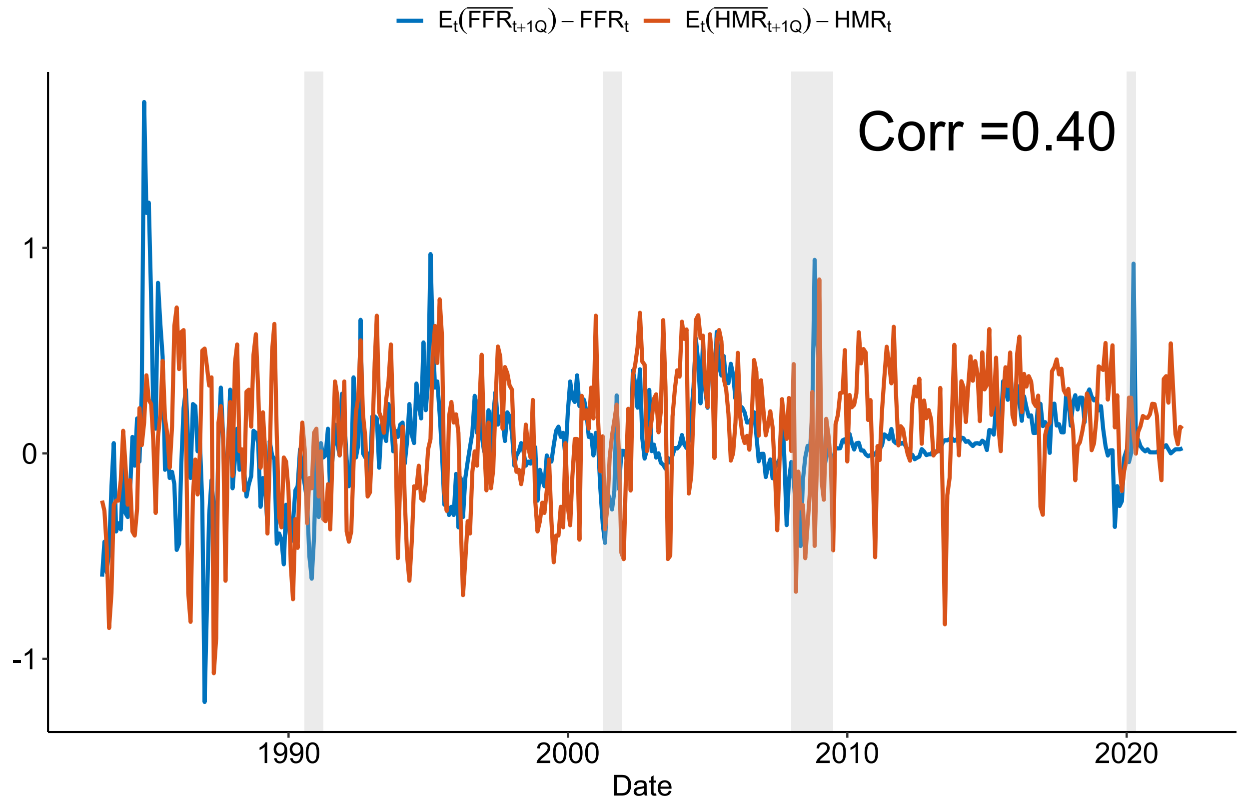
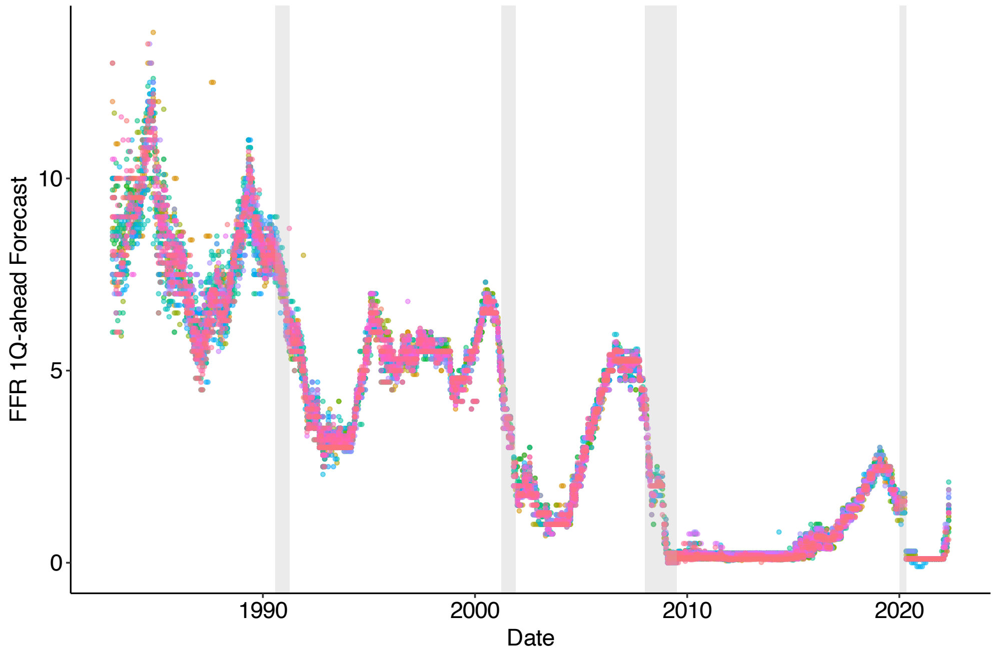
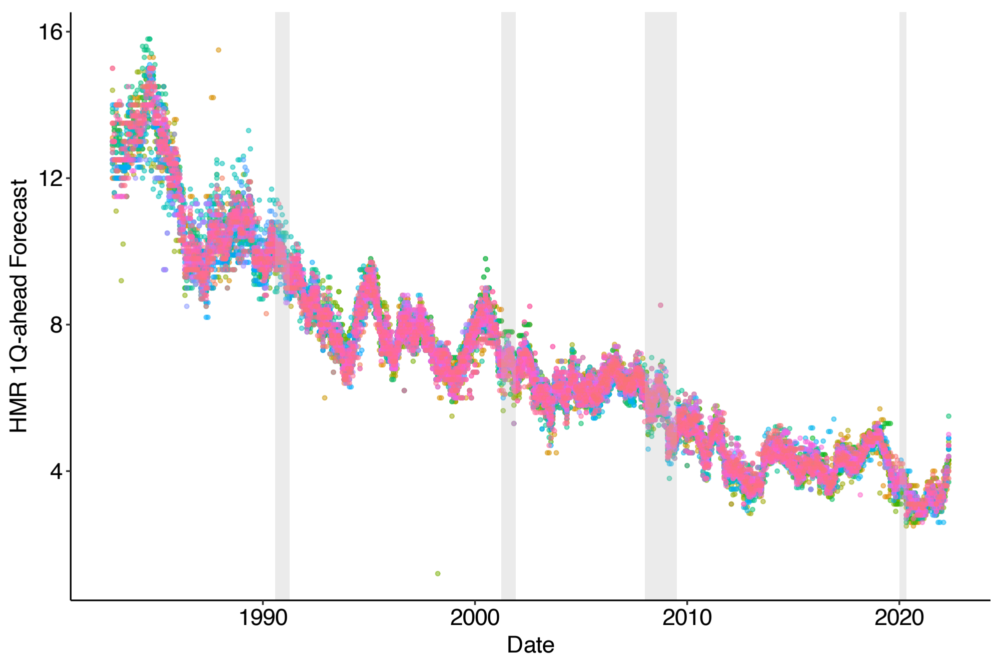


Figure 2 Time series of 1-quarter expected changes of FFR and HMR

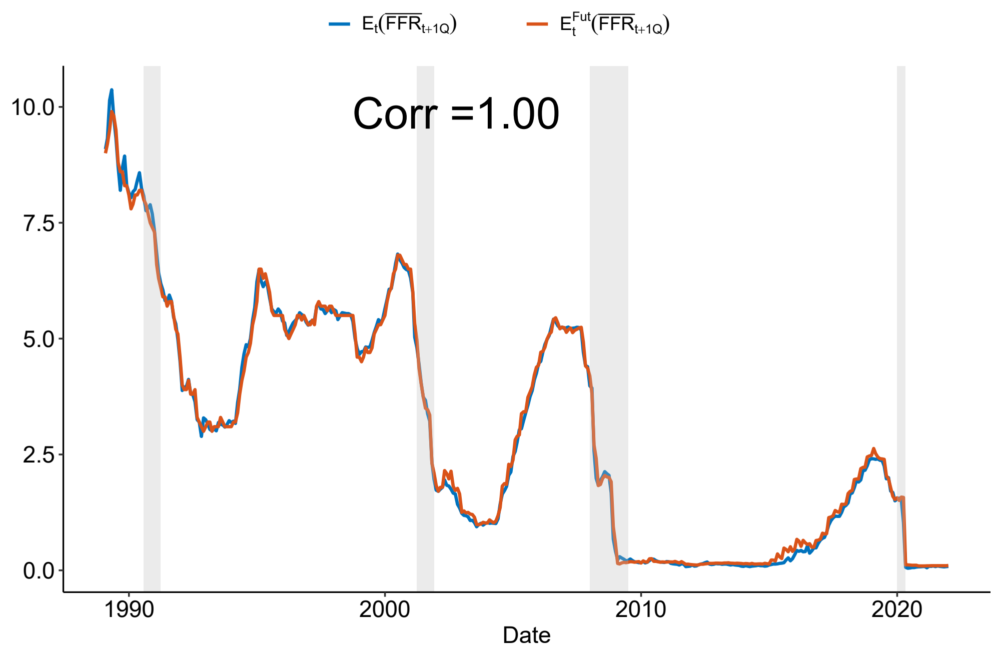


A. FFR Forecasts

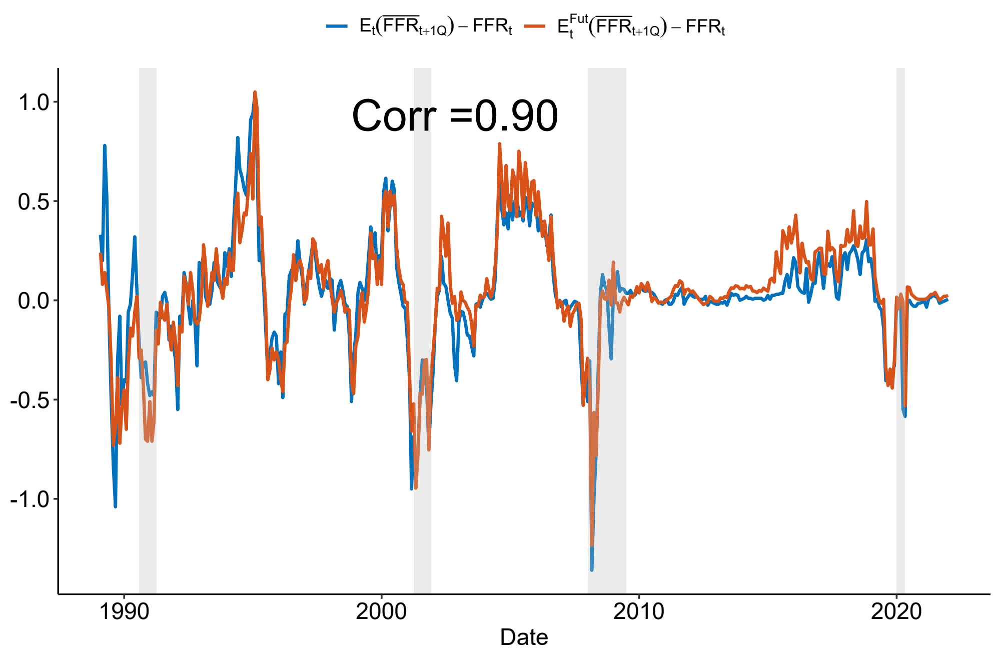


B. HMR Forecasts

Figure 3 Economist-level forecasts of 1-quarter-ahead FFR and HMR



A. Levels



B. Changes

Figure 4 Survey and futures-implied FFR expectations

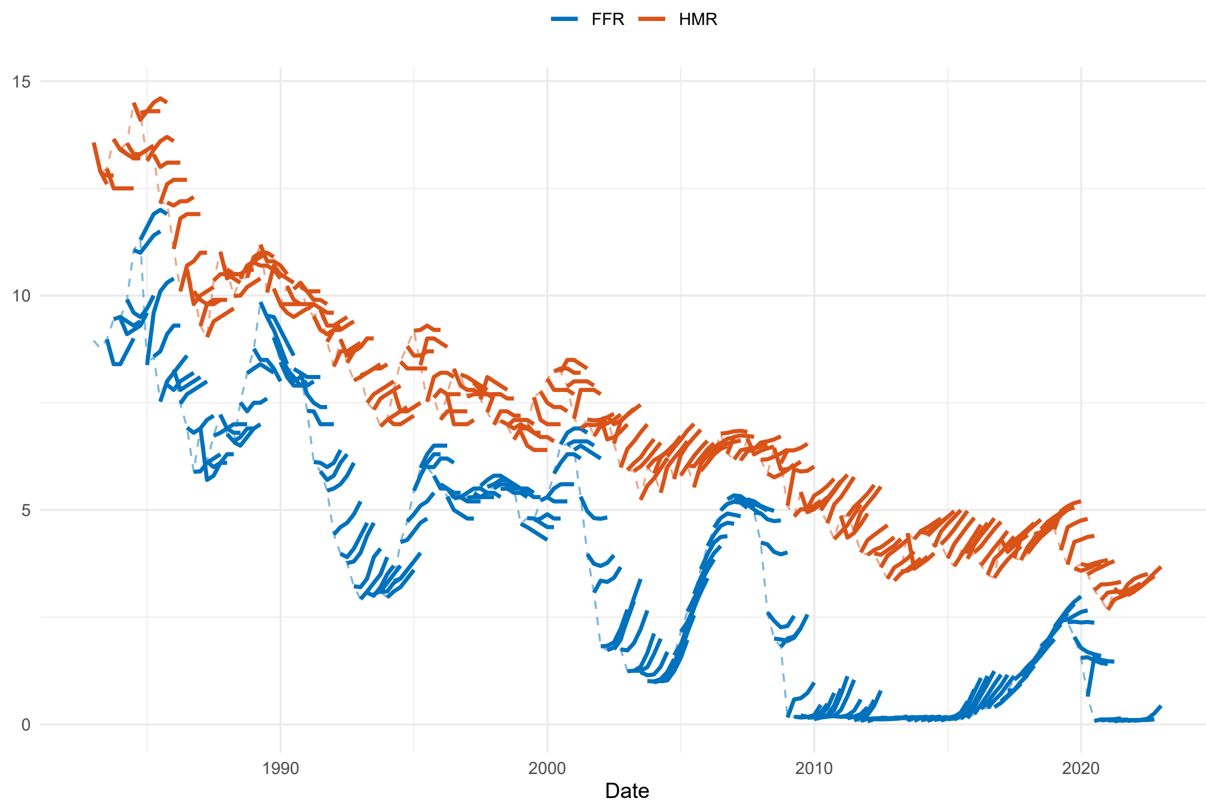


Figure 5 Term structure of FFR and HMR expectations across forecast horizons

Online Appendix for

Categorical Thinking about Interest Rates

Kelly Shue Richard Townsend Chen Wang

A Additional Tables and Figures

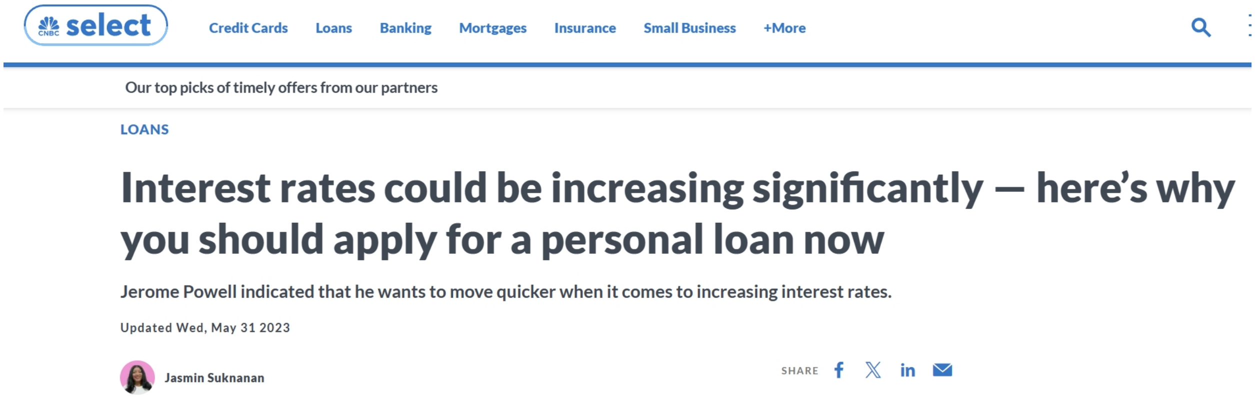


Figure A.1 An example of personal finance advice given by financial media

/* Q20b */ During the next 12 months, do you think home mortgage interest rates will go up, go down, or stay the same as where they are now?

1) Rates will go up
2) Rates will go down
3) Rates will remain about the same
4) Don't know **VOL**

Figure A.2 An example question from Fannie Mae National Housing Survey Questionnaire, Q1 2019

US Quarterly Forecasts
October 2019

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
	Effective Federal Funds Rate[1]	Prime Rate[2]	LIBOR 3-Mo Rate[3]	Commercial Paper 1-Mo Rate[4]	Treasury Bill 3-Mo Yield[5]	Treasury Bill 6-Mo Yield[5]	Treasury Bill 1-Yr Yield[5]	Treasury Note 2-Yr Yield[5]	Treasury Note 5-Yr Yield[5]	Treasury Note 10-Yr Yield[5]	Treasury Bond 30-Yr Yield[5]	Corporate Aaa Bond Yield[6]	Corporate Baa Bond Yield[7]	State & Local Bond Yield[8]	Mortgage Rate 30-Yr Fixed[9]	Fed's Advanced Foreign Economies (AFE) Index[10]	Real GDP (Q/Q %Chg, SAAR)[11]	GDP Price Index (Q/Q %Chg, SAAR)[12]	Consumer Price Index (Q/Q % Chg, SAAR)[13]
Q4 2019																			
Q1 2020																			
Q2 2020																			
Q3 2020																			
Q4 2020																			
Q1 2021																			

[1] Federal Funds Rate: Charged on loans of uncommitted reserve funds among banks; Federal Reserve Statistical Release (FRSR) H.15
[2] Prime Rate: One of several base rates used by banks to price short term business loans; FRSR H.15.
[3] London Interbank Offered Rate (LIBOR): The interbank offered rate for 3-month dollar deposits in the London market. The Wall Street Journal publishes a LIBOR quote on a daily basis, The Economist on a weekly basis.
[4] Commercial Paper: Financial; 1-month bank discount basis; Interest rates interpolated from data on certain commercial paper trades settled by The Depository Trust Company; The trades represent sales of commercial paper by dealers or direct issuers to investors; FRSR H.15
[5] Treasury Bills, Notes, and Bonds: 3-month, 6-month, 1-year bills, 2-year, 5-year, 10-year notes and 30-year bond; Yields on actively traded issues, adjusted to constant maturities; U.S. Treasury; FRSR H.15
[6] Aaa Corporate Bonds: BofA Merrill Lynch Corporate Bonds: AAA-AA: 15+ Years; Yield to Maturity (%)
[7] Baa Corporate Bond: BofA Merrill Lynch Corporate Bonds: A-BBB: 15+ Years; Yield to Maturity (%)
[8] State & Local Bonds: BofA Merrill Lynch Municipals: A Rated: 20-year; Yield to Maturity (%)
[9] Conventional Mortgages: Contract interest rates on commitments on 30-year fixed rate first mortgages; FreddieMac
[10] Federal Reserve Board's Advanced Foreign Economies (AFE) Nominal Dollar Index. FRB H.10
[11] Real Gross Domestic Product (Chain-type): Percent change (SAAR) Economic Indicators; BEA
[12] Chained Gross Domestic Product Price Index: Percent change (SAAR) Economic Indicators; BEA
[13] Consumer Price Index (All Urban Consumers): Percent change (SAAR); Economic Indicators; BLS

Figure A.3 Blue Chip Financial Forecasts sample survey questionnaire

This figure presents a screenshot of the latest iteration of the Blue Chip Financial Forecasts survey questionnaire. The definition of each target variable is specified in the footnote.

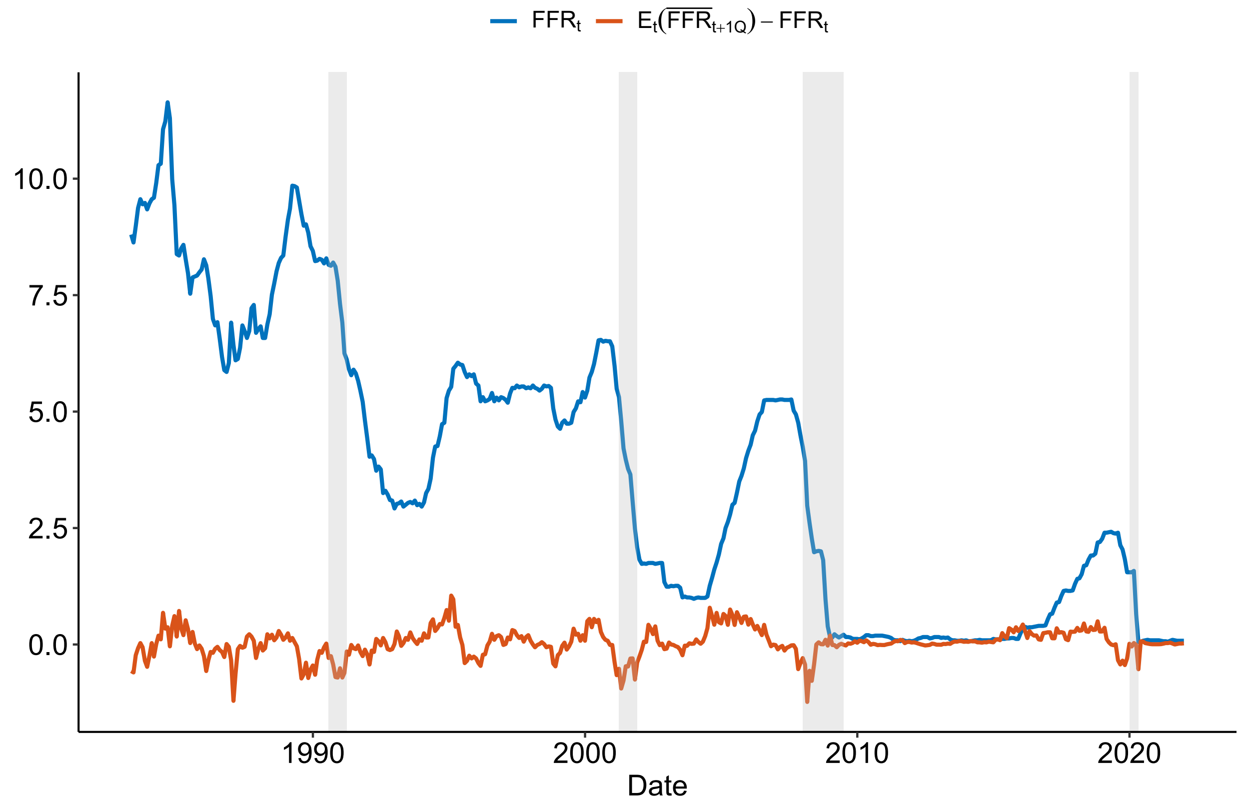
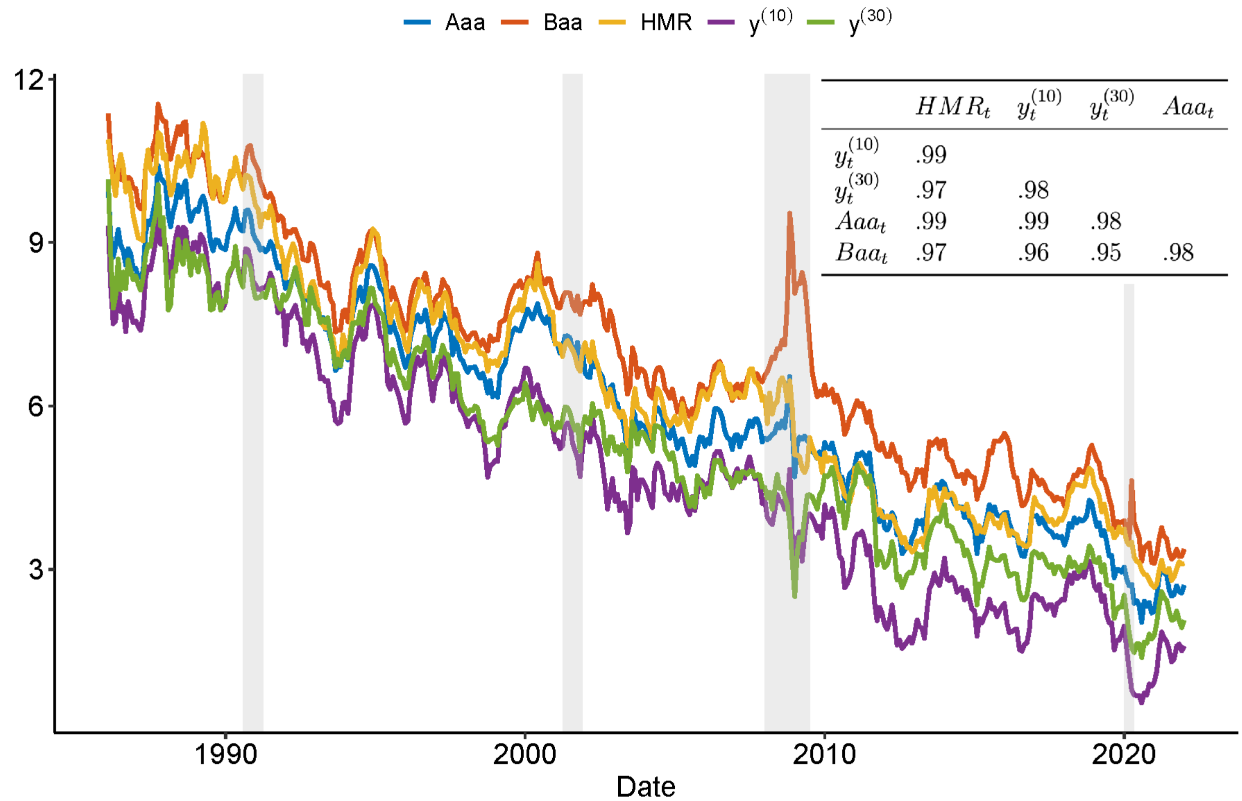


Figure A.4 Realized FFR and forecasted changes of FFR



	HMR_t	$y_t^{(10)}$	$y_t^{(30)}$	Aaa_t
$y_t^{(10)}$	.99			
$y_t^{(30)}$	.97	.98		
Aaa_t	.99	.99	.98	
Baa_t	.97	.96	.95	.98

Figure A.5 Various realized long rates

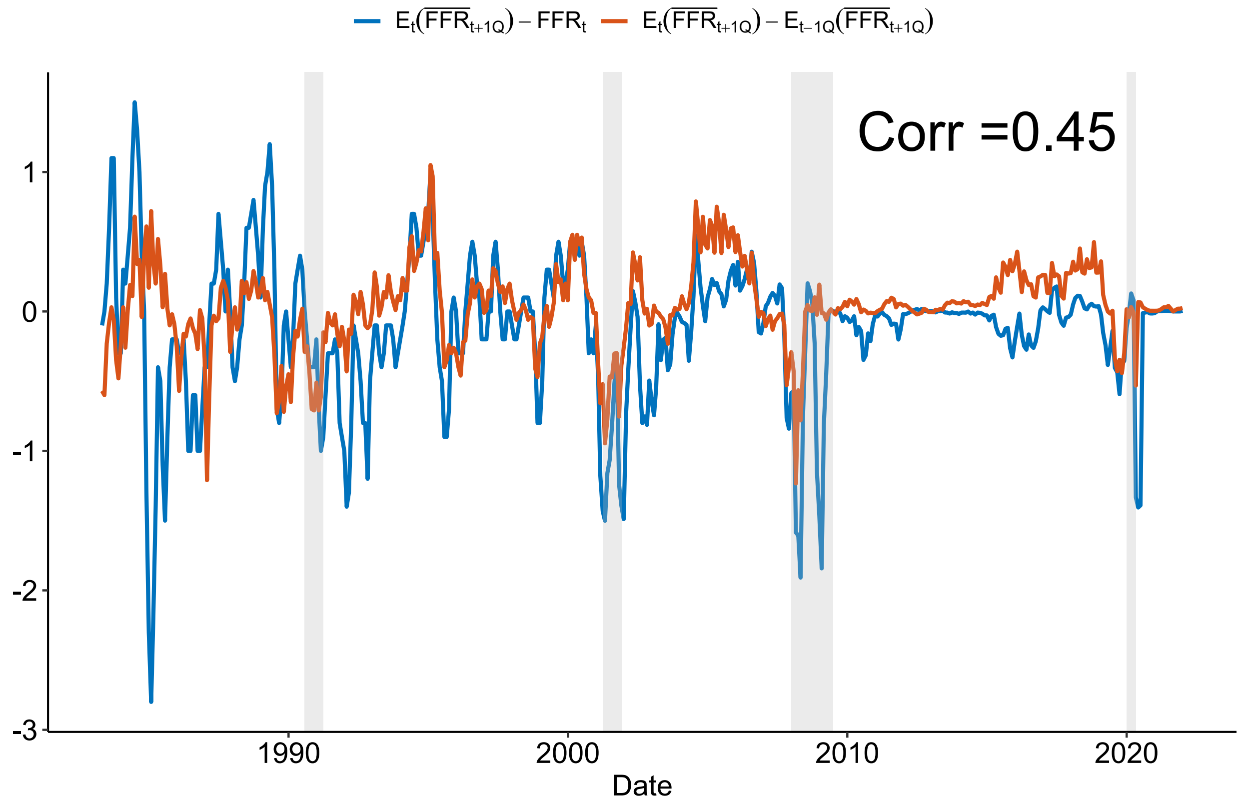


Figure A.6 Time series of forecasted changes and 3-month forecast revisions of the short rate

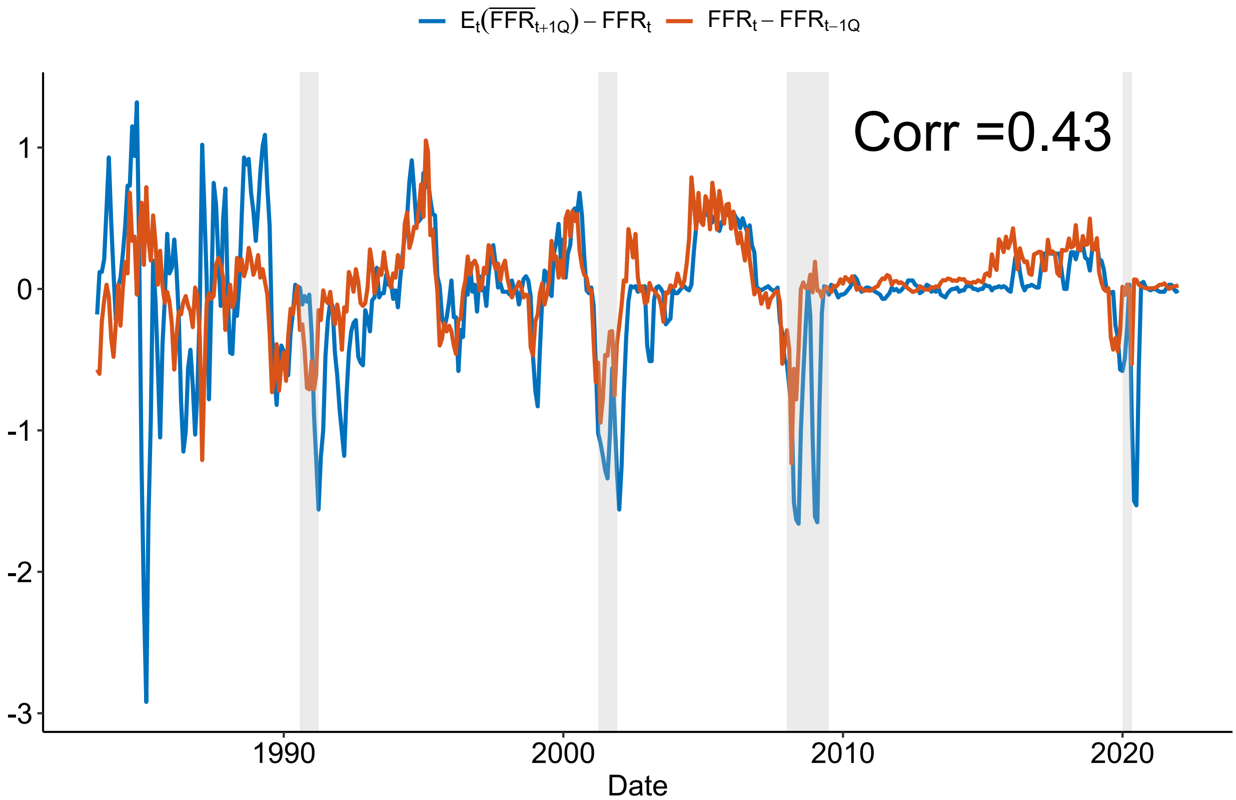


Figure A.7 Time series of forecasted changes and recent realized changes in the short rate

Table A.1 Blue Chip Financial Forecasts participants, grouped by institution types

Firms' commonly used names are reported, which may slightly differ from their legal names. I manually check the name changes of the forecasters—due to mergers and acquisitions or other reasons—using the information provided by the Federal Financial Institutions Examinations Council (FFIEC) and concatenate the observations that belong to the same entity. Only participants with more than 60 months of observations are reported. For institutions with multiple classifications, I report its primary type.

	Count	Institution Names
Asset Manager	13	ASB Capital Management, Sanford C. Bernstein, J.W. Coons, ING Aeltus, JPMorgan Chase Wealth Management, Loomis Sayles, Mesirow, Northern Trust, RidgeWorth, Stone Harbor, US Trust Company, Wayne Hummer, Wells Capital
Bank	26	Banc One Corp, Bankers Trust, First National Bank of Chicago/Bank One (Chicago), Barnett Banks, Bank of America, Comerica Bank, CoreStates Financial, First Fidelity Bancorp, First Interstate Bank, Fleet Financial Group, Huntington National Bank, JPMorgan, LaSalle National Bank, MUFG Bank, National City Bank of Cleveland, PNC Financial Corp, Bank of Nova Scotia, SunTrust, Tokai Bank, Valley National Bank, Wachovia, Wells Fargo
Broker/Dealer	15	Amherst Pierpont, Barclays, Bear Stearns, BMO, Chicago Capital, Daiwa, Deutsche Bank, Goldman Sachs, Lanston, Merrill Lynch, Nomura Securities, Prudential Securities, RBS, Societe Generale, UBS
Mortgage	2	Fannie Mae, Mortgage Bankers Association
Insurance	5	Kemper, Metropolitan Insurance Companies, New York Life, Prudential Insurance, Swiss Re
Rating	2	Moody's, Standard & Poor's
Research	21	Action Economics, Investor's Briefing, Chmura Economics & Analytics, ClearView, Cycledata, DePrince & Associates, Economist Intelligence Unit, Genetski & Associates, GLC Financial Economics, Independent Econ Advisory, Kellner Economic Advisers, MacroFin Analytics, MMS International, Moody's Economy.com, Naroff Economic Advisors, Oxford Economics, Maria Fiorini Ramirez, RDQ Economics, Technical Data, Thredgold Economic, Woodworth Holdings
Others	3	National Association of Realtors, US Chamber of Commerce, Georgia State University

Table A.2 Categorical thinking in consensus forecasts: Futures-implied FFR expectations

	$\mathbb{E}_t(\overline{HMR}_{t+1Q}) - HMR_t$				$\overline{HMR}_{t+1Q} - HMR_t$				$HMR_{t+1} - \mathbb{E}_t(\overline{HMR}_{t+1Q})$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$	0.33***		0.24***		-0.08		-0.19		-0.41***		-0.43***	
	(0.05)		(0.04)		(0.12)		(0.13)		(0.12)		(0.13)	
$\mathbb{E}_t^{Fut}(\overline{FFR}_{t+1Q}) - FFR_t$		0.18***		0.13***		0.00		-0.04		-0.19		-0.17
		(0.06)		(0.04)		(0.12)		(0.12)		(0.13)		(0.13)
FFR_t			-0.04***	-0.05***			-0.04*	-0.04			0.00	0.01
			(0.01)	(0.01)			(0.02)	(0.02)			(0.03)	(0.03)
$HMR_t - FFR_t$			-0.05***	-0.05***			-0.09**	-0.09***			-0.03	-0.05
			(0.01)	(0.01)			(0.04)	(0.04)			(0.04)	(0.04)
π_t			0.00	-0.01			-0.03	-0.03			-0.03	-0.02
			(0.01)	(0.01)			(0.03)	(0.03)			(0.03)	(0.03)
Baa credit spread$_t$			-0.20***	-0.22***			-0.33**	-0.30**			-0.13	-0.08
			(0.05)	(0.05)			(0.14)	(0.15)			(0.15)	(0.17)
Baa credit term spread$_t$			0.14**	0.15**			0.20	0.19			0.06	0.05
			(0.06)	(0.06)			(0.16)	(0.17)			(0.18)	(0.20)
Standard-Errors							NW					
R^2	0.223	0.068	0.467	0.400	0.003	0.000	0.121	0.106	0.073	0.015	0.095	0.039
Observations	396	396	396	396	396	396	396	396	396	396	396	396

Table A.3 Categorical thinking in consensus forecasts: Influential dates

	$\overline{HMR}_{t+1Q} - HMR_t$								
Influential FOMC Meetings	Full sample			FALSE			TRUE		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$	-0.15	-0.14	-0.19	-0.13	-0.13	-0.16	-0.03	-0.04	-0.24
	(0.12)	(0.12)	(0.13)	(0.13)	(0.13)	(0.13)	(0.30)	(0.91)	(2.08)
FFR_t		-0.03*	-0.01		-0.03*	-0.01		-0.08	-0.02
		(0.02)	(0.02)		(0.02)	(0.02)		(0.57)	(0.59)
$HMR_t - FFR_t$		-0.07**	-0.07*		-0.07**	-0.07**		-0.01	0.01
		(0.03)	(0.04)		(0.03)	(0.03)		(1.07)	(1.03)
π_t			-0.02			-0.02			-0.22
			(0.03)			(0.03)			(0.65)
Baa credit spread$_t$			-0.32**			-0.32**			-0.20
			(0.14)			(0.14)			(1.31)
Baa credit term spread$_t$			0.28*			0.29*			0.37
			(0.16)			(0.16)			(1.44)
Standard-Errors	NW								
R^2	0.010	0.052	0.079	0.007	0.049	0.077	0.001	0.069	0.186
Observations	465	465	465	455	455	455	10	10	10

Table A.4 Categorical thinking in consensus forecasts: Subsample by monetary policy surprises

	$\overline{HMR}_{t+1Q} - HMR_t$								
	Full Sample			Small FFR Shocks			Big FFR Shocks		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$E_t(\overline{FFR}_{t+1Q}) - FFR_t$	-0.14	-0.08	-0.19	-0.02	0.06	-0.03	-0.29*	-0.24*	-0.40***
	(0.14)	(0.13)	(0.14)	(0.15)	(0.14)	(0.15)	(0.15)	(0.12)	(0.14)
FFR_t		-0.04	-0.04		-0.03	-0.03		-0.06	-0.08*
		(0.03)	(0.03)		(0.03)	(0.03)		(0.04)	(0.04)
$HMR_t - FFR_t$		-0.08*	-0.07		-0.09**	-0.08*		-0.08	-0.08
		(0.05)	(0.04)		(0.05)	(0.05)		(0.08)	(0.07)
π_t			-0.03			-0.02			-0.08
			(0.03)			(0.03)			(0.06)
Baa credit spread$_t$			-0.30**			-0.32**			-0.31*
			(0.15)			(0.13)			(0.16)
Baa credit term spread$_t$			0.15			0.18			0.10
			(0.17)			(0.18)			(0.19)
Standard-Errors					NW				
R^2	0.009	0.044	0.099	0.000	0.042	0.085	0.056	0.091	0.200
Observations	348	348	348	252	252	252	96	96	96

Table A.5 Categorical thinking in consensus forecasts: Economist-level evidence

	$\mathbb{E}_t^j(\overline{HMR}_{t+1Q}) - HMR_t$			$\overline{HMR}_{t+1Q} - HMR_t$			$HMR_{t+1} - \mathbb{E}_t^j(\overline{HMR}_{t+1Q})$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mathbb{E}_t^j(\overline{FFR}_{t+1Q}) - FFR_t$	0.40***	0.41***	0.40***	-0.06	-0.04	-0.07	-0.48***	-0.46***	-0.47***
	(0.03)	(0.03)	(0.03)	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)
FFR_t		-0.04***	-0.04***		-0.07***	-0.05***		-0.03*	-0.01
		(0.01)	(0.01)		(0.01)	(0.02)		(0.02)	(0.02)
$HMR_t - FFR_t$		-0.06***	-0.06***		-0.13***	-0.12***		-0.07**	-0.07*
		(0.01)	(0.01)		(0.03)	(0.03)		(0.03)	(0.04)
π_t			0.00			-0.02			-0.03
			(0.01)			(0.03)			(0.03)
Baa credit spread$_t$			-0.11**			-0.27**			-0.15
			(0.05)			(0.13)			(0.12)
Baa credit term spread$_t$			0.08			0.23*			0.15
			(0.05)			(0.14)			(0.14)
Standard-Errors					Driscoll-Kraay				
R^2	0.320	0.346	0.351	0.029	0.099	0.119	0.180	0.190	0.196
Observations	23,768	23,768	23,768	26,434	26,434	26,434	23,768	23,768	23,768
Economist FE	✓	✓	✓	✓	✓	✓	✓	✓	✓