# Categorical Thinking about Interest Rates*

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**Abstract**

We identify a common misconception that expected future changes in short-term interest rates predict corresponding future changes in long-term interest rates. People forecast similar shapes for the paths of short and long rates over the next four quarters. This is a mistake because long rates should already incorporate public information about future short rates and do not positively comove with expected changes in short rates. We hypothesize that people group short- and long-term interest rates into the coarse category of "interest rates," leading to overestimation of their comovement. We show that this categorical thinking persists even among professional forecasters and distorts the real behavior of borrowers and investors. Expectations of rising short rates drive households and firms to rush to lock in long-term debt before further increases in long rates, reducing the effectiveness of forward guidance in monetary policy. Investors sell long-term bonds because they anticipate future increases in long rates. The resulting increase in supply and decrease in demand for long-term debt cause long rates to overreact to expected changes in short rates, and can help explain the excess volatility puzzle in long rates.

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> *With experts in agreement that mortgage rates will continue to rise as the Fed continues to update its economic policy, now is the time to lock in a low mortgage interest rate if you're planning on buying a home or refinancing your existing mortgage.* –Fox Business, Jan 4, 2022

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. Absent changes in beliefs about the term premium or short rates in the very long run, expected future changes in the short rate should not predict corresponding future changes in the long rate. Empirically, expected changes in short rates do not positively predict changes in long rates.

In this paper, we show that there is a widespread misconception that expected future movements in the short rate predict corresponding future movements in the long rate. The advice quoted above is incorrect: knowledge that the Federal Reserve (Fed) plans to increase short rates in the future does not mean that long rates will increase in tandem. Instead, the long rate jumps immediately in response to news that short rates will increase. Thus, there is no reason to rush to lock in long-term debt before the Fed raises short rates.

We hypothesize that this misconception occurs because people lump short- and long-term interest rates into the coarse category of "interest rates." This is a form of categorical thinking, 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 the 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 the financial media frequently refer to "interest rates" without distinguishing between interest rates of different maturities. Short and long rates indeed share many characteristics. The contemporaneous levels of short and long term rates are positively correlated. It is also true that Fed announcements of surprise changes to the federal funds rate simultaneously affect short and long rates in the same direction. However, people may 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 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. People believe that long rates will move in tandem with expected changes in the short rate. Specifically, they forecast similar shapes for the paths of long and short rates over the next four quarters. 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 growth in household and firm borrowing during monetary tightening cycles reduces the effectiveness of forward guidance in monetary policy. Thus, categorical thinking can help explain the forward guidance puzzle, in which forward guidance has been less effective than predicted by macroeconomic models (Del Negro et al. (2023); McKay et al. (2016); Campbell et al. (2019); Angeletos and Lian (2018)). 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). Symmetrically, expectations of *declining* short rates distort real behavior in the opposite direction: homebuyers and firms delay borrowing and bond investors rush to buy long-term bonds because they believe long yields will drop in the future.[1]

[1]For example, the Wall Street Journal advised households to delay long-term borrowing on March 20, 2024 following announcements by the Fed of three planned cuts over the next year: *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*

When short rates are expected to rise, the supply of long-term bonds increases as borrowers rush to borrow long, while demand decreases as investors sell long-term bonds. If these changes in supply and demand are not immediately absorbed by risk-averse arbitrageurs (Hanson, Lucca, and Wright, 2021), the price of long term debt falls and long rates rise, leading to overreaction to expected changes in short rates and subsequent reversal. 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 finance literature which shows that errors in financial 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.

We begin by showing that it is hard to rationalize the belief that long rates will move in tandem with expected changes in short rates based on publicly available historical data. *In theory*, beliefs about changes in long rates can be rationalized through beliefs about the term premium. If the expectations hypothesis holds (i.e., the term premium is zero), one could also rationalize any belief about changes in long rates through changes in beliefs about short rates in the very long run (e.g., the federal funds rate 10 to 30 years into the future). However, we find that reported beliefs about short rates in the very long run fail to justify this expectations hypothesis channel. Moreover, historical data provide no basis to believe that expected changes in short rates predict future changes in long rates in the same direction. Specifically, we proxy for beliefs about expected changes in short rates using the consensus forecasts for the federal funds rate from the Blue Chip Financial Forecasts

*rates. "So unless you're really hard pressed to buy a home, I would wait for the Fed to cut rates," he says.*

(BCFF). These publicly available consensus forecasts are largely driven by macroeconomic data and forecasts, along with forward guidance from the Fed. We show that when the Fed is expected to increase the federal funds rate over the next quarter, the federal funds rate does increase on average over the next quarter, 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 or bond fund flows) 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 Fed 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 more than 20 basis points. This belief is incorrect, as long rates actually decline on average, leading to predictable forecast errors of more than 40 basis points.

Most strikingly, we find that professional forecasters report similar shapes for the expected paths of short and long rates over the next four quarters (e.g., a V-shape or an N-shape), leading again to predictable forecast errors. In particular, the predicted change in the long rate in each of the next four quarters is more closely related to the expected change in the short rate in the same quarter than in any of the other three quarters. This belief in similar shapes for the expected paths of short and long rates is consistent with categorical thinking. It is also difficult to rationalize under the expectations hypothesis—to do so would require forecasters to believe that the four-quarter-ahead path of the federal funds rate 30 years in the future mirrors the same specific shape forecasted for the federal funds rate in the immediate next four quarters.

We explore several potential alternative explanations for our findings. First, we consider whether conflicts of interest might explain why professional forecasters predict that long rates will move with expected changes in short rates. While bank-employed forecasters might have an incentive to encourage borrowing by predicting rising long rates when short rates are expected to rise, we find that they also predict falling long rates when short rates are expected to fall—a prediction that would discourage immediate borrowing. Moreover, we find similar results among forecasters at independent research institutions.

We also examine whether our results could be explained by a mistaken belief that long rates respond sluggishly to short rate news. If this were the case, forecasters' predictions should be driven primarily by recent news about future short rates rather than by expected changes in short rates that were known well in advance. However, we find that expected changes in short rates remain strong predictors of expected changes in long rates even after controlling for news about short rates as measured by forecast revisions.

Finally, we consider whether forecasters might simply be extrapolating from recent trends in long rates, which happen to coincide with expected changes in short rates. While we find some evidence of extrapolation, it does not explain away the strong relationship between expected changes in short and long rates. Moreover, extrapolation cannot explain why forecasters predict similar shapes for the future paths of short and long rates over multiple quarters.

Next, we explore whether households also believe that long rates will move with anticipated changes to short rates. Using 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 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.

Overall, we find that both professional forecasters and households mistakenly believe that long rates will move with expected changes in short rates. Both groups exhibit categorical thinking: their beliefs reflect a genuine commonality within a category (levels and changes of long and short rates are positively correlated), but overlook subtle differences, such as the fact that long rates do not positively move with *expected* changes to short rates. However, we caution that the exact form of categorical thinking may differ across groups.[2] We also do not claim that this bias extends to all finance professionals. In contrast to the professional forecasters in the BCFF who typically occupy high level positions such as chief economist, bond traders interact directly with detailed, high-frequency bond pricing data, and thus may not exhibit the same biases. Investigating the exact mechanism and extent of this bias in each type of person is beyond the scope of this paper. Instead, in the remainder of this paper, we examine how categorical thinking can affect real behavior and how these behaviors can impact asset markets and the macroeconomy.

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

[2] Interviews with a professional forecaster suggest the following mechanism may be at play. While these professionals understand theoretically that the long rate equals the average of expected short rates over the life of the long bond plus a term premium, they make forecasts based on complex statistical models trained on historical data encompassing a large set of interest rates and macroeconomic variables. These models inevitably detect the strong positive correlation between contemporaneous short and long rates. When predictions of future changes in short rates are input, the models output similarly correlated predictions for future changes in long rates. The key error lies in failing to program the models to distinguish between expected versus unexpected changes in interest rates. Thus, while professional forecasters grasp the theoretical relationship between rates, they build and use statistical models that exhibit categorical thinking. A slightly different mechanism may apply to households. Some households may reason that different interest rates move together, while others may follow guidance from sources (financial media or professional forecasters) that display categorical thinking.

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 find that these changes in corporate borrowing are especially strong at turning points in the interest rate cycle. 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 1-2% of assets under management (AUM).

Our findings carry implications for monetary policy involving 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 Fed to adjust short rates slowly and flexibly, while immediately affecting long term borrowing because long rates immediately react to expected changes in short rates. Thus, forward guidance and gradualism provide the Fed 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 in the short run. Categorical thinking causes long rates to overreact to expected increases in short rates, leading to greater volatility. Moreover, when short rates are expected to gradually increase, the increase in long rates is associated with a net increase in long-term borrowing and housing demand in the present–the opposite of the intended outcome for monetary tightening. Likewise, when short rates are expected to gradually fall, the drop in long rates is associated with a net decrease in long-term borrowing in the present as firms and households wait to borrow until long rates fall further–again, the opposite of the intended effect of monetary loosening.

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 strongly predicted by expected changes in short rates. Third, HLW finds support for Stein (2013)'s recruitment channel in which excess 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 the effectiveness of monetary policy in the short run.

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 different 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 move in tandem even when movements in the short rate are anticipated.

Finally, our finding that some 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.[3]

# 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.

## 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

[3]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.

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 ($HMR$). 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, although we find similarly strong evidence of categorical thinking using forecasts of the 10-year Treasury yield. As depicted in Figure A.1 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.[4] 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 the 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.

### 1.1.2 Households beliefs

We obtain household housing expectations from the Fannie Mae National Housing Survey (NHS).[5] 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 representa-

[4] 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. Appendix Table A.1 provides a full list of institutions that participate in the BCFF survey, grouped by type of institution.

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

tive 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.[6]

We obtain detailed individual-level responses to all questions at a monthly frequency from 2010 to 2021. Besides information about household beliefs, NHS also provides 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 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. 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

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

by the book value of assets (AT) and lagged total debt, respectively, to adjust 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. In supplementary analyses, we also use aggregate data from the Fed's Flow of Funds data.

### 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, which is available separately for jumbo and conventional mortgage loans.

### 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 ($\pi$); 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 expected changes in interest rates 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, Panel A, 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. Panel B 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 Panel B 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 long 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:

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

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 over the life of the bond (the term premium, or TP, component). The expectations hypothesis component implies that the current long rate already incorporates all public information about the future path of the short rate. This identity is equivalent to the decomposition of Campbell and Shiller (1988) for the stock market.

Let $tp_t \equiv \frac{1}{n}\mathbb{E}_t\left(\sum_{\iota=0}^{n-2} rx_{t+\iota+1}^{(n-\iota)}\right)$ represent the term premium. We can iterate the yield identity and express the expected change in long rate over the next period as a function of the expected short rate in the very long run and the expected change in the term premium:

$$\mathbb{E}_t\left(y_{t+1}^{(n)}\right) - y_t^{(n)} = \frac{1}{n}\left(\mathbb{E}_t\left(i_{t+n}\right) - i_t\right) + \mathbb{E}_t(tp_{t+1}) - tp_t. \tag{2}$$

Equation (2) shows that it is possible to rationalize any belief about the change in the long rate through beliefs about the term premium. If the expectations hypothesis holds, i.e., the term premium is zero, it is still possible to rationalize any belief about the change in the long rate through beliefs about the short rate in the very long run, $\mathbb{E}_t\left(i_{t+n}\right)$, e.g., the federal funds rate 10 or 30 years into the future. Thus, it could be rational to believe that long rates will move with expected changes in short rates if beliefs about the term premium or the short rate in the very long run comove with expected changes in the short rate.[7]

Given that any belief about changes in the long rate can be justified *in theory*, we show that it is difficult to rationalize a belief that long rates will move with expected changes in short rates based on publicly available historical data. We will directly examine data on beliefs about the short rate in the very long run, $\mathbb{E}_t(i_{t+n})$, in later tests. For now, we show that there is no reason to believe the long rates will move in tandem with expected changes in the short rate based on the historical data. Table 2 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 BCFF. 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)

## 2.1 Categorical thinking hypothesis

We hypothesize that people mistakenly believe that expected shifts in the short-rate forecast corresponding future movements in the long rate. We further 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

[7] If people think that the short rate follows an AR(1) process (as in the Vasicek model), then a change in belief about the short rate next period would propogate to a change in the expected $n$-period ahead short rate of with a factor $\rho^n$, where $\rho$ is the autoregressive coefficient. Consequently, if people expect a change in the short rate next period, their beliefs about short rates in the very long run will differ accordingly.

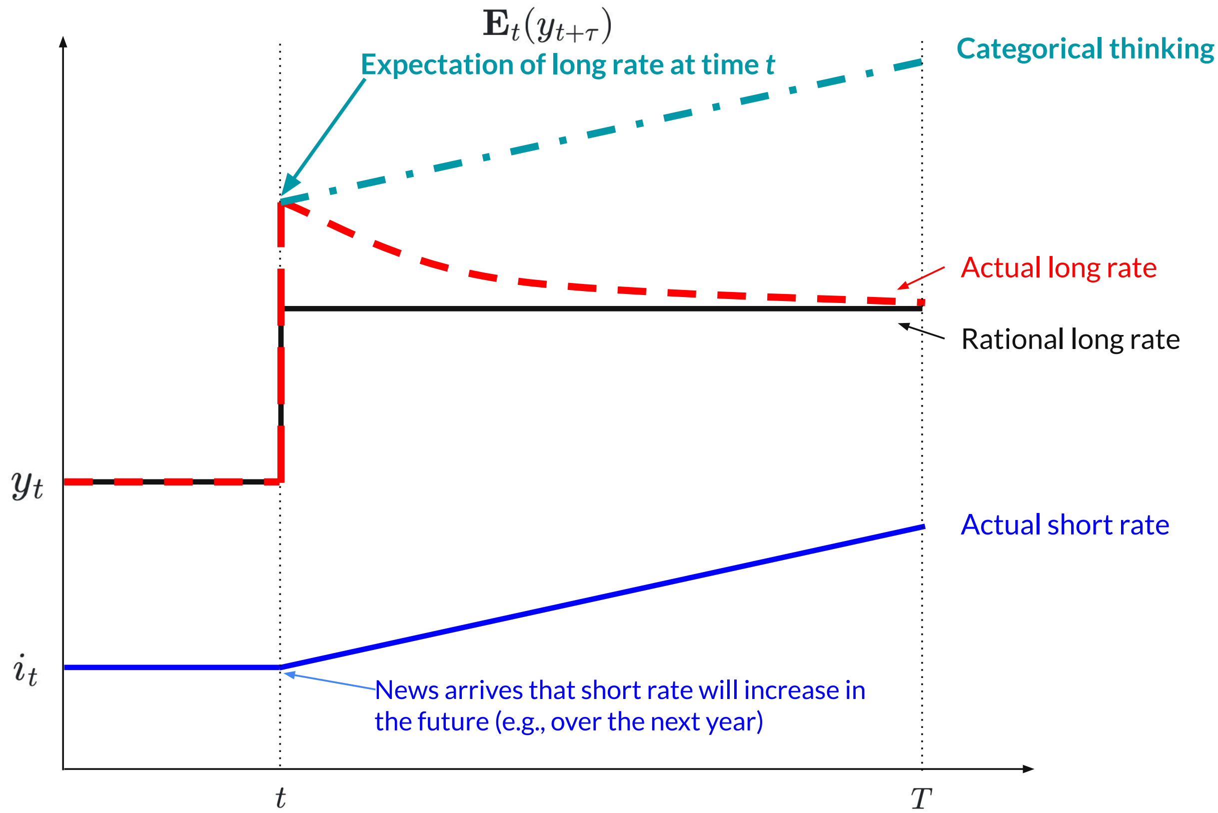


**Figure 1** An illustration of categorical thinking about short and long rates

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 Fed of planned rate hikes over the coming year. Note that actual short rate changes would resemble a step function, which we approximate here with an upward sloping line. If investors are fully rational, and the term premium and expectations of the short rate in the very long run remain constant, the long rate would immediately adjust upwards to reflect the expected higher short rates and then level off, 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 2. 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 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 further. 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 increase in supply and decrease in demand cause the price of the long bond to fall, and the long rate to rise beyond what would be expected under rational expectations. Thus, the categorical thinking error 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.

## 2.2 Forecasted changes over the next quarter

We begin by examining the relation between the forecasted next-quarter change in short and long rates.[8]

$$\underbrace{\mathbb{E}_t(y_{t+1q}^{(n)}) - y_t^{(n)}}_{\text{Expected changes}} = \alpha + \beta_1 \left[\mathbb{E}_t(i_{t+1q}) - i_t\right] + \gamma X_t + \epsilon_t \tag{3}$$

$$\underbrace{y_{t+1q}^{(n)} - y_t^{(n)}}_{\text{Actual changes}} = \alpha + \beta_2 \left[\mathbb{E}_t(i_{t+1q}) - i_t\right] + \gamma X_t + \epsilon_{t+1q} \tag{4}$$

$$\underbrace{y_{t+1q}^{(n)} - \mathbb{E}_t(y_{t+1q}^{(n)})}_{\text{Forecast errors}} = \alpha + \beta_3 \left[\mathbb{E}_t(i_{t+1q}) - i_t\right] + \gamma X_t + \epsilon_{t+1q} \tag{5}$$

We control for debt market conditions $X_t$ across all three tests. Controls include the current short rate, inflation, term spread (the difference between the relevant long yield and FFR), credit spreads, and credit term spread. Equation (3) explores the contemporaneous comovement between expected changes in short and long rates. Equation (4) 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 positive relation between expected changes in the short rate and changes in the long rate. If forecasters are influenced by categorical thinking, we expect $\beta_1$ to be positive. If they are fully rational and understand that long rates overshoot in the data, we expect $\beta_1$ to match $\beta_2$, which we estimate to be zero or negative.

The final specification in Equation (5) 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 $\beta_3$ 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,

[8]The subscript $t + 1q$ denotes forecasts for the next quarter, reflecting their quarterly horizon. Given the data availability, the regressions are estimated at a monthly frequency.

leading to $\beta_3 = 0$.

We can also directly test whether a positive $\beta_1$ in Equation (3) can be justified by beliefs about the short rate in the very long run rather than categorical thinking. Recall from Equation (2), that if the expectations hypothesis holds, $\mathbb{E}_t\left(y_{t+1}^{(n)}\right) - y_t^{(n)} = \frac{1}{n}\left[\mathbb{E}_t\left(i_{t+n}\right) - i_t\right]$. Thus, we can replace the dependent variable in Equation (3) with $\frac{1}{n}\left(\mathbb{E}_t\left(i_{t+n}\right) - i_t\right)$ and estimate the following regression:

$$\frac{1}{n}\left[\mathbb{E}_t\left(i_{t+n}\right) - i_t\right] = \alpha_1 + \beta_4\left[\mathbb{E}_t(i_{t+1q}) - i_t\right] + \gamma X_t + \epsilon_t. \tag{6}$$

If beliefs under the expectations hypothesis explains our results, we expect $\beta_4$ in the above regression to equal $\beta_1$. As we will show, we find that $\beta_4$ is very close to zero. In other words, the same people who forecast that long rates will move with expected changes in the short rate over the next quarter do not hold beliefs about the short rate in the very long run in a manner that is consistent with the expectations hypothesis.

## 2.3 Matching shapes over the next four quarters

We can also test the sharper prediction that categorical thinking should lead people to believe that the future path of the long rate will exhibit a similar shape to the expected path of the long rate. Let $s = 1, 2, 3, 4$ index the immediate next four quarters. Using data on long and short rate beliefs over each of the next four quarters, we estimate:

$$\begin{aligned}\mathbb{E}_t\left(y_{t+s}^{(n)}\right) - \mathbb{E}_t\left(y_{t+s-1}^{(n)}\right) = \alpha &+ \beta_1\left[\mathbb{E}_t(i_{t+1q}) - \mathbb{E}_t(i_t)\right] \\ &+ \beta_2\left[\mathbb{E}_t(i_{t+2q}) - \mathbb{E}_t(i_{t+1q})\right] \\ &+ \beta_3\left[\mathbb{E}_t(i_{t+3q}) - \mathbb{E}_t(i_{t+2q})\right] \\ &+ \beta_4\left[\mathbb{E}_t(i_{t+4q}) - \mathbb{E}_t(i_{t+3q})\right] \\ &+ \gamma X_t + \epsilon_t.\end{aligned} \tag{7}$$

We regress the forecasted change in the long rate in quarter $s$ on the forecasted change in the short rate in each of the next four quarters. Categorical thinking predicts that the forecasted change in the long rate in each of the next quarters is more closely related to the expected change in the short rate in the same quarter than in any of the other three quarters. In other words, we predict that for each quarter ahead $s$, $\beta_s$ should be positive and larger than the other $\beta$'s.

We also note that matching shapes in beliefs for the forecasted paths of the long and short rates is difficult to rationalize under the expectations hypothesis. Assuming a zero term premium, we can again iterate and express the forecasted change in long rates in each of the next $s$ quarters in terms of beliefs about short rates in the very long run:

$$\mathbb{E}_t\left(y_{t+s}^{(n)}\right) - \mathbb{E}_t\left(y_{t+s-1}^{(n)}\right) = \frac{1}{n}\mathbb{E}_t\left(i_{t+n+s-1} - i_{t+s-1}\right).$$

The above equation implies that people must hold very specific matching beliefs about short rates in the very long run to justify such forecasts under the expectations hypothesis. For example, in the case of the 10-year yield, if a person believes that the long and short rate will follow a similar V-shaped path over the next four quarters, she must believe that federal funds rate will move in a V-shape manner over a four quarter period starting exactly 10 years in the future.

# 3 Categorical thinking in interest rate expectations

## 3.1 Professional forecasters

We begin by implementing the baseline tests outlined in equations (3)-(5) using consensus forecasts. For short-term rates, we focus on the federal funds rate (FFR), while for long-term rates, we examine both the 30-year Home Mortgage Rate (HMR) and the 10-year Treasury yield. Our analysis utilizes 1-quarter ahead forecasts of short and long rates at a monthly frequency. We control for the current short rate (FFR), the term spread, the current inflation rate, the Baa credit spread, and the Baa credit term spread.

The results from these regressions are summarized in Table 3. Beginning with Panel A which examines the 30-year Home Mortgage Rate, the first three columns report the results for equation 3. Across all three specifications in which we incorporate the control variables incrementally, $\beta_1$ estimates are all positive and significant at the 1% level. The point estimate in column (3) shows that when a 1 percentage point increase in the short rate is expected, forecasters also expect a 24 basis point increase in the long rate over the same horizon. 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 $\beta_1$ 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) of Panel A estimate equation 4. They are slightly different from those in Table 2 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 forecaster beliefs, expected changes in the short rate bear no positive predictive power for future changes in the long rate.

Columns (7)-(9) of Panel A report the results for the third equation testing the predictability of HMR forecast errors. Estimates of $\beta_3$ 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 departure from rationality, consistent with categorical thinking about interest rates.

Finally, Panel B repeats the analysis of Panel A but using 10-year treasury yields as the long rate measure. As can be seen, the results remain similar for 10-year yields; when forecasters expect the federal fund rate to increase the following quarter, they also tend to expect 10-year yields to increase. The magnitudes are, if anything, larger for 10-year yields, with a 1 percentage point increase in the short rate forecast associated with a 41 basis point increase in the long rate forecast in column (3). Columns (4)-(6) show again that these beliefs tend to be incorrect. In fact, when short rates are expected to increase, 10-year yields tend to decrease—in this case the negative relationship is statistically significant. As a result, we again find predictable forecast errors in columns (7)-(9).

In Table 4, we show that our estimate of a large and positive $\beta_1$ in equation (3) cannot be rationalized by the expectations hypothesis and beliefs about the short rate in the very long run. To test this, we use data on forecasts of the 10-year ahead federal funds rate ($n = 40$ based on quarterly intervals), which is available in the same BCFF survey at a semi-annual frequency. We use the consensus forecast of the 10-year ahead federal funds rate, as well as the top and bottom 10% of forecasts to estimate upper and lower bounds.

As discussed in the previous section, the expected change in the long rate over the next quarter equals $\frac{1}{n}\left(\mathbb{E}_t\left(i_{t+n}\right) - i_t\right)$ if the expectations hypothesis holds. Estimating Equation (6), we find that $\beta_4$ estimates are very close to zero, even when using the top and bottom 10% of forecasts for $\mathbb{E}_t\left(i_{t+n}\right)$. In contrast, our estimates of the relation between expected changes in long rates and short rates over the next quarter yield a $\beta_1$ of over 0.6 (in Column 8) . Thus, our results cannot be explained by the expectations hypothesis and beliefs about the short rate in the very long run.

For the remainder of our analysis, we focus on home mortgage rates as our primary measure of long-term interest rates. This choice is motivated by two key factors. First, the BCFF data for home mortgage rates offers the longest historical time series among our long-rate variables. Second, this focus allows us to draw parallels with how consumers form beliefs about long-term rates, as consumer surveys typically ask about expected changed in home mortgage rates rather than 10-year treasury yields.

A natural question at this point is whether the pattern we have documented differs when short rates are expected to increase versus decrease. In other words, when short rates are expected in decrease, do forecasters expect a concurrent decrease in long rates, or is it mainly when short rates are expected to increase that forecasters expect a concurrent increase? To examine this, we repeat the analysis of Table 3 (Panel A), partitioning the expected change in short rates into two variables—one representing expected increases (and equal to zero for decreases) and one representing expected decreases (and equal to zero for increases). The results are presented in Appendix Table A.2. We find evidence of categorical thinking around both expected increases and decreases in short rates, with roughly similar magnitudes. This approximate symmetry also helps to rule out a potential concern that forecasters may simply tend to forecast increases in all rates during our sample period—not due to categorical thinking.[9]

#### 3.1.1 Forecasted paths of the long and short rates over the next four quarters

Our analysis thus far has concentrated on the relationship between 1-quarter ahead forecasts of short and long rates. The evidence suggests that forecasters systematically err by predicting increases in long rates when short rates are expected to rise. While this pattern aligns with categorical thinking about interest rates, it could potentially be explained by other behavioral biases. Specifically, forecasters may tend to believe that long rates will increase during times when short rates are expected to increase, but they may not believe that long rates will increase *because* short will increase. To further examine whether long rate beliefs are driven directly by short rate beliefs, we leverage the availability of rate forecasts for multiple future quarters. We have access to forecasts not only for one quarter ahead but

[9]However, even if forecasters did tend to forecast increases in all rates during our sample period, that would not explain the results in Table 3, because the average forecasted increase in long rates would be absorbed by the constant.

also for two, three, and four quarters ahead. This allows us to examine whether forecasters predict similar *shapes* for the paths of short and long rates over the next 4 quarters. For instance, if forecasters expect short rates to rise and then fall, do they anticipate a matching pattern for long rates? Such a finding would provide more compelling evidence of categorical thinking.

Figure 2 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 often expected to move along a similarly-shaped path. Further, when the short rate was expected to rise in the mid 2000s and again in the late 2010s under clear Fed 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).

To complement the graphical evidence in Figure 2, we also statistically test whether professional forecasters report similar shapes for the expected paths of short and long rates over the next four quarters. We measure the time $t$ forecasted change in an interest rate over some future quarter $n$ as the difference between the consensus forecasted rate for quarter $n$ and the consensus forecasted rate for quarter $n-1$. Table 5 Panel A shows that a 1 percentage point change in the forecasted short rate in each of the next four quarters is associated with an approximate 30 basis point forecasted change in the long rate over the same quarter.

In Panel B of Table 5, we show that such beliefs are not justified by the data. We regress the actual change in the long rate in each of the next four quarters on the forecasted change in the short rate for the same quarter. For each of the next four quarters, we find a negative insignificant relation. In other words, long rates do not move positively with expected changes in short rates in any of the next four quarters.

Finally, in Panel C of Table 5, we show that the forecasted change in long rates over some future quarter $n$ is better predicted by the forecasted change in short rates over the same quarter than by the forecasted change in short rates over the other three quarters. In each column $n$ of Panel C, we regress the forecasted change in long rates in quarter $n$ on the forecasted changes in short rates over the next 1, 2, 3, and 4 quarters. We find the strongest statistical relation along the diagonal of the panel. The forecasted change in the long rate is best predicted by the forecast change in the short rate *in the same quarter*. Forecasted changes in the long rate are not consistently related to forecasted changes in the short rate in other future quarters. Altogether, Table 5 provides statistical evidence that forecasters predict similar shapes for the paths of future short and long rates over the next four quarters, consistent with categorical thinking.

### 3.1.2 Accuracy of actual forecasts versus a "no change" forecast

The evidence so far suggests that professional forecasters make systematic errors in predicting long-term interest rates due to categorical thinking. Next, we compare how these forecasts compare to a simple "no change" benchmark that assumes long rates will stay constant. Appendix Table A.3 compares the root mean-squared errors (RMSE) of the consensus forecasts against this naive "no change" forecast across different long-term rates.

The results are striking. For 1-quarter ahead forecasts (Panel A), the consensus forecasts consistently perform worse than the no-change benchmark across all long rates. For example, for home mortgage rates (HMR), the RMSE of consensus forecasts is 0.51 compared to 0.47 for the no-change forecast. The Diebold-Mariano test statistics are all negative and highly significant, with p-values below 0.01, indicating that the no-change forecasts are statistically more accurate. The relative underperformance of professional forecasts is even more pronounced for 4-quarter ahead predictions (Panel B). For HMR, the RMSE gap widens to 1.05 versus 0.91. Similar patterns hold for Treasury yields and corporate bond rates.

These results remain robust when we explicitly test whether the poor forecast accuracy could be explained by forecasters simply having an upward bias–that is, consistently overestimating the probability of rate increases. Even after adjusting for any systematic bias in the mean level of consensus forecasts (Panels C and D), we continue to find that professional forecasts significantly underperform the naive no-change benchmark.

#### 3.1.3 Potential alternative explanations

In this section we discuss some potential alternative explanations for the patterns we have documented.

**Conflicts of interest among forecasters.** It is possible that the forecasters surveyed may not report their true beliefs due to conflicts of interest. Professional forecasters in our data tend to hold high level positions such as "chief economist" within large banks, asset management firms, and independent economics research institutions. See Appendix Table A.1 for details. Forecasts are public information that can be tied to the identities of each forecaster. Conversations with professional forecasters suggest that participation in the BCFF survey is considered highly prestigious. BCFF forecasters are motivated to provide accurate forecasts by a combination of intrinsic preferences, awards for accuracy, and public recognition. They are not directly monetarily compensated for their forecasts.

Nonetheless, it remains possible that those who work for banks have an incentive to predict that long rates will increase when short rates are expected to rise, as these predictions would cause potential borrowers to rush to borrow long before long rates rise further. However, as shown earlier in Appendix Table A.2, forecasters also predict that long rates will decline when short rates are expected to decline. It is unclear why conflicted forecasters would make such predictions, as they would lead to delayed long-term borrowing. In addition, Appendix Table A.4 shows that we find similar results when we limit the analysis to forecasters from independent research firms who are not affiliated with any financial institution.

**Forecasters believe that long rates respond sluggishly to short rate news.** Another possibility is that forecasters do not think categorically about interest rates but rather mistakenly believe that short rate news is slow to be priced into long rates. Under this view, forecasters might predict long rates will rise alongside short rates, even when the short rate increases are expected in advance, because the long-term bond market had not yet fully priced in the anticipated short rate changes. This bias would be distinct from the categorical thinking bias we have in mind.

To address this possibility, we repeat our baseline analysis but now lag the independent variables by one month. The idea is that forecasters are unlikely to believe that information in the consensus short rate forecast from the *previous* month is still yet to be priced into long rates. The results are shown in Appendix Table A.5. Even with a 1-month lag, the coefficient estimates remain close in magnitude to those in the baseline regressions and significant at the 1% level.

In addition, we also control directly for news about short rates as proxied for by short rate forecast revisions.[10] If the results were driven by a belief of slow information dispersion, we should find that short rate *news* matters more than the expected change in the short rate. For example, if there was a coming increase in the short rate that was known long in advance (no news), forecasters would not predict a simultaneous increase in the long rate. Whereas if the planned rate increase was only recently communicated by the Fed (news), forecasters would predict a simultaneous increase in the long rate. In contrast,

[10]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.

under categorical thinking, forecasters would predict the long rates increase in tandem with the expected increase in the short rate, regardless of how far in advance the increase in the short rate was known.

In Table 6, Panel A, 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. Overall, this evidence supports an important role for categorical thinking. Controlling for the arrival of news, if anything, strengthens the relation between the expected changes in short and long rates.

**Forecasters have extrapolative beliefs about long rates.** Another possibility is that forecasters form their beliefs about long rate movements separately from their beliefs about short rate movements, but the two just happen to coincide. As already discussed, this seems unlikely given that forecasters also predict similar *shapes* in the paths of short and long rates over the next 4 quarters. Nonetheless, we explore this possibility further.

Perhaps the most likely way in which forecasters may form beliefs about long rate movements separately from their beliefs about short rate movements is by extrapolating from recent past long rate movements. That is, forecasters may tend to predict increases in long rates following recent past increases in long rates, and such times may also happen to be times when the short rate is expected to increase. In that case, expected short rate increases would correlate with forecasts of long rate increases without categorical thinking.

In Table 6, Panel B, we re-estimate our baseline tests by running a horse race between expected changes in short rates and recent changes in long rates. Again, we find that, when introduced separately in columns (1) and (2), both expected changes in short rates and recent changes in long 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 stronger and more significant effect. These results are again consistent with an important role for categorical thinking. Controlling for recent trends in long rates and allowing for extrapolation of recent trends does not diminish the relation between the expected changes in short and long rates.

#### 3.1.4 Additional robustness

**Influential dates.** Bauer and Swanson (2023) find that certain FOMC dates feature significant new information about future short rates and these dates appear especially influential in shaping forecasters' beliefs about future monetary policy and macroeconomic conditions. A potential concern is that expected changes in the short rate may forecast changes in the long rate following these influential FOMC dates, even if the predictability does not hold in the full sample. If so, it would be rational to predict that long rates move with expected changes in short rates following these influential FOMC dates.

Following Bauer and Swanson (2023), we categorize months by the size of monetary policy shocks, which we obtain from Swanson (2021).[11] 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 Appendix Table A.6. Across both samples, the coefficient estimates ($\beta_2$) are always negative, refuting the possibility that short rate expectations can positively predict future long rates following influential monetary policy dates. Moreover, in the sample where the current month contains the influential FOMC date, 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 is even more pronounced in months containing these influential dates.

[11] 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.

**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 3. Though there is noticeable heterogeneity in short and long rate forecasts, especially in the earlier part of the sample, most of the individual forecasts are close to the consensus. We then re-estimate our baseline tests using these economist-level forecasts. The results are reported in Appendix Table A.7. Controlling for economist fixed effects, all previously documented patterns using consensus forecasts apply to the individual forecasts. The $\beta_1$ estimates of around 0.40 are 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 use of consensus forecasts instead of individual forecasts in our main regressions.

## 3.2 Household beliefs

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 Fed 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:

$$\mathbb{1}(\mathbb{E}_{it}(HMR_{t+12m}) - HMR_t > 0) = \beta \mathbb{1}(\mathbb{E}_t^f(FFR_{t+12m}) - FFR_t > 0) \ + \text{Controls} + \epsilon_{it}, \tag{8}$$

Where $\mathbb{E}_{it}(HMR_{t+12m}) - HMR_t$ is household $i$'s expected change in mortgage rates over the next 12 months and $\mathbb{E}_t^f(FFR_{t+12m}) - FFR_t$ is the consensus expected change in the federal funds rate over the next 12 months among professional forecasters. The results are shown in Table 7. As can be seen, we estimate $\beta$ 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 Figure 4, we re-estimate Table 7 by interacting our main independent variable of interest with a series of education level indicator variables. The marginal effects for each education level are displayed (i.e., the sum of the main effect and interaction). We find that categorical thinking about interest rates becomes monotonically stronger with education. In particular, those without a high school degree are only 5.7 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 26.3 percentage points more likely to expect increases in mortgage rates.

Figure 5 similarly explores heterogeneity by income. Categorical thinking about interest rates becomes monotonically stronger with income as well. In particular, those earning less than \$10,000 annually are only 2.4 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 33.1 percentage points more likely. Thus, the bias that we document in this paper is fairly unusual relative to the literature. It does not diminish with education and income but rather becomes stronger with these proxies for financial sophistication.

Note that our heterogeneity results cannot be explained by less sophisticated households being more likely to respond "don't know" to the question of what will happen to the home mortgage rate over the next 12 months. While less educated and wealthy households are indeed slightly more likely to choose this response, this pattern would not explain why they are less likely to predict that the home mortgage rate will increase when short rates are expected to increase over the same window. We also find similarly significant variation by household sophistication if we remove the "don't know" responses from our sample.

#### 3.2.1 Discussion of potential mechanisms underlying beliefs

So for, we have presented evidence that both professional forecasters and households mistakenly believe that long rates will move with expected changes in short rates. Both groups exhibit categorical thinking: their beliefs reflect a genuine commonality within a category (levels and changes of long and short rates are positively correlated), but overlook subtle differences, such as the fact that long rates do not positively move with *expected* changes to short rates.

However, we caution that the exact form of categorical thinking may differ across groups. Interviews with a professional forecaster suggest the following mechanism may be at play. While these professionals understand theoretically that the long rate equals the average of expected short rates over the life of the long bond plus a term premium, they make forecasts based on complex statistical models trained on historical data encompassing a large set of interest rates and macroeconomic variables. These models inevitably detect the strong positive correlation between contemporaneous short and long rates. When predictions of future changes in short rates are input, the models output correlated predictions for future changes in long rates. The key error lies in failing to program the models to distinguish between expected versus unexpected changes in interest rates. This suggests a mechanism in which professional forecasters grasp the theoretical relationship between rates, but they build and use statistical models that exhibit categorical thinking.

A slightly different mechanism may apply to households. Some households may reason that different interest rates move together, while others may follow guidance from sources (financial media or professional forecasters) that display categorical thinking.

Finally, we do not claim that this bias extends to all finance professionals. In contrast to the professional forecasters in the BCFF who typically occupy high level positions such as chief economist, bond traders interact directly with detailed, high-frequency bond pricing data. Because they receive frequent feedback through exposure to data and trading, we do not expect them to exhibit the same errors in beliefs. Indeed, in preliminary analysis of bond futures markets, we do not find evidence that bond traders price long term bond futures in a way consistent with categorical thinking.

Investigating the exact mechanism and extent of categorical thinking bias in each type of person is beyond the scope of this paper. Instead, in the remainder of this paper, we examine how categorical thinking can affect real behavior and how these behaviors can impact asset markets and the macroeconomy.

# 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 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 in the future. 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 a decrease in the demand for long-term debt.

Such changes in 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 to news about future changes in short rates as 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 in the way that we hypothesize, we estimate equations of the form:

$$Z_{i,t+1} = \alpha + \theta \times \left[\mathbb{E}_t(\overline{FFR}_{t+1q}) - FFR_t\right] + \gamma X_t + \epsilon_{i,t+1}, \tag{9}$$

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 $\theta$ 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 can be taken based on expectations of future interest rates.

## 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, $\text{LT Share}_t$. 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. Therefore, 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.

Table 8, Panel A, reports the results from the firm-level regressions with each column corresponding to one of our measures of long-term borrowing. These regressions include a number of controls as well as firm fixed effects. We estimate the $\theta$ coefficient to be 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 coefficients on the control variables go in the direction we would expect as well. 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 column (4) 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 estimate the same regressions. The results, reported in Table 8, Panel B, are consistent with the firm-level results, suggesting that the documented effect is widespread and not driven by a few smaller firms.

Intuitively, we expect the categorical thinking effect on real borrowing to be strongest at turning points in the interest rate cycle. When long rates have been low and the Fed communicates that a hiking cycle is coming, that may trigger an especially strong increase in long-term borrowing, as borrowers rush to lock in favorable rates. Similarly, when long rates have been high and the Fed communicates that a cutting cycle is coming, that may trigger an especially strong decrease in long-term borrowing, as borrowers wait for more favorable rates to materialize. This is exactly what we find in Appendix Table A.8, where we interact our main variable of interest with an indicator variable ("FirstChange") equal one if the current quarter is the quarter after the first rate change in a hiking/cutting cycle, and zero otherwise. As can be seen, the categorical thinking effect is approximately 2–7 times larger at these turning points.

A potential concern is that firms borrow long because of a change in investment opportunities rather than because of beliefs about interest rates. To address this concern, we replace the long-term borrowing measures with the subsequent one- to four-quarter capital expenditures (CAPX). The results, reported in Table A.9 in the Appendix, reveal no significant relationship between future investments and expected short-rate changes. This implies that the relation between long-term debt issuance and expected changes in short rates is not driven investment needs, and is instead consistent with a (mistaken) desire to strategically time long term debt issuance.

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 rates. In Appendix Table A.10, 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 the relationship we estimate 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.

We conduct analysis using observations at the loan type (conforming or jumbo) by month level. Conforming mortgages are for loans under the Federal Housing Finance Agency's conforming limit, which is between \$7,66K and \$1,450K in 2024, whereas jumbo loans exceed the limit. The results, reported in Table 9, 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 taken by wealthier households) compared to conforming 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.

We also find again in Appendix Table A.11 that the categorical thinking effect for real mortgage borrowing is strongest at turning points in the interest rate cycle.

### 4.3 Supply: Aggregate Evidence from Flow of Funds

To complement our micro-level evidence on firm and household borrowing behavior, we examine aggregate evidence from the Fed's Flow of Funds data. This allows us to analyze both household and corporate borrowing in a unified framework while validating our earlier findings using an alternative data source, which should be more comprehensive. Appendix Table A.12 presents these results. Whether examining household mortgage issuance or corporate long-term debt issuance (measured both directly and following (Greenwood, Hanson, and Stein, 2010)), we continue to find that expected increases in short rates predict significant increases in long-term borrowing. The effects are generally stronger in the post-2000 period.[12] These aggregate results provide corroborating evidence for our earlier findings using

[12]The stronger long-term borrowing response to expectations of changes in short rates in the post-2000 period could be associated with the rise of forward guidance and gradualism in monetary policy. After the early 2000's firms and households are likely to be more aware of the Fed's intended path for short rates. See

microdata—both households and firms increase their long-term borrowing when short rates are expected to rise.

### 4.4 Supply: Implications for monetary policy

US monetary policy since in the early 2000s has been characterized by gradualism (where the Federal Funds Rate is adjusted gradually over time) and forward guidance (where the Fed communicates the likely future path of the Federal Funds Rate). Many central banks outside of the US have adopted similar policies. Our results on aggregate firm and household borrowing imply that forward guidance of gradual monetary policy can have perverse effects in the short run in the opposite direction relative to the Fed's intended effect.

Our analysis implies the net impact of forward guidance from the Fed that it intends to gradually increase short rates, is likely to be an increase in long term 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 1 percentage point, the long rate typically rises by less than 1 percentage point. 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 (the difference between the long and short rate). We generally find that this coefficient is on the order of half as large in absolute magnitude as the positive coefficient on the expected change in the short rate (see Tables 8 and 9 and Appendix Table A.12). Therefore, our estimates indicate that the rush to borrow before long rates increase further dominates the direct dampening effect of higher long rates. Thus, the net effect of forward guidance of a gradual increase in the short rate is predicted to be an increase in long-term borrowing. Symmetrically, the net effect of forward guidance of a gradual *decrease* in the short rate is predicted to be a decrease in long-term borrowing. These shifts in long-term borrowing and associated shifts in home purchases (which can contribute to aggregate house price inflation) occur in the opposite of the Fed's intended directions for monetary tightening and loosening.

our discussion in the next section for details.

Note that the above discussion does not imply that monetary policy will be ineffective in the presence of categorical thinking—only that the forward guidance component of monetary policy may have perverse effects in the short run. In other words, when long-term interest rates are high, that will indeed lead to lower levels of long-term borrowing, as the Fed intends; however, if long rates are expected to go even higher due to forward guidance, that will lead to more long-term borrowing than there would be otherwise. Thus, categorical thinking can help explain the forward guidance puzzle, in which forward guidance has been less effective than predicted by macroeconomic models (see, e.g., Del Negro et al. (2023); McKay et al. (2016); Campbell et al. (2019); Angeletos and Lian (2018).

## 4.5 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.

The dependent variable is monthly mutual fund flows at the share class level, expressed as a percentage of the previous month's total net assets. This measure is evaluated in the month immediately following the forecast of the short rate. We run the tests separately for the full sample, institutional share classes, and retail share classes. Because previous research has shown that fund flows also depend on past returns and the relative performance of stocks versus bonds, we also include detailed controls for the fund's past returns, past flows, and the performance of the stock market and bond market over the past one, two and three months.

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 $\theta$. The findings, as shown in Table 10, corroborate this prediction: When short rates are expected to rise by 1 percentage point, bond funds experience average outflows of approximately 1-2% of AUM. 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 can contribute to the excess volatility and subsequent reversals observed in long-term interest rates.

Note that it is easier for non-institutional investors to trade long-term treasuries than to trade mortgages. This difference in ease of trading for different types of long-term debt may help explain why we find evidence of significant reversals in long-term Treasury yields but not mortgages (compare columns 4-6 of Panels A and B of Table 3). Changes in the demand for long term debt from bond investors may have a stronger effect on Treasury yields compared to the 30-year home mortgage rate.

# 5 Conclusion

We show that there is a widespread misconception that expected future shifts in short-term interest rates predict corresponding future movements in long-term interest rates. 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, who forecast similar shapes for the paths of long and short rates over the next four quarters. We also show that categorical thinking 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, and can help to explain the forward guidance puzzle of why forward guidance has been less effective than predicted by macroeconomic models. 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 and investor 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 variables as detailed in Section 1. Panel A includes the number of observations (n), mean, standard deviations (sd), and key percentiles (p5, p25, median, p75, p95) for each variable. Panel B reports correlations between the main time-series variables. 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.

Panel A: Summary Statistics

| | n | mean | sd | p5 | p25 | median | p75 | p95 |
|---|---|---|---|---|---|---|---|---|
| $\mathbb{E}_t(\overline{FFR}_{t+1q}) - FFR_t$ | 465 | 0.04 | 0.30 | -0.52 | -0.06 | 0.03 | 0.20 | 0.52 |
| $\mathbb{E}_t(\overline{HMR}_{t+1q}) - HMR_t$ | 465 | 0.08 | 0.22 | -0.31 | -0.07 | 0.10 | 0.24 | 0.39 |
| $\overline{HMR}_{t+1q} - HMR_t$ | 465 | -0.08 | 0.46 | -0.85 | -0.34 | -0.12 | 0.21 | 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 |
| $\mathbb{E}_t(\overline{y}^{(10)}_{t+1q}) - y^{(10)}_t$ | 417 | -0.02 | 0.29 | -0.51 | -0.20 | 0.02 | 0.19 | 0.38 |
| $\overline{y}^{(10)}_{t+1q} - y^{(10)}_t$ | 417 | -0.03 | 0.45 | -0.73 | -0.34 | -0.03 | 0.24 | 0.72 |
| $\overline{y}^{(10)}_{t+1q} - \mathbb{E}_t(\overline{y}^{(10)}_{t+1q})$ | 417 | -0.01 | 0.54 | -0.82 | -0.37 | -0.07 | 0.35 | 0.95 |
| **Control Variables** | | | | | | | | |
| $FFR_t$ | 465 | 3.71 | 3.06 | 0.09 | 0.41 | 3.30 | 5.82 | 9.10 |
| $y^{(5)}_t - FFR_t$ | 465 | 1.03 | 0.96 | -0.63 | 0.34 | 1.03 | 1.72 | 2.59 |
| $\pi_t$ | 465 | 2.68 | 1.35 | 0.48 | 1.74 | 2.64 | 3.53 | 4.95 |
| Baa credit spread$_t$ | 465 | 1.89 | 0.57 | 1.20 | 1.48 | 1.81 | 2.19 | 2.73 |
| Baa credit term spread$_t$ | 465 | 1.54 | 0.64 | 0.68 | 1.08 | 1.47 | 1.96 | 2.53 |
| **Other Long Rates** | | | | | | | | |
| $\bar{y}^{(10)}_{t+1q} - y^{(10)}_t$ | 417 | -0.03 | 0.45 | -0.73 | -0.34 | -0.03 | 0.24 | 0.72 |
| $\bar{y}^{(30)}_{t+1q} - y^{(30)}_t$ | 384 | -0.04 | 0.45 | -0.75 | -0.28 | 0.01 | 0.22 | 0.64 |
| $\overline{Aaa}_{t+1q} - Aaa_t$ | 456 | -0.14 | 0.46 | -0.92 | -0.41 | -0.15 | 0.15 | 0.60 |
| $\overline{Baa}_{t+1q} - Baa_t$ | 276 | -0.19 | 0.54 | -1.18 | -0.45 | -0.13 | 0.14 | 0.53 |
| **Firm-level Issuance** | | | | | | | | |
| $\mathbb{1}$(LT Issues$_{i,t} > 0$) | 750,698 | 0.38 | 0.48 | 0 | 0 | 0.00 | 1.00 | 1.00 |
| LT Issues$_{i,t}$/AT$_{i,t-1}$ | 746,807 | 0.03 | 0.08 | 0 | 0 | 0.00 | 0.01 | 0.17 |
| LT Issues$_{i,t}$/Total Debt$_{i,t-1}$ | 588,700 | 0.16 | 0.53 | 0 | 0 | 0.00 | 0.07 | 0.84 |
| LT Share$_{i,t}$ | 382,391 | 0.60 | 0.48 | 0 | 0 | 0.93 | 1.00 | 1.00 |
| **Aggregate-level Issuance** | | | | | | | | |
| Log LT Issues$_t$ | 155 | 12.91 | 1.42 | 10.75 | 11.85 | 13.13 | 13.96 | 14.88 |
| LT Issues$_t$/AT$_{t-1}$ | 155 | 0.02 | 0.01 | 0.01 | 0.01 | 0.01 | 0.02 | 0.04 |
| LT Issues$_t$/Total Debt$_{t-1}$ | 155 | 0.07 | 0.04 | 0.03 | 0.04 | 0.06 | 0.07 | 0.17 |
| LT Share$_t$ | 155 | 0.64 | 0.13 | 0.46 | 0.57 | 0.64 | 0.73 | 0.83 |
| **Bond Mutual Fund Flows** | | | | | | | | |
| $flow_{i,t}$, Full sample | 324,739 | 1.52 | 12.48 | -7.17 | -1.56 | -0.16 | 1.63 | 13.37 |
| $flow_{i,t}$, Retail funds | 177,610 | 1.06 | 11.61 | -7.09 | -1.86 | -0.40 | 1.30 | 11.96 |
| $flow_{i,t}$, Institutional funds | 147,129 | 2.08 | 13.43 | -7.32 | -1.17 | 0.05 | 2.04 | 15.08 |

| Panel B: Correlations | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (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) $\pi_t$ | -.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 2** 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 ($\pi_t$), 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.

| | $\bar{y}^{(10)}_{t+1q} - y^{(10)}_t$ | $\bar{y}^{(30)}_{t+1q} - y^{(30)}_t$ | $\overline{Aaa}_{t+1q} - Aaa_t$ | $\overline{Baa}_{t+1q} - Baa_t$ | $\overline{HMR}_{t+1q} - HMR_t$ |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (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) |
| $\pi_t$ | -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 3** Categorical thinking in consensus forecasts: Main specification

This table presents OLS regression coefficients from equations (3)-(5). 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 ($\pi_t$), 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.

Panel A: Home mortgage rate

| | $\mathbb{E}_t(\overline{HMR}_{t+1q}) - HMR_t$ | | | $\overline{HMR}_{t+1q} - HMR_t$ | | | $\overline{HMR}_{t+1q} - \mathbb{E}_t(\overline{HMR}_{t+1q})$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | (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) |
| $\pi_t$ | | | 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 |

Panel B: 10-Year Treasury yield

| | $\mathbb{E}_t(\overline{y}^{(10)}_{t+1q}) - y^{(10)}_t$ | | | $\overline{y}^{(10)}_{t+1q} - y^{(10)}_t$ | | | $\overline{y}^{(10)}_{t+1q} - \mathbb{E}_t(\overline{y}^{(10)}_{t+1q})$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $\mathbb{E}_t(\overline{FFR}_{t+1q}) - FFR_t$ | 0.38*** | 0.46*** | 0.41*** | -0.25** | -0.26** | -0.25** | -0.63*** | -0.71*** | -0.66*** |
| | (0.06) | (0.05) | (0.05) | (0.12) | (0.12) | (0.13) | (0.13) | (0.13) | (0.14) |
| $FFR_t$ | | -0.04*** | -0.05*** | | -0.02 | 0.01 | | 0.02 | 0.06*** |
| | | (0.01) | (0.01) | | (0.02) | (0.02) | | (0.02) | (0.02) |
| $y^{(10)}_t - FFR_t$ | | -0.14*** | -0.14*** | | -0.04 | -0.04 | | 0.10*** | 0.10*** |
| | | (0.01) | (0.01) | | (0.03) | (0.03) | | (0.04) | (0.04) |
| $\pi_t$ | | | 0.01 | | | -0.05 | | | -0.06 |
| | | | (0.01) | | | (0.03) | | | (0.04) |
| Baa credit spread$_t$ | | | -0.06 | | | -0.20 | | | -0.13 |
| | | | (0.08) | | | (0.15) | | | (0.14) |
| Baa credit term spread$_t$ | | | -0.02 | | | 0.25 | | | 0.28* |
| | | | (0.08) | | | (0.16) | | | (0.15) |
| Standard-Errors | | | | | NW | | | | |
| $R^2$ | 0.146 | 0.463 | 0.494 | 0.027 | 0.042 | 0.080 | 0.116 | 0.165 | 0.217 |
| Observations | 417 | 417 | 417 | 417 | 417 | 417 | 417 | 417 | 417 |

**Table 4** Benchmark of $\beta_1$ under Expectations Hypothesis

This table presents OLS regression coefficients from Equation (6) (Columns 1-6) and equation (3) (Columns 7-9). The dependent variable in Column 1-6 is $1/n$ of the expected changes of the federal funds rate 10 years from now, $\frac{1}{n}(\mathbb{E}_t FFR_{t+n} - FFR_t)$, based on the BCFF long range survey ($n = 40$). Columns 1–3, 4–6, and 7–9 display results for the consensus forecasts, the top 10% of forecasts, and the bottom 10% of forecasts, respectively. The dependent variable in Column 7-8 is the 1-quarter-ahead forecasted change in the 10-year Treasury yield, $\mathbb{E}_t(\bar{y}^{(10)}_{t+1q}) - y^{(10)}_t$. 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 $(\pi_t)$, 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 sample period is semi-annual from 1997:06 to 2021:12. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

| | $\frac{1}{n}(\mathbb{E}_t FFR_{t+n} - FFR_t)$ | | | | | | $\mathbb{E}_t(\bar{y}^{(10)}_{t+1q}) - y^{(10)}_t$ | |
|---|---|---|---|---|---|---|---|---|
| | Consensus | | Top 10% | | Bottom 10% | | Consensus | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\mathbb{E}_t(\overline{FFR}_{t+1q}) - FFR_t$ | 0.00 | -0.01 | 0.00 | -0.01 | 0.01 | 0.00 | 0.61*** | 0.61*** |
| | (0.03) | (0.01) | (0.03) | (0.01) | (0.03) | (0.01) | (0.15) | (0.09) |
| $FFR_t$ | | -0.01*** | | -0.01*** | | -0.01*** | | -0.10*** |
| | | (0.00) | | (0.00) | | (0.00) | | (0.03) |
| $HMR_t - FFR_t$ | | 0.01*** | | 0.02*** | | 0.01*** | | -0.16*** |
| | | (0.00) | | (0.00) | | (0.00) | | (0.03) |
| $\pi_t$ | | 0.00 | | 0.00* | | 0.00 | | 0.01 |
| | | (0.00) | | (0.00) | | (0.00) | | (0.03) |
| Baa credit spread$_t$ | | 0.00 | | 0.00 | | 0.01 | | 0.12 |
| | | (0.01) | | (0.01) | | (0.01) | | (0.17) |
| Baa credit term spread$_t$ | | -0.01 | | 0.00 | | -0.01 | | -0.21 |
| | | (0.01) | | (0.01) | | (0.01) | | (0.25) |
| $R^2$ | 0.000 | 0.951 | 0.000 | 0.942 | 0.001 | 0.941 | 0.166 | 0.466 |
| Observations | 50 | 50 | 50 | 50 | 50 | 50 | 50 | 50 |

**Table 5** Categorical thinking in consensus forecasts: Across forecast horizons

This table presents the OLS regression coefficients of expected changes in the home mortgage rate on the expected changes in the federal funds rate across different forecast horizons. In Panels A and C, the dependent variables are expected changes in home mortgage rate between two future quarters $\mathbb{E}_t(\overline{HMR}_{t+nq}) - \mathbb{E}_t\left(\overline{HMR}_{t+(n-1)q}\right)$. In Panel B, the dependent variable is the actual changes in home mortgage rate between two future quarters $\overline{HMR}_{t+nq} - \overline{HMR}_{t+(n-1)q}$. The main independent variables are the expected changes in the federal funds rate between the two future quarters $(\mathbb{E}_t(\overline{FFR}_{t+nq}) - \mathbb{E}_t(\overline{FFR}_{t+(n-1)q}))$ based on the consensus forecasts. We consider forecast horizons $n$ of 0, 1, 2, 3, 4 quarters, among which 0-quarter forecast is the nowcast. All panels include the following control variables: the current Federal Funds Rate ($FFR$), the term spread ($HMR_t - FFR_t$), inflation rate ($\pi_t$), 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.

| | $n=1$ | $n=2$ | $n=3$ | $n=4$ |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Panel A: | | | | |
| | $\mathbb{E}_t(\overline{HMR}_{t+nq}) - \mathbb{E}_t\left(\overline{HMR}_{t+(n-1)q}\right)$ | | | |
| $\mathbb{E}_t(\overline{FFR}_{t+nq}) - \mathbb{E}_t(\overline{FFR}_{t+(n-1)q})$ | 0.33*** | 0.36*** | 0.37*** | 0.35*** |
| | (0.03) | (0.04) | (0.04) | (0.03) |
| $FFR_t$ | -0.02*** | -0.02*** | -0.01*** | -0.01*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| $HMR_t - FFR_t$ | -0.01* | -0.01** | -0.02*** | -0.01* |
| | (0.00) | (0.00) | (0.01) | (0.00) |
| $\pi_t$ | 0.00 | 0.01 | 0.00 | 0.01* |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Baa credit spread$_t$ | 0.00 | -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) |
| $R^2$ | 0.589 | 0.587 | 0.658 | 0.723 |
| Observations | 465 | 465 | 465 | 465 |
| Panel B: | | | | |
| | $\overline{HMR}_{t+nq} - \overline{HMR}_{t+(n-1)q}$ | | | |
| $\mathbb{E}_t(\overline{FFR}_{t+nq}) - \mathbb{E}_t(\overline{FFR}_{t+(n-1)q})$ | -0.15 | -0.21 | -0.22 | -0.31 |
| | (0.13) | (0.20) | (0.24) | (0.25) |
| $FFR_t$ | -0.01 | -0.04* | -0.03 | -0.04 |
| | (0.02) | (0.02) | (0.02) | (0.02) |
| $HMR_t - FFR_t$ | -0.05* | -0.04 | -0.03 | -0.02 |
| | (0.03) | (0.03) | (0.04) | (0.04) |
| $\pi_t$ | -0.01 | 0.00 | -0.01 | 0.01 |
| | (0.03) | (0.04) | (0.04) | (0.03) |
| Baa credit spread$_t$ | -0.21* | 0.00 | -0.02 | -0.03 |
| | (0.12) | (0.11) | (0.13) | (0.12) |
| Baa credit term spread$_t$ | 0.18 | -0.05 | -0.02 | 0.04 |
| | (0.14) | (0.12) | (0.14) | (0.15) |
| $R^2$ | 0.058 | 0.070 | 0.060 | 0.060 |
| Observations | 465 | 465 | 462 | 459 |

| | $n=1$ | $n=2$ | $n=3$ | $n=4$ |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Panel C: | | | | |
| | $\mathbb{E}_t(\overline{HMR}_{t+nq}) - \mathbb{E}_t\left(\overline{HMR}_{t+(n-1)q}\right)$ | | | |
| $\mathbb{E}_t(\overline{FFR}_{t+1q}) - \mathbb{E}_t(\overline{FFR}_{t+0q})$ | 0.32*** | 0.04 | -0.06* | -0.06*** |
| | (0.05) | (0.03) | (0.03) | (0.02) |
| $\mathbb{E}_t(\overline{FFR}_{t+2q}) - \mathbb{E}_t(\overline{FFR}_{t+1q})$ | 0.11 | 0.26*** | 0.05 | 0.00 |
| | (0.08) | (0.06) | (0.04) | (0.04) |
| $\mathbb{E}_t(\overline{FFR}_{t+3q}) - \mathbb{E}_t(\overline{FFR}_{t+2q})$ | -0.09 | 0.08 | 0.26*** | 0.08* |
| | (0.07) | (0.06) | (0.06) | (0.04) |
| $\mathbb{E}_t(\overline{FFR}_{t+4q}) - \mathbb{E}_t(\overline{FFR}_{t+3q})$ | 0.13** | 0.08 | 0.13*** | 0.28*** |
| | (0.05) | (0.05) | (0.05) | (0.03) |
| $FFR_t$ | -0.02*** | -0.01*** | -0.01*** | -0.01*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| $HMR_t - FFR_t$ | -0.02*** | -0.02*** | -0.02*** | -0.01 |
| | (0.01) | (0.01) | (0.00) | (0.00) |
| $\pi_t$ | 0.00 | 0.01 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Baa credit spread$_t$ | 0.00 | 0.00 | -0.01 | 0.00 |
| | (0.03) | (0.02) | (0.02) | (0.02) |
| Baa credit term spread$_t$ | -0.02 | 0.02 | 0.02 | 0.02 |
| | (0.03) | (0.02) | (0.02) | (0.02) |
| $R^2$ | 0.603 | 0.603 | 0.683 | 0.734 |
| Observations | 465 | 465 | 465 | 465 |

**Table 6** Categorical thinking in consensus forecasts: Controlling for forecast revisions of the short rate and recent changes of the long rate

This table presents OLS regression coefficients from equations (3)-(5), controlling for forecast revision of the short rate and recent changes of the long 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. We control for the 3-month revision in the forecast of the federal funds rates ($\mathbb{E}_t(\overline{FFR}_{t+1q}) - \mathbb{E}_{t-1}(\overline{FFR}_{t+1q})$) in Panel A, and the 3-month changes in the home mortgage rate ($HMR_t - HMR_{t-1q}$) in Panel B. The regressions include the following control variables: the current Federal Funds Rate ($FFR$), the term spread ($HMR_t - FFR_t$), inflation rate ($\pi_t$), 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) |
| Panel A: Controlling for forecast revisions of the short rate | | | | | | | | | |
| $\mathbb{E}_t(\overline{FFR}_{t+1q}) - FFR_t$ | 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) |
| $\pi_t$ | 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 |
| Panel B: Controlling for recent changes in the long rate | | | | | | | | | |
| $\mathbb{E}_t(\overline{FFR}_{t+1q}) - FFR_t$ | 0.24*** | | 0.32*** | -0.19 | | -0.18 | -0.43*** | | -0.50*** |
| | (0.05) | | (0.05) | (0.13) | | (0.13) | (0.12) | | (0.12) |
| $HMR_t - HMR_{t-1q}$ | | -0.17*** | -0.22*** | | -0.04 | -0.01 | | 0.13* | 0.20*** |
| | | (0.03) | (0.02) | | (0.06) | (0.06) | | (0.07) | (0.07) |
| $FFR_t$ | -0.03*** | -0.03*** | -0.03*** | -0.01 | -0.01 | -0.01 | 0.02 | 0.03 | 0.03 |
| | (0.01) | (0.01) | (0.01) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| $HMR_t - FFR_t$ | -0.03*** | 0.00 | -0.02** | -0.07* | -0.08** | -0.07* | -0.03 | -0.08* | -0.04 |
| | (0.01) | (0.01) | (0.01) | (0.04) | (0.03) | (0.04) | (0.04) | (0.04) | (0.04) |
| $\pi_t$ | 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 | -0.13** | -0.07 | -0.32** | -0.28* | -0.32** | -0.22* | -0.15 | -0.24** |
| | (0.06) | (0.06) | (0.06) | (0.14) | (0.15) | (0.14) | (0.13) | (0.13) | (0.12) |
| Baa credit term spread$_t$ | 0.05 | 0.00 | -0.01 | 0.28* | 0.27 | 0.28* | 0.23 | 0.27* | 0.29* |
| | (0.06) | (0.06) | (0.06) | (0.16) | (0.17) | (0.17) | (0.16) | (0.16) | (0.15) |
| $R^2$ | 0.354 | 0.370 | 0.516 | 0.079 | 0.069 | 0.079 | 0.096 | 0.052 | 0.123 |
| Observations | 465 | 466 | 465 | 465 | 466 | 465 | 465 | 466 | 465 |

**Table 7** 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.

| | $\mathbb{E}_{it}(HMR_{t+12m}) - HMR_t > 0$ | |
|---|---|---|
| | (1) | (2) |
| $\mathbb{E}_t^f(FFR_{t+12m}) - FFR_t > 0$ | 0.162$^{***}$ | 0.194$^{***}$ |
| | (0.0104) | (0.0207) |
| $FFR_t$ | | 0.0718$^{***}$ |
| | | (0.0113) |
| $HMR_t - FFR_t$ | | 0.0530$^{***}$ |
| | | (0.0139) |
| $\pi_t$ | | 0.000215 |
| | | (0.00719) |
| Baa credit spread$_t$ | | -0.121$^{**}$ |
| | | (0.0577) |
| Baa credit term spread$_t$ | | 0.0161 |
| | | (0.0708) |
| $R^2$ | 0.007 | 0.021 |
| Observations | 119,278 | 119,278 |

**Table 8** Corporate long-term issuance: Firm and aggregate-level evidence

This table presents OLS regression of firms' long-term debt issuance on the expected short rate changes. Panel A reports evidence using quarterly firm-level Compustat data. The dependent variables include an indicator variable that equals one if a firm issues a long-term debt in the subsequent quarter ($\mathbb{1}(\text{LT Issues}_{i,t+1} > 0)$), long-term debt issue in the subsequent quarter normalized by total assets in the current quarter ($\frac{\text{LT Issues}_{i,t+1}}{\text{AT}_{i,t}}$), long-term debt issue in the subsequent quarter normalized by total debt in the current quarter ($\frac{\text{LT Issues}_{i,t+1}}{\text{Total Debt}_{i,t}}$), and long-term share of total new debt issues in the subsequent quarter ($\text{LT Share}_{i,t+1}$), respectively. Panel B aggregates the firm-level measures to the economy level. 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 ($\text{LT Share}_{t+1}$). 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 ($\pi_t$), Baa credit spread and Baa credit term spread. Standard errors are double clustered by firm and year-quarter in Panel A and are Newey-West standard errors with the automatic bandwidth selection in Panel B. Firm fixed effects are included in all regressions in Panel A. The sample period is from 1983:Q2 to 2021:Q4. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Firm-level long-term debt issuance

| | $\mathbb{1}(\text{LT Issues}_{i,t+1} > 0)$ | $\frac{\text{LT Issues}_{i,t+1}}{\text{AT}_{i,t}}$ | $\frac{\text{LT issues}_{t+1}}{\text{Total debt}_t}$ | $\text{LT Share}_{i,t+1}$ |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\mathbb{E}_t(\overline{FFR}_{t+1q}) - FFR_t$ | 0.0348*** | 0.0049*** | 0.0315*** | 0.0494*** |
| | (0.0096) | (0.0009) | (0.0068) | (0.0120) |
| $FFR_t$ | 0.0040*** | -0.0005*** | -0.0013 | -0.0123*** |
| | (0.0013) | (0.0002) | (0.0013) | (0.0020) |
| $y_t^{(5)} - FFR_t$ | -0.0122*** | -0.0027*** | -0.0086*** | -0.0264*** |
| | (0.0024) | (0.0003) | (0.0023) | (0.0033) |
| $\pi_t$ | -0.0061*** | -0.0013*** | -0.0058** | -0.0026 |
| | (0.0019) | (0.0003) | (0.0022) | (0.0022) |
| Baa credit $\text{spread}_t$ | 0.0102 | -0.0027*** | -0.0083 | -0.0098 |
| | (0.0090) | (0.0008) | (0.0076) | (0.0096) |
| Baa credit term $\text{spread}_t$ | -0.0152* | -0.0017* | -0.0160* | 0.0076 |
| | (0.0089) | (0.0009) | (0.0084) | (0.0110) |
| $R^2$ | 0.359 | 0.221 | 0.153 | 0.483 |
| Observations | 750,698 | 746,807 | 588,700 | 382,391 |
| Firm FE | ✓ | ✓ | ✓ | ✓ |

| Panel B: Aggregate long-term debt issuance | | | | |
|---|---|---|---|---|
| | $\text{Log(LT Issues)}_{t+1}$ | $\frac{\text{LT Issues}_{t+1}}{\text{AT}_t}$ | $\frac{\text{LT Issues}_{t+1}}{\text{Total Debt}_t}$ | $\text{LT Share}_{t+1}$ |
| | (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) |
| $\pi_t$ | 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 9** 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 $\text{Loan}_{t+1}$). 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 ($\pi_t$), 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 $\text{Loan}_{t+1}$ | |
|---|---|---|
| | (1) | (2) |
| $\mathbb{E}_t(FFR_{t+1q}) - FFR_t$ | 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) |
| $\pi_t$ | | 0.0552$^{**}$ |
| | | (0.0019) |
| Baa credit $\text{spread}_t$ | | -0.9530 |
| | | (0.3808) |
| Baa credit term $\text{spread}_t$ | | 0.6925 |
| | | (0.2875) |
| $R^2$ | 0.690 | 0.786 |
| Observations | 192 | 192 |

**Table 10** 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 ($flow_{i,t+1}$) 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 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 ($\pi_t$), Baa credit spread and Baa credit term spread. We additionally control for lagged fund returns, fund flows, stock market excess returns (from Fama-French) and the 10-Year Treasury returns (from CRSP US Treasury Database Fixed Term Indexes) in the past three months. 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.

| | $flow_{i,t+1m}$ | | | | | |
|---|---|---|---|---|---|---|
| Share class | Full sample | | Institutional | | Retail | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\mathbb{E}_t(\overline{FFR}_{t+1q}) - FFR_t$ | -1.6022*** | -1.8958*** | -1.9787*** | -1.9550*** | -1.1587* | -1.6428*** |
| | (0.4221) | (0.4217) | (0.3364) | (0.3419) | (0.6282) | (0.6039) |
| $FFR_t$ | 0.6649*** | 0.7151*** | 0.6220*** | 0.6848*** | 0.6719*** | 0.7083*** |
| | (0.0609) | (0.0636) | (0.0662) | (0.0689) | (0.0841) | (0.0846) |
| $y_t^{(5)} - FFR_t$ | 0.9932*** | 1.0885*** | 1.1306*** | 1.2406*** | 0.9165*** | 0.9903*** |
| | (0.0976) | (0.0971) | (0.1031) | (0.1036) | (0.1326) | (0.1301) |
| $\pi_t$ | 0.0488 | -0.0105 | -0.0261 | -0.0282 | 0.1155 | 0.0074 |
| | (0.0624) | (0.0654) | (0.0611) | (0.0631) | (0.0815) | (0.0858) |
| Baa credit spread$_t$ | 0.9942** | 0.4689 | 0.7290** | 0.5893 | 1.2769** | 0.5588 |
| | (0.3978) | (0.4411) | (0.3325) | (0.3652) | (0.5408) | (0.5720) |
| Baa credit term spread$_t$ | -0.2860 | 0.0410 | -0.3943 | -0.2770 | -0.3430 | 0.0429 |
| | (0.4719) | (0.4764) | (0.3589) | (0.3753) | (0.6466) | (0.6225) |
| Fund return$_{i,t-1m}$ | 20.6435*** | 16.4313*** | 12.5256** | 8.4947* | 33.0838*** | 30.6836*** |
| | (5.5747) | (6.1148) | (5.1867) | (4.7145) | (6.1324) | (7.1298) |
| Fund return$_{i,t-2m}$ | 13.0410*** | 6.3276* | 8.2588** | 3.3579 | 19.4536*** | 9.9078 |
| | (3.9031) | (3.3480) | (3.5655) | (2.7111) | (5.7508) | (6.2253) |
| Fund return$_{i,t-3m}$ | 12.9504*** | 7.8536** | 8.5155** | 6.0622* | 19.5594*** | 10.2529* |
| | (4.1687) | (3.6673) | (3.8671) | (3.5344) | (5.6957) | (5.6248) |
| $flow_{i,t-1m}$ | 0.0956*** | 0.0945*** | 0.0976*** | 0.0972*** | 0.0888*** | 0.0857*** |
| | (0.0078) | (0.0078) | (0.0082) | (0.0082) | (0.0128) | (0.0127) |
| $flow_{i,t-2m}$ | 0.0796*** | 0.0792*** | 0.0624*** | 0.0621*** | 0.0960*** | 0.0955*** |
| | (0.0055) | (0.0055) | (0.0061) | (0.0061) | (0.0089) | (0.0088) |
| $flow_{i,t-3m}$ | 0.0669*** | 0.0669*** | 0.0497*** | 0.0496*** | 0.0841*** | 0.0849*** |
| | (0.0050) | (0.0050) | (0.0057) | (0.0057) | (0.0080) | (0.0079) |
| $r_{t-1m}^{Stock}$ | | -0.0489** | | 0.0086 | | -0.0979*** |
| | | (0.0201) | | (0.0170) | | (0.0261) |
| $r_{t-2m}^{Stock}$ | | -0.0053 | | 0.0244 | | -0.0267 |
| | | (0.0159) | | (0.0166) | | (0.0203) |
| $r_{t-3m}^{Stock}$ | | 0.0063 | | 0.0119 | | 0.0080 |
| | | (0.0180) | | (0.0166) | | (0.0228) |
| $r_{t-1m}^{Treas}$ | | 0.0862** | | 0.0920** | | 0.0545 |
| | | (0.0424) | | (0.0433) | | (0.0452) |
| $r_{t-2m}^{Treas}$ | | 0.1206*** | | 0.1056*** | | 0.1330*** |
| | | (0.0330) | | (0.0359) | | (0.0421) |
| $r_{t-3m}^{Treas}$ | | 0.0927*** | | 0.0739** | | 0.1119** |
| | | (0.0350) | | (0.0363) | | (0.0438) |
| $R^2$ | 0.087 | 0.088 | 0.070 | 0.070 | 0.108 | 0.110 |
| Observations | 315,760 | 315,760 | 142,684 | 142,684 | 173,076 | 173,076 |
| Fund FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

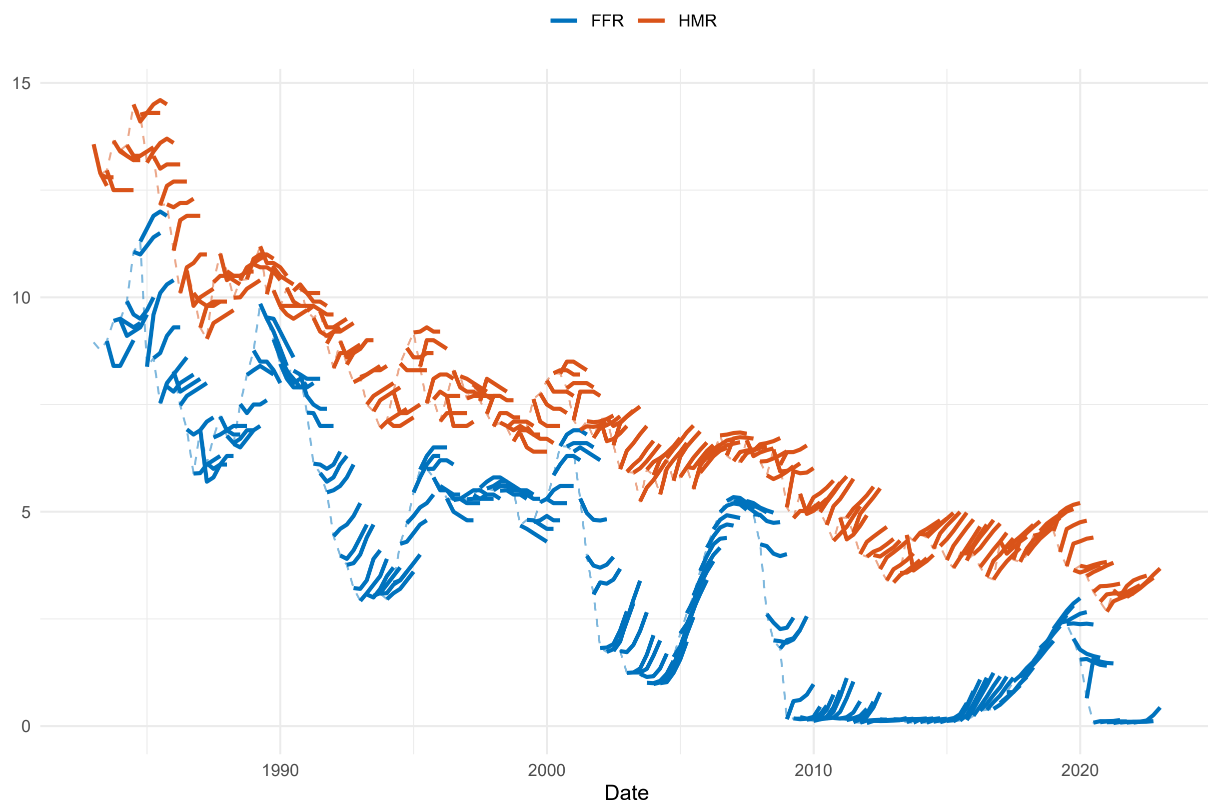
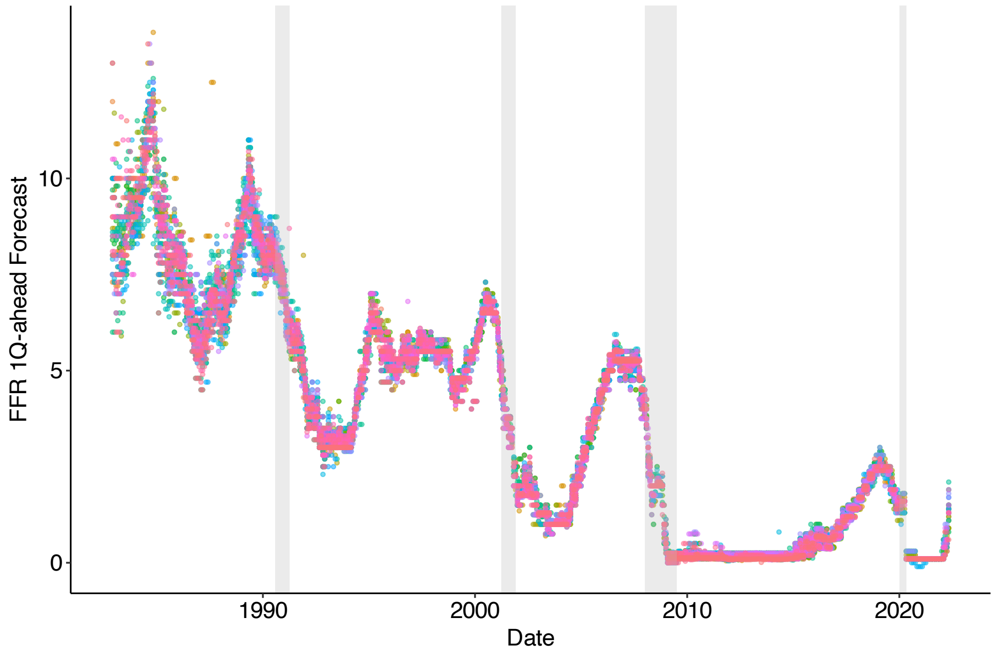
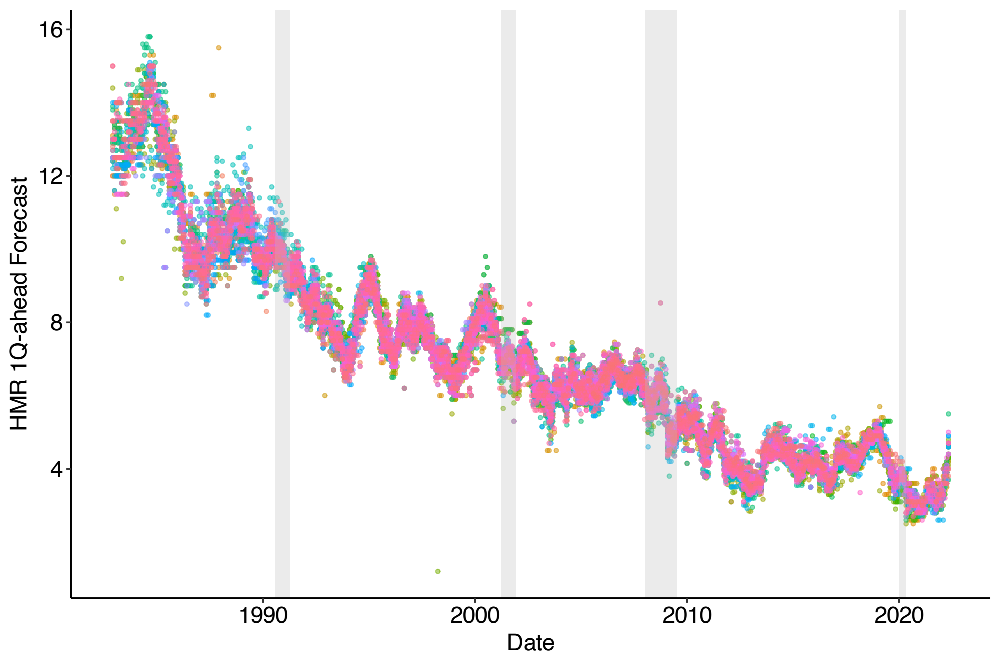



**Figure 2** Term structure of FFR and HMR expectations across forecast horizons

The dotted red and blue lines show the realized paths of the home mortgage rate and federal funds rate over time, respectively. The solid-colored "hairlines" leading away from the dotted lines represent the consensus forecast by professional forecasters in the Blue Chip Financial Forecasts (BCFF) of the home mortgage rate and federal funds rate over the next four quarters.




**A.** FFR Forecasts




**B.** HMR Forecasts

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

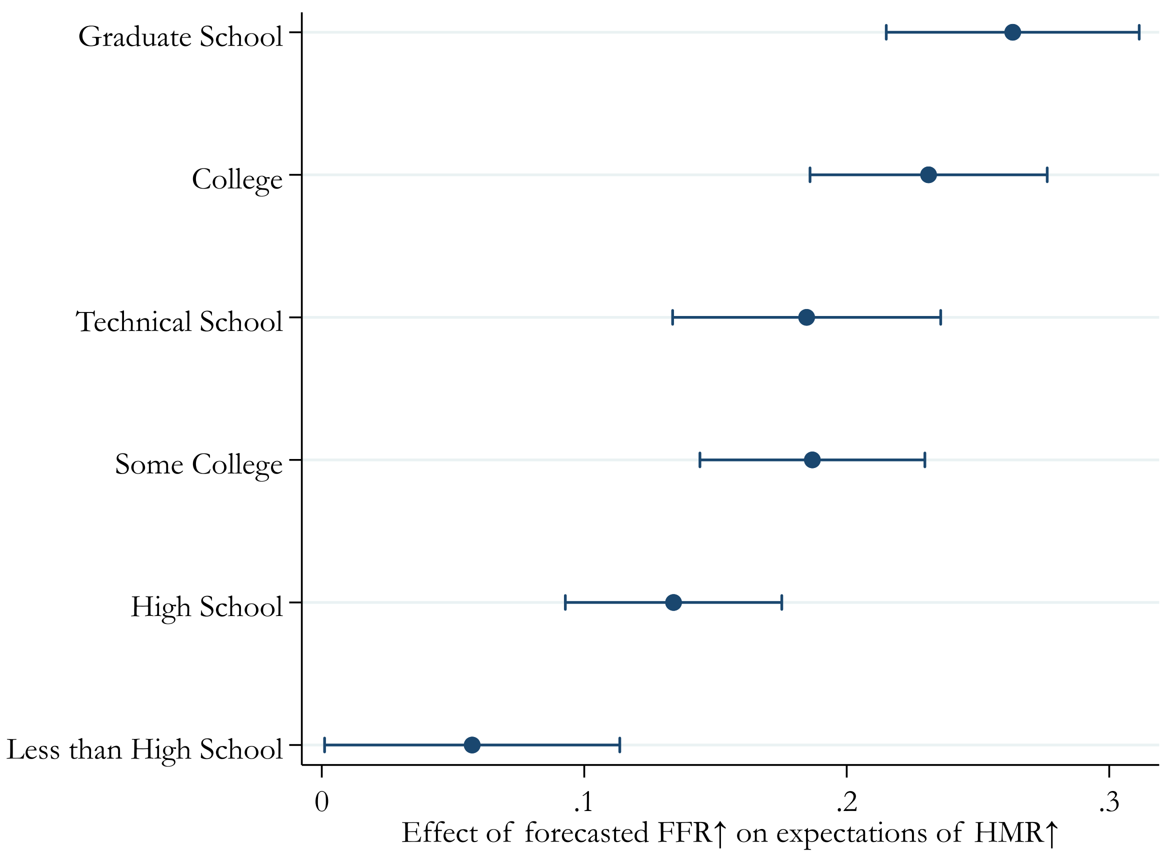



**Figure 4** Categorical thinking in household beliefs: Heterogeneity by education

In this figure, we re-estimate Table 7 (column 2) interacting our main independent variable of interest with a series of education level indicator variables. The marginal effects for each education level are displayed (i.e., the sum of the main effect and interaction).

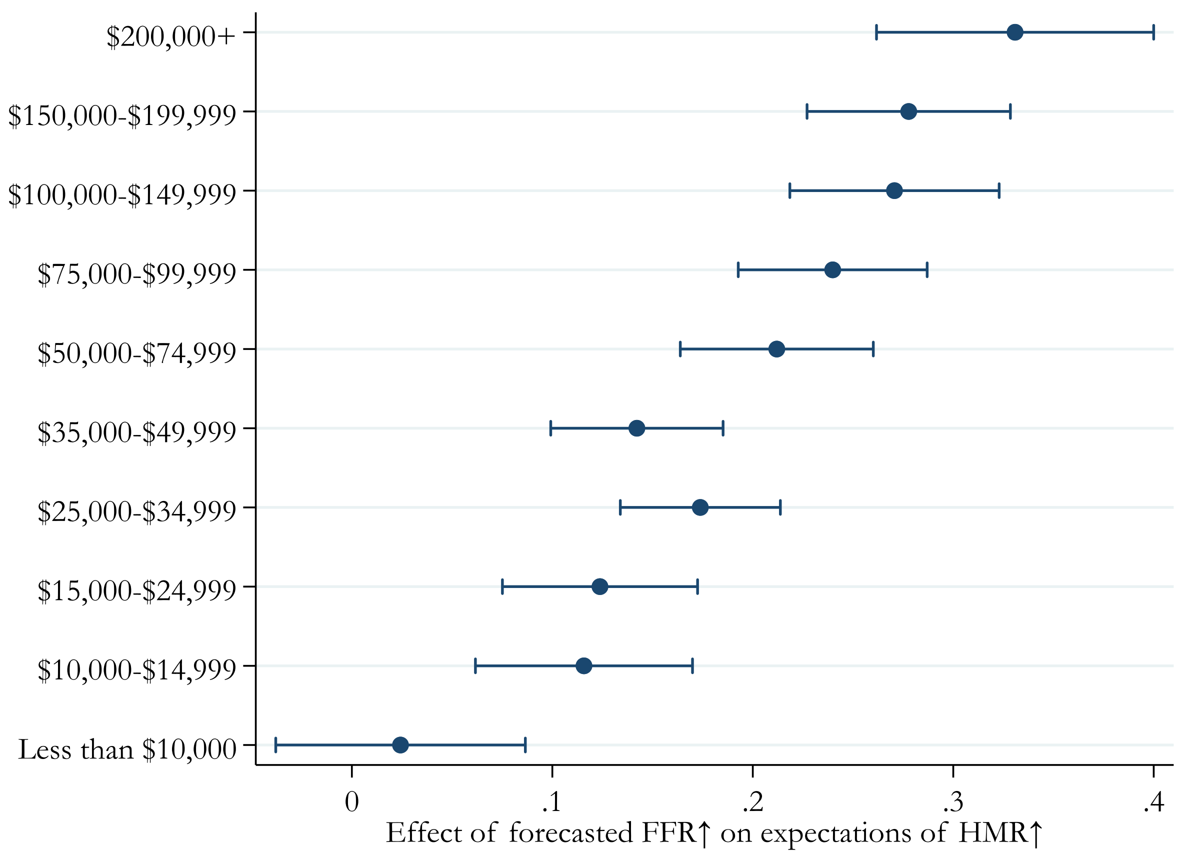


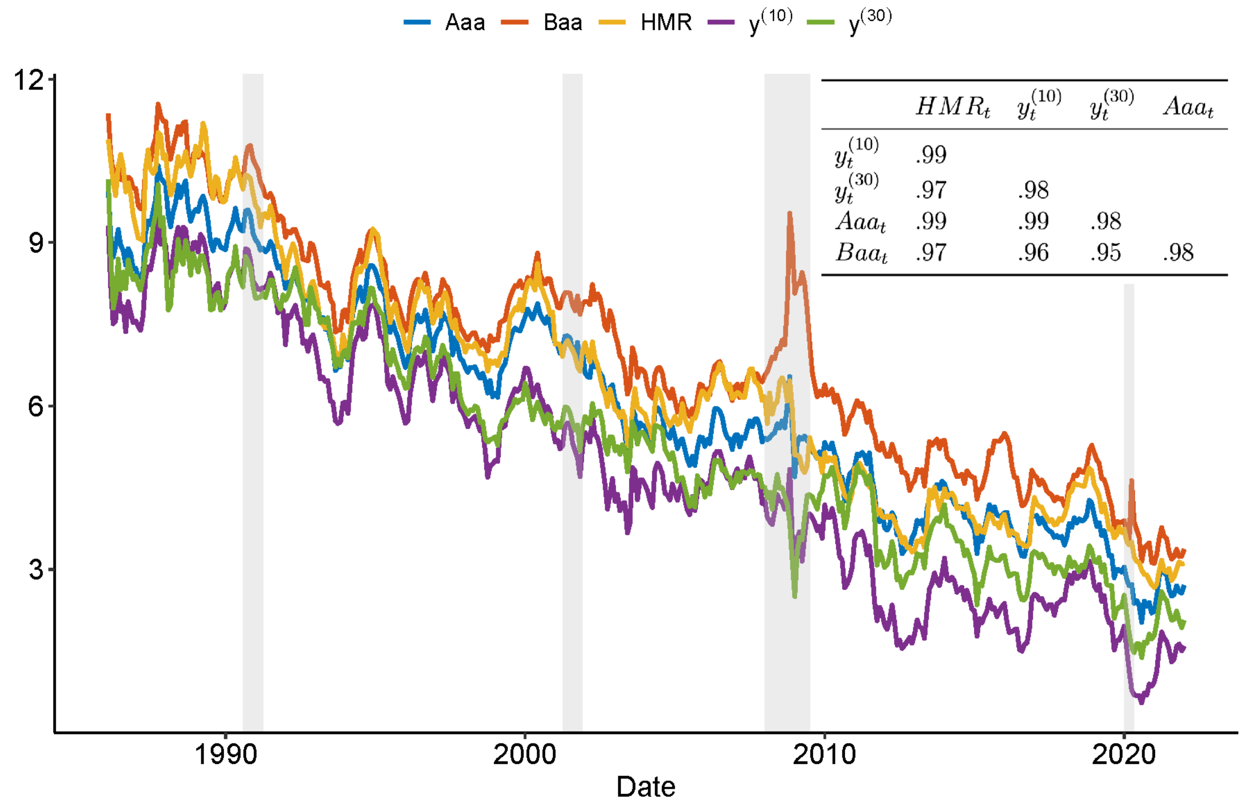

**Figure 5** Categorical thinking in household beliefs: Heterogeneity by income

In this figure, we re-estimate Table 7 (column 2) interacting our main independent variable of interest with a series of income level indicator variables. The marginal effects for each education level are displayed (i.e., the sum of the main effect and interaction).

Online Appendix for

# Categorical Thinking about Interest Rates

## A Additional Tables and Figures




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

**Figure A.1** Various realized long rates

**/* 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

**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 consensus forecasts: Asymmetry in FFR forecasts

This table presents OLS regression coefficients from equations (3)-(5). 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 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, interacted with whether the expected change is positive or negative. The regressions include the following control variables: the current Federal Funds Rate ($FFR$), the term spread ($y_t^{(10)} - FFR_t$), inflation rate ($\pi_t$), 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.

| | $\mathbb{E}_t(\overline{HMR}_{t+1q}) - HMR_t$ | | | $\overline{HMR}_{t+1q} - HMR_t$ | | | $HMR_{t+1} - \mathbb{E}_t(\overline{HMR}_{t+1q})$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $\mathbb{E}_t(\overline{FFR}_{t+1q}) - FFR_t \times \mathbb{1}_{\mathbb{E}_t(\overline{FFR}_{t+1q})-FFR_t \geq 0}$ | 0.22** | 0.28*** | 0.26*** | -0.10 | -0.04 | -0.05 | -0.31 | -0.32 | -0.31 |
| | (0.10) | (0.08) | (0.07) | (0.22) | (0.21) | (0.20) | (0.20) | (0.20) | (0.20) |
| $\mathbb{E}_t(\overline{FFR}_{t+1q}) - FFR_t \times \mathbb{1}_{\mathbb{E}_t(\overline{FFR}_{t+1q})-FFR_t < 0}$ | 0.37*** | 0.25*** | 0.22** | -0.21 | -0.26 | -0.34* | -0.58*** | -0.51*** | -0.55*** |
| | (0.08) | (0.08) | (0.09) | (0.18) | (0.19) | (0.20) | (0.16) | (0.17) | (0.18) |
| $FFR_t$ | | -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) | (0.03) | | (0.04) | (0.04) |
| $\pi_t$ | | | 0.00 | | | -0.02 | | | -0.02 |
| | | | (0.01) | | | (0.03) | | | (0.03) |
| Baa credit spread$_t$ | | | -0.10 | | | -0.33** | | | -0.23* |
| | | | (0.06) | | | (0.14) | | | (0.13) |
| Baa credit term spread$_t$ | | | 0.05 | | | 0.29* | | | 0.23 |
| | | | (0.06) | | | (0.16) | | | (0.16) |
| $R^2$ | 0.169 | 0.338 | 0.354 | 0.011 | 0.054 | 0.083 | 0.077 | 0.082 | 0.098 |
| Observations | 465 | 465 | 465 | 465 | 465 | 465 | 465 | 465 | 465 |

**Table A.3** Accuracy of consensus versus "no change" forecasts of long rates

This table compares the root mean-squared errors (RMSE) of the consensus forecasts and the "no change" forecasts of the main long rates. The "no change" forecasts are the current realized rates. Panels A and B use 1 and 4-quarter ahead forecasts, respectively. Last rows in each panel report the Diebold and Mariano (1995) statistics and the corresponding one-sided p-values for testing the null hypothesis of equal forecast accuracy against the alternative that "no change" forecasts are more accurate.

| | $HMR$ | $y^{(10)}$ | $y^{(30)}$ | $Aaa$ | $Baa$ |
|---|---|---|---|---|---|
| Panel A: $h = 1q$ | | | | | |
| Consensus forecast | 0.51 | 0.54 | 0.55 | 0.49 | 0.54 |
| "No change" forecast | 0.47 | 0.45 | 0.45 | 0.41 | 0.42 |
| DM statistic | -2.69 | -3.84 | -2.71 | -3.94 | -4.35 |
| $p$-value | (0.01) | (0.00) | (0.01) | (0.00) | (0.00) |
| Panel B: $h = 4q$ | | | | | |
| Consensus forecast | 1.05 | 0.96 | 0.91 | 1.02 | 1.00 |
| "No change" forecast | 0.91 | 0.84 | 0.71 | 0.83 | 0.78 |
| DM statistic | -2.49 | -2.04 | -2.24 | -3.76 | -2.30 |
| $p$-value | (0.01) | (0.04) | (0.03) | (0.00) | (0.02) |
| Panel C: $h = 1q$, adjusted for bias in the mean of consensus forecasts | | | | | |
| Consensus forecast | 0.51 | 0.54 | 0.55 | 0.49 | 0.54 |
| "No change" forecast | 0.46 | 0.45 | 0.45 | 0.41 | 0.42 |
| DM statistic | -2.77 | -3.96 | -2.89 | -3.77 | -4.12 |
| $p$-value | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 |
| Panel D: $h = 4q$, adjusted for bias in the mean of consensus forecasts | | | | | |
| Consensus forecast | 1.05 | 0.96 | 0.91 | 1.02 | 1.00 |
| "No change" forecast | 0.87 | 0.83 | 0.69 | 0.79 | 0.75 |
| DM statistic | -2.31 | -1.69 | -2.07 | -3.13 | -2.21 |
| $p$-value | 0.02 | 0.09 | 0.04 | 0.00 | 0.03 |

**Table A.4** Categorical thinking in economist-level forecasts, by economist groups

This table presents OLS regression coefficients from equations (3)-(5), using economist-level forecasts and separately for different groups of forecasters. The dependent variables are expected one-quarter changes in home mortgage rate, $\mathbb{E}_t^j(\overline{HMR}_{t+1q}) - HMR_t$ (columns 1, 4 and 7); the actual one-quarter changes in home mortgage rate $\overline{HMR}_{t+1q} - HMR_t$ (columns 2, 5, and 8), and the forecast error of the one-quarter-ahead home mortgage rate, $\overline{HMR}_{t+1q} - \mathbb{E}_t^j(\overline{HMR}_{t+1q})$ (columns 3, 6, and 9), respectively. The main independent variable is the expected changes in the federal funds rate ($\mathbb{E}_t^j(\overline{FFR}_{t+1q}) - FFR_t$) 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 ($\pi_t$), Baa credit spread and Baa credit term spread. Economists are grouped by their employer types: asset managers, banks, insurance companies, mortgage-related firms, independent research firms, and others. Driscoll-Kraay standard errors with optimal lag lengths are reported in parentheses. All regressions include economist fixed effects. The sample period is from 1983:04 to 2021:12. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | Asset Manager | | | Bank | | | Insurance | | |
| $\mathbb{E}_t^j(\overline{FFR}_{t+1q}) - FFR_t$ | 0.48*** | -0.03 | -0.51*** | 0.36*** | -0.09 | -0.46*** | 0.29*** | -0.03 | -0.34*** |
| | (0.06) | (0.08) | (0.09) | (0.03) | (0.06) | (0.06) | (0.05) | (0.07) | (0.08) |
| $FFR_t$ | -0.06*** | -0.06*** | 0.00 | -0.04*** | -0.07*** | -0.03 | -0.07*** | -0.11*** | -0.05 |
| | (0.01) | (0.02) | (0.03) | (0.01) | (0.02) | (0.02) | (0.02) | (0.03) | (0.04) |
| $HMR_t - FFR_t$ | -0.10*** | -0.14*** | -0.04 | -0.05*** | -0.14*** | -0.09** | -0.13*** | -0.20*** | -0.07 |
| | (0.02) | (0.03) | (0.04) | (0.01) | (0.03) | (0.04) | (0.03) | (0.04) | (0.06) |
| $\pi_t$ | -0.03* | -0.04 | -0.01 | 0.01 | -0.02 | -0.03 | 0.01 | 0.00 | 0.00 |
| | (0.02) | (0.03) | (0.03) | (0.02) | (0.03) | (0.03) | (0.02) | (0.03) | (0.04) |
| Baa credit spread$_t$ | -0.12** | -0.31** | -0.19 | -0.12** | -0.26** | -0.12 | -0.12 | -0.16 | -0.04 |
| | (0.06) | (0.14) | (0.13) | (0.06) | (0.12) | (0.12) | (0.10) | (0.14) | (0.15) |
| Baa credit term spread$_t$ | 0.04 | 0.24 | 0.20 | 0.08 | 0.22* | 0.14 | 0.22** | 0.19 | -0.04 |
| | (0.06) | (0.15) | (0.15) | (0.05) | (0.13) | (0.14) | (0.10) | (0.15) | (0.18) |
| $R^2$ | 0.405 | 0.140 | 0.202 | 0.367 | 0.127 | 0.219 | 0.262 | 0.139 | 0.117 |
| Observations | 3,394 | 3,494 | 3,394 | 10,647 | 13,009 | 10,647 | 1,194 | 1,259 | 1,194 |
| Economist FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| | Mortgage-Related Firm | | | Other | | | Independent Research Firm | | |
| $\mathbb{E}_t^j(\overline{FFR}_{t+1q}) - FFR_t$ | 0.29*** | -0.01 | -0.30*** | 0.31*** | -0.05 | -0.36*** | 0.50*** | -0.03 | -0.53*** |
| | (0.05) | (0.10) | (0.10) | (0.05) | (0.09) | (0.10) | (0.04) | (0.06) | (0.06) |
| $FFR_t$ | -0.04** | -0.18*** | -0.14*** | -0.03** | -0.06*** | -0.04 | -0.05*** | -0.06*** | -0.01 |
| | (0.02) | (0.04) | (0.05) | (0.01) | (0.02) | (0.03) | (0.01) | (0.02) | (0.02) |
| $HMR_t - FFR_t$ | -0.04 | -0.23*** | -0.20*** | -0.07*** | -0.16*** | -0.09** | -0.07*** | -0.14*** | -0.07* |
| | (0.03) | (0.04) | (0.05) | (0.02) | (0.03) | (0.04) | (0.02) | (0.03) | (0.04) |
| $\pi_t$ | 0.00 | -0.05 | -0.04 | -0.01 | 0.00 | 0.01 | 0.00 | -0.02 | -0.02 |
| | (0.01) | (0.03) | (0.04) | (0.02) | (0.03) | (0.03) | (0.01) | (0.03) | (0.03) |
| Baa credit spread$_t$ | -0.10 | -0.06 | 0.03 | -0.18** | -0.35** | -0.18 | -0.03 | -0.27** | -0.24** |
| | (0.07) | (0.12) | (0.14) | (0.07) | (0.15) | (0.17) | (0.06) | (0.13) | (0.12) |
| Baa credit term spread$_t$ | 0.10 | 0.02 | -0.08 | 0.14* | 0.41** | 0.27 | -0.01 | 0.22 | 0.23 |
| | (0.08) | (0.14) | (0.16) | (0.08) | (0.18) | (0.21) | (0.07) | (0.14) | (0.14) |
| $R^2$ | 0.469 | 0.208 | 0.246 | 0.403 | 0.167 | 0.221 | 0.361 | 0.133 | 0.209 |
| Observations | 774 | 774 | 774 | 2,179 | 2,193 | 2,179 | 5,580 | 5,705 | 5,580 |
| Economist FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

**Table A.5** Categorical thinking in consensus forecasts: Alternative timing

This table presents OLS regression coefficients from equation (3) with alternative dependent variables allowing for delays in information incorporation. The dependent variable is expected one-quarter changes in home mortgage rate from month $t+1m$ ($\mathbb{E}_{t+1m}(\overline{HMR}_{t+1q}) - HMR_{t+1m}$). 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 ($\pi_t$), 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) | (2) | (3) |
| $\mathbb{E}_{t-1}(\overline{FFR}_{t+1q}) - FFR_{t-1}$ | 0.34*** | 0.29*** | 0.27*** |
| | (0.07) | (0.07) | (0.07) |
| $FFR_{t-1}$ | | -0.02*** | -0.03*** |
| | | (0.01) | (0.01) |
| $HMR_{t-1} - FFR_{t-1}$ | | 0.01 | 0.02 |
| | | (0.02) | (0.02) |
| $\pi_{t-1}$ | | | 0.00 |
| | | | (0.02) |
| Baa credit spread$_{t-1}$ | | | 0.06 |
| | | | (0.07) |
| Baa credit term spread$_{t-1}$ | | | -0.11 |
| | | | (0.08) |
| $R^2$ | 0.105 | 0.151 | 0.164 |
| Observations | 464 | 464 | 464 |

**Table A.6** Expected changes in short rates and actual changes in long rates: Subsamples by monetary policy surprises

This table presents OLS regression coefficients from equation (4), estimated separately for subsamples divided by the magnitude of monetary policy shocks from Swanson (2021). The full sample is split at the median of the FFR shocks. The dependent variable is the actual one-quarter changes in home mortgage rate ($\overline{HMR}_{t+1q} - HMR_t$). 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 ($\pi_t$), 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.

| | $\overline{HMR}_{t+1q} - HMR_t$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 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) |
| $\pi_t$ | | | -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.7** Categorical thinking in economist-level forecasts

This table presents OLS regression coefficients from equations (3)-(5), using economist-level forecasts. The dependent variables are expected one-quarter changes in the home mortgage rate based on economist $j$'s forecast, $\mathbb{E}_t^j(\overline{HMR}_{t+1q}) - HMR_t$; the actual one-quarter changes in home mortgage rate $\overline{HMR}_{t+1q} - HMR_t$, and economist $j$'s forecast error of the one-quarter-ahead home mortgage rate, $\overline{HMR}_{t+1q} - \mathbb{E}_t^j(\overline{HMR}_{t+1q})$, respectively. The main independent variable is the expected changes in the federal funds rate ($\mathbb{E}_t^j(\overline{FFR}_{t+1q}) - FFR_t$) 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 ($\pi_t$), Baa credit spread and Baa credit term spread. Driscoll-Kraay standard errors with optimal lag lengths are reported in parentheses. All regressions include economist fixed effects. The sample period is from 1983:04 to 2021:12. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

| | $\mathbb{E}_t^j(\overline{HMR}_{t+1q}) - HMR_t$ | | | $\overline{HMR}_{t+1q} - HMR_t$ | | | $\overline{HMR}_{t+1q} - \mathbb{E}_t^j(\overline{HMR}_{t+1q})$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | (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) |
| $\pi_t$ | | | 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.8** Corporate long-term issuance: Firm and aggregate-level evidence conditional on the first FFR change in a rate change cycle

This table presents OLS regression of firms' long-term debt issuance on the expected short rate changes, conditional on the first Fed Rate change in a rate hike/cut cycle. The table reports evidence using quarterly firm-level Compustat data. The dependent variable include an indicator variable that equals one if a firm issues a long-term debt in the subsequent quarter ($\mathbb{1}(\text{LT Issues}_{i,t+1} > 0)$), long-term debt issue in the subsequent quarter normalized by total assets in the current quarter ($\frac{\text{LT Issues}_{i,t+1}}{\text{AT}_{i,t}}$), long-term debt issue in the subsequent quarter normalized by total debt in the current quarter ($\frac{\text{LT Issues}_{i,t+1}}{\text{Total Debt}_{i,t}}$), and long-term share of total new debt issues in the subsequent quarter ($\text{LT Share}_{i,t+1}$), 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. The indicator variable FirstChange equals one if the current quarter is the quarter after the first rate change in a rate hike/cut cycle, and zero otherwise. Control variables include the current Federal Funds Rate ($FFR$), the term spread ($y_t^{(5)} - FFR_t$), inflation rate ($\pi_t$), Baa credit spread and Baa credit term spread. Standard errors are double clustered by firm and year-quarter and firm fixed effects are included in all regressions. 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) | $\frac{\text{LT issues}_{t+1}}{\text{AT}_t}$ (2) | $\frac{\text{LT issues}_{t+1}}{\text{Total debt}_t}$ (3) | LT share (imputed) (4) |
|---|---|---|---|---|
| $\mathbb{E}_t(\overline{FFR}_{t+1q}) - FFR_t$ | 0.0119 | 0.0039*** | 0.0241*** | 0.0553*** |
| | (0.0080) | (0.0013) | (0.0092) | (0.0110) |
| FirstChange | -0.0108** | -0.0020*** | -0.0152*** | -0.0137* |
| | (0.0051) | (0.0006) | (0.0052) | (0.0081) |
| FirstChange × $\mathbb{E}_t(\overline{FFR}_{t+1q}) - FFR_t$ | 0.0920*** | 0.0087*** | 0.0561** | 0.0592** |
| | (0.0236) | (0.0024) | (0.0243) | (0.0280) |
| $FFR_{t-1}$ | 0.0036** | -0.0006*** | -0.0018 | -0.0133*** |
| | (0.0015) | (0.0002) | (0.0013) | (0.0021) |
| $y_t^{(5)} - FFR_t$ | -0.0120*** | -0.0029*** | -0.0093*** | -0.0284*** |
| | (0.0025) | (0.0003) | (0.0023) | (0.0029) |
| $\pi_t$ | -0.0057*** | -0.0012*** | -0.0052** | -0.0010 |
| | (0.0019) | (0.0003) | (0.0022) | (0.0022) |
| Baa credit spread$_t$ | 0.0163 | -0.0017* | -0.0017 | -0.0014 |
| | (0.0114) | (0.0009) | (0.0078) | (0.0111) |
| Baa credit term spread$_t$ | -0.0198* | -0.0023** | -0.0202** | 0.0056 |
| | (0.0114) | (0.0011) | (0.0088) | (0.0122) |
| Standard-Errors | Firm & Year-Quarter | | | |
| $R^2$ | 0.358 | 0.221 | 0.153 | 0.483 |
| Observations | 750,698 | 746,807 | 588,700 | 382,391 |
| Firm FE | ✓ | ✓ | ✓ | ✓ |

**Table A.9** Corporate investment

This table presents OLS regression results of firms' subsequent investment (CAPX) on the expected changes in the short rate, using quarterly firm-level Compustat data. The dependent variables include an indicator variable that equals one if a firm invests in CAPX between quarter $t$ and $t+\tau$ ($\mathbb{1}\left(CAPX_{t\to t+\tau} > 0\right)$), CAPX between quarter $t$ and $t+\tau$ normalized by total assets in the current quarter ($CAPX_{t\to t+\tau}/AT_{t-1}$), and CAPX between quarter $t$ and $t+\tau$ normalized by total debt in the current quarter ($CAPX_{t\to t+\tau}/TotalDebt_{t-1}$), respectively. We consider $\tau$ of 1, 2, and 4 quarters. 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 ($\pi_t$), Baa credit spread and Baa credit term spread. Standard errors are double clustered by firm and year-quarter and firm fixed effects are included in all regressions. The sample period is from 1983:Q2 to 2021:Q4. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

| | $\mathbb{1}\left(CAPX_{t\to t+\tau} > 0\right)$ | | | $CAPX_{t\to t+\tau}/AT_{t-1}$ | | | $CAPX_{t\to t+\tau}/TotalDebt_{t-1}$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\tau = 1$ | $\tau = 2$ | $\tau = 4$ | $\tau = 1$ | $\tau = 2$ | $\tau = 4$ | $\tau = 1$ | $\tau = 2$ | $\tau = 4$ |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $\mathbb{E}_t(\overline{FFR}_{t+1q}) - FFR_t$ | 0.0041 | 0.0033 | 0.0011 | -0.0007 | -0.0017* | -0.0035 | -0.0072 | -0.0057 | -0.0345 |
| | (0.0039) | (0.0032) | (0.0022) | (0.0005) | (0.0010) | (0.0027) | (0.0297) | (0.0584) | (0.1267) |
| $FFR_t$ | -0.0004 | -0.0003 | -0.0001 | 0.0014*** | 0.0029*** | 0.0061*** | 0.0315*** | 0.0646*** | 0.1221*** |
| | (0.0006) | (0.0005) | (0.0004) | (0.0000) | (0.0001) | (0.0004) | (0.0039) | (0.0097) | (0.0216) |
| $y_t^{(5)} - FFR_t$ | -0.0005 | -0.0003 | 0.0005 | 0.0013*** | 0.0028*** | 0.0062*** | 0.0393*** | 0.0859*** | 0.1824*** |
| | (0.0010) | (0.0008) | (0.0006) | (0.0002) | (0.0003) | (0.0007) | (0.0081) | (0.0165) | (0.0376) |
| $\pi_t$ | -0.0003 | -0.0006 | -0.0005 | -0.0003** | -0.0008*** | -0.0024*** | -0.0128** | -0.0236* | -0.0426 |
| | (0.0001) | (0.0005) | (0.0004) | (0.0001) | (0.0003) | (0.0007) | (0.0060) | (0.0135) | (0.0315) |
| Baa credit spread$_t$ | -0.0032 | -0.0032 | -0.0008 | -0.0000 | -0.0002 | -0.0011** | -0.0230 | -0.0525 | -0.1340 |
| | (0.0038) | (0.0027) | (0.0018) | (0.0005) | (0.0009) | (0.0018) | (0.0301) | (0.0650) | (0.1463) |
| Baa credit term spread$_t$ | -0.0002 | 0.0008 | -0.0000 | -0.0007 | -0.0019* | -0.0044** | -0.0192 | -0.0425 | -0.1084 |
| | (0.0042) | (0.0030) | (0.0019) | (0.0005) | (0.0010) | (0.0022) | (0.0294) | (0.0629) | (0.1379) |
| $R^2$ | 0.563 | 0.635 | 0.741 | 0.420 | 0.475 | 0.529 | 0.293 | 0.305 | 0.319 |
| Observations | 785,853 | 758,107 | 709,231 | 781,829 | 754,346 | 705,711 | 622,029 | 599,626 | 560,305 |
| Firm FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

**Table A.10** Firm long-term issuance: Controlling for uncertainty

This table presents OLS regression of firms' long-term debt issuance on the expected short rate changes, controlling for measures of uncertainty. The dependent variables include an indicator variable that equals one if a firm issues a long-term debt in the subsequent quarter ($\mathbb{1}(\text{LT Issues}_{i,t+1} > 0)$), long-term debt issue in the subsequent quarter normalized by total assets in the current quarter ($\frac{\text{LT Issues}_{i,t+1}}{\text{AT}_{i,t}}$), and long-term share of total new debt issues in the subsequent quarter ($\text{LT Share}_{i,t+1}$), 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. Control variables include the current Federal Funds Rate ($FFR$), the term spread ($y_t^{(5)} - FFR_t$), inflation rate ($\pi_t$), Baa credit spread and Baa credit term spread. We additionally control for uncertainty measured as forecast dispersion across professional forecasters ($\text{Dispersion}_t$) and the VIX. Standard errors are double clustered by firm and year-quarter, and firm fixed effects are included in all regressions. The sample period is from 1983:Q2 to 2021:Q4. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

| | $\mathbb{1}(\text{LT Issues}_{t+1} > 0)$ | | | $\frac{\text{LT issues}_{t+1}}{\text{AT}_t}$ | | | $\text{LT Share}_{t+1}$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | (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) |
| $\pi_t$ | -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 $\text{spread}_t$ | 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 $\text{spread}_t$ | -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) |
| $\text{Dispersion}_t$ | | -0.0917*** | | | -0.0092*** | | | -0.0620** | |
| | | (0.0194) | | | (0.0032) | | | (0.0246) | |
| $\text{VIX}_t$ | | | 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 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

**Table A.11** Aggregate mortgage issuance: Home purchase loans conditional on the first FFR change in a rate change cycle

This table presents OLS regression of aggregate home purchase Jumbo mortgage loan origination on the expected short rate changes, conditional on the first Fed Rate change in a rate hike/cut cycle. The dependent variable is the logarithm of the total dollar volume of new mortgages originated in the subsequent quarter (Log Total $\text{Loan}_{t+1}$). 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. The indicator variable FirstChange equals one if the current quarter is the quarter after the first rate change in a rate hike/cut cycle, and zero otherwise. Control variables include the current Federal Funds Rate ($FFR$), the term spread ($HMR_t - FFR_t$), inflation rate ($\pi_t$), 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 contains only Jumbo mortgages (larger loans typically exceeding $750K) from the quarterly FHFA NMDB Aggregate Statistics from 1983:Q2 to 2021:Q4. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

| | Log total amount | |
|---|---|---|
| | (1) | (2) |
| $\mathbb{E}_t(\overline{FFR}_{t+1q}) - FFR_t$ | 0.7196** | 0.6483** |
| | (0.3024) | (0.2971) |
| FirstChange | | -0.0502 |
| | | (0.1958) |
| FirstChange $\times$ $\mathbb{E}_t(\overline{FFR}_{t+1q}) - FFR_t$ | | 1.8089* |
| | | (0.9759) |
| $FFR_{t-1}$ | 0.0162 | 0.0152 |
| | (0.0630) | (0.0641) |
| $HMR_t - FFR_{t-1}$ | -0.1924* | -0.2094* |
| | (0.1083) | (0.1100) |
| $\pi_t$ | 0.0535 | 0.0564 |
| | (0.0660) | (0.0660) |
| Baa credit $\text{spread}_t$ | -0.9588*** | -0.9642*** |
| | (0.2373) | (0.2389) |
| Baa credit term $\text{spread}_t$ | 0.6352** | 0.6523** |
| | (0.2843) | (0.2858) |
| Constant | 11.5292*** | 11.5569*** |
| | (0.4334) | (0.4447) |
| $R^2$ | 0.480 | 0.492 |
| Observations | 96 | 96 |

**Table A.12** Firm and household long-term borrowing: Evidence from Flow of Funds data

This table presents OLS regression of corporate and household long-term debt issuance on the expected short rate changes, using the quarterly Flow of Funds data. The dependent variables are household mortgage issues in the subsequent quarter (Household Mortgage Issue$_{t+1}$); long-term corporate debt issue, directly measured from quarterly transaction variables (Corp LT Issue$_{t+1}$ (direct)); long-term corporate debt issue, imputed from long-term debt levels following Greenwood et al. (2010) (Corp LT Issue$_{t+1}$ (GHS)); and long-term corporate debt share, imputed from long-term debt levels following Greenwood et al. (2010) (Corp LT Share$_{t+1}$ (GHS)), 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. Control variables include the current Federal Funds Rate ($FFR$), the term spread ($HMR_t - FFR_t$ and $y_t^{(5)} - FFR_t$), inflation rate ($\pi_t$), 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.

| | HH Mortgage Issue$_{t+1}$ | Corp LT Issue$_{t+1}$ (direct) | Corp LT Issue$_{t+1}$ (GHS) | Corp LT Share$_{t+1}$ (GHS) |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Panel A: Full sample | | | | |
| $\mathbb{E}_t(\overline{FFR}_{t+1q}) - FFR_t$ | 0.0647* | 0.0834** | 0.1099** | 0.0215 |
| | (0.0376) | (0.0368) | (0.0442) | (0.0181) |
| $FFR_t$ | -0.0029 | -0.0077** | -0.0286*** | -0.0021 |
| | (0.0036) | (0.0033) | (0.0057) | (0.0016) |
| $HMR_t - FFR_t$ | -0.0196** | | | |
| | (0.0094) | | | |
| $y_t^{(5)} - FFR_t$ | | -0.0319*** | -0.0628*** | -0.0120*** |
| | | (0.0060) | (0.0112) | (0.0043) |
| $\pi_t$ | 0.0116 | -0.0036 | 0.0044 | -0.0075** |
| | (0.0078) | (0.0058) | (0.0099) | (0.0034) |
| Baa credit spread$_t$ | -0.0742*** | 0.0155 | -0.0059 | 0.0016 |
| | (0.0264) | (0.0341) | (0.0431) | (0.0181) |
| Baa credit term spread$_t$ | 0.0555** | -0.0108 | 0.0216 | 0.0117 |
| | (0.0255) | (0.0305) | (0.0397) | (0.0155) |
| $R^2$ | 0.192 | 0.409 | 0.656 | 0.323 |
| Observations | 155 | 155 | 155 | 155 |
| Panel B: Post-2000 | | | | |
| $\mathbb{E}_t(\overline{FFR}_{t+1q}) - FFR_t$ | 0.1536** | 0.2011** | 0.2657*** | 0.0685** |
| | (0.0667) | (0.0812) | (0.0884) | (0.0337) |
| $FFR_t$ | 0.0262** | -0.0164** | -0.0478*** | -0.0015 |
| | (0.0125) | (0.0070) | (0.0095) | (0.0035) |
| $HMR_t - FFR_t$ | 0.0058 | | | |
| | (0.0168) | | | |
| $y_t^{(5)} - FFR_t$ | | -0.0547*** | -0.1074*** | -0.0146*** |
| | | (0.0114) | (0.0174) | (0.0055) |
| $\pi_t$ | 0.0126 | -0.0074 | -0.0066 | -0.0075** |
| | (0.0111) | (0.0074) | (0.0122) | (0.0035) |
| Baa credit spread$_t$ | -0.1438*** | -0.0026 | -0.0397 | -0.0260* |
| | (0.0347) | (0.0324) | (0.0343) | (0.0136) |
| Baa credit term spread$_t$ | 0.1078** | -0.0181 | 0.0015 | 0.0235 |
| | (0.0435) | (0.0374) | (0.0417) | (0.0166) |
| $R^2$ | 0.400 | 0.449 | 0.595 | 0.226 |
| Observations | 89 | 89 | 89 | 89 |