Categorical Thinking about Interest Rates*

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Abstract

Rational expectations imply that the current long-term interest rate should already incorporate public information about 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 households and firms to rush to lock in long-term debt before further increases in long rates, reducing the effectiveness of monetary policy. Investors sell 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.

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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 information 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 changes in the short rate do not positively predict changes in the long rate in the data.

In this paper, we show that there is a widespread misconception that expected future shifts in the short rate predict 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; Huang, 2015).

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 positively correlated. It is also true that Federal Reserve announcements of surprise changes to the federal funds rate simultaneously affect 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 households 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 sell long-term bonds because they anticipate future increases in long rates (implying a decline in the prices of long bonds). Likewise, expectations of declining short rates prompt homebuyers and firms to delay borrowing until long rates fall and prompt bond investors to buy long term bonds.[1]

The combined changes in supply and demand for long-term debt are not immediately

[1]For example, the Wall Street Journal advised households to delay long-term borrowing on March 20, 2024 following announcements by the Federal Reserve of three planned cuts to the federal funds rate over the next year: *Banks set their mortgage interest rates largely in relation to the 10-year Treasury bond yield. But falling short-term rates can help prompt lenders to adjust mortgage rates downward. Falling short-term rates also make it cheaper for banks to borrow, which enables them to offer more competitive mortgage rates... Financial advisors say home buying decisions should hinge on how urgently you need to buy that new home. Blancato argues that while the Fed's rate cuts have been delayed, they'll happen within the next year or two and help to ease mortgage rates. "So unless you're really hard pressed to buy a home, I would wait for the Fed to cut rates," he says.*

absorbed by risk-average arbitrageurs (Hanson, Lucca, and Wright, 2021), and cause long rates to overreact to expected changes in short rates and subsequently reverse. 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. In particular, people must be aware of public information about expected changes in short rates to conflate them with expected changes in long rates. This is important because we would not expect categorical thinking about interest rates to have meaningful real effects if those who are sophisticated enough to actually issue and trade long-term debt did not suffer from the bias.

We begin by showing that there is no reason, based on historical 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. These publicly available consensus forecasts are largely driven by the forward guidance provided by the Federal Reserve combined with economic data. We show that when the Federal Reserve is expected to increase the federal funds rate over the next quarter, the federal funds rate does increase on average, but long rates do not; if anything, they decrease. This is consistent with the excess volatility puzzle in which long rates overreact to expected changes in the short rate and subsequently correct.

Next, we examine whether professional forecasters make errors consistent with categorical thinking. One benefit of starting with forecast data is that doing so allows us to directly investigate mistaken beliefs. In contrast, analyzing real outcomes (e.g., long term debt issuance) can only provide indirect evidence of mistaken beliefs, and effects could potentially be driven by other factors. Consistent with categorical thinking, we find that when the Federal Reserve is expected to increase the federal funds rate by 1 percentage point over the next quarter, professional forecasters believe that long rates will increase by 20 to 30 basis points. This belief is incorrect, as long rates actually decline on average, leading to predictable forecast errors of 40 to 45 basis points.

We conduct several tests to explore whether such predictable forecast errors may be due to factors other than categorical thinking about interest rates. First, the long rate may not price information about expected changes in short rates instantaneously. To rule out this explanation, we allow the long rate a full month to price public information about expected movements in the short rate, and find similar results. Second, individual forecasters may not be fully aware of consensus forecasts of the short rate when they make forecasts for the long rate. However, we find similar results when we look at the relation between forecasted changes in the long rate and last month's consensus forecasts of expected changes in the short rate. Finally, professional forecasters may possess private information about future movements in short rate. This private information 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 obtain similar results when we proxy for short rate expectations using consensus forecasts from the previous month, which is public information by the time long term forecasts are made.

We are also able to distinguish a categorical thinking error from a different behavioral phenomenon in which investors overreact to news or extrapolate from recent trends. Imagine a situation in which it is well-known in advance that the Federal Reserve will increase short-term interest rates at time t. There is no news released at time t for investors to overreact to. Likewise, there is no movement in short rates prior to time t for investors to extrapolate. Thus, overreaction and extrapolation would not would not lead people to believe that the long rate will increase at time t. On the other hand, 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 (a) forecast revisions, i.e., *a proxy for news* about movements in short rates or (b) recent changes in short rates. We also show graphically that professional forecasters report similar shapes for the expected paths 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.

If professional forecasters think categorically about interest rates, it seems natural that households would as well. To explore whether there is evidence of a similar bias among households, we use data from the Fannie Mae National Housing Survey. We find that households are 19 percentage points more likely to believe that mortgage interest rates will go up over the next year when the consensus forecast is for short rates to increase over the same interval.

Interestingly, household categorical thinking about interest rates increases monotonically with education and income. For example, individuals without a high school degree are only 5.3 ppt more likely to expect increases in mortgage rates over the next year during times when the consensus forecast is for the federal funds rate to increase. In contrast, those with a graduate degree are 26 ppt more likely to expect increases in mortgage rates during such times. Similarly, those earning less than $10,000 annually are only 1.5 ppt more likely to expect an increase, whereas those earning over $200,000 are 32.8 ppt more likely.

In the second half of the 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. Expectations of falling short rates would lead to the opposite behavior. 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. 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. We also show that these changes in corporate long term debt issuance cannot be explained by hedging demand for interest rate uncertainty or real changes in capital investments.

We see similar shifts in the borrowing behavior of households. We find that expectations of rising short rates are associated with a large increase in the volume of mortgages, in particular jumbo loans (typically larger loans exceeding $750K in 2024). These patterns are consistent with our earlier findings related to sophistication, as wealthier households are more likely to have the flexibility to engage in market timing and to be aware of publicly available information about the path of short rates.

Finally, we examine the behavior of investors in intermediate and long term bond funds. We find that when short rates are expected to rise by 1 percentage point, these 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 changes 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 behavior that can limit the effectiveness of monetary policy and can help explain the puzzle of excess movement and reversals in long rates.

Our findings carry important implications for monetary policy, which, in modern contexts, typically involves forward guidance and gradualism (Woodford, 2003; Stein and Sunderam, 2018; Bernanke, 2020). It is commonly argued that, unlike the "cold turkey" approach of abruptly adjusting short rates to a target, gradual adjustments allow the Federal Reserve to adjust short rates slowly and flexibly, while immediately affecting long term borrowing. Thus, gradualism provides the Federal Reserve with "greater influence over the long-term interest rates that most affect the economy ... and reduces risks to financial stability" (Bernanke, 2004). However, we demonstrate that categorical thinking can cause such monetary policies to have perverse effects. Categorical thinking causes long rates to overreact to expected increases in short rates, leading to greater volatility. Moreover, the increase in long rates is associated with a net increase in long-term borrowing–the opposite of what the Federal Reserve intended.

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 refinancing and extrapolative beliefs, whereas we focus on a categorical thinking error as the main driver of shifts in demand. Second, HLW examine the contemporaneous correlation of long and short rates, whereas 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 mechanism that can drive large belief errors and distortions in real behavior. We show that accurate beliefs about one variable (short rates) can lead to large forecast errors for a related variable (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 changes in short rates is related to the mistake of trading 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.[2]

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 the real behavior of borrowers and investors.

[2]While categorical thinking can lead investors to trade on stale news, the two biases are not identical. For example, investors who bet that prices will drift in the direction of cash flow news in the week after the cash flow news becomes public may be trading on stale news because they mistakenly believe that public news is still private or that the market has underreacted to public news. On the other hand, a categorical thinker would place stock prices and cash flow realizations into the same category, and expect prices to move when cash flows are realized.

1.1 Data on beliefs

1.1.1 Professional forecasts

We use data on interest rate expectations from 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, 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 the 10-year and 30-year Treasury yields ($y^{(10)}$ and $y^{(30)}$), and Aaa and Baa corporate bond rates (Aaa and Baa).

We use the HMR as the representative long rate in our main analysis due to its longer time series in the BCFF and its relevance to mortgage borrowers. As depicted in Figure A.4 in the Appendix, the realized values of various long rates are highly correlated. HMR has a correlation of at least 0.97 with the 10-year and 30-year Treasury yields ($y^{(10)}$ and $y^{(30)}$) and Aaa and Baa corporate bond rates (Aaa and Baa). 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.[3] 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 their associated levels of education. This feature allows us to keep track of the time series of each economist'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).

Realized values. We obtain data on 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.

[3]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.

1.1.2 Households beliefs

We obtain household housing expectations from the Fannie Mae National Housing Survey (NHS).[4] After the housing crisis of 2007-08, Fannie Mae launched the National Housing Survey in 2010 to generate new information about household attitudes, intentions, and financial conditions that pertain to housing and mortgage markets. It is the only large, national, monthly survey of households focused primarily on housing. NHS is a nationally representative telephone survey polling 1,000 households a month about owning and renting a home, home and rental price changes, the economy, household finances, and overall household 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.[5]

We obtain detailed individual-level responses to all questions at a monthly frequency from 2010 to 2021. 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.

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

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

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

during the quarter, respectively. We compute long term issuance by converting the year-to-date long-term debt issued (DLTISY) by the firm to a 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 at the share class (institutional and retail) level as: $flow_{i,t} = \frac{TNA_{i,t}}{TNA_{i,t-1}} - (1 + R_{i,t})$, 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 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.

The correlations in Table 2 offer a preview of our main results. We find that expected changes in the short rate are positively correlated with expected changes in the long rate (correlation = 0.40) and negatively correlated with realized changes in the long rate (correlation = -0.10).

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 federal 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 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 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 the

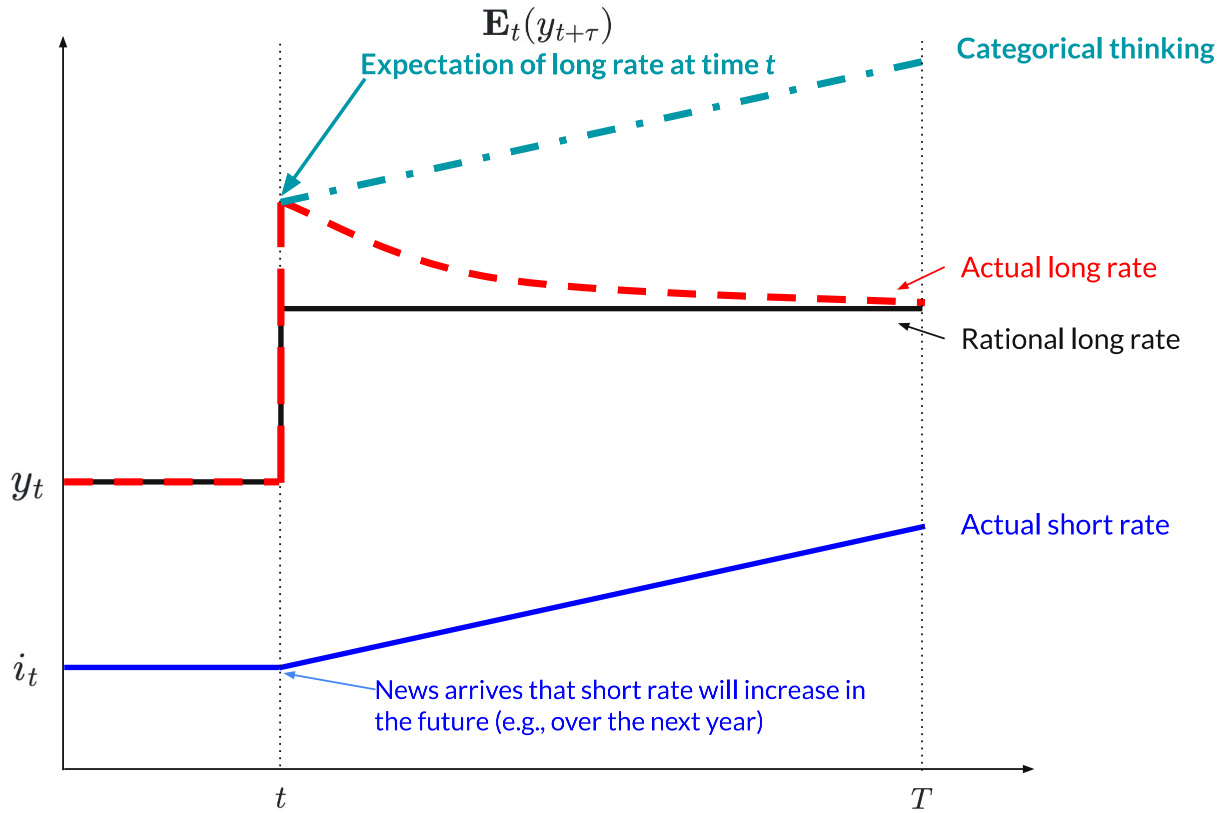

Figure 1 An illustration of categorical thinking about short and long rates

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 resemble a flat horizontal line. 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:

$$\underbrace{\mathbb{E}_t(y^{(n)}_{t+1Q}) - y^{(n)}_t}_{\text{Expected changes}} = \alpha_1 + \beta_1 \left[\mathbb{E}_t(i_{t+1Q}) - i_t\right] + \gamma X_t + \epsilon_t \tag{2}$$

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

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

We control for 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 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 in Equation (1) 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 in Equation (3) examines the relation between actual changes in the long rate and 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 realizations of the long rate.

The final specification in Equation (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.

$$\mathbb{E}_t(\overline{HMR}_{t+1Q}) - HMR_t = \alpha_1 + \beta_1 \left[\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t\right] + \gamma X_t + \epsilon_t \tag{6}$$

$$\overline{HMR}_{t+1Q} - HMR_t = \alpha_1 + \beta_2 \left[\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t\right] + \gamma X_t + \epsilon_{t+1Q} \tag{7}$$

$$\overline{HMR}_{t+1Q} - \mathbb{E}_t(\overline{HMR}_{t+1Q}) = \alpha_1 + \beta_3 \left[\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t\right] + \gamma X_t + \epsilon_{t+1Q} \tag{8}$$

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 percentage point increase in the short rate forecast leading to a 24 basis point increase in the long rate forecast based on the coefficient estimated with the full set of controls. These results reject the null of $\beta_1 < 0$, which matches the empirical relation between actual movements in the long rate and expected changes in the short rate. These results also reject the $1/n = 0.0083$ benchmark described in Section 2. The large estimate for β_1 indicates 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 because we now control for the term spread using the difference between HMR and FFR, which is more relevant to the pair of interest rates 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 no positive 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. Estimates of β_3 across all specifications are negative and significant at the 1% level; forecast errors in the long rate are negatively predicted 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 categorical thinking about interest rates.

3.1.1 Robustness and potential alternative explanations

In what follows, we present a series of robustness checks to our baseline analysis of professional forecasters and explore potential alternative explanations for the empirical patterns.

Delayed pricing of new information into the long rate. The long rate in month t may price public information about expected changes in short rates with a delay instead of instantaneously as implied by the yield identity in Equation (1). Of course, if that were the case, expected increases in short rates over the next quarter should predict increases in long rates over the next quarter, perhaps concentrated at the beginning of the quarter when the information about short rates impounds into long rates. However, columns (4)-(5) of Table 4, do not show such a pattern. Nonetheless, to further explore this possibility, we allow the HMR an additional month to adjust to the anticipated changes in the future short rate. Specifically, we re-estimate 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 5. The coefficient estimates are almost identical to those in the baseline regressions and significant at the 1% level, showing that the excessive co-movement between short and long rate expectations is not due to the slow adjustment of the current HMR_t to short rate news.

Delayed learning of public information by forecasters. A related concern is that individual forecasters may not be fully aware of all public information about expected movements in the short rate (as proxied by the consensus forecast in month t of expected movements in the short rate) when they make forecasts of changes in the long rate. We address this concern by moving our measure of expected changes in the long rate forward by one month and re-estimate the first equation using $\mathbb{E}_{t+1}(\overline{HMR}_{t+1Q}) - HMR_{t+1}$ as the dependent variable. This gives forecasters one month to react to the public information released in the consensus forecast of expected short rates released in the previous month. The results are reported in columns (4)-(6) of Table 5. Again, the coefficient estimates are close in magnitude to those in the baseline regressions and significant at the 1% level.

Categorical thinking versus overreaction to news or extrapolation. In this section, we present tests to distinguish a categorical thinking error from alternative behavioral explanations in which investors overreact to news or extrapolate from recent trends. Note that the purpose of these tests is not to reject the existence of other biases, but rather to rule in a large distortion in beliefs due to categorical thinking.

One key alternative explanation is overreaction to news. In seminal work by Coibion and Gorodnichenko (2015), forecast revisions, i.e., changes in forecasters' beliefs about the same quantity across different periods, are used as a measure of 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.

A related alternative explanation is that people extrapolate too much from recent trends, possibly because they overestimate the persistence of shocks. 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.[6] 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.

To see how these alternative behavioral explanations generate different empirical predictions from categorical thinking, consider a situation in which it is well-known in advance that the Federal Reserve will increase short-term interest rates at time t. There is no news released at time t for investors to overreact to. Likewise, there is no movement in short rates prior to time t for investors to extrapolate. Thus, overreaction and extrapolation would not 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 will rise together at time t, regardless of whether movements in the short rate are known in advance.

Further, suppose it is well-known in advance that the Federal Reserve will change short rates starting at time t in a particular way. For example, we may expect a linear increase or decrease in short rates, or a non-linear path leading to a J-shape, N-shape, or V-shape in the path of future short rates. Since no news is released at t and the short rate does not move prior to t, overreaction and extrapolation would not lead people to believe that the long rate will change at time t. In comparison, categorical thinkers believe that long and short rates move together in tandem. Thus, categorical thinkers will believe that the future path of long rates takes the same *shape* as the future path of short rates.

To distinguish categorical thinking from these other behavioral channels, we compare the predictive power of (a) expected changes in the short rate $\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$, (b) forecast revisions of the short rate over the past quarter $\mathbb{E}_t(\overline{FFR}_{t+1Q}) - \mathbb{E}_{t-1Q}(\overline{FFR}_{t+1Q})$, and (c) recent one-quarter realized change in the short rate $\mathbb{E}_t(\overline{FFR}_{t+1Q}) - \mathbb{E}_{t-1Q}(\overline{FFR}_{t+1Q})$. Categorical thinking, overreaction, and extrapolation predict high explanatory power for

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

measures (a), (b), and (c), respectively. In Appendix Figures A.5 and A.6, we plot the time series paths of these three variables. It is evident that these three variables exhibit only moderate correlations of approximately 0.45, suggesting that we may be able to tease out differences in their predictive power.

In Table 6, we re-estimate our baseline tests by running a horse race between expected changes in short rates and forecast revisions. When introduced separately in columns (1) and (2), both expected changes in short rates and forecast revisions positively predict expected changes in long rates, with the former exhibiting greater predictive power. When controlling for both variables in column (3), only expected changes in short rates predict expected changes in long rates. Controlling for forecast revisions, expected changes in short rates negatively and significantly predict a reversal in actual long rates (column 6) and negative forecast errors (column 9). Overall, the evidence supports an important role for categorical thinking. Controlling for the arrival of news and allowing for overreaction to news, if anything, strengthens the relation between the expected changes in short and long rates.

In Table 6, we re-estimate our baseline tests by running a horse race between expected changes in short rates and recent changes in short rates. We again find that, when introduced separately in columns (1) and (2), both expected changes in short rates and recent changes in short rates predict expected changes in long rates. When controlling for both variables in column (3), both significantly predict expected changes in long rates, with expected changes in short rates having a slightly stronger and more significant effect. Controlling for recent changes in short rates, expected changes in short rates negatively and significantly predict a reversal in actual long rates (column 6) and negative forecast errors (column 9). These results are again consistent with an important role for categorical thinking. Controlling for recent trends in short rates and allowing for extrapolation of recent trends does not diminish the relation between the expected changes in short and long rates.

We also show graphically that professional forecasters report similar shapes for the expected paths of short and long rates over the next four quarters. Figure 3 shows the actual path of the short rate (FFR) and long rate (HMR) as dashed blue and red lines, respectively. Each solid blue line that branches off from the dashed blue line represents the consensus forecast of the path of the short rate over the next four quarters. Likewise, each solid red line that branches off from the dashed red line represents consensus forecasts of the path of the long rate over the next four quarters.

It is apparent from the graph that forecasted paths for short and long rates over the next four quarters tend to have matching shapes. When the short rate is expected to increase or decrease in a linear, concave, or convex manner, or exhibit a V-shape or N-shape, the long rate is expected to move along a similarly-shaped path. Further, when the short rate was expected to rise in 2005 and again in the late 2010s under clear Federal Reserve guidance, we see that professional forecasters believed that long rates would similarly rise over the next four quarters, leading to large deviations between forecasted levels (solid red lines) and actual long rates (dotted red line).

We further show in Appendix Table A.7 that expected changes in the short rate in each of the next four quarters predict expected changes in the the long rate in the corresponding next four quarters. The coefficients are approximately stable across horizons. In each of the next four quarters, an expected 1 percentage point increase in the short rate is associated with an expected 0.35 percentage point increase in the long rate. These regression estimates complement the graphical evidence in Figure 3: professional forecasters mistakenly predict that future short and long rates will move in tandem over the next four quarters.

Influential dates. Bauer and Swanson (2023) find that certain FOMC dates appear more influential in shaping the relationship between monetary shocks 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 could 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).[7] 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 re-estimate 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 overshooting and the predictability of long rate forecast errors are even more pronounced in months containing these influential dates.

Economist-level forecasts. Bordalo et al. (2020) have highlighted the crucial differences between individual and consensus forecasts. Because 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 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 4. 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 re-estimate our baseline tests using these economist-level forecasts. The results are reported in Table A.5 in the Appendix. Controlling for economist fixed effects, all previously documented patterns using consensus forecasts apply to the individual forecasts. The β_1 estimates of around 0.40 are

[7] 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.

larger in magnitude and deviate even more from the rational benchmarks, suggesting that the excessive co-movement between short and long rate expectations is not due to the consensus forecasts.

3.1.2 Public 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 co-movement 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.

However, we have already shown in columns (4)-(6) Table 5 that the consensus short rate forecast from the *previous* month is significantly positively related to long rate forecasts made at the end of the next month. Because of the 1-month difference, the consensus short rate forecast is already sure to be public information. Forecasters, are unlikely to believe that the consensus short rate forecast from the previous month is private information not yet impounded into long rates.

3.2 Household beliefs

If professional forecasters think categorically about interest rates, it seems natural that households would as well. In this section, we explore whether there is evidence of a similar bias among households. 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 households 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 Federal Reserve will increase the federal funds rate over the next 12 months, that information should already be reflected in current mortgage rates. Therefore, households should not expect future mortgage rate increases during such times.

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

$$\begin{aligned}&\mathbb{1}(\text{Household Expected Change in Mortgage Rate} > 0)_{it} = \\ &\qquad \beta\mathbb{1}(\text{Analyst Expected Change in FF Rate} > 0)_t + \text{Controls} + \epsilon_{it} \quad (9)\end{aligned}$$

The results are shown in Table 8. As can be seen, we estimate β to be positive and statistically significant. The magnitudes in column (2) suggest that, on average, households 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 federal 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 households. 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 9, we re-estimate Table 8 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 federal funds rate to increase. In contrast, those with a graduate degree are 26 percentage points more likely to expect increases in mortgage rates.

Table 10 similarly explores heterogeneity by income. Interestingly, the results suggest that categorical thinking about interest rates becomes monotonically stronger with income as well. In particular, the results from column (2) suggest that those earning less than $10,000 annually are only 1.5 percentage points more likely to expect an increase in mortgage rates when an increase in the federal funds rate is expected, whereas those earning over $200,000 are 32.8 percentage more likely. 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 with these proxies for sophistication.

4 Supply and demand for long-term debt

Having shown direct evidence of categorical thinking about interest rates by both professional forecasters and households, our next objective is to explore how this bias may affect equilibrium market outcomes. In our context, we explore whether categorical thinking affects the supply and demand for long-term debt.

On the supply side, we hypothesize that if people suffer from categorical thinking about interest rates, expectations of rising short rates will drive borrowers (i.e., firms and households) to rush to lock in long-term debt as they anticipate that long-term rates will rise simultaneously with short-term rates. This will lead to an increase in the supply of long-term debt.

On the demand side, we hypothesize that expectations of rising short rates will lead investors to be reluctant to buy or hold long-term debt instruments, as they also anticipate that long-term rates will rise and prices will fall. This will lead to an decrease in the demand for long-term debt.

Such effects on the supply and demand for long-term debt could then amplify the response of long rates to news about short rates, as in (Hanson, Lucca, and Wright, 2021). In other words, these supply and demand effects could help explain why the long rate overreacts in Figure 1. In that case, categorical thinking about interest rates would help to 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).

To investigate whether categorical thinking about interest rates affects supply and demand for long-term debt in the way that we hypothesize, we estimate equations of the form:

$$Z_{i,t+1} = \alpha + \theta \times \left[\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t\right] + \gamma X_t + \epsilon_{i,t+1} \tag{10}$$

where Z_{t+1} is a measure of the supply or demand for long-term debt, $\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$ is the expected change in short-term interest rates based on the consensus forecast, and $X_{i,t}$ is a vector of control variables. We expect θ to be positive for supply-related outcomes and negative for demand-related outcomes.

Note, we forward the dependent variable Z_{t+1} by one period (depending on the frequency of the data). There is likely to be a lag in timing between when beliefs about long-term rates are formed and when subsequent borrowing or investing activities are realized. 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 are available at the quarterly frequency, so we 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 the 5-year Treasury yield and FFR. We double 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 11 to 14 report the results from the firm-level regressions with each table corresponding to one of our measures of long-term borrowing. 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 FE. Notably, the coefficients on the control variables go in the direction we would expect. In particular, firms issue less long-term debt when short-term rates are high, when the yield curve is steep, and when credit spreads are wide, consistent with known determinants of corporate debt issuance decisions.

Despite our controls, it remains possible that times when the short rate is expected to rise are also times when the economy is booming, and therefore firms may be borrowing as a result of the boom rather than categorical thinking about interest rates. However, we note that our results in Table 14 show that not only is borrowing increasing during these times but the *share* of borrowing that is long-term is increasing. This is more consistent with categorical thinking, as 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.

To put the economic magnitudes of the findings in perspective, a one percentage point expected increase in next-quarter's short rate is associated with a 3.5 percentage point increase in the likelihood of issuing long-term debt (mean likelihood of 38%), a 0.5 percentage point increase in the ratio of long-term borrowing to total assets (mean ratio of 3%), and a 5 percentage point 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 15, are consistent with the firm-level results, suggesting that the documented effect is widespread and not driven by a few smaller firms.

These results imply that the net impact of forward guidance from the Federal Reserve that it intends to gradually increase short rates is likely to be an increase in long term firm borrowing (at least in the short run), instead of the intended reduction in borrowing. Empirically, when news arrives that the short rate will increase by an additional 1 percent, the long rate typically rises by less than 1 percent. The direct effect of this increase in the long rate is a reduction in long term borrowing. This effect is captured by the negative coefficient on the term spread. In Tables 11-tab:firm4, this coefficient is approximately half as large in absolute magnitude as the positive coefficient on the expected change in the short rate. These estimates indicate that the rush to borrow before long rates increase further dominates the direct dampening effect of higher long rates. The net effect of forward guidance of a gradual increase in the short rate is predicted to be an increase in long term borrowing in the short run.

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 investment projects, further underscoring the influence of categorical thinking on their borrowing decisions.

We also explore whether firms may issue long term debt to hedge against uncertainty in interest rate policy that may be correlated with expected changes in short rate. In Appendix Table A.11, we control for uncertainty using forecast dispersion across professional forecasters and the VIX. Controlling for these proxies of interest rate uncertainty does not substantially alter our estimated relationship between expected changes in the short rate and long term corporate issuance.

4.2 Supply: Household mortgage decisions

Our second analysis on the supply side explores 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 results, reported in 16, indicate that expectations of rising short rates are associated with a large increase in the volume of mortgages. We find a significantly stronger effect for jumbo mortgages (larger loans typically exceeding $750K in 2024 dollars) compared to conventional mortgages. These patterns for the household supply of long term debt are consistent with our earlier findings related to sophistication. Wealthier households associated with jumbo mortgages are more likely to have the flexibility to engage in market timing and to be aware of publicly available information about the path of short rates.

Echoing our earlier analysis of firm borrowing, these results imply that the net impact of forward guidance from the Federal Reserve that it intends to gradually increase short rates is likely to be an increase in long term household borrowing (at least in the short run), instead of the intended reduction in borrowing. Empirically, when news arrives that the short rate will increase by an additional 1 percent, the long rate typically rises by less than 1 percent. The direct effect of this increase in the long rate is a reduction in mortgage issuance. This effect is captured by the negative coefficient on the term spread. In Tables 16, this coefficient is approximately half as large in absolute magnitude as the positive coefficient on the expected change in the short rate. These estimates indicate that the rush to lock in mortgage rates before long rates increase further dominates the direct dampening effect of higher long rates. The net effect of forward guidance of a gradual increase in the short rate is predicted to be an increase in mortgage borrowing in the short run.

4.3 Demand: Bond mutual fund investment

In the final segment of our analysis, we turn to the demand for long-term debt, specifically focusing on mutual fund investors' allocation decisions in long-term bond funds.

Our dependent variables are the monthly mutual fund flows at the share class level, expressed both in billion of dollars ("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 shown in Table 17, 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. Additionally, we find similar substantial outflows for bond funds targeted at retail and institutional investors. Overall, the evidence across multiple settings indicates that categorical thinking in beliefs translates to distortions in the supply and demand for long term debt. In times when short rates are expected to rise, categorical thinking leads the supply of long-term debt to increase and the demand to decrease. This interplay contributes to the excess volatility and subsequent reversals observed in long-term interest rates.

5 Conclusion

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 households 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

This table presents summary statistics for key time-series and firm-level variables as detailed in Section 1. It includes the number of observations (n), mean, standard deviations (sd), key percentiles (p5, p25, median, p75, p95), and first-order autocorrelation (AR(1)) for each variable. Interest rate and macroeconomic variables, along with their forecasts, are reported on a monthly basis in percentage points. Corporate variables are reported on a quarterly basis.

	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-level Issuance									
$\mathbb{1}$(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
Aggregate-level Issuance									
Log LT Issues$_t$	155	12.91	1.42	10.75	11.85	13.13	13.96	14.88	0.88
LT Issues$_t$/AT$_{t-1}$	155	0.02	0.01	0.01	0.01	0.01	0.02	0.04	0.68
LT Issues$_t$/Total Debt$_{t-1}$	155	0.07	0.04	0.03	0.04	0.06	0.07	0.17	0.77
LT Share$_t$	155	0.64	0.13	0.46	0.57	0.64	0.73	0.83	0.71

Table 2 Correlations between main time series variables

This table presents the correlation matrix of key time-series variables. The definitions of the variables are detailed in Section 1. The variables are numbered. Correlations of ones are omitted.

		(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

This table presents OLS regressions of future long rate changes on the expected short rate changes. The dependent variables are the differences between the next quarter's daily average long rates and current long rates for 10-year and 30-year Treasury yields ($y^{(10)}$ and $y^{(30)}$), Aaa and Baa corporate bond yields (Aaa and Baa), and the 30-year home mortgage rate (HMR). The main independent variable is the expected changes in the federal funds rate ($\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$) based on the consensus forecast. The regressions include a full set of control variables, including the current Federal Funds Rate (FFR), the term spread ($y_t^{(10)} - FFR_t$), inflation rate (π_t), Baa credit spread and Baa credit term spread. Newey-West standard errors with the automatic bandwidth selection following Newey and West (1994) are reported in parentheses. The constant term is omitted for brevity. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	$\bar{y}^{(10)}_{t+1Q} - y^{(10)}_t$ (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)
$y_t^{(10)} - FFR_t$	-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)
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

This table presents OLS regression coefficients from equations (6)-(8). The dependent variables are expected one-quarter changes in home mortgage rate ($\mathbb{E}_t(\overline{HMR}_{t+1Q}) - HMR_t$), the actual one-quarter changes in home mortgage rate ($\overline{HMR}_{t+1Q} - HMR_t$), an and the forecast error of the one-quarter-ahead home mortgage rate, respectively. The main independent variable is the expected changes in the federal funds rate ($\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$) based on the consensus forecast. The regressions include the following control variables: the current Federal Funds Rate (FFR), the term spread ($HMR_t - FFR_t$), inflation rate (π_t), Baa credit spread and Baa credit term spread. Newey-West standard errors with the automatic bandwidth selection following Newey and West (1994) are reported in parentheses. The constant term is omitted for brevity. The sample period is from 1983:04 to 2021:12. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	$\mathbb{E}_t(\overline{HMR}_{t+1Q}) - HMR_t$			$\overline{HMR}_{t+1Q} - HMR_t$			$\overline{HMR}_{t+1Q} - \mathbb{E}_t(\overline{HMR}_{t+1Q})$		
	(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 timing

This table presents OLS regression coefficients from equation (6) with alternative dependent variables allowing for delays in information incorporation. The dependent variable for columns (1)-(3) is the difference between the expectation of home mortgage rate at month t and the actual rate at month $t+1$ ($\mathbb{E}_t(\overline{HMR}_{t+1Q}) - HMR_{t+1}$). The dependent variable for columns (4)-(6) is expected one-quarter changes in home mortgage rate from month $t+1$ ($\mathbb{E}_{t+1}(\overline{HMR}_{t+1Q}) - HMR_{t+1}$). The main independent variable is the expected changes in the federal funds rate ($\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$) based on the consensus forecast. The regressions include the following control variables: the current Federal Funds Rate (FFR), the term spread ($HMR_t - FFR_t$), inflation rate (π_t), Baa credit spread and Baa credit term spread. Newey-West standard errors with the automatic bandwidth selection following Newey and West (1994) are reported in parentheses. The constant term is omitted for brevity. The sample period is from 1983:04 to 2021:12. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	$\mathbb{E}_t(\overline{HMR}_{t+1Q}) - HMR_{t+1}$			$\mathbb{E}_{t+1}(\overline{HMR}_{t+1Q}) - HMR_{t+1}$		
	(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)
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: Expected changes in the short rate versus forecast revisions

This table presents OLS regression coefficients from equations (6)-(8), controlling for forecast revision of the short rate. The dependent variables are expected one-quarter changes in home mortgage rate ($\mathbb{E}_t(\overline{HMR}_{t+1Q}) - HMR_t$), the actual one-quarter changes in home mortgage rate ($\overline{HMR}_{t+1Q} - HMR_t$), an and the forecast error of the one-quarter-ahead home mortgage rate, respectively. The main independent variables are the expected changes in the federal funds rate ($\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$) based on the consensus forecast and the 3-month revision in the forecast of the federal funds rates ($\mathbb{E}_t(\overline{FFR}_{t+1Q}) - \mathbb{E}_{t-1}(\overline{FFR}_{t+1Q})$). The regressions include the following control variables: the current Federal Funds Rate (FFR), the term spread ($HMR_t - FFR_t$), inflation rate (π_t), Baa credit spread and Baa credit term spread. Newey-West standard errors with the automatic bandwidth selection following Newey and West (1994) are reported in parentheses. The constant term is omitted for brevity. The sample period is from 1983:04 to 2021:12. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	$\mathbb{E}_t(\overline{HMR}_{t+1Q}) - HMR_t$			$\overline{HMR}_{t+1Q} - HMR_t$			$\overline{HMR}_{t+1Q} - \mathbb{E}_t(\overline{HMR}_{t+1Q})$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$	0.24***		0.24***	-0.19		-0.31**	-0.43***		-0.55***
	(0.05)		(0.05)	(0.13)		(0.14)	(0.12)		(0.13)
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - \mathbb{E}_{t-1Q}(\overline{FFR}_{t+1Q})$		0.06*	0.00		0.07	0.16**		0.01	0.15**
		(0.03)	(0.03)		(0.06)	(0.07)		(0.07)	(0.07)
FFR_t	-0.03***	-0.03***	-0.03***	-0.01	-0.01	-0.01	0.02	0.03	0.02
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$HMR_t - FFR_t$	-0.03***	-0.02	-0.03***	-0.07*	-0.08**	-0.06*	-0.03	-0.07*	-0.02
	(0.01)	(0.01)	(0.01)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
π_t	0.00	-0.01	0.00	-0.02	-0.01	-0.02	-0.02	0.00	-0.02
	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Baa credit spread$_t$	-0.10	-0.12**	-0.10	-0.32**	-0.27*	-0.30**	-0.22*	-0.15	-0.20*
	(0.06)	(0.06)	(0.06)	(0.14)	(0.14)	(0.13)	(0.13)	(0.14)	(0.12)
Baa credit term spread$_t$	0.05	0.05	0.05	0.28*	0.29*	0.29*	0.23	0.23	0.23
	(0.06)	(0.06)	(0.06)	(0.16)	(0.16)	(0.15)	(0.16)	(0.17)	(0.14)
R^2	0.354	0.284	0.354	0.079	0.073	0.100	0.096	0.041	0.114
Observations	465	465	465	465	465	465	465	465	465

Table 7 Categorical thinking in consensus forecasts: Expected changes versus recent changes in the short rate

This table presents OLS regression coefficients from equations (6)-(8), controlling for forecast recent changes in the short rate. The dependent variables are expected one-quarter changes in home mortgage rate ($\mathbb{E}_t(\overline{HMR}_{t+1Q}) - HMR_t$), the actual one-quarter changes in home mortgage rate ($\overline{HMR}_{t+1Q} - HMR_t$), an and the forecast error of the one-quarter-ahead home mortgage rate, respectively. The main independent variables are the expected changes in the federal funds rate ($\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$) based on the consensus forecast and current 3-month changes in the federal funds rate ($FFR_t - FFR_{t-1Q}$). The regressions include the following control variables: the current Federal Funds Rate (FFR), the term spread ($HMR_t - FFR_t$), inflation rate (π_t), Baa credit spread and Baa credit term spread. Newey-West standard errors with the automatic bandwidth selection following Newey and West (1994) are reported in parentheses. The constant term is omitted for brevity. The sample period is from 1983:04 to 2021:12. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	$\mathbb{E}_t(\overline{HMR}_{t+1Q}) - HMR_t$			$\overline{HMR}_{t+1Q} - HMR_t$			$\overline{HMR}_{t+1Q} - \mathbb{E}_t(\overline{HMR}_{t+1Q})$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$	0.24***		0.16***	-0.19		-0.24*	-0.43***		-0.39***
	(0.05)		(0.06)	(0.13)		(0.14)	(0.12)		(0.14)
$FFR_t - FFR_{t-1Q}$		0.14***	0.10***		0.01	0.07		-0.14*	-0.04
		(0.04)	(0.04)		(0.06)	(0.07)		(0.07)	(0.07)
FFR_t	-0.03***	-0.03***	-0.03***	-0.01	-0.01	-0.01	0.02	0.03	0.02
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$HMR_t - FFR_t$	-0.03***	-0.01	-0.03**	-0.07*	-0.08**	-0.06*	-0.03	-0.07*	-0.04
	(0.01)	(0.01)	(0.01)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
π_t	0.00	0.00	0.00	-0.02	-0.01	-0.02	-0.02	-0.01	-0.02
	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Baa credit spread$_t$	-0.10	-0.10*	-0.08	-0.32**	-0.28**	-0.31**	-0.22*	-0.19	-0.23*
	(0.06)	(0.06)	(0.05)	(0.14)	(0.14)	(0.14)	(0.13)	(0.14)	(0.13)
Baa credit term spread$_t$	0.05	0.06	0.05	0.28*	0.28*	0.29*	0.23	0.23	0.23
	(0.06)	(0.06)	(0.06)	(0.16)	(0.16)	(0.16)	(0.16)	(0.18)	(0.16)
R^2	0.354	0.367	0.397	0.079	0.067	0.083	0.096	0.058	0.097
Observations	465	466	465	465	466	465	465	466	465

Table 8 Categorical thinking in household beliefs: Baseline results

This table presents OLS regression of expected long rate changes on the expected short rate changes in household beliefs. The dependent variable is an indicator variable that equals one if the household expects an increase in mortgage rates over the next year ($\mathbb{1}$(Consumer Expected Change in Mortgage Rate > 0)), based on Fannie Mae National Housing Survey data. The main independent variable is an indicator variable that equals one if the professional economists expect an increase in the federal funds rate over the next year ($\mathbb{1}$(Analyst Expected Change in FF Rate > 0)), based on BCFF consensus forecasts. Control variables include the current Federal Funds Rate (FFR) and the current home mortgage rate (HMR). The constant term is omitted for brevity. The sample period is from 2010:01 to 2021:12. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	$\mathbb{1}$(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 9 Categorical thinking in household beliefs: Heterogeneity by education

This table presents OLS regression of expected long rate changes on the expected short rate changes in household beliefs, exploring heterogeneity by education. The dependent variable is an indicator variable that equals one if the household expects an increase in mortgage rates over the next year ($\mathbb{1}$(Consumer Expected Change in Mortgage Rate $>$ 0)), based on Fannie Mae National Housing Survey data. The main independent variable is an indicator variable that equals one if the professional economists expect an increase in the federal funds rate over the next year ($\mathbb{1}$(Analyst Expected Change in FF Rate $>$ 0)), based on BCFF consensus forecasts. We include interaction terms between the main independent variable and education level indicator variables, including less than high school (omitted), High School, Some College, Technical School, College, and Graduate. Control variables include the current Federal Funds Rate (FFR) and the current home mortgage rate (HMR). The constant term is omitted for brevity. The sample period is from 2010:01 to 2021:12. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	$\mathbb{1}$(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) $\times$ High School	0.0783***	0.0774***
	(0.0225)	(0.0224)
$\mathbb{1}$(Analyst Expected Change in FF Rate $>$ 0) $\times$ Some College	0.131***	0.131***
	(0.0183)	(0.0183)
$\mathbb{1}$(Analyst Expected Change in FF Rate $>$ 0) $\times$ Technical School	0.133***	0.130***
	(0.0221)	(0.0219)
$\mathbb{1}$(Analyst Expected Change in FF Rate $>$ 0) $\times$ College	0.176***	0.175***
	(0.0227)	(0.0225)
$\mathbb{1}$(Analyst Expected Change in FF Rate $>$ 0) $\times$ 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 10 Categorical thinking in household beliefs: Heterogeneity by income

This table presents OLS regression of expected long rate changes on the expected short rate changes in household beliefs, exploring heterogeneity by income. The dependent variable is an indicator variable that equals one if the household expects an increase in mortgage rates over the next year ($\mathbb{1}$(Consumer Expected Change in Mortgage Rate $>$ 0)), based on Fannie Mae National Housing Survey data. The main independent variable is an indicator variable that equals one if the professional economists expect an increase in the federal funds rate over the next year ($\mathbb{1}$(Analyst Expected Change in FF Rate $>$ 0)), based on BCFF consensus forecasts. We include interaction terms between the main independent variable and income level indicator variables, including less than \$10,000 (omitted), \$10,000-\$14,999, \$15,000-\$24,999, \$25,000-\$34,999, \$35,000-\$49,999, \$50,000-\$74,999, \$75,000-\$99,999, \$100,000-\$149,999, \$150,000-\$199,999, and over \$200,000. Control variables include the current Federal Funds Rate (FFR) and the current home mortgage rate (HMR). The constant term is omitted for brevity. The sample period is from 2010:01 to 2021:12. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	$\mathbb{1}$(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) $\times$ Income \$10,000-\$14,999	0.0920***	0.0947***
	(0.0311)	(0.0307)
$\mathbb{1}$(Analyst Expected Change in FF Rate $>$ 0) $\times$ Income \$15,000-\$24,999	0.101***	0.102***
	(0.0291)	(0.0283)
$\mathbb{1}$(Analyst Expected Change in FF Rate $>$ 0) $\times$ Income \$25,000-\$34,999	0.151***	0.153***
	(0.0270)	(0.0268)
$\mathbb{1}$(Analyst Expected Change in FF Rate $>$ 0) $\times$ Income \$35,000-\$49,999	0.120***	0.122***
	(0.0325)	(0.0320)
$\mathbb{1}$(Analyst Expected Change in FF Rate $>$ 0) $\times$ Income \$50,000-\$74,999	0.189***	0.193***
	(0.0232)	(0.0224)
$\mathbb{1}$(Analyst Expected Change in FF Rate $>$ 0) $\times$ Income \$75,000-\$99,999	0.217***	0.220***
	(0.0344)	(0.0340)
$\mathbb{1}$(Analyst Expected Change in FF Rate $>$ 0) $\times$ Income \$100,000-\$149,999	0.248***	0.251***
	(0.0300)	(0.0292)
$\mathbb{1}$(Analyst Expected Change in FF Rate $>$ 0) $\times$ Income \$150,000-\$199,999	0.257***	0.261***
	(0.0340)	(0.0334)
$\mathbb{1}$(Analyst Expected Change in FF Rate $>$ 0) $\times$ 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 11 Firm long-term issuance: Likelihood of issuance

This table presents OLS regression of firms' long-term debt issuance on the expected short rate changes. The dependent variable is an indicator variable that equals one if a firm issues a long-term debt in the subsequent quarter ($\mathbb{1}(\text{LT Issues}_{t+1} > 0)$), constructed from the Compustat quarterly data. The main independent variables are the expected changes in the federal funds rate ($\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$), based on the consensus forecast. Control variables include the current Federal Funds Rate (FFR), the term spread ($y_t^{(5)} - FFR_t$), inflation rate (π_t), Baa credit spread and Baa credit term spread. Standard errors are double clustered by firm and year-quarter. Firm fixed effects are included in columns (3) and (4). The constant term is omitted for brevity. The sample period is from 1983:Q2 to 2021:Q4. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	$\mathbb{1}(\text{LT Issues}_{t+1} > 0)$			
	(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)
R^2	0.001	0.001	0.358	0.359
Observations	750,698	750,698	750,698	750,698
Firm FE			✓	✓

Table 12 Firm long-term issuance: Issuance scaled by assets

This table presents OLS regression of firms' long-term debt issuance on the expected short rate changes. The dependent variable is the long-term debt issue in the subsequent quarter normalized by total assets in the current quarter ($\frac{\text{LT Issues}_{t+1}}{\text{AT}_t}$), constructed from the Compustat quarterly data. The main independent variables are the expected changes in the federal funds rate ($\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$), based on the consensus forecast. Control variables include the current Federal Funds Rate (FFR), the term spread ($y_t^{(5)} - FFR_t$), inflation rate (π_t), Baa credit spread and Baa credit term spread. Standard errors are double clustered by firm and year-quarter. Firm fixed effects are included in columns (3) and (4). The constant term is omitted for brevity. The sample period is from 1983:Q2 to 2021:Q4. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	$\frac{\text{LT Issues}_{t+1}}{\text{AT}_t}$			
	(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)
R^2	0.001	0.003	0.221	0.221
Observations	746,807	746,807	746,807	746,807
Firm FE			✓	✓

Table 13 Firm long-term issuance: Issuance scaled by total debt

This table presents OLS regression of firms' long-term debt issuance on the expected short rate changes. The dependent variable is the long-term debt issue in the subsequent quarter normalized by total debt in the current quarter ($\frac{\text{LT Issues}_{t+1}}{\text{Total Debt}_t}$), constructed from the Compustat quarterly data. The main independent variables are the expected changes in the federal funds rate ($\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$), based on the consensus forecast. Control variables include the current Federal Funds Rate (FFR), the term spread ($y_t^{(5)} - FFR_t$), inflation rate (π_t), Baa credit spread and Baa credit term spread. Standard errors are double clustered by firm and year-quarter. Firm fixed effects are included in columns (3) and (4). The constant term is omitted for brevity. The sample period is from 1983:Q2 to 2021:Q4. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	$\frac{\text{LT issues}_{t+1}}{\text{Total debt}_t}$			
	(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)
R^2	0.001	0.002	0.153	0.153
Observations	588,700	588,700	588,700	588,700
Firm FE			✓	✓

Table 14 Firm long-term issuance: Long-term issuance share

This table presents OLS regression of firms' long-term debt issuance on the expected short rate changes. The dependent variable is the long-term share of total new debt issues in the subsequent quarter (LT Share$_{t+1}$), constructed from the Compustat quarterly data. The main independent variables are the expected changes in the federal funds rate ($\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$), based on the consensus forecast. Control variables include the current Federal Funds Rate (FFR), the term spread ($y_t^{(5)} - FFR_t$), inflation rate (π_t), Baa credit spread and Baa credit term spread. Standard errors are double clustered by firm and year-quarter. Firm fixed effects are included in columns (3) and (4). The constant term is omitted for brevity. The sample period is from 1983:Q2 to 2021:Q4. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	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)
R^2	0.022	0.022	0.483	0.483
Observations	382,391	382,391	382,391	382,391
Firm FE			✓	✓

Table 15 Firm long-term issuance: Aggregate evidence

This table presents OLS regression of aggregate long-term debt issuance on the expected short rate changes, using aggregated quarterly Compustat data. The dependent variables are the logarithm of the total long-term debt issues ($\log(\text{LT Issues}_{t+1})$) in the subsequent quarter, total long-term debt issue in the subsequent quarter normalized by total assets in the current quarter ($\frac{\text{LT Issues}_{t+1}}{\text{AT}_t}$), total long-term debt issue in the subsequent quarter normalized by total debt in the current quarter ($\frac{\text{LT Issues}_{t+1}}{\text{Total Debt}_t}$), and long term share of total new debt issues in the subsequent quarter (LT Share_{t+1}). The main independent variables are the expected changes in the federal funds rate ($\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$), based on the consensus forecast. Control variables include the current Federal Funds Rate (FFR), the term spread ($y_t^{(5)} - FFR_t$), inflation rate (π_t), Baa credit spread and Baa credit term spread. Newey-West standard errors with the automatic bandwidth selection following Newey and West (1994) are reported in parentheses. The constant term is omitted for brevity. The sample period is from 1983:Q2 to 2021:Q4. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	$\text{Log(LT Issues)}_{t+1}$	$\frac{\text{LT Issues}_{t+1}}{\text{AT}_t}$	$\frac{\text{LT Issues}_{t+1}}{\text{Total Debt}_t}$	LT Share_{t+1}
	(1)	(2)	(3)	(4)
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$	1.1027***	0.0075***	0.0332***	0.1012***
	(0.2271)	(0.0026)	(0.0125)	(0.0338)
FFR_t	-0.4202***	-0.0011***	-0.0055***	-0.0273***
	(0.0451)	(0.0002)	(0.0011)	(0.0077)
$y_t^{(5)} - FFR_t$	-0.6547***	-0.0037***	-0.0166***	-0.0482***
	(0.0801)	(0.0011)	(0.0052)	(0.0119)
π_t	0.0361	-0.0002	0.0000	-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)	(0.0615)
Baa credit term spread_t	-0.2569	-0.0006	0.0062	-0.0501
	(0.3412)	(0.0028)	(0.0127)	(0.0642)
R^2	0.821	0.306	0.359	0.486
Observations	155	155	155	155
Dep. Var. Mean	12.91	0.02	0.07	0.64

Table 16 Aggregate mortgage issuance: Home purchase loans

This table presents OLS regression of aggregate home purchase mortgage loan origination on the expected short rate changes, using the quarterly FHFA NMDB Aggregate Statistics. The dependent variable is the logarithm of the total dollar volume of new mortgages originated in the subsequent quarter (Log Total Loan$_{t+1}$). The main independent variables are the expected changes in the federal funds rate ($\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$), based on the consensus forecast. We include an interaction term between the expected changes in the federal funds rate and a binary indicator for jumbo mortgages, which represent larger loans typically exceeding \$750K. Control variables include the current Federal Funds Rate (FFR), the term spread ($HMR_t - FFR_t$), inflation rate (π_t), Baa credit spread and Baa credit term spread. Standard errors are clustered by loan type, which includes conventional and jumbo loans. The constant term is omitted for brevity. The sample period is from 1983:Q2 to 2021:Q4. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	Log Total Loan$_{t+1}$	
	(1)	(2)
$\mathbb{E}_t(FFR_{t+1}) - FFR_t$	0.4228**	0.8025
	(0.0193)	(0.1775)
Jumbo	-1.4207***	-1.4207***
	(0.0000)	(0.0000)
FFR_{t-1}	-0.0337	-0.0016
	(0.0222)	(0.0415)
$HMR_t - FFR_{t-1}$	-0.2149*	-0.1848*
	(0.0254)	(0.0153)
$\mathbb{E}_t(FFR_{t+1}) - FFR_t \times$ Jumbo	0.3941***	0.3941***
	(0.0000)	(0.0000)
π_t		0.0552**
		(0.0019)
Baa credit spread$_t$		-0.9530
		(0.3808)
Baa credit term spread$_t$		0.6925
		(0.2875)
R^2	0.690	0.786
Observations	192	192

Table 17 Long-term bond mutual fund flows

This table presents OLS regression of long-term bond mutual fund flows on the expected short rate changes, using the monthly data from the CRSP Mutual Fund Database. The dependent variables are share-class level mutual fund flows in the subsequent month, scaled by the lagged total net asset of the fund (Fund flows, %) and in billion-dollar terms (Fund flows, \$B). The main independent variables are the expected changes in the federal funds rate ($\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$), based on the consensus forecast. We define long-term bond funds as those with a Lipper objective code in the following categories: IUG, GUS, GUT, A, BBB, and IID. Control variables include the current Federal Funds Rate (FFR), the term spread ($y_t^{(5)} - FFR_t$), inflation rate (π_t), Baa credit spread and Baa credit term spread. Columns (1) and (2) use the full sample, columns (3) and (4) restrict the sample to institution share classes, and columns (5) and (6) restrict the sample to retail share classes. Standard errors are clustered by fund and date. Mutual fund (share class) fixed effects are included in all columns. The constant term is omitted for brevity. The sample period is from 1997:01 to 2021:12. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Share class:	Full sample		Institutional		Retail	
	Fund flows, %	Fund flows, \$B	Fund flows, %	Fund flows, \$B	Fund flows, %	Fund flows, \$B
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$	-3.0420***	-5.1075**	-2.6981***	-6.9854*	-3.2653***	-3.5672***
	(0.6518)	(2.0944)	(0.5547)	(4.0877)	(0.8509)	(1.0036)
FFR_t	1.0389***	0.5374**	0.9179***	0.0374	1.1191***	0.8468***
	(0.0838)	(0.2234)	(0.0903)	(0.3838)	(0.1128)	(0.2264)
$y_t^{(5)} - FFR_t$	1.4167***	0.1375	1.5446***	-0.8346	1.3346***	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$_t$	1.0689**	-0.4366	1.0438**	-1.2920	1.1267*	0.5334
	(0.4845)	(0.7271)	(0.4544)	(1.1874)	(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)	(1.2525)	(0.7481)	(0.7312)
R^2	0.064	0.162	0.054	0.170	0.077	0.145
Observations	324,739	324,739	147,129	147,129	177,610	177,610
Fund FE	✓	✓	✓	✓	✓	✓

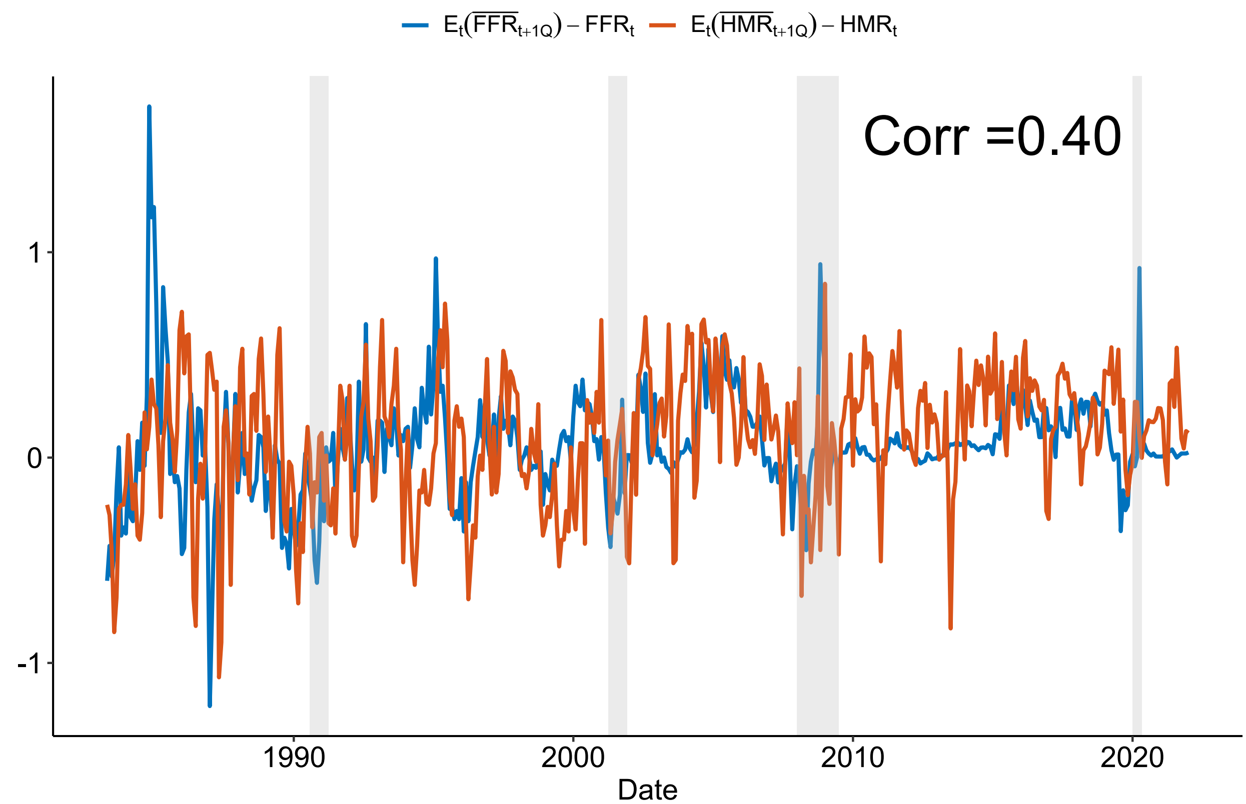


Figure 2 Time series of 1-quarter expected changes of FFR and HMR

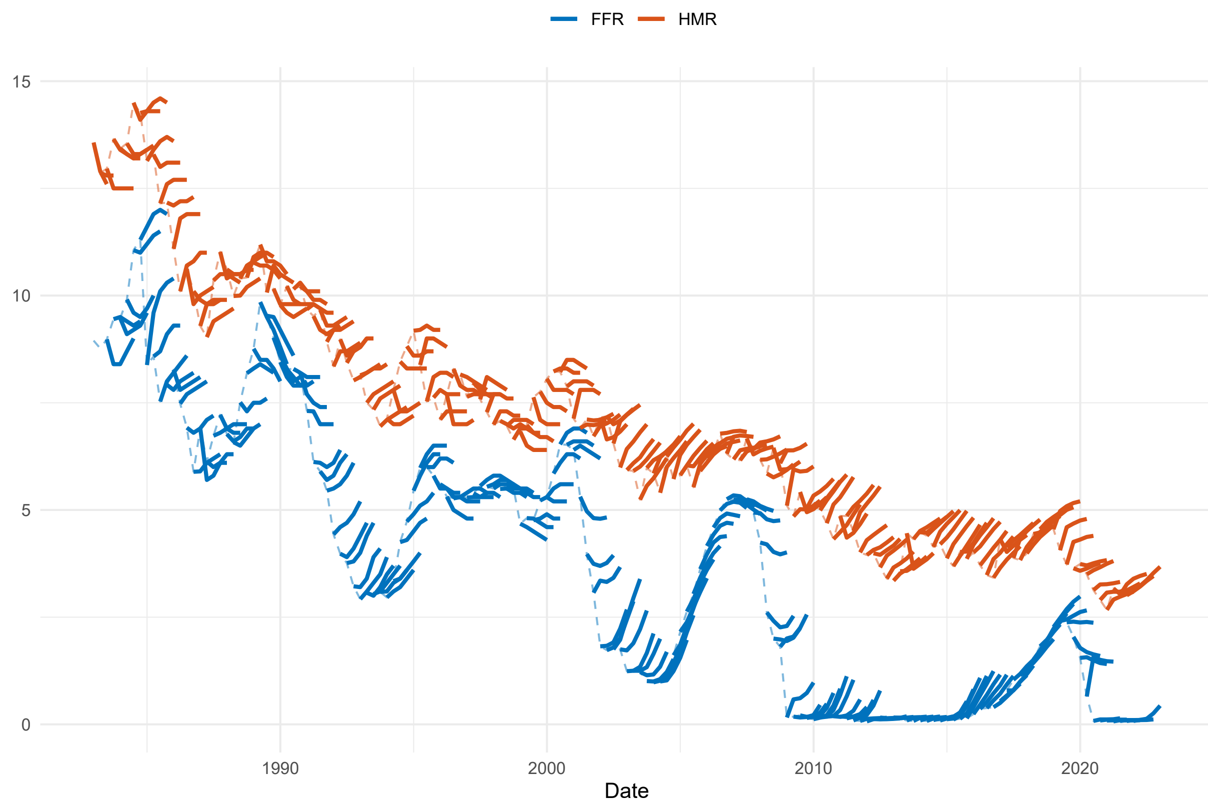
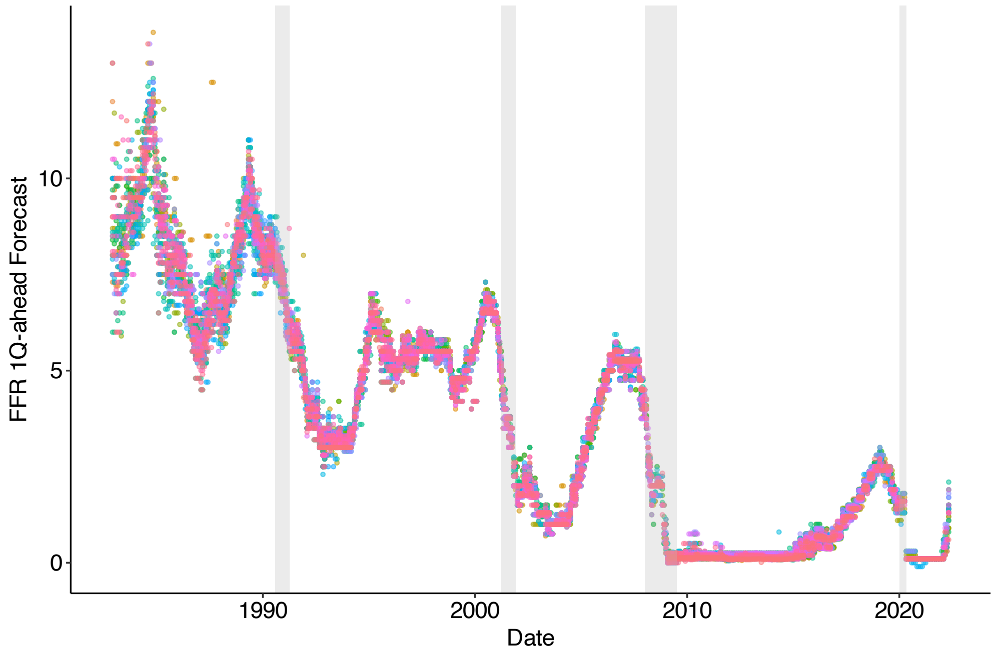
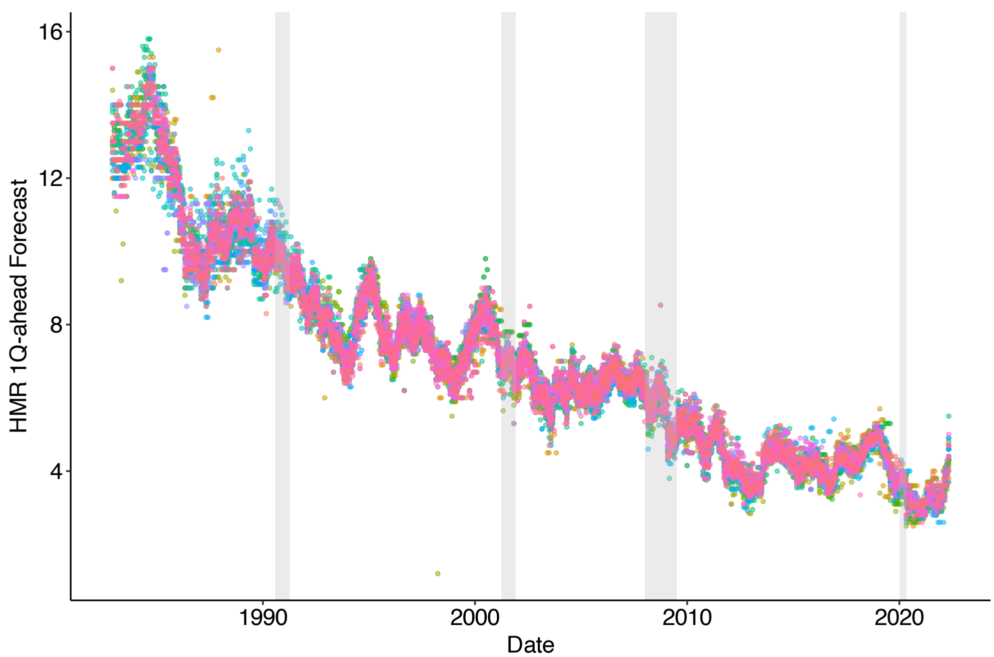


Figure 3 Term structure of FFR and HMR expectations across forecast horizons



A. FFR Forecasts



B. HMR Forecasts

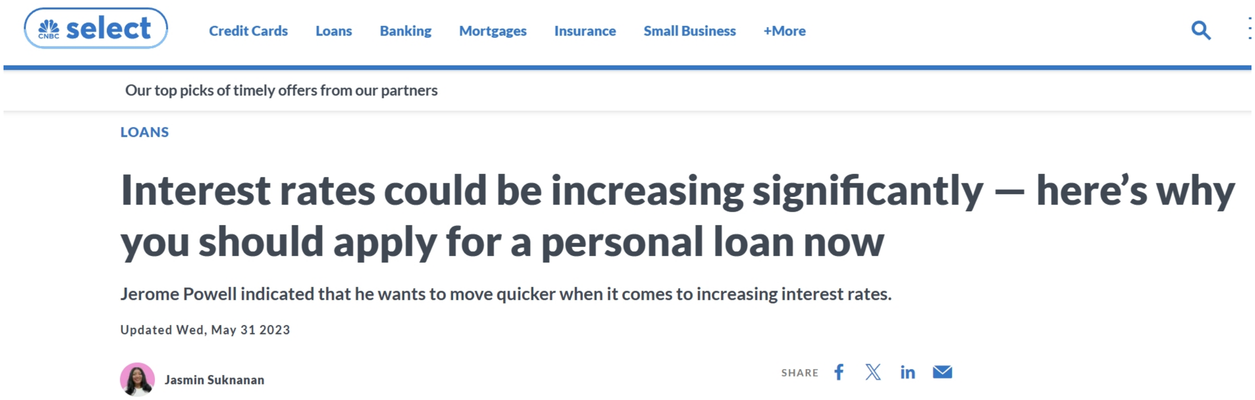
Figure 4 Economist-level forecasts of 1-quarter-ahead FFR and HMR

Online Appendix for

Categorical Thinking about Interest Rates

Kelly Shue Richard Townsend Chen Wang

A Additional Tables and Figures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Interest rates could be increasing significantly — here's why you should apply for a personal loan now

Jerome Powell indicated that he wants to move quicker when it comes to increasing interest rates.

Updated Wed, May 31 2023

Jasmin Suknanan

SHARE

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

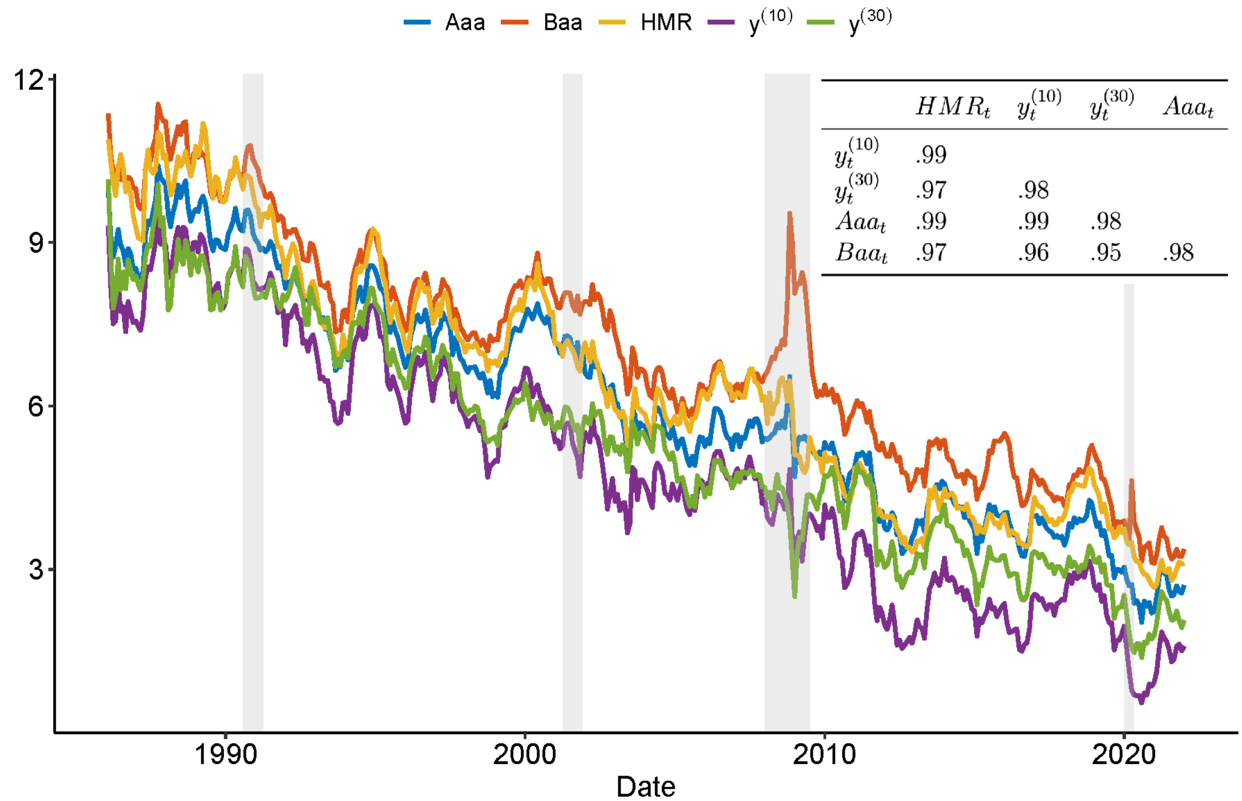
US Quarterly Forecasts
October 2019

	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.



	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.4 Various realized long rates

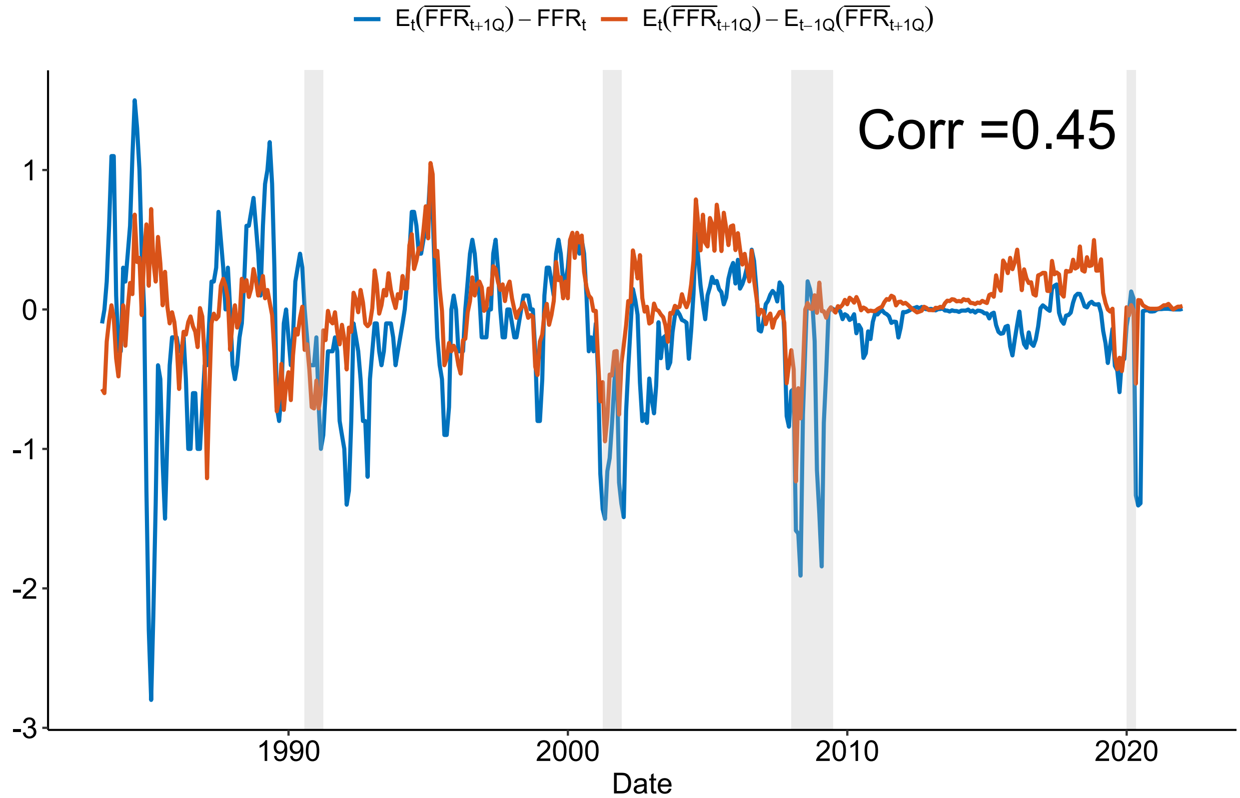


Figure A.5 Time series of forecasted changes and 3-month forecast revisions of the short rate

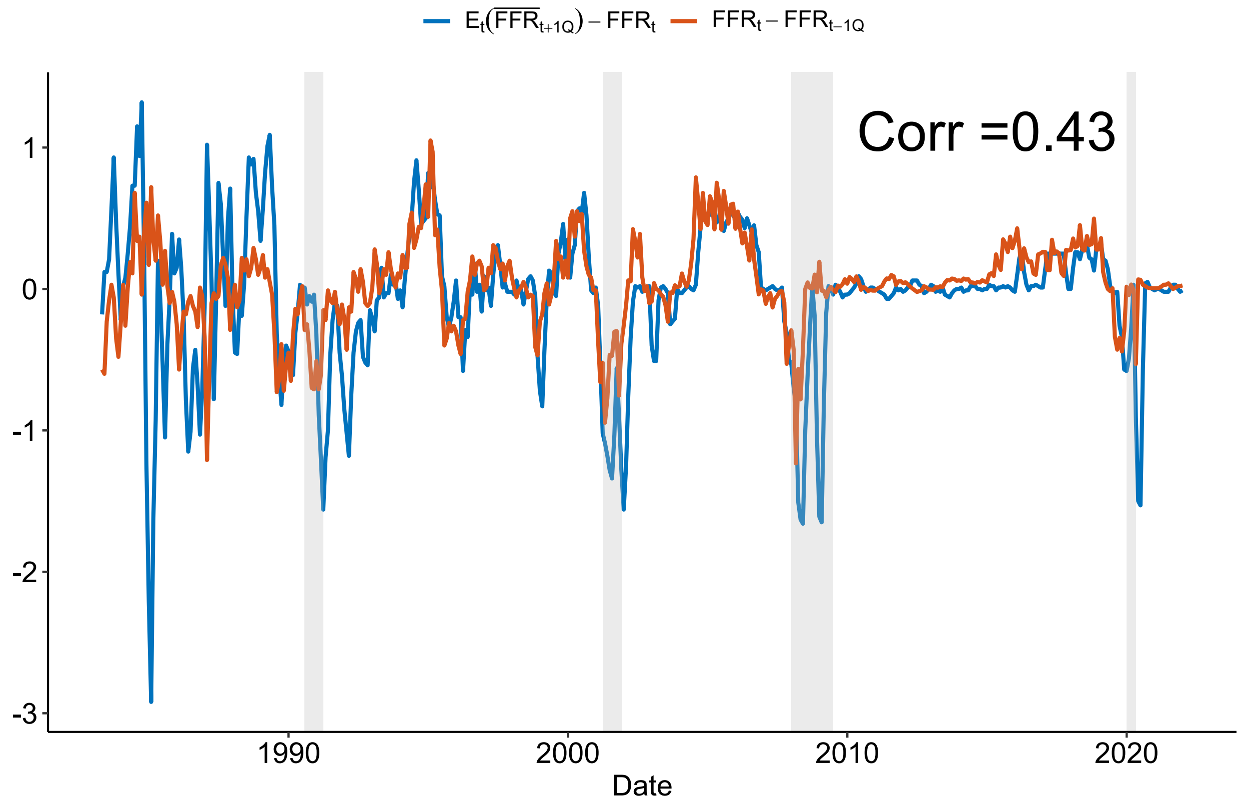


Figure A.6 Time series of forecasted changes and recent realized changes in the short rate

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. We 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, we 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 interest rate forecasts: Expected increase indicator

	$\mathbb{1}_{\mathbb{E}_t^j(\overline{HMR}_{t+1})>HMR_t}$			
	(1)	(2)	(3)	(4)
$\mathbb{1}_{\mathbb{E}_t^j(\overline{FFR}_{t+1})>FFR_t}$	0.30***	0.29***	0.23***	0.22***
	(0.06)	(0.06)	(0.02)	(0.02)
FFR_t	-0.06***	-0.04***	-0.05***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
$HMR_t - FFR_t$	-0.09***	-0.09***	-0.06***	-0.05***
	(0.03)	(0.03)	(0.01)	(0.01)
π_t		-0.02		-0.01
		(0.03)		(0.01)
Baa credit spread$_t$		-0.29**		-0.23***
		(0.11)		(0.04)
Baa credit term spread$_t$		0.25**		0.15***
		(0.11)		(0.04)
Economist FE			✓	✓
Standard-Errors	NW		Economist & Date	
R^2	0.270	0.291	0.208	0.222
Observations	465	465	23,768	23,768
Sample	Consensus	Consensus	Economists	Economists

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	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table A.6 Categorical thinking in consensus forecasts: 4Q-ahead consensus forecasts

	$\mathbb{E}_t(\overline{HMR}_{t+4Q}) - HMR_t$			$\overline{HMR}_{t+4Q} - HMR_t$			$\overline{HMR}_{t+4Q} - \mathbb{E}_t(\overline{HMR}_{t+4Q})$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mathbb{E}_t(\overline{FFR}_{t+4Q}) - FFR_t$	0.42***	0.37***	0.37***	-0.13	-0.09	-0.16	-0.55***	-0.46***	-0.52***
	(0.04)	(0.04)	(0.04)	(0.13)	(0.17)	(0.18)	(0.11)	(0.16)	(0.17)
FFR_t		-0.07***	-0.07***		-0.11***	-0.07		-0.03	0.00
		(0.01)	(0.01)		(0.04)	(0.05)		(0.04)	(0.06)
$HMR_t - FFR_t$		-0.07***	-0.08***		-0.19**	-0.16		-0.12	-0.08
		(0.02)	(0.02)		(0.10)	(0.10)		(0.10)	(0.10)
π_t			0.02			-0.13*			-0.15**
			(0.02)			(0.07)			(0.07)
Baa credit spread$_t$			-0.08			-0.21			-0.12
			(0.11)			(0.31)			(0.30)
Baa credit term spread$_t$			0.12			0.08			-0.04
			(0.10)			(0.37)			(0.36)
Standard-Errors					NW				
R^2	0.368	0.629	0.635	0.008	0.139	0.163	0.135	0.155	0.183
Observations	465	465	465	459	459	459	459	459	459

Table A.7 Categorical thinking in consensus forecasts: Across horizons

	$\mathbb{E}_t(\overline{HMR}_{t+nQ}) - \mathbb{E}_t\left(\overline{HMR}_{t+(n-1)Q}\right)$			
	$n=1$	$n=2$	$n=3$	$n=4$
	(1)	(2)	(3)	(4)
$\mathbb{E}_t(\overline{FFR}_{t+nQ}) - \mathbb{E}_t\left(\overline{FFR}_{t+(n-1)Q}\right)$	0.36^{***}	0.36^{***}	0.37^{***}	0.35^{***}
	(0.06)	(0.04)	(0.04)	(0.03)
FFR_t	-0.02^{***}	-0.02^{***}	-0.01^{***}	-0.01^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
$HMR_t - FFR_t$	-0.02^{***}	-0.01^{**}	-0.02^{***}	-0.01^{*}
	(0.01)	(0.00)	(0.01)	(0.00)
π_t	0.00	0.01	0.00	0.01^{*}
	(0.01)	(0.00)	(0.00)	(0.00)
Baa credit spread$_t$	-0.02	-0.01	0.00	0.00
	(0.03)	(0.02)	(0.02)	(0.02)
Baa credit term spread$_t$	-0.02	0.03	0.02	0.02
	(0.03)	(0.02)	(0.02)	(0.02)
Standard-Errors	NW			
R^2	0.467	0.587	0.658	0.723
Observations	465	465	465	465

Table A.8 Categorical thinking in consensus forecasts: Pre and post-2000

	$\mathbb{E}_t(\overline{HMR}_{t+1Q}) - HMR_t$			$\overline{HMR}_{t+1Q} - HMR_t$			$HMR_{t+1} - \mathbb{E}_t(\overline{HMR}_{t+1Q})$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Pre-2000									
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$	0.16^{**}	0.19^{**}	0.17	-0.32	-0.32	0.23	-0.48^{**}	-0.51^{**}	0.06
	(0.07)	(0.08)	(0.10)	(0.21)	(0.22)	(0.25)	(0.21)	(0.22)	(0.24)
FFR_t		-0.01	-0.01		-0.06^{*}	-0.18^{***}		-0.05	-0.17^{***}
		(0.01)	(0.02)		(0.04)	(0.05)		(0.04)	(0.05)
$HMR_t - FFR_t$		-0.03^{*}	-0.02		-0.06	-0.29^{***}		-0.02	-0.27^{***}
		(0.02)	(0.03)		(0.06)	(0.07)		(0.07)	(0.08)
π_t			0.01			0.09			0.09
			(0.03)			(0.07)			(0.07)
Baa credit spread$_t$			0.04			0.46^{**}			0.41^{*}
			(0.11)			(0.22)			(0.22)
Baa credit term spread$_t$			-0.08			0.48^{**}			0.57^{***}
			(0.07)			(0.19)			(0.20)
Standard-Errors					NW				
R^2	0.060	0.095	0.109	0.031	0.080	0.240	0.064	0.090	0.258
Observations	201	201	201	201	201	201	201	201	201
Panel B: Post-2000									
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$	0.34^{***}	0.34^{***}	0.27^{***}	0.00	0.02	-0.07	-0.35^{***}	-0.32^{**}	-0.34^{**}
	(0.05)	(0.04)	(0.04)	(0.11)	(0.12)	(0.13)	(0.12)	(0.13)	(0.13)
FFR_t		-0.04^{***}	-0.03^{**}		-0.08^{***}	-0.05^{**}		-0.04	-0.03
		(0.01)	(0.01)		(0.03)	(0.03)		(0.03)	(0.03)
$HMR_t - FFR_t$		-0.04^{**}	-0.02		-0.13^{***}	-0.11^{***}		-0.09^{**}	-0.08^{*}
		(0.02)	(0.02)		(0.04)	(0.04)		(0.04)	(0.04)
π_t			-0.03^{***}			-0.01			0.01
			(0.01)			(0.03)			(0.03)
Baa credit spread$_t$			-0.19^{***}			-0.34^{**}			-0.15
			(0.04)			(0.14)			(0.14)
Baa credit term spread$_t$			0.08			0.26			0.17
			(0.05)			(0.17)			(0.18)
Standard-Errors					NW				
R^2	0.258	0.337	0.467	0.000	0.111	0.167	0.067	0.107	0.114
Observations	264	264	264	264	264	264	264	264	264

Table A.9 Categorical thinking in consensus forecasts: Zero lower bound (ZLB) subsamples

	$\mathbb{E}_t(\overline{HMR}_{t+1Q}) - HMR_t$			$\overline{HMR}_{t+1Q} - HMR_t$			$\overline{HMR}_{t+1Q} - \mathbb{E}_t(\overline{HMR}_{t+1Q})$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: non-ZLB period									
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$	0.28***	0.26***	0.25***	-0.15	-0.16	-0.22	-0.43***	-0.42***	-0.47***
	(0.05)	(0.05)	(0.05)	(0.13)	(0.13)	(0.13)	(0.12)	(0.12)	(0.13)
FFR_t		-0.03***	-0.03***		-0.03*	-0.01		0.00	0.01
		(0.01)	(0.01)		(0.02)	(0.02)		(0.02)	(0.02)
$HMR_t - FFR_t$		-0.04***	-0.04***		-0.06	-0.05		-0.02	-0.01
		(0.01)	(0.01)		(0.04)	(0.04)		(0.04)	(0.04)
π_t			0.00			-0.01			-0.01
			(0.02)			(0.04)			(0.04)
Baa credit spread$_t$			-0.08			-0.36**			-0.28*
			(0.07)			(0.16)			(0.14)
Baa credit term spread$_t$			0.06			0.27			0.21
			(0.06)			(0.17)			(0.17)
R^2	0.174	0.330	0.337	0.010	0.048	0.076	0.077	0.078	0.094
Observations	381	381	381	381	381	381	381	381	381
Panel B: ZLB period (2008/12-2015/11)									
$\mathbb{E}_t(\overline{FFR}_{t+1Q}) - FFR_t$	0.77***	0.71***	0.67***	-0.41	-0.60	-0.76**	-1.19**	-1.31**	-1.43***
	(0.19)	(0.16)	(0.17)	(0.49)	(0.45)	(0.38)	(0.58)	(0.51)	(0.45)
FFR_t		-0.55	0.13		0.62	0.06		1.17	-0.07
		(0.47)	(0.48)		(1.04)	(0.99)		(1.09)	(1.29)
$HMR_t - FFR_t$		-0.02	0.00		-0.29***	-0.30***		-0.28**	-0.30***
		(0.03)	(0.02)		(0.10)	(0.10)		(0.11)	(0.11)
π_t			-0.01			-0.09***			-0.07**
			(0.01)			(0.03)			(0.03)
Baa credit spread$_t$			-0.07			-0.34*			-0.27
			(0.08)			(0.20)			(0.23)
Baa credit term spread$_t$			-0.05			0.40*			0.44*
			(0.10)			(0.22)			(0.24)
R^2	0.157	0.192	0.386	0.011	0.248	0.411	0.068	0.223	0.403
Observations	84	84	84	84	84	84	84	84	84

Table A.10 Categorical thinking in consensus forecasts: Using 1-year Treasury yield as the short rate

	$E_t(\overline{HMR}_{t+1Q}) - HMR_t$			$\overline{HMR}_{t+1Q} - HMR_t$			$\overline{HMR}_{t+1Q} - E_t(\overline{HMR}_{t+1Q})$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Full sample									
$\mathbb{E}_t(\overline{y^{(1)}}_{t+1Q}) - y_t^{(1)}$	0.63***	0.57***	0.54***	-0.23	-0.34**	-0.37**	-0.86***	-0.90***	-0.91***
	(0.06)	(0.05)	(0.05)	(0.14)	(0.15)	(0.15)	(0.14)	(0.15)	(0.15)
$y_t^{(1)}$		-0.03***	-0.03***		-0.05***	-0.05**		-0.02	-0.02
		(0.01)	(0.01)		(0.02)	(0.02)		(0.02)	(0.02)
$HMR_t - y_t^{(1)}$		-0.05***	-0.04***		-0.10***	-0.08**		-0.05	-0.05
		(0.02)	(0.01)		(0.04)	(0.04)		(0.04)	(0.04)
π_t			0.00			-0.02			-0.02
			(0.01)			(0.03)			(0.03)
Baa credit spread$_t$			-0.13			-0.14			-0.01
			(0.08)			(0.14)			(0.13)
Baa credit term spread$_t$			0.05			0.04			-0.02
			(0.08)			(0.15)			(0.15)
R^2	0.387	0.456	0.499	0.014	0.078	0.097	0.160	0.172	0.174
Observations	408	408	408	408	408	408	408	408	408
Panel B: non-ZLB period									
$\mathbb{E}_t(\overline{y^{(1)}}_{t+1Q}) - y_t^{(1)}$	0.61***	0.58***	0.56***	-0.21	-0.35**	-0.40**	-0.83***	-0.93***	-0.96***
	(0.06)	(0.05)	(0.05)	(0.15)	(0.16)	(0.17)	(0.14)	(0.16)	(0.17)
$y_t^{(1)}$		-0.02***	-0.02**		-0.05***	-0.07***		-0.03*	-0.05*
		(0.01)	(0.01)		(0.02)	(0.02)		(0.02)	(0.02)
$HMR_t - y_t^{(1)}$		-0.05***	-0.05***		-0.08*	-0.06		-0.03	-0.02
		(0.02)	(0.02)		(0.04)	(0.04)		(0.04)	(0.05)
π_t			0.00			0.00			0.00
			(0.01)			(0.03)			(0.03)
Baa credit spread$_t$			-0.13			-0.17			-0.04
			(0.08)			(0.16)			(0.14)
Baa credit term spread$_t$			0.06			-0.05			-0.11
			(0.08)			(0.14)			(0.14)
R^2	0.411	0.472	0.501	0.013	0.073	0.115	0.164	0.180	0.195
Observations	324	324	324	324	324	324	324	324	324
Panel C: ZLB period (2008/12-2015/11)									
$\mathbb{E}_t(\overline{y^{(1)}}_{t+1Q}) - y_t^{(1)}$	0.72***	0.95***	0.89***	-0.57	-0.27	-0.21	-1.29**	-1.22***	-1.10**
	(0.19)	(0.17)	(0.21)	(0.47)	(0.37)	(0.47)	(0.49)	(0.42)	(0.55)
$y_t^{(1)}$		-0.37***	0.10		0.14	-0.60**		0.51	-0.70*
		(0.13)	(0.16)		(0.27)	(0.27)		(0.31)	(0.37)
$HMR_t - y_t^{(1)}$		-0.04	-0.07**		-0.31***	-0.22**		-0.27**	-0.15
		(0.04)	(0.03)		(0.09)	(0.09)		(0.10)	(0.10)
π_t			0.01			-0.09**			-0.10**
			(0.01)			(0.04)			(0.04)
Baa credit spread$_t$			-0.22***			-0.34*			-0.12
			(0.07)			(0.20)			(0.20)
Baa credit term spread$_t$			0.13			0.45*			0.32
			(0.09)			(0.25)			(0.25)
R^2	0.219	0.369	0.525	0.035	0.231	0.388	0.130	0.229	0.402
Observations	84	84	84	84	84	84	84	84	84

Table A.11 Firm long-term issuance: Controlling for uncertainty

	$\mathbb{1}(\text{LT Issues}_{t+1} > 0)$			$\frac{\text{LT issues}_{t+1}}{\text{AT}_t}$			LT Share_{t+1}		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mathbb{E}_t(FFR_{t+1}) - FFR_t$	0.0348***	0.0296***	0.0406***	0.0049***	0.0044***	0.0046***	0.0494***	0.0465***	0.0531***
	(0.0096)	(0.0084)	(0.0131)	(0.0009)	(0.0009)	(0.0014)	(0.0120)	(0.0118)	(0.0114)
FFR_t	0.0040***	0.0025*	0.0025	-0.0005***	-0.0006***	-0.0008***	-0.0123***	-0.0132***	-0.0141***
	(0.0013)	(0.0014)	(0.0015)	(0.0002)	(0.0002)	(0.0002)	(0.0020)	(0.0021)	(0.0020)
$y_t^{(5)} - FFR_t$	-0.0122***	-0.0114***	-0.0154***	-0.0027***	-0.0027***	-0.0033***	-0.0264***	-0.0258***	-0.0325***
	(0.0024)	(0.0023)	(0.0029)	(0.0003)	(0.0003)	(0.0004)	(0.0033)	(0.0033)	(0.0030)
π_t	-0.0061***	-0.0078***	-0.0057***	-0.0013***	-0.0015***	-0.0012***	-0.0026	-0.0037	-0.0033*
	(0.0019)	(0.0019)	(0.0019)	(0.0003)	(0.0003)	(0.0003)	(0.0022)	(0.0023)	(0.0019)
Baa credit spread_t	0.0102	0.0143*	0.0068	-0.0027***	-0.0023***	-0.0029**	-0.0098	-0.0068	-0.0197*
	(0.0090)	(0.0085)	(0.0090)	(0.0008)	(0.0008)	(0.0013)	(0.0096)	(0.0092)	(0.0112)
Baa credit term spread_t	-0.0152*	-0.0135*	-0.0195**	-0.0017*	-0.0015*	-0.0024**	0.0076	0.0086	0.0072
	(0.0089)	(0.0080)	(0.0087)	(0.0009)	(0.0009)	(0.0012)	(0.0110)	(0.0106)	(0.0117)
Dispersion_t		-0.0917***			-0.0092***			-0.0620**	
		(0.0194)			(0.0032)			(0.0246)	
VIX_t			0.0652*			0.0034			0.1197***
			(0.0365)			(0.0050)			(0.0324)
Standard-Errors	Firm & Year-Quarter								
R^2	0.359	0.359	0.385	0.221	0.221	0.245	0.483	0.483	0.511
Observations	750,698	750,698	635,827	746,807	746,807	632,956	382,391	382,391	309,272
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓