Under- and Over-Reaction in Yield Curve Expectations*

Chen Wang†

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Abstract

I study how professional forecasts of interest rates across maturities respond to new information. I document that forecasts for short-term rates underreact to new information while forecasts for long-term rates overreact. I propose a new explanation based on "autocorrelation averaging," whereby, due to limited cognitive processing capacity, forecasters' estimate of the autocorrelation of a given process is biased toward the average autocorrelation of all the processes they observe. Consistent with this view, I show that forecasters *over*-estimate the autocorrelation of the less persistent term premium component of interest rates and *under*-estimate the autocorrelation of the more persistent short rate component. A calibrated model quantitatively matches the documented pattern of misreaction. Finally, I explore the pattern's implication for asset prices. I show that an overreaction-motivated predictor, the realized forecast error for the 10-year Treasury yield, robustly predicts excess bond returns.

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†University of Notre Dame. E-mail: chen.wang@nd.edu

1 Introduction

Expectations are a central element in most macroeconomic and finance models. For decades, the predominant approach to model beliefs has been the rational expectations framework. Recently, spurred by the renewed attention to survey data, an emerging strand of literature has documented systematic departures from rational expectations. These departures, in the form of predictable forecast errors, exhibit various forms: some variables appear to underreact to new information, while some other variables tend to overreact. For example, underreaction is common in macroeconomic forecasts and has been interpreted using models with information rigidities; in financial markets, both under- and over-reaction haven been documented. As one of the most liquid markets in the world, the Treasury market is situated at the intersection of financial markets and the macroeconomy: the short-term interest rate is an important monetary policy instrument to achieve macroeconomic stability, and the yield curve is a fundamental building block for pricing fixed-income assets. As such, the Treasury market presents a unique setting to study expectations formation and to understand what type of information people in the economy under- and over-react to.

In this paper, I study professional forecasts of interest rates across the entire yield curve from Blue Chip Financial Forecasts, and examine the term structure of under- and over-reaction to new information. I apply the methodology developed by Coibion and Gorodnichenko (2015, CG), which investigates the predictability of forecast errors (FE) from forecast revisions (FR), to assess misreaction to information for individual- and consensus-level forecasts. I document that, when updating beliefs about future interest rates, professional forecasters react very differently across maturities: they underreact for short-maturity and overreact for long-maturity interest rates.[1] In particular, the FE-on-FR regression coefficients, as a function of maturity, are downward sloping and cross zero at around the two-year maturity. Furthermore, the downward-sloping term structure of under- and over-reaction is evident at *both* the individual and consensus levels, indicating a similar departure from rationality at both levels. These findings present a challenge for existing models of expectation formation that deviate from rational expectations. None of the commonly-used models of biased beliefs, such as sticky expectations, extrapolative expectations, or diagnostic expectations, can explain the under- and over-reaction pattern in their standard formulations.

[1]Some indication of this pattern is noted by Bordalo et al. (2019b), whose focus, different from this paper, is on the contrasting patterns of misreaction in individual- and consensus-level forecasts.

To explain the results I obtain, I propose a simple bounded-rationality framework based on "autocorrelation averaging". Investors and forecasters are exposed to many different time series. They may not have the cognitive processing capacity to learn the true autocorrelation of each series.[2] Instead, when forecasting, they may use something closer to an average of the true autocorrelations of the series that they are exposed to. Simply put, if the series they are working with have true autocorrelations ranging from 0.7 to 0.9, investors may instead forecast all variables using an autocorrelation in the neighborhood of 0.8. An immediate consequence of this is that investors will *over*-react to information about variables with less persistent processes – for example, those with autocorrelations close to 0.7 – but will *under*-react to information about variables with more persistent processes, those with autocorrelations closer to 0.9.

I bring these ideas to the context of the yield curve. The yield on a bond has two components: one that is an average of expected short rates over the life of the bond (the expectations hypothesis, or EH component), and one that captures the term premium (TP component). Suppose that the true autocorrelation of the EH component exceeds that of the TP component. Also suppose that, due to bounded rationality, investors forecast both components using an intermediate, average autocorrelation. As described above, this "autocorrelation averaging" means that they will underreact to news about the EH component, but overreact to news about the TP component. Since, for short-maturity bonds, the EH component is more important than the TP component in driving the yield variation, this predicts under-reaction to information about short-term bond yields; and since, for long-maturity bonds, the TP component is more important, this predicts over-reaction to information about long-term bond yields. This is precisely the under- and over-reaction pattern I document in the data.

I present several pieces of evidence to support the above story. I compute the sample autocorrelations of the short rate and the term premium across maturities. I show that the short rate is very persistent, with an autocorrelation close to 0.97, while the term premia are less persistent, with autocorrelations close to 0.75.[3] I then use the survey forecasts to estimate forecasters' perceived autocorrelations of the short rate and term premium. I find that they are similar – in the range of 0.87 to 0.97 – and that they lie between

[2] Processing capacity can refer to the forecaster's cognitive ability or to institutional resources.

[3] All autocorrelations are at a quarterly frequency.

the estimated true autocorrelations of 0.75 and 0.97. These estimates are consistent with the "autocorrelation averaging" explanation: instead of using the true autocorrelations of the time series, forecasters are using an average autocorrelation. This, in turn, generates underreaction to short-rate information and overreaction to term-premium information. Moreover, I calibrate my autocorrelation-averaging model with the estimated true and perceived autocorrelations. Though the model makes no assumption about the relative importance of the short rate and term premia, it successfully generates the downward-sloping term structure of misreaction, with the FE-on-FR coefficients quantitatively close to the empirical estimates.

Two features of the Blue Chip Financial Forecasts are worth noting. First, the forecasters, whose identities are known, are either significant players in the Treasury market or are likely to influence important market participants through their client services. Second, I show that the allocations to Treasury securities of the banks participating in the surveys vary positively with their subjective expectations of bond returns. Therefore, the Blue Chip forecasts are likely to represent the beliefs of major market participants; this, in turn, means that the pattern of under- and over-reaction could impact asset prices.[4]

I investigate the implications for bond prices of investors' overreaction to information. If the forecasters and investors overreact to information about the long rate, then, when they revise up their forecast of the long rate, they push the bond price down too low, after which it corrects back up to a sensible level. Therefore, an increase in the forecast revision should forecast higher bond returns in the future. Since the forecast revision is primarily driven by the contemporaneous *realized* forecast error, I turn this into a prediction that is easier to test: the forecast error should predict the subsequent bond return with a positive sign. I confirm this prediction in the data. I document that the realized forecast errors of 10-year Treasury yield predict excess bond returns in and out of sample, subsuming several commonly-used bond return predictors and strongly rejecting the spanning hypothesis using the robust procedure of Bauer and Hamilton (2017). I also confirm the analogous prediction that underreaction to information has for short-term bond prices and Federal funds futures prices.

[4]Most previous surveys are about the aggregate stock market; many survey participants are individual investors, whose impact on the aggregate market may be more limited.

Related literature. The main contributions of this paper are three-folded: (1) using individual and consensus forecasts of interest rates, I document a downward-sloping term structure of under- and over-reaction. (2) I propose a new framework based on incorrectly perceived autocorrelations to understand this pattern and provide empirical support for the "autocorrelation averaging" behavior. (3) I explore the predictions of under- and over-reaction for asset prices and confirm them in the data.

There has been renewed attention to using subjective expectations to study deviations from rationality. This paper, together with recent work such as Bouchaud et al. (2019) and Bordalo et al. (2019b), follows the methodology developed by Coibion and Gorodnichenko (2015), which evaluates under- and over-reaction to information via the predictability of forecast errors from forecast revisions. With the exception of Bordalo et al. (2019b), previous studies of survey expectations typically find one form of misreaction for different series.[5] In this paper, I organize the test of rationality along interest rate maturities and document different reactions to new information for short and long rates.

Bordalo et al. (2019b), analyzing professional forecasts of 22 macroeconomic variables, find that individual forecasts tend to overreact to information but that the consensus forecasts underreact. They couple rational inattention with diagnostic expectations developed by Bordalo et al. (2018) to explain the puzzling facts. Bordalo et al. (2019b), focusing on the distinct patterns of misreaction at individual and consensus levels, provide some early evidence on underreachtion for short rates and overreaction to long rates. I strengthen their results on the interest rates forecasts and establish the downward-sloping term structure of under- and over-reaction, which is robust at *both* individual and consensus levels and is a challenge to the diagnostic expectations explanation.

Models that depart from full rationality have been developed to explain the under- and over-reaction patterns. For macroeconomic variables and short-term earnings forecasts, rational inattention and information rigidities have been the main frameworks used to explain underreaction.[6] Finance models aiming at understanding overreaction are often built on psychological foundations such as representativeness and overconfidence. Early models of under- and over-reaction include those of Barberis, Shleifer, and Vishny (1998), Daniel,

[5] In an experimental study of expectation formation, Landier, Ma, and Thesmar (2019) document both under- and over-reaction in individual forecasts, and that overreaction, in the form of extrapolative expectations, predominates.

[6] See Sims (2003), Woodford (2003), Carroll (2003), Mankiw and Reis (2002), and Gabaix (2014) for discussion of underreaction to macroeconomic variables.

Hirshleifer, and Subrahmanyam (1998), and Rabin (2002).[7]

I propose and estimate a simple model based on "autocorrelation averaging", in which the forecaster, due to limited processing capacity, uses something closer to an average autocorrelation to make forecasts for different processes. The calibrated model quantitatively matches the pattern of misreaction. This explanation is different from the representativeness heuristic approach followed by Bordalo et al. (2019b). It is related to the bounded-rationality models (e.g., Gabaix, 2019), in which the decision-makers anchor their perceived autocorrelations on the average autocorrelation. In particular, I answer the challenge from Gabaix (2019) and offer direct empirical support for a bounded-rationality origin of under- and over-reactions. Empirically, "autocorrelation averaging" is consistent with other recently documented "averaging" behaviors, such as averaging in correlations (Matthies, 2018) and the persistence of stock market volatility (Lochstoer and Muir, 2019).

There is a growing body of research that studies the link between investors' subjective beliefs and bond prices.[8] The papers most related to this one are Cieslak (2018) and Crump, Eusepi, and Moench (2018), both of which use survey expectations of the short rate. Cieslak (2018) finds sizable and cyclical forecast errors in the *consensus* forecasts of the Federal Fund Rates and links the predictive power of real-activity variables for bond returns to FFR forecast errors. Crump, Eusepi, and Moench (2018) study the dynamics of the term premia, computed as the difference between bond yields and short-rate survey expectations, and highlight the clear rejection of the expectations hypothesis. I instead focus on both individual and consensus forecasts of the entire term structure of interest rates; I also propose a framework based on bounded rationality by imposing structure on people's perceived autocorrelation of different components of bond yields, while Cieslak (2018) links the forecast errors to extrapolative expectations.

[7]In the finance literature, overreaction to news is often modeled using extrapolative beliefs, which has been developed in generations of models such as De Long et al. (1990), Frankel and Froot (1990), Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999) and, more recently, Barberis et al. (2015, 2018) and Glaeser and Nathanson (2017). Greenwood and Shleifer (2014) find strong evidence of extrapolative expectations in several surveys of stock market returns.

[8]Early work of Froot (1989) focuses on tests of the expectations hypothesis at different maturities. Many recent papers use survey data, as does this paper. Piazzesi, Salomao, and Schneider (2015) contend that bond risk premia implied by survey forecasts are less volatile and less cyclical than those obtained with statistical approaches. Buraschi, Piatti, and Whelan (2018) focuses on heterogeneity in forecasting skill and aggregate individual expectations to reflect those of the marginal investor. Giacoletti, Laursen, and Singleton (2019) study bond risk premia through the lens of a Bayesian learner who learns from the disagreement among Blue Chip forecasters; they find distinct predictive power from disagreement for yields.

In using the predictions of overreaction to forecast bond returns, this paper contributes to the literature that documents "excess" predictability in bond returns beyond the information contained in current yields (Cochrane and Piazzesi, 2005; Duffee, 2011; Joslin, Priebsch, and Singleton, 2014; and Cieslak and Povala, 2015).[9] The evidence strongly rejects the hypothesis that the current yields spans all information relevant for forecasting future returns, and is robust to the small-sample procedure proposed by Bauer and Hamilton (2017). The origin of the predictive power of realized forecast errors stems from overreaction to new information, which is similar to the belief-based interpretation pursued by Cieslak (2018), but different from the conventional explanations of hidden factors or measurement errors.

The rest of the paper is organized as follows. In Section 2, I describe the Blue Chip Financial Forecasts data and examine the accuracy of the survey forecasts. In Section 3, I document how forecasters react to new information for short- and long-maturity interest rates. In Section 4, I build a bounded-rationality model, empirically estimate the actual and perceived autocorrelations, and calibrate the model to match the term structure of under- and over-reaction. In Section 5, I explore the implications of under- and over-reaction for asset prices. Section 6 concludes.

2 Data

2.1 Survey expectation data

The primary dataset used in this paper is the survey forecasts of U.S. Treasury bond yields across maturities and other interest rates, which I obtain from the Blue Chip Financial Forecasts (BCFF) survey. BCFF survey is a monthly survey, maintains a stable and large panel of professional forecasters, and has a long sample that dates back to the 1980s. Among various datasets of professional forecasts, it is especially suitable for the study of expectations formation and asset prices.

Each month, the BCFF survey collects forecasts from a panel of, on average, over 40 economists from leading financial institutions and economic consulting firms. The surveyed economists are asked to provide point forecasts of future financial and macroeconomic

[9] A related strand of literature has found excess sensitivity of long rates (e.g., Gürkaynak, Sack, and Swanson, 2005; Hanson and Stein, 2015; Giglio and Kelly, 2018; Hanson, Lucca, and Wright, 2018; and Brooks, Katz, and Lustig, 2019). The overreaction for long rates expectations, documented in this paper, complements these findings in bond prices.

variables at horizons from the current quarter ("nowcast") to four quarters ahead (five quarters since January 1997). 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. A sample BCFF survey questionnaire is presented in the Appendix.

Variables. To study the subjective expectations of the bond yields across the entire yield curve and other interest rates, I require that the forecasts have reasonably long and continuous time series. Specifically, I focus on the forecasts of the following interest rate variables: Treasury bills with maturities of three months and one year ($tb3m$ and $tb1y$), Treasury notes and bonds with maturities of 2, 5, 10 and 30 years ($tn2y$, $tn5y$, $tn10y$ and $tn30y$), Federal Funds Rate (ffr), one-month commercial paper rate ($cp1m$), prime bank rate (pr), three-month LIBOR rate ($libor$), Aaa and Baa corporate bond rates (aaa and baa) and home mortgage rate (hmr). For each target variable at each forecast horizon, I obtain both the individual forecasts from different professional forecasters and the consensus forecast (cross-sectional mean).

Forecasters. One of the advantages of the BCFF survey is that the identity of each forecaster, names of the economist and his/her affiliated institution, is revealed.[10] This feature allows us to keep track of the time series of each firm's forecasts and hence make the BCFF forecasts a panel dataset. However, the institution names change from time to time due to mergers and acquisitions and other reasons. To make the panel of forecasts as balanced as possible, I manually check the name changes of the forecasters using the information provided by the Federal Financial Institutions Examinations Council (FFIEC) and concatenate the observations that belong to the same entity. This manual match gives us 86 unique forecasters with more than 60 monthly forecasts, among which 26 are banks, 15 are broker-dealers, and 17 are primary dealers of the Federal Reserve Bank of New York. Table A.1 in the Appendix provides a full list of institutions that participate in the BCFF survey grouped by the type of institution.

One may naturally question how seriously the surveyed economists take the tasks at hand. To allay this concern, I show, in the Appendix, that bank forecasters' allocations to the Treasury securities of a given maturity vary positively with their expectation of bond

[10]As the forecasts mostly reflect collective expectations of the institutions, for the rest of the paper, I use "forecaster" to refer to the institution.

returns for that maturity. This evidence suggests that the forecasts proxy for beliefs of the market participants and that people put their money behind these numbers.

The final BCFF survey forecast dataset has a sample period from January 1988 to December 2018. I choose the start date such that the forecasts of all Treasury yields that I study are available.

2.2 Realized interest rates and macro data

The nominal zero-coupon Treasury yields are mainly from two sources. I obtain the U.S. Treasury yields and forward rates from the fitted Treasury yield curve of Gürkaynak, Sack, and Wright (2006, GSW). The GSW data is updated regularly and available on the Federal Reserve Board website. It contains only bonds with maturities from one year to 30 years; hence I use constant maturity Treasury (CMT) yields from the H.15 statistical release of the Federal Reserve for Treasury bills for maturities shorter than one year.[11]

I use Fama and Bliss bond yields and forward rates from the Center for Research in Securities Prices (CRSP) to reproduce the Cochrane and Piazzesi (2005) bond return predictor (CP). To complement the bond returns constructed from the fitted Treasury yields of GSW, I obtain from CRSP the returns of the Fama Maturity Portfolios, which are actual coupon bond portfolios sorted by maturity.

The realized values of other interest rates, such as the effective Federal Funds Rate (FFR), are obtained from the St. Louis Fed FRED database. I sample the daily data at a monthly (quarterly) frequency by using the last observation of each month (quarter). The interest rates are expressed in percent per annum. I also obtain macroeconomic and aggregate financial variables from FRED.

2.3 Notation

Bond notation. I follow the standard notation in the bond literature in which the maturity is given in parentheses as a superscript. Assume that interest rates are continuously compounded. The log price and the yield of a n-year bond at time t are denoted as $p_t^{(n)}$ and $y_t^{(n)} = -\frac{1}{n}p_t^{(n)}$ respectively. The h-year holding period return on a n-year zero-coupon bond is defined as

[11] I use the GSW zero-coupon yields so as to follow the bond return predictability literature. The results in this paper are not materially changed if I instead use the Fed's H.15 statistical release for all analyses.

the change in the log price:

$$r_{t+h}^{(n)} \equiv ny_t^{(n)} - (n-h)y_{t+h}^{(n-h)}.$$

In the asset pricing analyses in this paper, I follow the literature and focus on the one-year holding period excess return:

$$rx_{t+1}^{(n)} \equiv ny_t^{(n)} - (n-1)y_{t+1}^{(n-1)} - y_t^{(1)}.$$

Expectation notation. There are several different forms of expectations studied in this paper. With a slight abuse of notation, I denote the rational expectation by the expectation operator $\mathbb{E}(.)$. The BCFF survey-based subjective expectation and the expectation using the econometrician's real-time information set are denoted as $\mathbb{E}^S(.)$ and $\widehat{\mathbb{E}}(.)$ respectively.

2.4 Properties of survey expectations of Treasury yields

I examine the accuracy, in the form of forecast errors and out-of-sample predictability, of the survey-based expectations of interest rates. Forecast errors are the differences between the ex-post realized values and forecasts. For an n-year Treasury bond, I define the h period ahead forecast error (FE) as

$$FE_t\left(y_{t+h}^{(n)}\right) = y_{t+h}^{(n)} - \mathbb{E}_t^S\left(y_{t+h}^{(n)}\right). \tag{1}$$

A non-zero forecast error may stem from a shock that occurs between the time when a forecast is made and the outcome is realized, or from a systematic departure from rationality. Panel A of Table 1 reports the summary statistics of the individual forecast errors of FFR and Treasury yields across maturities. The forecasts are pooled across horizons h.[12] Similar to a previous studiy on consensus short-rate forecasts by Cieslak (2018), the average and median forecast errors for interest rates across maturities are negative and small in magnitude – The means are less than 0.4% in absolute value, and the standard deviations are around 1% – indicating that the professional forecasters regularly overestimate the future Treasury yields to a moderate degree. Interest rates with different maturities have quantitatively similar forecast errors on average. The forecast errors normalized by contemporaneous realized

[12] Summary statistics of individual forecasts of each horizon h are reported in the Appendix.

interest rates also have similar medians. The statistics are similar, albeit less variable, when we look at the consensus level forecasts reported in theAppendix.

Apart from checking the average accuracy, I use the out-of-sample (OOS) R^2 to examine the predictive power of individual- and consensus-level survey forecasts against several alternative statistical models:

$$R^2_{OOS,i} = 1 - \frac{\sum_t \left(y^{(n)}_{t+1} - \mathbb{E}^S_t \left(y^{(n)}_{t+1} \right) \right)^2}{\sum_t \left(y^{(n)}_{t+1} - \mathbb{E}^i_t \left(y^{(n)}_{t+1} \right) \right)^2}, \tag{2}$$

where $\mathbb{E}^i_t \left(y^{(n)}_{t+1} \right)$ is the prediction from model i at time t. The OOS R^2 contrasts errors of the subjective survey forecasts to those from an alternative model. A positive OOS R^2 indicates superior predictive power of the survey forecasts over the alternative model, and vice versa. I consider several commonly-used statistical models: moving average (Mean), AR(1), AR(p) and ARIMA(1,1,0).[13] The moving average is a default alternative model in the forecast evaluation and asset pricing literature, and ARIMA class models are known to model the level of the interest rate well with an R^2 close to 1.[14] Panels C and D of Table 1 summarize the results for all interest rates by tabulating the median individual OOS R^2 and consensus OOS R^2. The results for the ARIMA class models offer a mixed picture. While professional forecasters make better predictions than statistical models at short maturities, they perform poorly at longer maturities in general, even though the statistical fitness of the ARIMA models are comparable at short- and long-maturity interest rates.

The moving average is too smooth to capture the business cycle frequency fluctuation of interest rates; thus, we see that survey forecasts perform much better, on average, at both the individual and consensus levels. Overall, professional forecasters, on average, overestimate interest rates moderately across maturities. Moreover, the accuracy of the short- and long-maturity forecasts diverge when compared to predictions from commonly-used statistical models. Potentially due to the sophistication of the survey participants, the short-rate forecasts are reasonably accurate; however, those for long-maturity rates are much less so.

[13] To prevent the alternative models from using future information, I estimate AR(1), AR(p) and ARIMA(1,1,0) recursively with rolling windows.

[14] See Goyal and Welch (2008) and Clark and McCracken (2013) for reviews of forecast evaluation.

3 Misreaction to Information across Maturities

In this section, I formally test whether the professional forecasts of interest rates across maturities are rational, and more precisely, whether the deviation from rationality stems from under- or over-reaction to the new information that professional forecasters receive in real-time. To do this, I follow the methodology developed by Coibion and Gorodnichenko (2015), which assesses under- and over-reaction by examining the predictability of forecast errors from forecast revisions and has been used extensively in recent work to study the dynamics of expectations. CG use forecast revisions to capture the new information available to forecasters; this circumvents the problem that the real-time information set of the forecasters is not observable to the econometrician ex-post. They derive the predicted relationship between ex-post forecast errors and ex-ante forecast revisions at the consensus level from sticky-information and noisy-information models. However, CG's methodology can also be applied to the individual-level forecasts, as in Bouchaud et al. (2019) and Bordalo et al. (2019b), as long as individual forecasts deviate from rational Bayesian updating.

Consider a target variable x_t. Formally, the forecast revision (FR) at time t is defined as the difference between the time t forecast for x_{t+h} and the forecast for the same quantity made at time $t-k$:

$$FR_t(x_{t+h}) \equiv \mathbb{E}_t^S\left(x_{t+h}\right) - \mathbb{E}_{t-k}^S\left(x_{t+h}\right). \tag{3}$$

The extent to which individual and average professional forecasters under- or over-react to new information can be evaluated by estimating the following regression

$$FE_{i,t}\left(x_{t+h}\right) = \alpha_i + \beta FR_{i,t}\left(x_{t+h}\right) + \epsilon_{i,t,h}, \tag{4}$$

where x_t is the underlying interest rate variable and h denotes the specific forecast horizon ranging from one (next quarter) to four quarters ahead. As noted by Coibion and Gorodnichenko (2012, 2015), this structure accommodates patterns of both under- and over-reaction. When $\beta > 0$, the forecaster insufficiently incorporates new information into her forecasts, indicating underreaction and expectation stickiness. When $\beta < 0$, the forecaster responds too much to new information, indicating overreaction. When $\beta = 0$, the subjective forecasts are consistent with rational expectations.

Several details warrant emphasis regarding the above regression. First, the regressions are estimated at the quarterly frequency for ease of interpretation, and $k = 1Q$ indicates a one-quarter forecast revision. In the Appendix, I estimate equation (4) at the monthly frequency and with one-month forecast revisions, and the results are similar. Second, I run the above regression for each interest rate for both *individual*-level and *consensus*-level forecasts. When applied to the individual level, the regression includes forecaster (institution) fixed effects to control for cross-sectional unobserved heterogeneity across forecasters. This individual-level regression specification is different from the main test in Coibion and Gorodnichenko (2015); they assume rational Bayesian learning of private information at the individual level, which predicts $\beta = 0$ at the individual level. Third, when estimating equation (4) for each interest rate at both the individual and consensus level, I pool the observations across different forecast horizons to make full use of all information from the subjective expectations and hence increase the statistical power of the test.[15] Previous studies mostly focus on one specific forecast horizon (e.g., $h = 3Q$ in Coibion and Gorodnichenko (2015)) due, in some cases, to data availability. In the baseline results, I include the Federal Funds Rate and Treasury yields for maturities of 3 months, and 1, 2, 5, 10, and 30 years as the underlying interest rates.

Main results. Figure 1 presents the regression coefficients $\hat{\beta}$ for each interest rate from the individual-level panel regressions. The dot depicts the point estimates, and the range of each bar represents the 95% confidence interval of each point estimate. The standard errors are clustered by forecaster and time. A clear pattern emerges as maturity increases. The term structure of the CG regression coefficients is downward sloping. Short-maturity interest rates (less than two years) have $\hat{\beta} > 0$ while long-maturity interest rates (greater than two years) have $\hat{\beta} < 0$. An early indication of this pattern is noted by Bordalo et al. (2019a), whose FE-on-FR regression specification, slightly different from this paper, fixes forecast horizon at 3 quarters. Moreover, I show that the same pattern of misreaction is manifested in the consensus-level regressions as well. Figure 2 plots regression coefficients estimated using consensus forecast data. The standard errors are calculated as in Driscoll and Kraay (1998), which allows for cross-sectional and serial correlations, and heteroskedasticity in the errors.

The shape of the coefficients, at both the individual and consensus levels, indicates that

[15] Coibion and Gorodnichenko (2015) also find very little cross-horizon heterogeneity in inflation expectations.

the individual forecasters *underreact* to new information regarding short-maturity interest rates and *overreact* to new information regarding long-maturity interest rates, despite the strong factor structure and high correlations between all interest rates. Table 2 reports the details of the regression results at both individual and consensus levels. In Panel A, except for the 2-year Treasury note that is situated in between short- and long-maturity interest rates, all β estimates are significant, statistically and economically. Take the 10-year Treasury yield as an example: a one percentage point increase in the past forecast revision indicates that the future realized yields are, on average, 0.24 percentage points lower than the previous forecasts. Panel B reports results for consensus-level regressions. The sign and statistical significance of β estimates are similar to those in individual-level regressions. There are two differences from Panel A: the absolute values of $\hat{\beta}$ across maturities are higher in Panel B, especially at the short end of the yield curve; the $\hat{\beta}$ of the two-year Treasury note is statistically significant.

The downward-sloping pattern in FE-on-FR regression coefficients is robust to several alternative specifications, especially at the individual level. In the Appendix, I report results for equation (4) estimated (1) using all available forecast data from 1982, (2) without firm fixed effects at the individual level, (3) at a monthly frequency using one-month forecast revisions, and (4) separately for each forecast horizon.[16] All alternative specifications preserve the downward-sloping term structure of under- and over-reaction and the beta coefficients cross zero at around the two-year maturity.

To examine the different reactions to new information for short- and long-maturity rates more extensively, I estimate equation (4) for a few additional interest rates, which I divide, broadly, into two groups based on their maturities. The new interest-rate variables include 1-month commercial paper rate (cp1m), prime bank rate (pr), three-month LIBOR rate (libor), Aaa and Baa corporate bond rates (aaa and baa), and home mortgage rate (hmr)[17]. Though these interest rates contain additional risks, such as default risk and prepayment risk, compared with Treasury yields, they correlate strongly with Treasury yields at each maturity. However, the correlations of forecast errors/revisions are high within maturity

[16]The underlying interest rate variables were introduced in the survey in a staggered fashion. Some interest rates, such as the Federal Funds Rate, appears in the survey earlier than 1988. Alternative specification (1) uses all available forecasts for each interest rate.

[17]Both Aaa and Baa indexes are calculated based on corporate bonds with maturities 20 years and above. The home mortgage rate has a maturity of 30 years

groups and low across maturity groups[18]. I focus on the individual-level regressions. Figure 3 plots the β estimates of the additional short-maturity (Panel A) and long-maturity (Panel B) interest rates, and Table 3 reports the details of the corresponding regressions. The dichotomy of forecasters' reactions to new information for the extended set of short and long rates is evident in the figure. Moreover, the downward-sloping pattern of coefficients is largely preserved. The point estimates are positive for all short-term interest rates and negative for all long-term interest rates. All but the two-year Treasury yield are statistically different from zero. The regression results are also robust if I restrict the sample to the forecasters who make forecasts for the complete set of interest rates.

In summary, I document a robust downward-sloping term structure of under- and over-reaction to new information in the professional forecasts of interest rates. This pattern is evident at both individual and consensus levels.

Commonly-used models of expectations. How does the above evidence square with commonly-used models of expectations? In what follows, I consider several candidate models in addition to the full information rational expectation (FIRE) benchmark. I briefly discuss the implications of each model and explain why none of the commonly-used models, at least in their standard form, can deliver the under- and over-reaction pattern that I document. I relegate all related derivations to the Appendix.

- The benchmark full-information rational expectations model (FIRE) posits that the forecast errors are noise that is orthogonal to any information known to the forecaster and are therefore not predictable: there should be no relationship between an individual's past forecast revisions and subsequent forecast errors. Thus, FIRE cannot explain the under- and over-reaction to information for short- and long-maturity interest rates.

- Sticky expectations capture the idea that the forecaster is sluggish when updating her beliefs, so that the current forecast gives significant weight to previous beliefs. Coibion and Gorodnichenko (2015) apply sticky expectations to the aggregate consensus forecast; such expectations can be derived from infrequent information updating (Mankiw and

[18] In the Appendix, I plot pairwise correlations of the level, one-year changes, forecast errors, and forecast revisions of different interest rates. The interest rates include the Treasury and additional interest rates. The level of all interest rates correlates strongly, while there is a clear two-group structure in the correlations of forecast errors and forecast revisions of different interest rates

Reis (2002)) or signal extraction from heterogeneous signals. When applied at the individual level as in the setting of equation (4), sticky expectations predict a positive relationship between forecast errors and forecast revisions, indicating underreaction to information across all maturities. Therefore, sticky expectations cannot explain the evidence that I document.

- Extrapolative expectations, under the functional form reviewed by Barberis (2018), model the current forecast as a weighted average of past realizations. The weights are exponentially decaying and higher for the more recent past. Extrapolative expectations typically generate overreaction in the stock market when people form expectations about the non-persistent stock returns. In the Appendix, I show that, when the underlying process is persistent enough, as is the case for *all* interest rates, underreaction to information prevails, and the coefficient in the FE-on-FR regression is always positive. Another frequently-used form of extrapolative expectations, as surveyed by Landier et al. (2019), is a backward-looking extrapolative expectation in which forecasts are determined by the current outcome and the recent one-period trend: $\mathbb{E}_t^S(x_{t+h}) = x_t + \theta(x_t - x_{t-1})$. As shown in the Appendix, this framework nests both underreaction (when $\theta < 0$) and overreaction (when $\theta > 0$). However, it is difficult to argue that people have drastically different extrapolative parameters θ, with opposite signs, for highly correlated processes such as short- and long-maturity interest rates.

- Diagnostic expectations, formalized by Bordalo et al. (2018, 2019a), incorporate a belief distortion rooted in the concept of representativeness first introduced by Kahneman and Tversky (1972, 1973). Under diagnostic expectations, individual forecasts overweight future outcomes in light of incoming data, and thus, the individual-level CG regression coefficient is always negative. Bordalo et al. (2019b) extend the framework to allow for imperfectly correlated heterogeneous private information. The new elements of the model can generate underreaction to aggregate (average) information when applied to the consensus-level forecasts. However, neither the original nor the richer diagnostic expectations model can deliver underreaction in short rates and overreaction to long rates simultaneously at both individual and consensus levels.

- Natural expectations, formalized by Fuster et al. (2010), posit that forecasters obtain their expectations by taking an average of expectations under both the true model and a more parsimonious but misspecified intuitive model. Under the specification studied in Fuster et al. (2010), the true data generating process is a stationary AR(2) while the forecasters' intuitive model contains a unit root in the first lag. This deviation from rationality gives rise to overreaction. Therefore, the natural expectations framework cannot generate underreaction without making implausible assumptions about the true and intuitive models of expectations.

4 A Model Based on "Autocorrelation Averaging"

In this section, I propose a simple bounded-rationality framework for understanding the above results. The framework is based on the incorrect subjective perception of autocorrelations. The boundedly-rational forecaster has limited working memory or finite processing capacity for carrying out complex calculations.[19] When facing multiple time series with different autocorrelations, the forecaster may not attend promptly to all relevant information to correctly estimate each autocorrelation. Instead, she uses something closer to an average autocorrelation of all the processes that she is exposed to and only imperfectly adjusts toward the true autocorrelations. Simply put, if the series have true autocorrelations ranging from 0.7 to 0.9, the forecaster may instead forecast all variables using an autocorrelation in the neighborhood of 0.8. An immediate consequence of this is that she will overreact to information about variables with less persistent processes – for example, those with autocorrelations close to 0.7 – but will underreact to information about variables with more persistent processes, those with autocorrelations closer to 0.9. Formally, I call this behavior "autocorrelation averaging".

In the context of interest rates, the yield on a bond has two components: one that is an average of expected short rates over the life of the bond (the expectations hypothesis (EH) component), and one that captures the term premium (TP). For each maturity n, the forecaster needs to estimate two separate autocorrelations for the EH and TP components. Suppose for a moment that the true autocorrelation of the EH component exceeds that of the TP component. Also, suppose that, due to bounded-rationality, the forecaster forecasts both components using an intermediate, average autocorrelation. Given such a large number of autocorrelations to estimate, she anchors her subjective autocorrelation to the simple average

[19] See Gabaix (2019) for a detailed review.

autocorrelation across all processes. As described above, this means that she will underreact to news about the EH component, but overreact to news about the TP component. Since, for short-maturity bonds, the EH component is more important than the TP component, this predicts under-reaction to information about short-term bond yields; and since, for long-maturity bonds, the TP component is relatively more important, this predicts over-reaction to information about long-term bond yields. This prediction is precisely the under- and over-reaction pattern I document in the data.

I first formalize the predictions of misreaction in a model where the boundedly-rational forecaster uses an average autocorrelation to forecast the interest rate components. I then empirically estimate the subjective and actual autocorrelations of the EH and TP components to corroborate the critical assumption made in the model. Last, I show that the "autocorrelation averaging" model, calibrated to the estimated autocorrelations, can quantitatively match the downward-sloping term structure of under- and over-reaction.

4.1 Incorrect subjective autocorrelation

I start by exploring the effect of biased perceived autocorrelations on the forecaster's reaction to new information, specifically in the form of the FE-on-FR regression coefficient. Suppose that an underlying variable z_t follows an AR(1) process

$$z_{t+1} = \rho z_t + \varepsilon_{t+1}, \quad \varepsilon_t \sim \mathcal{N}\left(0, \sigma^2\right).$$

A boundedly-rational forecaster uses her subjectively perceived autocorrelation $\rho^s \neq \rho$ of the underlying process. She forms her subjective expectation of the h-period ahead value of z_t as

$$\mathbb{E}_t^S\left(z_{t+h}\right) = \rho^s z_t,$$

so that

$$\mathbb{E}_t^S\left(z_{t+h}\right) = \left(\frac{\rho^s}{\rho}\right)^h \mathbb{E}_t\left(z_{t+h}\right).$$

Following the previous definitions, her forecast error and one-period forecast revision are

$$\begin{aligned}
FE_t\left(z_{t+h}\right) &= z_{t+h} - \mathbb{E}_t^S\left(z_{t+h}\right) = \left(\rho - \rho^s\right) z_t + \varepsilon_{t+h}, \\
FR_t\left(z_{t+h}\right) &= \mathbb{E}_t^S\left(z_{t+h}\right) - \mathbb{E}_{t-1}^S\left(z_{t+h}\right) = \rho^s\left(\rho - \rho^s\right) z_{t-1} + \rho^s \varepsilon_t.
\end{aligned}$$

The covariance between forecast error and past forecast revision, the numerator of the FE-on-FR regression coefficient, can be derived as

$$\mathrm{Cov}\left(FE_t\left(z_{t+h}\right), FR_t\left(z_{t+h}\right)\right) = \frac{\rho^s\left(\rho-\rho^s\right)\left(1-\rho^s\rho\right)\sigma^2}{1-\rho^2}, \tag{5}$$

which gives us the following proposition regarding the sign of the FE-on-FR regression and subjective autocorrelation ρ^s.

Proposition 1 *As long as* $\frac{\rho^s(1-\rho^s\rho)}{1-\rho^2} > 0$*, which is satisfied when both actual and subjective autocorrelations are persistent and stationary, we have*

1. *when* $\rho^s > \rho$*, the FE-on-FR regression coefficient is negative, indicating overreaction to new information;*
2. *when* $\rho^s < \rho$*, the FE-on-FR regression coefficient is positive, indicating underreaction to new information.*

4.2 FE-on-FR regression coefficient for interest rates

I now apply the bounded-rationality framework to the context of interest rates across maturities. Denote the one-period nominal short rate as i_t. We can iterate the definition of holding period excess returns forward and obtain an identity that relates the long rate to the short rate as follows

$$\begin{aligned} rx_{t+1}^{(n)} &= ny_t^{(n)} - (n-1)\,y_{t+1}^{(n-1)} - i_t \\ y_t^{(n)} &= \underbrace{\frac{1}{n}\mathbb{E}_t\left(\sum_{i=0}^{n-1} i_{t+i}\right)}_{\text{Expectations Hypothesis}, eh_t^{(n)}} + \underbrace{\frac{1}{n}\mathbb{E}_t\left(\sum_{i=0}^{n-2} rx_{t+i+1}^{(n-i)}\right)}_{\text{Term Premium}, tp_t^{(n)}}. \end{aligned} \tag{6}$$

The current n-year bond yield is the sum of the expected future average short rate and the average expected excess returns earned over the life of the bond. The identity, similar to the Campbell and Shiller (1988) identity in the aggregate stock market, decomposes the current bond yield into an expectations hypothesis (EH) component and a term premium (TP) component. Notice that the above identity holds both ex-ante and ex-post, so we can apply an arbitrary expectation operator to both sides, including the forecaster's subjective expectation. Empirically, the autocorrelations of the short rate and the term premia are different.

Suppose that the underlying processes of the short rate (i_t) and n-year term premium ($tp_t^{(n)}$) are both AR(1) with autocorrelations ρ_1 and $\rho_p^{(n)}$ respectively, and that term premium shocks are uncorrelated with short rate shocks[20]

$$i_{t+1} = \rho_1 i_t + \varepsilon_{t+1}, \quad \varepsilon_t \sim \mathcal{N}\left(0, \sigma_1^2\right) \tag{7}$$
$$tp_{t+1}^{(n)} = \rho_p^{(n)} tp_t^{(n)} + \upsilon_{t+1}, \quad \upsilon_t \sim \mathcal{N}\left(0, \sigma_p^2\right). \tag{8}$$

For exposition purposes, I suppress the superscript in the term premium autocorrelation and simply denote it as ρ_p. Under these assumptions, I can specify the EH component in equation (6) using the dynamics of the short rate i_t. I thus rewrite the decomposition of the n-year long rate using the true short rate autocorrelation as

$$y_t^{(n)} = \frac{1}{n}\frac{1-\rho_1^n}{1-\rho_1} i_t + tp_t^{(n)}, \tag{9}$$

or using the subjective autocorrelation as

$$y_t^{(n)} = \frac{1}{n}\frac{1-(\rho_1^s)^n}{1-\rho_1^s} i_t + tp_t^{(n)}. \tag{10}$$

Since TP components are not observable, the above two equations can be used to recover the actual and subjective TP components. I derive the covariance between long-rate forecast errors and forecast revisions by applying the results of Proposition 1:

$$\begin{aligned}
&\mathrm{Cov}\left(FE_t\left(y_{t+1}^{(n)}\right), FR_t\left(y_{t+1}^{(n)}\right)\right) \\
&\quad = \frac{1}{n}\frac{1-(\rho_1^s)^n}{1-\rho_1}\mathrm{Cov}\left(FE_t\left(i_{t+1}\right), FR_t\left(i_{t+1}\right)\right) + \mathrm{Cov}\left(FE_t\left(tp_{t+1}^{(n)}\right), FR_t\left(tp_{t+1}^{(n)}\right)\right) \\
&\quad = \frac{1}{n}\frac{1-(\rho_1^s)^n}{1-\rho_1^s}\frac{\rho_1^s\left(\rho_1-\rho_1^s\right)\left(1-\rho_1^s\rho_1\right)\sigma_1^2}{1-\rho_1^2} + \frac{\rho_p^s\left(\rho_p-\rho_p^s\right)\left(1-\rho_p^s\rho_p\right)\sigma_p^2}{1-\rho_p^2}.
\end{aligned} \tag{11}$$

I assume for now, and in the next subsection corroborate, that the short rate, equivalently the EH component, is more persistent than the TP components.

[20]The assumption of no correlation between the EH and TP components is empirically verified in the results of Cieslak and Povala (2016) and Duffee (2018).

Assumption 1 (Autocorrelation of EH and TP components) *The true autocorrelations satisfy* $\rho_{EH} = \rho_1 > \rho_p^{(n)}$ *for all* n.

The forecaster deals with many EH and TP processes with various autocorrelations, each of which demands allocation of her limited processing power. Define the average autocorrelation across the all components as

$$\bar{\rho} = \frac{1}{2N}\left(\sum_{n=1}^{N}\rho_{EH}^{(n)} + \sum_{n=1}^{N}\rho_p^{(n)}\right) = \frac{1}{2N}\left(N\rho_1 + \sum_{n=1}^{N}\rho_p^{(n)}\right), \tag{12}$$

where N is number of interest rates that the forecaster is exposed to. For a given process, the forecaster only imperfectly perceives the true autocorrelation and anchors her subjective autocorrelation on the average autocorrelation $\bar{\rho}$. Therefore, "autocorrelation averaging", under the same formulation as in Gabaix (2019), dictates that her perceived autocorrelation is a weighted average

$$\rho_i^s = (1-m)\rho_i + m\bar{\rho}, \quad i \in \{1, p\}, \tag{13}$$

where weight m measures the strength of "autocorrelation averaging". When $m = 1$, she uses average autocorrelation for all processes. The "averaging" behavior in beliefs has gained some attention lately. There has been some recent empirical evidence in other settings, such as for correlations in Matthies (2018) and for the persistence of stock market volatility in Lochstoer and Muir (2019), that are also consistent with the bounded-rationality approach.[21] "Autocorrelation averaging", together with the above assumption, has direct implications for under- and over-reaction to information.

Proposition 2 (Under/overreaction of EH and TP) *Forecasters underreact to information in the expectations hypothesis (EH) component* ($\rho_1^s < \rho_1$) *and overreact to information in the term premium (TP) component* ($\rho_p^s > \rho_p$).

Since short rates have only EH components, we immediately obtain underreaction for

[21] Alternatively, I can motivate the "autocorrelation averaging" behavior with "slow" learning. Suppose that the forecaster holds a prior that autocorrelations are drawn from a distribution with mean $\bar{\rho}$. As long as the forecaster learns slowly, either because she penalizes heavily any deviation from her prior, or because the noise to signal ratio is too low, her perceived autocorrelations of the EH and TP components stay close to the mean autocorrelation $\bar{\rho}$. I therefore obtain the same "autocorrelation averaging" behavior. See the Appendix for more details.

short rates. Long rates have both EH and TP components; the following lemma establishes the condition under which the forecaster overreacts for long rates.

Lemma 1 *If the overreaction effect from the term premium component dominates the underreaction effect from the short rate component, i.e.*

$$\left|\frac{\rho_p^s\left(\rho_p-\rho_p^s\right)\left(1-\rho_p^s\rho_p\right)\sigma_p^2}{1-\rho_p^2}\right| > \left|\frac{1}{n}\frac{1-\left(\rho_1^s\right)^n}{1-\rho_1^s}\frac{\rho_1^s\left(\rho_1-\rho_1^s\right)\left(1-\rho_1^s\rho_1\right)\sigma_1^2}{1-\rho_1^2}\right|,$$

the coefficient in the FE-on-FR regression for long-maturity interest rates is negative.

4.3 Estimation of the subjective autocorrelations

The above simple model shows that "autocorrelation averaging" can potentially explain the documented pattern. The goals of the empirical exercise below are to (1) empirically verify "autocorrelation averaging" and (2) show that this model can quantitatively match the term structure of under and overreaction. To corroborate the main assumption about autocorrelations, I empirically estimate the actual and subjective autocorrelations of interest rate components. The estimation of actual autocorrelations follows the standard AR model estimation procedure. I rely on the relationships of survey expectations between different maturities and across different horizons to estimate the subjective autocorrelations of the *short rate*. I then recover the subjective autocorrelations for term premia using only the relationships of the forecasts across horizons.

To better match the dynamics of interest rates, I allow the AR(1) process for interest rates and their components to have non-zero long-run means. The process for the short rate i_t follows

$$i_{t+1} = \left(1-\rho_1\right)\bar{i} + \rho_1 i_t + \varepsilon_{t+1}$$

and its subjective expectation is

$$\mathbb{E}_t^S\left(i_{t+h}\right) = \left(1-\left(\rho_1^s\right)^h\right)\bar{i} + \left(\rho_1^s\right)^h i_t. \tag{14}$$

Substituting equation (14) into the decomposition in equation (6), I obtain

$$\mathbb{E}_t^S\left(y_{t+h}^{(n)}\right) - \bar{i} = \frac{1}{n}\frac{1-\rho_1^n}{1-\rho_1}\left[\mathbb{E}_t^S\left(i_{t+h}\right)-\bar{i}\right] + tp_t^{(n),S}, \tag{15}$$

where $tp_t^{(n),S}$ denotes subjective term premium with maturity n. Given the empirically consistent assumption that the short rate and term premium shocks are uncorrelated, the presence of TP does not bias the estimation of the short rate subjective autocorrelation.

GMM moment conditions. Since there are two sets of moment conditions concerning the perceived short rate autocorrelation ρ_1^s, I estimate ρ_1^s using the generalized method of moments (GMM). The advantage of using such an over-identified GMM estimation over a non-linear regression to recover the subjective autocorrelation is that GMM moment conditions take into account both the time-series (equation 16) and cross-sectional (equation 17) restrictions. Therefore, GMM estimation imposes the sensible requirement that the forecaster uses the same short rate subjective autocorrelation ρ_1^s in all relevant forecasts. The two sets of moment conditions are as follows.

1. (Forecasts of future short rates at different horizons) For forecast horizon $h \in \{1, 2, 3, 4\}$ quarters, the loadings of the short-rate forecasts on the current short rate follow a geometric progression as implied by the AR(1) structure[22]

$$\mathbb{E}_t^S\left(i_{t+h}\right) - \left(1 - \left(\rho_1^s\right)^h\right)\bar{i} - \left(\rho_1^s\right)^h i_t = 0. \tag{16}$$

2. (Cross-maturity relationship) For maturity $n \in \{2, 5, 10\}$ years and forecast horizon $h \in \{1, 2, 3, 4\}$ quarters, the yield decomposition equation binds long-maturity yields to the short rate

$$\mathbb{E}_t^S\left(y_{t+h}^{(n)}\right) - \bar{i} - \frac{1}{n}\frac{1 - \left(\rho_1^s\right)^n}{1 - \rho_1^s}\left[\mathbb{E}_t\left(i_{t+h}\right) - \bar{i}\right] + c = 0. \tag{17}$$

In total, there are 16 moment conditions and ρ_1^s is the parameter of interest to be estimated.

Short rate subjective autocorrelation estimation procedure. I estimate the model using monthly observations, forecaster-by-forecaster, and with rolling windows of 10 years (120 months). With the monthly frequency, I use all available forecasts, which increases the sample size and thus the accuracy of the rolling GMM estimation. Next, estimating ρ_1^s for each forecaster allows for cross-sectional heterogeneity in forecasting methodology, which

[22] Notice that the forecast horizons are in quarters, so the estimated autocorrelations are at a quarterly frequency.

may originate from the different levels of "autocorrelation averaging" across forecasters. Moreover, as the data sample spans more than three decades, macroeconomic conditions and inflation regimes change, and the economists who lead the forecasting effort at each institution change too. Hence it is reasonable to allow the subjective autocorrelation of the short rate to fluctuate over time. The window length of 10-year is close to the typical tenure of a forecasting economist with a firm in the sample.

To estimate the over-identified system, I use the two-step GMM of Hansen (1982) in which the efficient weighting matrix is used in the second step. I follow Cieslak (2018) and choose the Federal Funds Rate (ffr) as the primary measure for the short rate, but the results are quantitatively similar if I use the one-year Treasury bill yield instead. I use the average short rate, estimated using an expanding window and available to the forecasters in real-time, as the empirical measure of the long-run mean of the short rate $\bar{i}$.[23] Fixing the long-run mean reduces the degree of freedom and enables more accurate estimations for the parameter of interest, ρ_1^s.

As reported in Table 4, Panel A, the GMM estimation generates 10,743 and 314 valid subjective autocorrelations at the individual and consensus levels, respectively. The GMM procedure almost always produces statistically significant estimates with p-values close to zero. I therefore focus on the point estimates and omit the statistical significance from the table. The mean ρ_1^s estimates for individual- and consensus-level forecasts are both 0.87, which are close but lower than the mean ρ_1 estimate of 0.98 of realized short rate.[24] Consequently, the forecasters under-perceive the persistence of the short rate. This empirical relationship between the subjective and actual autocorrelations of the short rate guarantees that the short rate expectations underreact to information at both the individual and consensus level, as prescribed in Proposition 1. Figure 4 plots the histogram of ρ_1^s estimates where Panel A pools estimates across time and forecasters and Panel B plots the median estimate for each forecaster. In both panels, the majority of ρ_1^s estimates lie between 0.75 and 1. This indicates that the subjective short rate autocorrelations, though lower than the actual counterpart, do not deviate much from the actual autocorrelation. With the time-varying ρ_1^s estimates, I further show that the EH components, which are linear

[23]Since the full history of the short rate is available to the forecasters, I start the expanding windows from the beginning of the Federal Funds Rate data, namely, July 1954.

[24]In comparison, the autocorrelation estimated using the longest available sample of the Federal Funds Rate is 0.97.

transformations of the short rates for a given ρ_1^s, also have lower subjective autocorrelations.

Subjective autocorrelations of the term premium components. I now turn to the autocorrelation of the term premium (TP) components. With the subjective and actual autocorrelation estimates of the short rate, I recover both the subjective and actual TP components according to equations (10) and (9) respectively. There is only one set of moment conditions regarding TP components. Since TP follows an AR(1) process, regressing the TP forecast at horizon h quarters on that at horizon $h-1$ quarters reveals the subjective autocorrelation of the TP component:

$$\mathbb{E}_t^S\left(tp_{t+h}^{(n)}\right) = \alpha + \rho_p^s \mathbb{E}_t^S\left(tp_{t+h-1}^{(n)}\right) + \varepsilon_t. \tag{18}$$

The regression is run separately for each forecaster and for TP with different maturities.[25]

Statistics for the TP autocorrelations are reported in Panels B to D of Table 4. The dispersion of the subjective TP autocorrelation estimates is smaller than that of the short rate or EH components. Several findings are worth highlighting. The mean and median estimates of subjective autocorrelations ρ_p^s at the individual and consensus levels (Panels B and C) range from 0.9 to 0.97 across maturities, which are much higher than those of actual autocorrelation estimates of around 0.75 (Panel D). Moreover, the actual autocorrelations of TPs $\rho_p^{(n)}$ are lower than the actual short rate autocorrelation ρ_1. This relationship corroborates the critical Assumption 1 that the short rate is more persistent than the term premia. Finally, the subjective autocorrelations of the short rate and TP components are close, which is consistent with the bounded-rationality explanation based on "autocorrelation averaging".

Figure 5 summarizes the relationship between the subjective and actual autocorrelations of the short rate and the term premium. It plots the joint distribution of median autocorrelations of short rate and 10-year TP for each forecaster, the consensus forecast, and the actual values.[26] Each blue circle represents one forecaster's median ρ_1^s and ρ_p^s estimates. The size of the circle corresponds to the number of each forecaster's valid estimates. The orange diamond

[25]The reason that the actual TP is not on the right-hand side of equation (18) is because realized TP requires separate estimation of the actual autocorrelation, which brings in additional noise and bias to the subjective autocorrelation estimation. Using only subjective forecasts of TP does not introduce this problem.

[26]Using mean or median autocorrelation of each forecaster generate similar plots. The same plots with other TP maturities are presented in the Appendix.

and green square, respectively, represent the median autocorrelations for the consensus forecasts and the realized series. The boundaries of the dashed box are determined by actual short rate and TP autocorrelations. "Autocorrelation averaging" implies that all subjective autocorrelations should be within the box. As is evident in the plot, the majority of the individual blue dots and the consensus orange diamond are located within the box (i.e., $\rho_p < \rho_1^s, \rho_p^s < \rho_1$), and a significant mass of individual dots centers around the consensus estimate. In sum, the relative positions of subjective and actual autocorrelations in the figure lends strong support to the "autocorrelation averaging" hypothesis.

Under- and over-reaction for EH and TP components. A direct implication of Proposition 1 is that the forecasters underreact to new information in EH components and overreact to new information in TP components in CG regressions. I confirm this implication in Table 6 at the individual (Panel A) and consensus (Panel B) levels. Compared with Table 2, there are fewer observations since the estimation of ρ_1^s and ρ_p^s requires 120 months of data to begin with. In Panel A, I obtain positive and significant regression coefficients for the EH components of 2-, 5-, and 10-year bonds; the coefficients are slightly higher than those of the short rates in Table 2. The coefficients of TP regressions across all maturities are significant and negative, exhibiting stronger overreaction than in Table 2. The sign and statistical significance of the coefficient estimates largely persist at the consensus level in Panel B. The consensus level regressions show that the regression coefficients for EH components are bigger, and for TPs are smaller, in magnitude than the individual-level ones. Consistent with the relationship between *average* subjective and actual autocorrelations, the average forecaster underreacts to the news in EH and overreacts to the news in TP significantly.

4.4 Model calibration and discussion

Calibration. To evaluate the performance of the simple model quantitatively, I calibrate the model with the estimated subjective and actual autocorrelations, and compare the model-generated FE-on-FR regression coefficients with the empirical ones. Because the estimated subjective autocorrelations are, on average, close at individual and consensus levels, I use the individual-level mean autocorrelation estimates as inputs to the model. Also, because the estimation starts in 1998, I re-estimate the FE-on-FR regressions from 1998 to compare with the model predictions. Consistent with the choice made in the autocorrelation estimations, I use the FFR to measure the short rate and focus on the FE-on-FR regression coefficients of FFR, 2, 5, 10, and 30-year bonds. I calculate the CG regression coefficients based on equation (11) and the realized variance of forecast revisions. The parameter values and other details of the calibration are reported in Table 5.

Figure 6 depicts the calibrated FE-on-FR coefficients against the individual- and consensus-level regression estimates for interest rates across maturities. The blue circles and orange triangles are the individual- and consensus-level empirical results and the green squares are the calibrated results. The figure shows that the calibration exercise generates the same downward-sloping pattern of CG regression coefficients. Moreover, except for the 30-year bond, the calibration-generated coefficients are mostly within the 95% confidence interval of those estimated in the data. The simple model, based on the discrepancy between perceived and realized autocorrelations, makes no assumption about the relative importance of the EH and TP components for each interest rate. Nevertheless, the model successfully matches the downward-sloping term structure of under- and over-reaction and generates CG regression coefficients quantitatively close to those from regressions.

Under- and over-reaction during recessions. The underlying psychological foundation of the bounded-rationality framework is that the forecasters and investors have limited processing power, especially given that they face many demanding tasks. During periods when a forecaster's processing capacity is more constrained, she is expected to deviate further from rationality, and her misreaction to new information would be exacerbated. One instance of such periods is the recession. Previous studies have documented that, during the recessions, forecasters make larger mistakes (Cieslak, 2018), and investors allocate resources to different tasks than during normal times (Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2014). To test the above prediction, I split the sample into recession and non-recession periods and rerun the previous FE-on-FR regressions. Figure A.4 in the Appendix plots the term structure of CG regression coefficients. The downward-sloping term structure of misreaction is also present during recession times. However, across maturities, the absolute values of the CG coefficients during recession times are larger than, though not statistically different from, those during the normal periods. This suggestive evidence lends support to the argument that under- and over-reaction are stronger when the boundedly-rational forecaster's processing capacity is more constrained.

5 Forecast Misreaction and Asset Prices

The pattern of under- and over-reaction to information is evident not only at the individual level but also at the *aggregate* consensus level. Furthermore, the BCFF professional forecasts proxy for the beliefs of market participants since the forecasters are either significant players in the Treasury markets themselves or likely to influence many important market participants through their client services. One would therefore expect the deviations from rationality to manifest themselves in asset prices. In this section, I explore the implications of the under- and over-reaction for bond and interest rate futures prices. I focus primarily on the predictions of overreaction for future bond returns. Most studies of Treasury bond returns focus on the one-year holding period return of bonds with maturities greater than one year. Based on the empirical evidence documented in previous sections, overreaction is the dominant feature for these bonds. However, in the last part of this section, I also test the predictions of underreaction for short-term bond prices and the Federal Funds Futures.

5.1 Return predictability from overreaction

In the case of overreaction, when investors revise up their forecast of the long yield following the arrival of new information, they push the bond price down too low (and bond yields too high). However, this price pressure gradually subsides, and the price corrects back to a sensible level. A direct prediction of this predictable price movement, therefore, is that an increase in the forecast revision of long rates predicts higher bond returns in the future. I empirically confirm this predictability in Table A.8 in the Appendix.

Decomposing the variance of forecast revisions reveals that the contemporaneous *realized* forecast error is one of, if not the most important contributor to, the variation in forecast revisions. For instance, the realized forecast errors of 10-year Treasury yields explain 61% of the variation of the forecast revision at the consensus level for the one-quarter horizon and 36% for the one-year horizon:

$$FR_t\left(y_{t+1Q}^{(10)}\right) = -0.11 + \underset{(t=14.10)}{0.56} \times FE_{t-1Q}\left(y_t^{(10)}\right) + \varepsilon_t, \quad R^2 = 0.61$$

Table A.9 in the Appendix reports the contemporaneous relationship between forecast revisions and realized forecast errors across maturities at the one-quarter and one-year forecast horizons.

Across all interest rates, realized forecast errors explain a significant portion of the variation of the forecast revisions. We can therefore turn the prediction into one that is easier to test: the forecast error should predict the subsequent bond return with a positive sign.[27]

There are two reasons that the *realized* forecast error is preferred to forecast revision as a bond return predictor. First, the bond literature focuses on the one-year holding period return for ease of construction and interpretation. Matching the one-year holding period requires survey forecasts with a horizon longer than one year to calculate the forecast revision, shortening the available sample for the return predictability exercise. Second, the interval at which the forecast revision is calculated is arbitrary. This additional degree of freedom is not essential to establish return predictability from overreaction as other intervals also pick up the same overreaction dynamic. Conversely, the realized forecast error does not suffer from these deficiencies and thus is a simpler measure of information updates. I therefore choose the realized forecast errors as the main predictor and make the following prediction regarding the effect of overreaction on bond returns.

Prediction 1 (Overreaction and subsequent bond returns) *Realized forecast errors of the long rate should positively predict future Treasury bond returns.*

To operationalize tests of this prediction, I pick the 10-year Treasury yield as the workhorse long rate, given the strong one-factor structure in Treasury bond yields and returns (Cochrane and Piazzesi (2009)). The 10-year Treasury note rate is a widely-used benchmark bond yield followed by both market participants and academic researchers. For example, Brooks and Moskowitz (2017) use the 10-year yield as an empirical proxy for the yield curve level factor and show that it traces the statistical level factor well. Formally, the return predictor is the difference between the time t realized 10-year Treasury yield and forecast made one year ago: $FE_{t-1Y}\left(y_t^{(10)}\right)$. For brevity, I label it as $FE10Y_t$. The forecast horizon of one year is picked to match the one-year holding period of the bond returns. The time-series dynamics of $FE10Y_t$ are plotted in Figure 7, Panel A. The realized forecast errors for the 10-year Treasury exhibit counter-cyclical fluctuations over time at the business cycle frequency.

I start by running simple return predictive regressions at the monthly frequency with

[27] A feature of the forecast errors that is consistent with overreaction is that, empirically, they are negatively autocorrelated.

overlapping one-year holding period excess returns as the dependent variable:

$$rx_{t+1}^{(n)} = \alpha + \beta FE10Y_t + \gamma \cdot X_t + \varepsilon_{t+1} \tag{19}$$

where $rx_{t+1}^{(n)}$ is the excess return of an n-year bond; $FE10Y_t$ is the main overreaction-motivated return predictor; and X_t is a vector of control variables, such as the first three principal components (PC) of the yield curve, and other bond predictors. To take into account the heteroskedasticity and autocorrelation in the error terms and the overlapping structure of the excess returns on the left-hand side, I construct two robust standard errors: Newey and West (1987) standard errors with 12 lags and Hodrick (1992) standard errors which retain correct size in small samples for overlapping returns. I follow the implementation of Wei and Wright (2013) to calculate the Hodrick standard error by running the "reverse regression".[28]

Table 7 reports the results of estimating equation (19) with no controls (Panel A) and controlling for the first three PCs of the yield curve. In particular, I use $FE10Y$ to predict the future one-year holding period excess returns of Treasury bonds with 2, 3, 5, 7, 20, and 30-year maturities. The dependent variable in the last column is an average excess return weighted by the inverse of bond maturities $\overline{rx}_{t+1} = (1/\sum \frac{1}{n}) \sum \frac{1}{n} rx_{t+1}^{(n)}$ that does not overweight long maturity returns.[29] As is clearly shown in Table 7, Panel A, $FE10Y$ positively and significantly predicts the future excess returns across all maturities, which is consistent with the prediction of overreaction. The coefficients are significant under the more stringent Hodrick (1992) standard errors. $FE10Y$ predicts the average excess return $\overline{rx}_{t+1}$ with an R^2 of 0.25. In economic magnitude, a one standard deviation increase in $FE10Y$, according to the point estimates from Panel A, is associated with a 3.38% increase in the average return of Treasury bonds in the coming year, which is 98% of the unconditional mean of $\overline{rx}$. The statistical significance and magnitude are barely changed in Panel B when I control for the first three PCs. The noticeable difference is that the two-year regression coefficient becomes less significant, which is mostly consistent with the weaker (or absent) overreaction at the two-year maturity in Section 3. Under the null hypothesis of no additional

[28] The reverse regressions use the one-month excess returns on Treasury bonds as the left-hand-side variable. I obtain them by interpolating the available yields using the cubic spline method to get the yield of a bond with maturity $(n - 1/12)$.

[29] Constructing $\overline{rx}$ as simple cross-sectional average generates similar results from predictive regressions.

predictive power beyond the information contained in yields (the "spanning hypothesis"), the yield curve variation summarized by the three PCs should span all auxiliary bond return predictors. However, the evidence in Panel B strongly rejects the null of no incremental predictability from $FE10Y$.

This "excess" predictability from $FE10Y$ stems from overreaction to information. The underlying mechanism shares some similarities with the one in Cieslak (2018) who finds that a wedge between investors' perceived and realized dynamics of the *short rate* has predictive power for bond returns. Though both papers are exploring the information embedded in subjective expectations, I focus on investors' overreaction to information in the long rate or, more precisely, the term premium component. To support this interpretation, I construct the realized forecast error of the 10-year term premium as $FE_{t-1}\left(tp_t^{(10)}\right)$ using TP from the consensus-level yield decomposition detailed in Section 4.3. Table 8, Panel A reports the results of the predictive regressions using forecast errors of TP. The sample is shorter due to the rolling window estimation of the subjective autocorrelations. Nonetheless, the predictive power from the overreaction for the TP component is comparable to that from $FE10Y$. Admittedly, the point estimates are less significant as a result of the noise introduced in the autocorrelation estimation. As a placebo test, I use the realized forecast error of the short rate (FFR, three-month, or one-year T-bill rates) and the EH components in the same predictive regression. Panel B tabulates the results using FFR; here, there is barely any predictability. Unreported results show that the same conclusion holds for other short rate variables.

5.1.1 Robustness

Other bond return predictors. One may worry that the predictive power from overreaction is driven by exposure to existing bond return predictors. To address this concern, I include the following known predictors as additional independent variables: 1) the first three PCs of the yield curve, which explain 99.9% of the cross-sectional yield variation in the sample, 2) the Cochrane and Piazzesi (2005) factor (CP), which is a tent-shaped linear combination of the forward rates across various maturities and constructed using the Fama-Bliss yields, 3) the cycle factor (cf) from Cieslak and Povala (2015), obtained from yields and trend inflation predictive regressions of excess returns, 4) a growth factor (GRO) which is the three-month moving average of the Chicago Fed National Activity Index (CFNAI), and an inflation factor

($INFL$) which is the Blue Chip survey forecast of the one-year forward inflation rate from Joslin, Priebsch, and Singleton (2014), and 5) the eight PCs of a large set of macroeconomic variables from Ludvigson and Ng (2009).[30] The correlations between $FE10Y$ and these predictors are reported in Table A.10. Notice that $FE10Y$ has positive correlations with CP, GRO, the first yield curve PC, and especially with the two inflation-related factors: cf (0.57) and $INFL$ (0.55).

Table 9 runs the multivariate predictive regressions as "horse races". Panel A includes PCs, CP and cf, and Panel B adds two additional predictors from Joslin, Priebsch, and Singleton (2014). Despite the presence of other predictors, the strong predictability from $FE10Y$ survives, albeit with slightly weaker statistical significance, given the positive correlations with other predictors. Interestingly, none of these alternative return predictors offers consistent and significant predictive power across maturities, and $FE10Y$ has the most robust statistical significance across predictors. If we focus on the average return, only cf has similar but weaker predictive power. Moreover, the economic magnitudes of $FE10Y$ in these two panels are close to those in Table 7. Table A.13 in the Appendix reports the "horse race" with the eight bond factors from Ludvigson and Ng (2009) where the strong performance of $FE10Y$ persists. Admittedly, there are limitations in interpreting the results from the multivariate regressions when many of the regressors are correlated. I run bivariate regressions of $FE10Y$ with each alternative predictor, and the predictive power of $FE10Y$ is still clearly evident.

Prediction coupone bond returns. I test the predictive power of $FE10Y$ using actual coupon bond excess returns across different maturity brackets. The coupon bond returns are available from the CRSP Fama bond portfolios for the sample period 1988–2018. The actual bond returns can address potential measurement issues with the synthetic zero-coupon yields used in the previous regressions. Each maturity-sorted portfolio return is calculated as the equal-weighted average of unadjusted holding period returns for all bonds in the portfolio. I convert the return to an excess return by subtracting T-bill rates of the corresponding holding periods. Table A.11 in the Appendix reports the predictability results for 1, 3, 6, and 12-month holding-period coupon bond excess returns. The return in the last column is the average return across maturities. At the one-month holding period, $FE10Y$ is statistically significant, but the predictive power is limited. The predictability increases as the holding

[30] I am grateful to Sydney Ludvigson for sharing the updated series.

periods increase. The one-year holding period evidence is close to that in Table 7 for the synthetic zero-coupon bond returns.

Robust test of the spanning hypothesis. Bauer and Hamilton (2017) cast doubt on the statistical power of auxiliary bond predictors in addition to yields and point out significant small-sample distortions in many recently discovered predictors. To establish the robustness of the "excess" predictive evidence of $FE10Y$, I use the parametric bootstrap procedure of Bauer and Hamilton (2017) to test the statistical significance under the "spanning hypothesis". I simulate 5,000 artificial samples of bond yields with the same historical length as the data under the null hypothesis. I then calculate the bootstrap p-value as the fraction of samples in which the t-stat of predictor $FE10Y$ exceeds the typical threshold. The detailed results using the bootstrap procedure are reported in Table A.12 in the Appendix. Regression model 1 contains only three PCs, and model 2 adds $FE10Y$. In Panel A, the column "Wald" reports results for the χ^2 test that $FE10Y$ has no additional predictive power, which is firmly rejected by both the Newey-West and bootstrap inference. Panel B reports the R^2 of models 1 and 2, and their difference. The bootstrap procedure also rejects the null of no difference in R^2: the incremental predictive power in R^2 is sizable (24.7%) and well beyond the 95% confidence interval. Unlike the commonly-used predictors analyzed by Bauer and Hamilton (2017), the overreaction-based realized forecast error $FE10Y$ passes the scrutiny of small-sample inference, underscoring the uniqueness of the belief channel.

5.1.2 Unique information in forecast errors

Given the robust return predictability from the survey-based realized forecast errors $FE10Y$, a natural question arises: do these results reflect unique information in professional forecasts and to what extent could other related measures from the yield curve replicate the return predictability? To answer these questions, I consider several distinct but closely related measures that can help us tease out the unique information that the survey-based forecast error $FE10Y$ carries: 1) forecast errors using an econometrician's real-time information set, 2) realized yield changes which can be regarded as a measure of the forecast error under FIRE, $\Delta y_{t+1}^{(10)} = y_{t+1}^{(10)} - y_t^{(10)}$, and 3) differences between the realized and the contemporaneous forecasts of the 10-year yield defined as $y_t^{(10)} - \mathbb{E}_t^S\left(y_{t+1}^{(10)}\right)$.

Following Cieslak (2018), I proxy for the econometrician's one-year ahead forecast of the 10-year yield using a simple linear system which captures the yield variation well in-sample:

$$y_{t+1}^{(10)} = \gamma_0 + \gamma_1 y_t^{(10)} + \gamma_2 FFR_t + \gamma_3 \Delta Unemp_t + \gamma_4 CFNAI_t + \gamma_5 \Delta CPI_t + \epsilon_{t+1}. \tag{20}$$

The additional independent variables include the unemployment rate ($Unemp$), the Chicago Fed National Activity Index ($CFNAI$), and changes in inflation (ΔCPI). This predictive regression augments the past realizations of the bond yield with information from the macroeconomy, making it a reasonable approximation of the econometrician's information set. In the full sample estimation, regression (20) has an R^2 over 0.9, and all regressors except the change in the unemployment rate are statistically significant. I estimate regression (20) recursively each month using information that is available in real time and obtain the one-step-forward forecast based on the estimated coefficients. I define the econometrician's forecast errors as $\widehat{FE}10Y = y_t^{(10)} - \widehat{\mathbb{E}}_{t-1}\left(y_t^{(10)}\right)$. The correlation between the survey and the econometrician's forecast errors is 0.86.

Table 10 contrasts the predictive power of $FE10Y$ to that of the related measures. The dependent variable is the average return $\overline{rx}_{t+1}$. Panel A runs univariate predictive regressions, Panel B adds yield curve PCs as control variables, and Panel C adds the full set of auxiliary predictors from Table 9, Panel B. The first column reproduces the average return predictability from $FE10Y$; columns 2-4 are the results for the four alternative measures, respectively. When entering the regression alone, both the econometrician's forecast error $\widehat{FE}(y^{(10)})_t$ and changes in yields $\Delta y_t^{(10)}$ significantly predict future average returns, though the predictability is about half of that from $FE10Y$. When more control variables are added in Panels B and C, neither of these two alternative forecast errors maintains the same level of statistical significance. The contemporaneous differences $y_t^{(10)} - \mathbb{E}_t^S\left(y_{t+1}^{(10)}\right)$, both terms available at time t, does not have any predictive power across panels.

Table A.14, Panel A in the Appendix directly contrasts $FE10Y$ with each alternative forecast error measure by running bivariate regressions predicting average excess returns. Interestingly, all columns feature only $FE10Y$ as a significant predictor, and almost the same amount of variation is explained across specifications. As different measures of the forecast error are highly correlated, I project $FE10Y$ on each alternative measure and test the residual's predictive power. The results are reported in Table A.14, Panel B, where all coefficients of the residuals are significantly positive

To sum up, the survey-based forecast errors contain unique information concerning future price movements in the Treasury bond market. The predictability of $FE10Y$ cannot be easily replicated using other related but distinct forecast error measures such as an econometrician's forecast errors.

5.2 Underreaction and asset prices

I complete this section by testing the implications of underreaction for asset prices. Since the mechanism from under- and over-reaction to asset prices is symmetric, the prediction of underreaction for short-term bond prices is the opposite of that from overreaction for long-term bond prices: realized forecast errors of the short rate should *negatively* predict the future short-term bond returns. Calculating the return on a bond with maturity less than two years requires additional assumptions regarding interpolation, which adds measurement error. Instead, I use the changes in yields of six-month and one-year T-bill rates, which has the same sign as the bond returns, as the dependent variables. I complement the yield changes with short-term coupon bond excess returns with less than 12 month and less than 24 month maturities from Fama Maturity Portfolios. Consistent with the previous sections, I use the Federal Funds Rate (FFR) as the benchmark short rate and define the realized forecast errors accordingly. To accommodate the short maturities of the bonds, I use the one-quarter horizon to calculate the forecast errors, yield changes, and excess returns. The predictive regressions are estimated at the monthly frequency. The short-term predictive regression results are reported in Table 11, where I regress future inverse yield changes (Columns 1 and 2) and the excess returns to the two short-term bond portfolios (Columns 3 and 4) on the realized forecast errors of FFR. Across the four columns, the coefficients are all negative and statistically significant using Newey-West standard errors with 3 lags. These results are consistent with the predictions of underreaction.

Underreaction in Federal funds futures. Another market to test the predictions of underreaction is the Federal funds futures market.[31] The Federal funds futures contracts have

[31] The Treasury futures contracts have hypothetical coupon rates; the futures implied yields are therefore different from both the survey forecasts and zero-coupon yields.

high trading volumes, which ensures that the prices fully reflect investors' expectations.[32] Underreaction implies that investors only partially incorporate into the futures prices the new information captured by forecast revisions. Since the Federal funds futures payoff is determined by the average effective FFR in a given month, I define the futures-based forecast error of FFR as

$$FE_t^{FUT}\left(ffr_{t+h}\right) = \overline{ffr}_{t+h} - \mathbb{E}_t^{FUT}\left(ffr_{t+h}\right),$$

where $\overline{ffr}_{t+h}$ is the within-month average FFR and $\mathbb{E}_t^{FUT}\left(ffr_{t+h}\right)$ is the end-of-month futures implied FFR.

Consistent with Cieslak (2018), the statistical properties of futures- and survey-based expectations are similar for FFR. The correlation between survey and futures-based forecast errors is around 0.6.[33] As I have shown that survey expectations proxy for the beliefs of market participants, I use the survey-based forecast revisions to capture information updates and test underreaction in the Federal funds futures by estimating the following FE-on-FR regression:

$$FE_t^{FUT}\left(ffr_{t+h}\right) = \alpha + \beta FR_t^S\left(ffr_{t+h}\right) + \epsilon_{t,h}, \tag{21}$$

where $FE_t^{FUT}\left(ffr_{t+h}\right)$ is the futures forecast error and $FR_t^S\left(ffr_{t+h}\right)$ is the *survey*-based forecast revision at the consensus level. I estimate regression (21) at a quarterly frequency (1) by pooling across forecast horizons, and (2) separately for horizons from 1 to 4 quarters.

Table 12 reports the regression. The coefficients are all positive and statistically significant, confirming the prediction of underreaction in the Federal funds futures market. The point estimates of the FE-on-FR regression are larger in absolute terms than those from the individual- and consensus-level forecasts because the futures forecast errors are much more volatile than the survey forecasts ones. The evidence is another manifestation of underreaction in asset prices.

[32]The futures data are from Datastream, from which I obtain daily settlement prices and resample them to the monthly and quarterly frequencies. Federal funds futures have one contract for each month, and illiquidity is not an issue for contracts that expire in about a year.

[33]The summary statistics are reported in the Appendix.

6 Conclusion

In this paper, I investigate how survey expectations of interest rates across maturities respond to new information. Applying the methodology developed by Coibion and Gorodnichenko (2015) to the professional forecast data from Blue Chip Financial Forecasts, I document a robust downward-sloping term structure of under- and over-reaction: forecasters underreact for short-term bonds and overreact for long-term bonds. The pattern is evident in both individual- and consensus-level forecasts and difficult to reconcile with commonly-used models of expectations.

To accommodate the pattern of under- and over-reaction, I propose a simple bounded-rationality model based on "autocorrelation averaging". Investors and forecasters, facing many different time series of short rate and term premia, may not have the cognitive processing capacity to learn the true autocorrelation of each series. Instead, when forecasting, they use perceived autocorrelations which are closer to an average of the true autocorrelations of the series that they are exposed to. They overreact to less persistent term-premium processes and underreact to more persistent short-rate processes. This theoretical explanation is borne out by the survey data. The model calibrated to the estimated true and perceived autocorrelations quantitatively matches the downward-sloping term structure of misreaction.

Since the professional forecasts are likely to represent the beliefs of market participants, under- and over-reaction in interest rate expectations have direct predictions for asset prices: an overreaction-motivated predictor, the realized forecast errors of 10-year Treasury yields, robustly forecasts future excess bond returns. I also confirm the analogous prediction of underreaction for short-term bond and Federal funds futures prices.

The bounded-rationality origin of under- and over-reaction provides useful guidance for reconciling similar phenomena in other markets. A direct application and out of sample evaluation of the explanation can be made in the stock market where one can similarly estimate financial analysts' perceived persistence of cash flows and discount rates. Moreover, understanding the psychological or institutional foundation underlying investors' finite processing capacity is another useful direction for future research.

Tables and Figures

Table 1 Summary statistics and out-of-sample performance of the interest rate forecasts

Panels A and B report summary statistics of the individual-level forecast errors and forecast revisions. The results are pooled across forecast horizons h. The last rows of Panels A and B are medians of forecast errors and forecast revisions normalized by the contemporaneous interest rates. Panels C and D evaluate the out-of-sample (OOS) performance of survey forecasts against alternative models including moving average ($Mean$), AR(1), AR(p), and ARIMA(1,1,0) ($ARIMA$), respectively. Panel C reports median OOS R^2 of the individual forecasts, and Panel D reports OOS R^2 of the consensus forecasts. The underlying variables are the Federal Funds Rate (ffr) and Treasury bill, note and bond yields with maturities of 3-month, 1-, 2-, 5-, 10- and 30-years ($tb3m$, $tb1y$, $tn2y$, $tn5y$, $tn10y$ and $tn30y$). The data cover the period 1988 to 2018.

	ffr	$tb3m$	$tb1y$	$tn2y$	$tn5y$	$tn10y$	$tn30y$
Panel A: Individual forecast errors $FE_{i,t}\left(x_{t+h}\right)$, pooled across horizons							
Count	22833	22456	21051	22627	22569	22785	21966
Mean	-0.27	-0.33	-0.32	-0.41	-0.38	-0.22	-0.22
SD	0.98	1.04	1.11	1.05	0.93	0.84	0.78
Min	-5.38	-5.16	-4.98	-5.03	-3.88	-3.69	-3.94
p25	-0.57	-0.74	-0.87	-0.99	-0.96	-0.75	-0.67
p50	-0.06	-0.12	-0.17	-0.27	-0.32	-0.25	-0.22
p75	0.18	0.19	0.25	0.17	0.21	0.30	0.29
Max	6.22	4.73	4.45	3.96	3.34	4.38	6.52
p50 (Normalized)	-0.05	-0.10	-0.09	-0.10	-0.08	-0.05	-0.04
Panel B: Individual forecast revisions $FR_{i,t}\left(x_{t+h}\right)$, pooled across horizons							
Count	20852	20406	18831	20440	20346	20613	19821
Mean	-0.14	-0.15	-0.15	-0.16	-0.15	-0.14	-0.12
SD	0.60	0.59	0.61	0.61	0.59	0.53	0.49
Min	-6.00	-5.50	-4.80	-4.30	-5.10	-6.10	-6.00
p25	-0.34	-0.38	-0.40	-0.41	-0.42	-0.40	-0.40
p50	0.00	-0.02	-0.06	-0.09	-0.10	-0.10	-0.10
p75	0.10	0.10	0.14	0.15	0.20	0.15	0.15
Max	6.30	6.00	2.50	2.80	5.89	5.60	5.20
p50 (Normalized)	0.00	-0.02	-0.03	-0.03	-0.03	-0.02	-0.02
Panel C: Median OOS R^2 of individual forecasts							
$R^2_{OOS,Mean}$	0.72	0.73	0.69	0.73	0.78	0.86	0.72
$R^2_{OOS,AR(1)}$	0.16	-0.07	-0.05	-0.15	-0.23	-0.15	-0.28
$R^2_{OOS,AR(p)}$	0.27	-0.03	0.02	-0.13	-0.19	-0.15	-0.28
$R^2_{OOS,ARIMA}$	0.04	0.04	-0.11	-0.16	-0.33	-0.44	-0.85
Panel D: OOS R^2 of consensus forecasts							
$R^2_{OOS,Mean}$	0.86	0.81	0.83	0.84	0.87	0.90	0.79
$R^2_{OOS,AR(1)}$	0.23	-0.03	0.06	-0.04	-0.12	0.00	-0.12
$R^2_{OOS,AR(p)}$	0.34	0.00	0.13	-0.02	-0.06	0.00	-0.12
$R^2_{OOS,ARIMA}$	0.11	0.06	-0.02	-0.13	-0.22	-0.24	-0.65

Table 2 Forecast error on forecast revision regression results for interest rates across maturities

This table reports the coefficients from the forecast error on forecast revision regression of Coibion and Gorodnichenko (2015) for each interest rate:

$$FE_{i,t}\left(x_{t+h}\right) = \alpha_i + \beta FR_{i,t}\left(x_{t+h}\right) + \epsilon_{i,t,h},$$

where the forecasts are pooled across horizon h. Panel A reports the baseline results using individual-level forecasts. The standard errors are clustered by both forecaster and time, and forecaster fixed effects are included. Panel B reports the results using consensus-level forecasts. The standard errors are calculated following Driscoll and Kraay (1998). The underlying variables are the Federal Funds Rate (ffr), Treasury bill, note and bond yields with maturities of 3-month, 1-, 2-, 5-, 10- and 30-years ($tb3m$, $tb1y$, $tn2y$, $tn5y$, $tn10y$ and $tn30y$). The data are quarterly and cover the period 1988 to 2018. *, ** and *** indicate statistical significance at 10, 5, and 1% levels, respectively.

	Dependent variable: $FE_{i,t}\left(x_{t+h}\right)$						
	ffr	$tb3m$	$tb1y$	$tn2y$	$tn5y$	$tn10y$	$tn30y$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Individual forecasts							
$FR_{i,t}\left(x_{t+h}\right)$	0.35***	0.30***	0.20**	0.04	-0.18**	-0.24***	-0.29***
	(0.08)	(0.09)	(0.09)	(0.09)	(0.08)	(0.08)	(0.07)
N	20,440	20,041	18,503	20,049	19,976	20,222	19,447
R^2	0.09	0.08	0.06	0.04	0.06	0.08	0.11
Panel B: Consensus forecasts							
$FR_{i,t}\left(x_{t+h}\right)$	0.72***	0.70***	0.55***	0.29***	-0.05*	-0.18***	-0.26***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)
Constant	-0.16***	-0.22***	-0.25***	-0.38***	-0.40***	-0.25***	-0.26***
	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)
N	449	449	446	446	446	446	449
R^2	0.15	0.12	0.07	0.02	-0.002	0.01	0.01

Table 3 Forecast error on forecast revision regression results for extended short and long rates at the individual level

This table reports the coefficients from the forecast error on forecast revision regression of Coibion and Gorodnichenko (2015) for each interest rate:

$$FE_{i,t}\left(x_{t+h}\right) = \alpha_i + \beta FR_{i,t}\left(x_{t+h}\right) + \epsilon_{i,t,h},$$

where the individual-level forecasts are pooled across horizon h, standard errors are clustered by both forecaster and time, and forecaster fixed effects are included. Panel A reports results for short-maturity interest rates. Panel B reports results for long-maturity interest rates. The underlying variables are the Federal Funds Rate (ffr), Treasury bill, note and bond yields with maturities of 3-month, 1-, 2-, 5-, 10- and 30-years ($tb3m$, $tb1y$, $tn2y$, $tn5y$, $tn10y$ and $tn30y$), one-month commercial paper rate ($cp1m$), prime bank rate (pr), three-month LIBOR rate ($libor$), Aaa and Baa corporate bond yields (aaa and baa) and home mortgage rate (hmr). The data are quarterly and cover the period 1988 to 2018. *, ** and *** indicate statistical significance at 10, 5, and 1% levels, respectively.

	Dependent variable: $FE_{i,t}\left(x_{t+h}\right)$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Short-maturity interest rates							
	ffr	$tb3m$	$tb1y$	$tn2y$	$cp1m$	pr	$libor$
$FR_{i,t}\left(x_{t+h}\right)$	0.35***	0.30***	0.20**	0.04	0.38***	0.31***	0.29***
	(0.08)	(0.09)	(0.09)	(0.09)	(0.10)	(0.08)	(0.09)
N	20,440	20,041	18,503	20,049	12,134	19,696	18,202
R^2	0.09	0.08	0.06	0.04	0.09	0.09	0.07
Panel B: Long-maturity interest rates							
	$tn5y$	$tn10y$	$tn30y$	aaa	baa	hmr	
$FR_{i,t}\left(x_{t+h}\right)$	-0.18**	-0.24***	-0.29***	-0.22***	-0.25***	-0.22***	
	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	
N	19,976	20,222	19,447	17,925	10,660	18,824	
R^2	0.06	0.08	0.11	0.11	0.10	0.09	

Table 4 Summary statistics of short-rate and term-premium autocorrelation estimates

This table reports subjective and actual autocorrelation estimates of the short rate and term premia. Panel A summarizes short-rate subjective autocorrelations (ρ_1^s) at individual and consensus levels (lines 1 and 2), and actual short-rate autocorrelations ρ_1 (line 3). Panels B and C summarize estimates of the subjective autocorrelation of the term premia (ρ_p^s) at the individual (Panel B) and consensus (Panel C) levels. Panel D summarizes estimates of the actual autocorrelation of the term premia (ρ_p). Term premia have maturities of 2, 5, 10, and 30 years. Details of the estimation are in Section 4.3.

	Count	Mean	SD	Min	p25	p50	p75	Max
Panel A: Short rate autocorrelation estimates ρ_1^s								
ρ_1^s Individual	10743	0.87	0.17	-0.94	0.88	0.92	0.94	1.00
ρ_1^s Consensus	314	0.87	0.16	0.06	0.89	0.93	0.94	0.95
ρ_1 Actual	314	0.97	0.06	0.64	0.96	0.98	1.00	1.16
Panel B: Term premium autocorrelation estimates: Individual subjective $\rho_{p,i}^s$								
2Y	6559	0.91	0.08	-0.25	0.88	0.92	0.96	1.18
5Y	6559	0.93	0.07	-0.57	0.91	0.94	0.96	1.65
10Y	6559	0.95	0.07	-0.91	0.93	0.96	0.98	1.11
30Y	6559	0.97	0.06	-0.47	0.94	0.98	1.00	1.21
Panel C: Term premium autocorrelation estimates: Consensus subjective $\rho_{p,con}^s$								
2Y	314	0.90	0.02	0.80	0.89	0.90	0.91	0.94
5Y	314	0.92	0.02	0.89	0.92	0.92	0.93	1.20
10Y	314	0.94	0.02	0.89	0.94	0.94	0.94	1.24
30Y	314	0.97	0.06	0.92	0.95	0.96	0.97	2.02
Panel D: Term premium autocorrelation estimates: Actual ρ_p								
2Y	309	0.69	0.13	0.00	0.69	0.73	0.75	0.80
5Y	309	0.74	0.13	0.01	0.71	0.78	0.82	0.85
10Y	309	0.77	0.16	0.02	0.73	0.83	0.86	0.90
30Y	309	0.77	0.18	0.02	0.74	0.83	0.88	0.93

Table 5 Model Calibration with individual-level forecasts

This table reports the results from the calibration exercise. The model is calibrated with individual-level average estimates of the subjective and actual autocorrelations (reported in the left two sections). The empirical and model-generated (Coibion and Gorodnichenko, 2015) coefficients for each interest rate are reported in the right section, where the last column presents p-values of a test that empirical and model-generated coefficients are statistically different. The calibration uses the Federal funds rate (ffr) as short rate and Treasury yields with maturities of 2-, 5-, 10- and 30-years ($tn2y$, $tn5y$, $tn10y$ and $tn30y$) as long rates.

	Subjective autocorrelation		Actual autocorrelation		FE-on-FR coefficients		
	Short rate ρ_1^s	TP ρ_p^s	Short rate ρ_1	TP ρ_p	Data	Model	p(Data $\neq$ Model)
ffr	0.87		0.98		0.36	0.31	0.64
$tn2y$		0.91		0.69	0.06	0.18	0.28
$tn5y$		0.93		0.74	-0.19	0.02	0.03
$tn10y$		0.95		0.77	-0.28	-0.26	0.79
$tn30y$		0.97		0.77	-0.31	-0.84	0.00

Table 6 Forecast error on forecast revision regression results for expectations hypothesis (EH) and term premium (TP) components

This table reports coefficients from the forecast error on forecast revision regression of Coibion and Gorodnichenko (2015) for expectations hypothesis (EH) and term premium (TP) components:

$$FE_{i,t}\left(x_{t+h}\right) = \alpha_i + \beta FR_{i,t}\left(x_{t+h}\right) + \epsilon_{i,t,h},$$

where the forecasts are pooled across horizon h. Panel A reports the results using individual-level forecasts. The standard errors are clustered by both forecaster and time, and forecaster fixed effects are included. Panel B reports the results using consensus-level forecasts. The standard errors are calculated following Driscoll and Kraay (1998). The underlying variables are expectations hypothesis (EH) and term premium (TP) components with maturities of 2, 5, 10, and 30 years. For each maturity n, forecasts of EH and TP are constructed by decomposing yield forecasts using the estimated subjective short rate autocorrelation, and realized EH and TP are constructed by decomposing realized yields using the estimated actual short rate autocorrelation. *, ** and *** indicate statistical significance at 10, 5, and 1% levels, respectively.

	Dependent variable: $FE_{i,t}\left(x_{t+h}\right)$							
	$eh^{(2)}$	$eh^{(5)}$	$eh^{(10)}$	$eh^{(30)}$	$tp^{(2)}$	$tp^{(5)}$	$tp^{(10)}$	$tp^{(30)}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Individual level EH and TP								
$FR_{i,t}\left(x_{t+h}\right)$	0.31***	0.27***	0.22**	0.11	-0.21***	-0.20***	-0.17**	-0.20***
	(0.10)	(0.09)	(0.09)	(0.08)	(0.06)	(0.07)	(0.07)	(0.07)
N	11,628	11,628	11,628	11,628	11,439	11,340	11,427	10,703
R^2	0.08	0.08	0.08	0.10	0.05	0.04	0.03	0.04
Panel B: Consensus level EH and TP								
$FR_t\left(x_{t+h}\right)$	0.56***	0.52***	0.42***	0.32***	-0.05	-0.07**	-0.06**	-0.10***
	(0.05)	(0.05)	(0.05)	(0.06)	(0.03)	(0.03)	(0.03)	(0.04)
Constant	-0.01	-0.02	-0.04	-0.04**	-0.004	-0.02	-0.03	-0.05**
	(0.07)	(0.06)	(0.04)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
N	371	371	371	371	371	371	371	371
R^2	0.08	0.07	0.05	0.03	-0.002	-0.001	-0.001	0.001

Table 7 Predicting one-year excess bond returns with overreaction-motivated predictor $FE10Y$

This table presents results of the predictive regressions of one-year bond excess returns on the overreaction-motivated predictor $FE10Y$:

$$rx_{t+1}^{(n)} = \alpha + \beta FE10Y_t + \gamma \cdot X_t + \varepsilon_{t+1},$$

where $rx_{t+1}^{(n)}$ is the one-year holding period excess return of a n-year bond and $\overline{rx}_{t+1}$ is the average excess return weighted by the inverse of bond maturities. Panel A includes no additional independent variable and Panel B includes the first three yield curve principal components (PCs). T-statistics are reported for two types of standard errors: Newey and West (1987) standard errors with 12 lags (in parentheses) and Hodrick (1992) standard errors obtained from reverse regressions (in brackets). The data are monthly and cover the period 1988 to 2018. The results for the intercept are omitted.

	$rx_{t+1}^{(2)}$ (1)	$rx_{t+1}^{(3)}$ (2)	$rx_{t+1}^{(5)}$ (3)	$rx_{t+1}^{(7)}$ (4)	$rx_{t+1}^{(10)}$ (5)	$rx_{t+1}^{(20)}$ (6)	$rx_{t+1}^{(30)}$ (7)	$\overline{rx}_{t+1}$ (8)
Panel A: No controls								
$FE10Y_t$	0.55	1.11	2.12	3.04	4.33	7.82	10.23	3.81
	(4.68)	(5.14)	(5.57)	(5.72)	(5.68)	(5.15)	(4.36)	(5.69)
	[4.01]	[3.80]	[3.51]	[3.41]	[3.35]	[3.13]	[2.80]	[3.21]
N	348	348	348	348	348	348	348	348
R^2	0.14	0.16	0.18	0.20	0.22	0.25	0.20	0.25
Panel B: Controlling for PCs								
$FE10Y_t$	0.23	0.60	1.42	2.36	3.92	8.88	12.94	3.78
	(1.78)	(2.47)	(3.33)	(4.11)	(5.19)	(6.45)	(6.04)	(5.90)
	[1.87]	[2.10]	[2.38]	[2.67]	[3.03]	[3.39]	[3.22]	[3.35]
PCs	✓	✓	✓	✓	✓	✓	✓	✓
N	348	348	348	348	348	348	348	348
R^2	0.27	0.28	0.33	0.38	0.43	0.45	0.35	0.42

Table 8 Predicting one-year excess bond returns with realized forecast errors of short rates and 10-year term premium

This table presents results of the predictive regressions of one-year bond excess returns on the short rate and 10-year term premium

$$rx_{t+1}^{(n)} = \alpha + \beta FE_{t-1}(z_t) + \gamma' PC_t + \varepsilon_{t+1}, \quad z \in \{tp^{(10)}, ffr\}$$

where $rx_{t+1}^{(n)}$ is the one-year holding period excess return of a n-year bond and $\overline{rx}_{t+1}$ is the average excess return weighted by the inverse of bond maturities. Panels A and B report results of the 10-year term premium and the the Federal Funds Rate, respectively. The first three yield curve principal components (PCs) are included in both panels. T-statistics are reported for two types of standard errors: Newey and West (1987) standard errors with 12 lags (in parentheses) and Hodrick (1992) standard errors obtained from reverse regressions (in brackets). The data are monthly and cover the period 1988 to 2018. The results for the intercept are omitted.

	$rx_{t+1}^{(2)}$	$rx_{t+1}^{(3)}$	$rx_{t+1}^{(5)}$	$rx_{t+1}^{(7)}$	$rx_{t+1}^{(10)}$	$rx_{t+1}^{(20)}$	$rx_{t+1}^{(30)}$	$\overline{rx}_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: 10-year term premium								
$FE_{t-1}\left(tp_t^{(10)}\right)$	0.42	0.94	1.94	2.91	4.22	6.75	7.15	3.34
	(3.65)	(4.03)	(4.64)	(5.08)	(5.25)	(3.89)	(2.14)	(4.53)
	[2.72]	[2.64]	[2.49]	[2.37]	[2.20]	[1.78]	[1.36]	[1.84]
PCs	✓	✓	✓	✓	✓	✓	✓	✓
N	273	273	273	273	273	273	273	273
R^2	0.10	0.14	0.18	0.22	0.24	0.21	0.10	0.23
Panel B: Federal Funds Rate								
$FE_{t-1}(ffr_t)$	-0.18	-0.38	-0.70	-0.91	-1.05	-0.65	0.34	-0.60
	(-1.37)	(-1.52)	(-1.69)	(-1.70)	(-1.56)	(-0.59)	(0.19)	(-1.06)
	[-1.09]	[-1.11]	[-1.05]	[-0.97]	[-0.83]	[-0.32]	[0.12]	[-0.35]
PCs	✓	✓	✓	✓	✓	✓	✓	✓
N	360	360	360	360	360	360	360	360
R^2	0.04	0.05	0.05	0.04	0.03	0.00	0.00	0.02

Table 9 Predicting one-year excess bond returns with overreaction-motivated predictor $FE10Y$: Controlling for other return predictors

This table presents results of the predictive regressions of one-year bond excess returns on the overreaction-motivated predictor $FE10Y$, controlling for other commonly-used predictors

$$rx_{t+1}^{(n)} = \alpha + \beta FE10Y_t + \gamma \cdot X_t + \varepsilon_{t+1},$$

where $rx_{t+1}^{(n)}$ is the one-year holding period excess return of a n-year bond and $\overline{rx}_{t+1}$ is the average excess return weighted by the inverse of bond maturities. Panel A includes Cochrane and Piazzesi (2005) factor (CP) and Cieslak and Povala (2015) factor (cf). Panel B adds growth (GRO) and inflation $INFL$ factors from Joslin et al. (2014). The first three yield curve principal components (PCs) are included in both panels. T-statistics are reported for two types of standard errors: Newey and West (1987) standard errors with 12 lags (in parentheses) and Hodrick (1992) standard errors obtained from reverse regressions (in brackets). The data are monthly and cover the period 1988 to 2018. The results for the intercept are omitted.

	$rx_{t+1}^{(2)}$ (1)	$rx_{t+1}^{(3)}$ (2)	$rx_{t+1}^{(5)}$ (3)	$rx_{t+1}^{(7)}$ (4)	$rx_{t+1}^{(10)}$ (5)	$rx_{t+1}^{(20)}$ (6)	$rx_{t+1}^{(30)}$ (7)	$\overline{rx}_{t+1}$ (8)
Panel A: CP and cf								
$FE10Y_t$	0.25	0.56	1.08	1.62	2.64	6.24	8.05	2.63
	(1.18)	(1.45)	(1.61)	(1.83)	(2.37)	(3.45)	(2.75)	(2.88)
	[1.73]	[1.74]	[1.72]	[1.81]	[2.04]	[2.32]	[2.01]	[2.23]
CP_t	0.04	0.04	-0.12	-0.39	-0.71	0.18	2.79	-0.02
	(0.35)	(0.17)	(-0.26)	(-0.58)	(-0.77)	(0.11)	(1.13)	(-0.02)
	[0.01]	[0.08]	[0.01]	[-0.06]	[-0.07]	[0.36]	[0.79]	[0.40]
cf_t	0.12	0.54	2.02	3.79	6.14	12.76	23.33	5.70
	(0.16)	(0.38)	(0.84)	(1.24)	(1.64)	(2.31)	(2.89)	(1.89)
	[0.19]	[0.54]	[0.99]	[1.23]	[1.39]	[1.63]	[1.99]	[1.70]
R^2	0.25	0.28	0.34	0.41	0.47	0.50	0.46	0.47
Panel B: CP, cf, GRO and $INFL$								
$FE10Y_t$	0.46	0.89	1.43	1.89	2.75	6.02	7.32	2.73
	(2.41)	(2.34)	(1.98)	(1.91)	(2.19)	(3.14)	(2.42)	(2.70)
	[3.37]	[2.85]	[2.24]	[2.04]	[2.07]	[2.31]	[1.99]	[2.27]
CP_t	0.40	0.58	0.45	0.02	-0.59	-0.32	1.38	0.09
	(3.15)	(2.33)	(0.93)	(0.03)	(-0.64)	(-0.22)	(0.63)	(0.13)
	[2.01]	[1.50]	[0.76]	[0.31]	[0.02]	[0.30]	[0.64]	[0.39]
cf_t	0.87	1.83	3.72	5.54	7.89	15.07	25.18	7.34
	(1.17)	(1.22)	(1.36)	(1.52)	(1.72)	(2.26)	(2.67)	(1.99)
	[1.62]	[1.57]	[1.51]	[1.48]	[1.45]	[1.63]	[1.92]	[1.74]
GRO_t	-0.01	-0.01	-0.01	-0.01	-0.00	0.01	0.04	-0.00
	(-3.30)	(-2.80)	(-1.79)	(-1.00)	(-0.18)	(0.90)	(1.67)	(-0.19)
	[-2.88]	[-2.11]	[-1.10]	[-0.51]	[-0.07]	[0.02]	[-0.02]	[-0.10]
$INFL_t$	0.00	0.01	0.02	0.02	0.03	0.05	0.06	0.02
	(1.07)	(1.11)	(1.05)	(1.02)	(1.11)	(1.50)	(1.17)	(1.30)
	[1.20]	[1.09]	[0.87]	[0.75]	[0.67]	[0.65]	[0.58]	[0.68]
R^2	0.42	0.39	0.39	0.43	0.49	0.52	0.48	0.49
PCs	✓	✓	✓	✓	✓	✓	✓	✓
N	328	328	328	328	328	328	328	328

Table 10 Comparing the return predictability of survey-based realized forecast error $FE10Y$ with related measures

This table compares the predictive power of overreaction-motivated predictor $FE10Y$ and other related measures for one-year bond excess returns

$$\overline{rx}_{t+1} = a + bX_t + \gamma \cdot \Gamma_t + \varepsilon_{t+1},$$

where $\overline{rx}_{t+1}$ is the one-year average excess return weighted by the inverse of bond maturities. Related measures include the econometrician's realized forecast error $\widehat{FE}10Y_t$, the changes in realized yields $\Delta y_t^{(10)}$, and the contemporaneous differences between realized yields and forecasts $y_t^{(10)} - \mathbb{E}_t^S\left(y_{t+1}^{(10)}\right)$. Panel A runs univariate predictive regressions for each measure, Panel B adds first three yield curve principal components (PCs), and Panel C adds the full set of auxiliary predictors from Table 9, Panel B. T-statistics are reported for two types of standard errors: Newey and West (1987) standard errors with 12 lags (in parentheses) and Hodrick (1992) standard errors obtained from reverse regressions (in brackets). The data are monthly and cover the period 1988 to 2018. The results for intercept and control variables are omitted.

	$\overline{rx}_{t+1} = a + bX_t + \gamma \cdot \Gamma_t + \varepsilon_{t+1}$			
$X_t =$	$FE10Y_t$	$\widehat{FE}10Y_t$	$\Delta y_t^{(10)}$	$y_t^{(10)} - E_t^S(y_{t+1}^{(10)})$
	(1)	(2)	(3)	(4)
Panel A: No control				
b	3.81	3.10	3.20	2.28
	(5.69)	(2.83)	(4.46)	(1.80)
	[3.21]	[2.00]	[2.85]	[0.96]
N	348	348	348	348
R^2	0.25	0.13	0.16	0.03
Panel B: Controlling for PCs				
b	3.78	2.52	3.09	0.20
	(5.90)	(2.52)	(5.08)	(0.14)
	[3.35]	[1.83]	[3.29]	[0.73]
N	348	348	348	348
R^2	0.42	0.30	0.38	0.25
Panel C: Full set of controls				
b	2.73	0.16	1.75	0.85
	(2.70)	(0.13)	(1.93)	(0.54)
	[2.27]	[0.55]	[2.11]	[2.65]
N	328	328	328	328
R^2	0.49	0.43	0.45	0.43

Table 11 Predicting future short-maturity bond returns with underreaction-motivated predictor

This table presents results from testing the asset pricing prediction of underreaction,

$$Z_{t+1Q} = \alpha + \beta FE_{t-1Q}(ffr_t) + \varepsilon_{t+1Q},$$

where the left-hand-side variables in Columns 1 and 2 are the one-quarter yield changes of one-year and six-month T-bills and in Columns 3, and 4 are one-quarter holding period excess returns of the coupon bond portfolios with less than 12-month and 24-month maturities, respectively. The underreaction-motivated predictor is the realized forecast error of the Federal Funds Rate $FE_{t-1Q}(ffr_t)$. T-statistics based on Newey and West (1987) standard errors with 3 lags are reported in parentheses. The data are monthly and cover the period 1982 to 2018. *, ** and *** indicate statistical significance at 10, 5, and 1% levels, respectively.

$Z_{t+1Q} =$	$y_t^{(1)} - y_{t+1Q}^{(1)}$	$y_t^{(6m)} - y_{t+1Q}^{(6m)}$	$rx < 12m$	$rx < 24m$
	(1)	(2)	(3)	(4)
$FE_{t-1Q}(ffr_t)$	-0.19***	-0.23***	-0.05*	-0.19**
	(-2.64)	(-3.33)	(-1.76)	(-2.01)
Constant	0.02	0.02	0.11***	0.27***
	(0.56)	(0.48)	(6.03)	(4.48)
N	428	428	428	428
R^2	0.05	0.08	0.02	0.03

Table 12 Predicting futures-based forecast errors with survey-based forecast revisions

This table presents results of the predictive regressions of futures-based forecast errors on survey-based forecast revisions of the Federal Funds Rate

$$FE_t^{FUT}\left(ffr_{t+h}\right) = \alpha + \beta FR_t^{S}\left(ffr_{t+h}\right) + \epsilon_{t,h}.$$

The regressions use consensus-level forecasts. In Column 1, observations are pooled across horizon h. Columns 2 to 5 report results for each forecast horizon. The futures-based forecast error of FFR is defined as

$$FE_t^{FUT}\left(ffr_{t+h}\right) = \overline{ffr}_{t+h} - \mathbb{E}_t^{FUT}\left(ffr_{t+h}\right),$$

where $\overline{ffr}_{t+h}$ is the within-month average FFR and $\mathbb{E}_t^{FUT}\left(ffr_{t+h}\right)$ is the end-of-month futures implied FFR. The standard errors are calculated following Driscoll and Kraay (1998) and reported in parentheses. The data are quarterly and cover the period 2002 to 2018. *, ** and *** indicate statistical significance at 10, 5, and 1% levels, respectively.

	Dependent variable: $FE_t^{FUT}\left(x_{t+h}\right)$				
	Pooled	$h = 1Q$	$h = 2Q$	$h = 3Q$	$h = 4Q$
	(1)	(2)	(3)	(4)	(5)
$FR_t^S\left(x_{t+h}\right)$	1.24**	1.19**	0.68**	1.45***	1.49**
	(0.49)	(0.60)	(0.29)	(0.56)	(0.65)
Constant	-0.22	-0.19	-0.24	-0.14	-0.29
	(0.14)	(0.13)	(0.15)	(0.12)	(0.18)
N	258	68	66	63	61
R^2	0.14	0.12	0.03	0.21	0.15

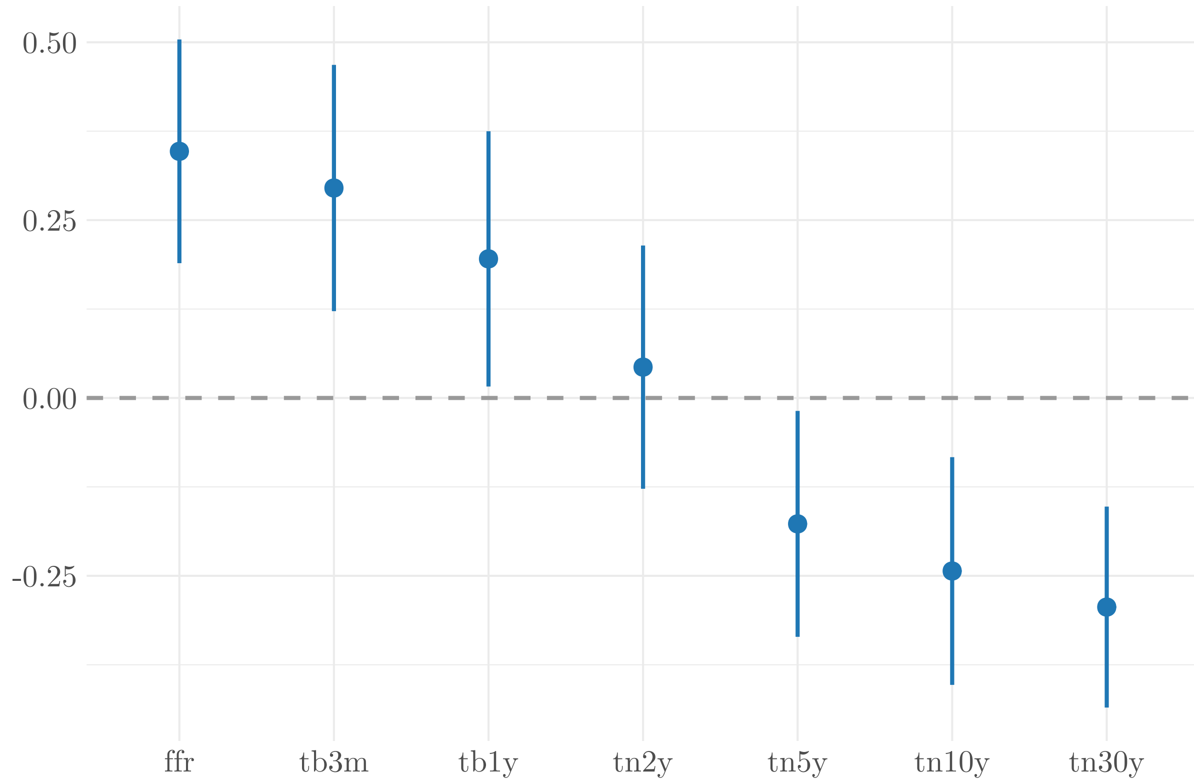


Figure 1 Forecast error on forecast revision regression coefficients for short- and long-maturity interest rates: Baseline individual-level evidence

This figure plots the coefficients from the forecast error on forecast revision regression of Coibion and Gorodnichenko (2015) for each interest rate using individual-level forecasts

$$FE_{i,t}\left(x_{t+h}\right) = \alpha_i + \beta FR_{i,t}\left(x_{t+h}\right) + \epsilon_{i,t,h},$$

where the forecasts are pooled across horizon h, the standard errors are clustered by both forecaster and time, and forecaster fixed effects are included. The underlying variables are the Federal Funds Rate (ffr), and the Treasury bill, note and bond yields with maturities of 3-month, 1-, 2-, 5-, 10- and 30-years ($tb3m$, $tb1y$, $tn2y$, $tn5y$, $tn10y$ and $tn30y$). The data are quarterly and cover the period 1988 to 2018. The range of each whisker depicts the 95% confidence interval.

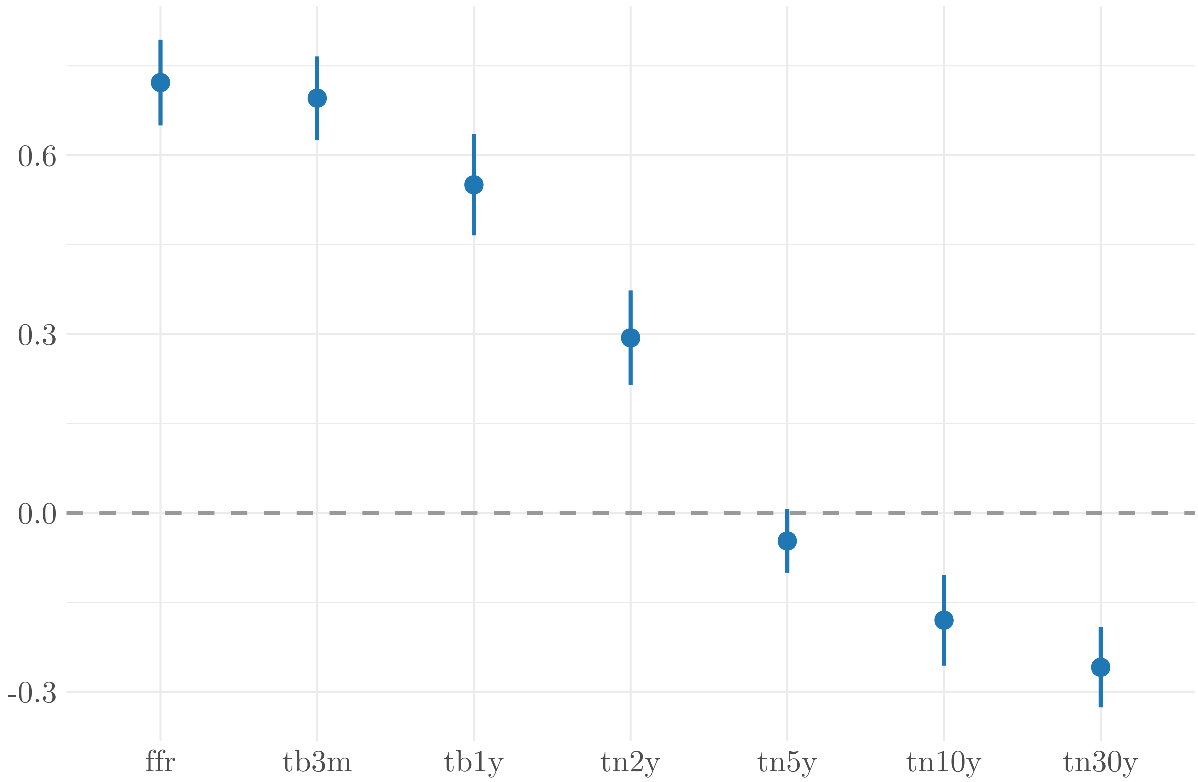
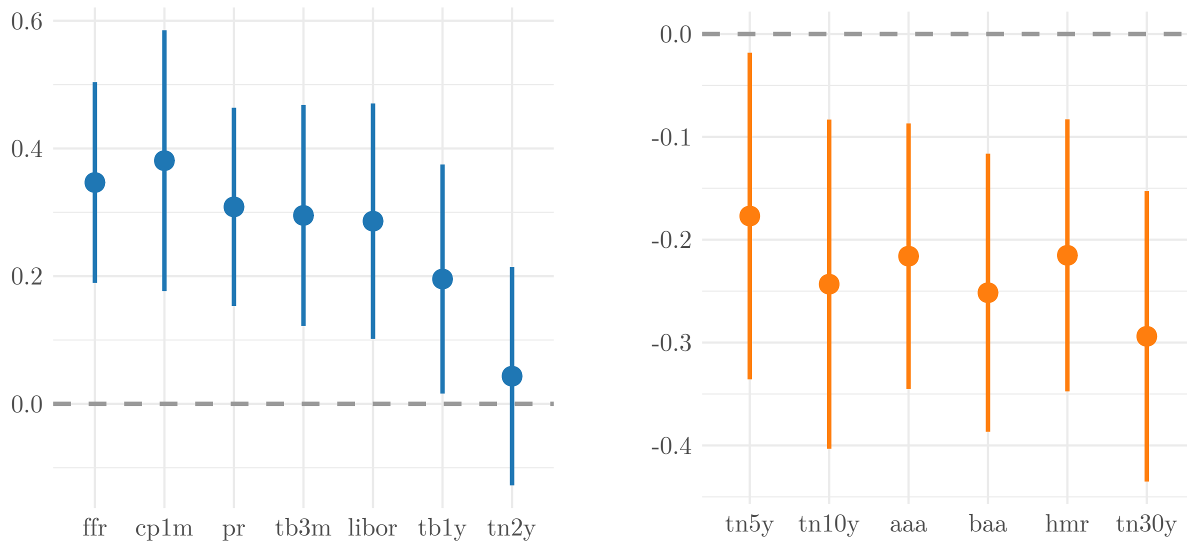


Figure 2 Forecast error on forecast revision regression coefficients for short- and long-maturity interest rates: Baseline consensus-level evidence

This figure plots the coefficients from the forecast error on forecast revision regression of Coibion and Gorodnichenko (2015) for each interest rate using consensus-level forecasts

$$FE_t\left(x_{t+h}\right) = \alpha_i + \beta FR_t\left(x_{t+h}\right) + \epsilon_{t,h},$$

where the forecasts are pooled across horizon h and the standard errors are calculated following Driscoll and Kraay (1998). The underlying variables are the Federal Funds Rate (ffr), and the Treasury bill, note and bond yields with maturities of 3-month, 1-, 2-, 5-, 10- and 30-years ($tb3m$, $tb1y$, $tn2y$, $tn5y$, $tn10y$ and $tn30y$). The data are quarterly and cover the period 1988 to 2018. The range of each whisker depicts the 95% confidence interval.



A. Short Rates

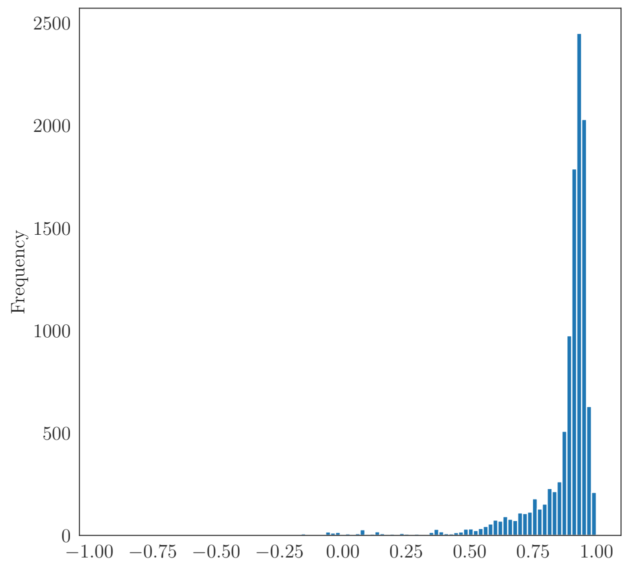
B. Long Rates

Figure 3 Forecast error on forecast revision regression coefficients for short- and long-maturity interest rates: Additional individual-level evidence

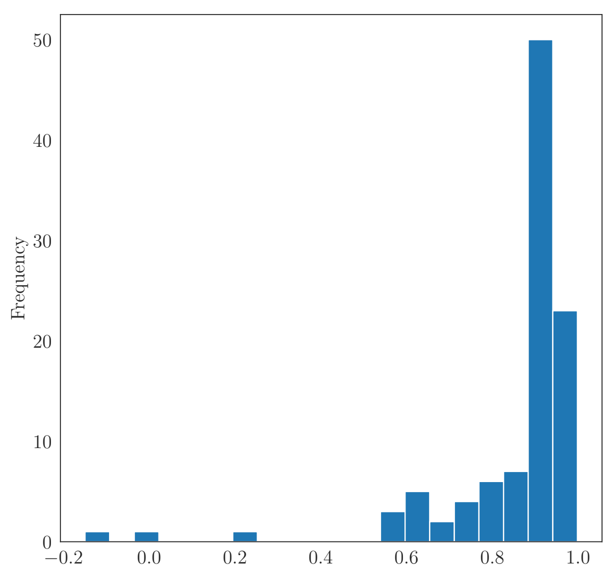
This figure plots the coefficients from the forecast error on forecast revision regression of Coibion and Gorodnichenko (2015) for an extended list of interest rate using individual-level forecasts

$$FE_{i,t}\left(x_{t+h}\right) = \alpha_i + \beta FR_{i,t}\left(x_{t+h}\right) + \epsilon_{i,t,h},$$

where the forecasts are pooled across horizon h, the standard errors are clustered by both forecaster and time, and forecaster fixed effects are included. The underlying variables are divided into short rates (Panel A) and long rates (Panel B), and ordered by their maturities in each panel. Short rates include Federal Funds Rate (ffr) and Treasury yields with maturities of 3-month and 1-, 2-years ($tb3m$, $tb1y$ and $tn2y$), one-month commercial paper rate ($cp1m$), prime bank rate (pr), three-month LIBOR rate ($libor$). Long rates include Treasury yields with maturities of 5-, 10- and 30-year ($tn5y$, $tn10y$ and $tn30y$), Aaa and Baa corporate bond yields (aaa and baa), and home mortgage rate (hmr). The range of each whisker depicts the 95% confidence interval.



A. All ρ_1^s estimates



B. Forecaster-level median ρ_1^s estimates

Figure 4 Histograms of the short rate subjective autocorrelation ρ_1^s estimates

This figure summarizes GMM estimation results of the short rate subjective autocorrelation ρ_1^s. Subjective autocorrelations are estimated forecaster-by-forecaster and on a 120-month rolling basis. Panel A plots all ρ_1^s estimates across time and forecasters. Panel B plots forecaster-level median ρ_1^s estimates. The details of the estimation are in Section 4.3.

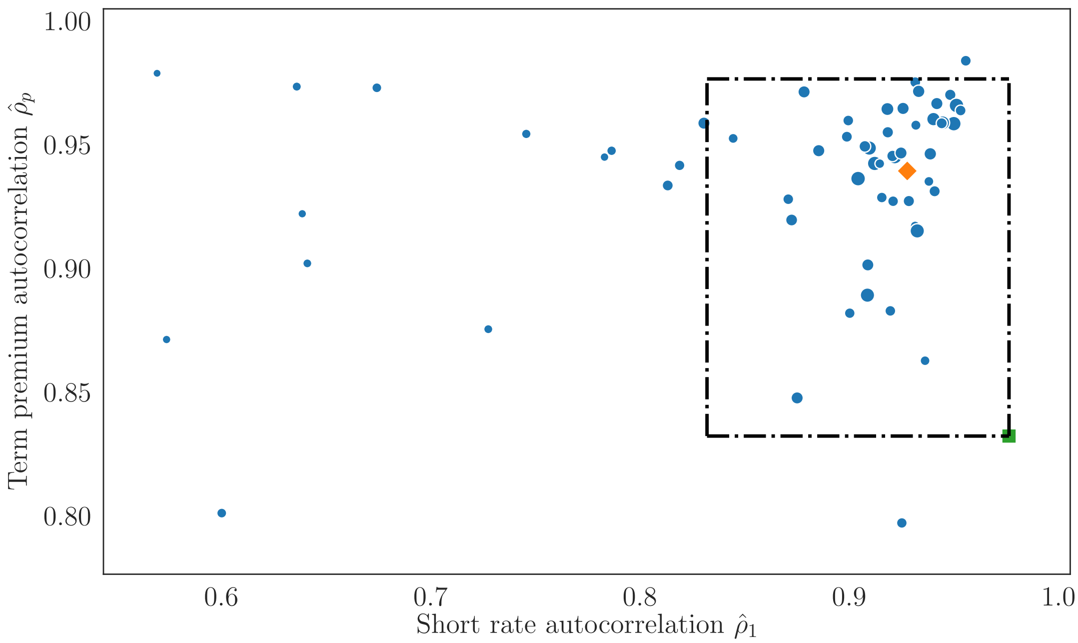


Figure 5 Forecaster-level median autocorrelation estimates of the short rate and 10-year term premium

This figure plots the median autocorrelation estimates of the short rate and 10-year term premium. It includes both subjective and actual autocorrelation estimates. Each blue circle represents a forecaster's median subjective autocorrelation estimates of short rate ρ_1^s and term premium ρ_p^s. The size of the circle corresponds to the number of this forecaster's valid autocorrelation estimates. The orange diamond represents the median subjective autocorrelation estimates for the consensus forecasts. The green square at the bottom-right corner represents the median actual autocorrelation estimates of short rate ρ_1 and term premium ρ_p. "Autocorrelation averaging" implies that all subjective autocorrelations should be within the dashed box (i.e., $\rho_p < \rho_1^s, \rho_p^s < \rho_1$). The details of the estimation are in Section 4.3.

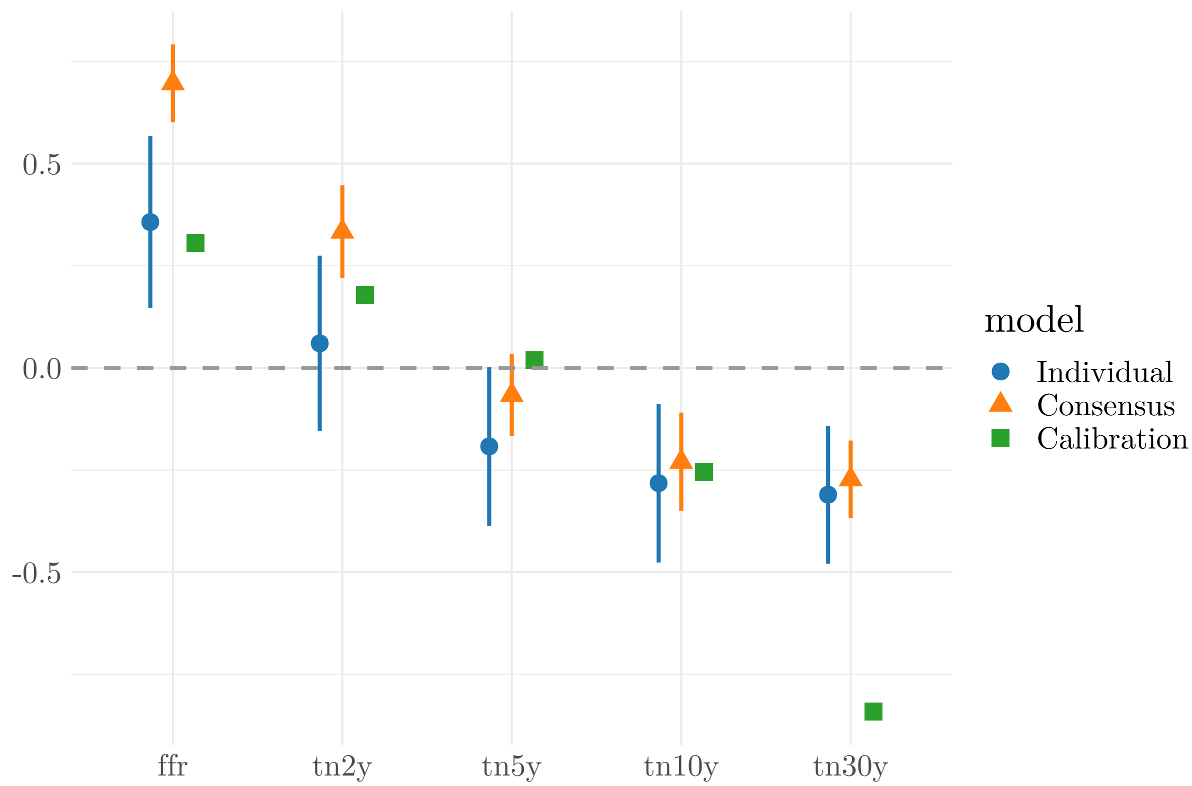


Figure 6 Calibrated vs. empirically estimated FE-on-FR regression coefficients at the individual level

This figure plots the Coibion and Gorodnichenko (2015) regression coefficients estimated from both individual- and consensus-level forecasts and from the calibrated model. The model is calibrated with individual-level average estimates of the subjective and actual autocorrelations. The blue dots and orange triangles represent empirically estimated coefficients at individual and consensus levels, respectively. The green squares represent model-generated coefficients. The calibration exercise uses the Federal funds rate (ffr) as short rate and Treasury yields with maturities of 2-, 5-, 10- and 30-years ($tn2y$, $tn5y$, $tn10y$ and $tn30y$) as long rates.

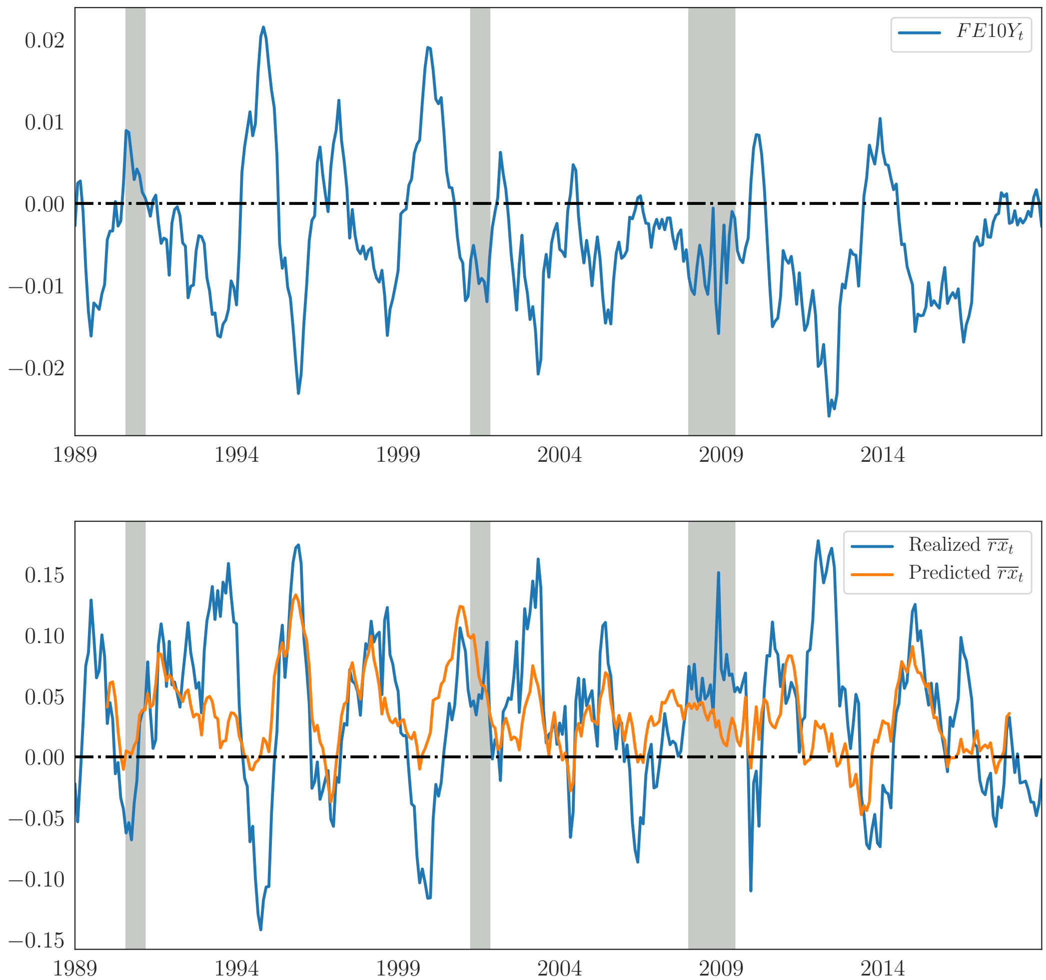


Figure 7 The time series of return predictor $FE10Y$ and its predicted average bond excess returns

Panel A plots the monthly time-series of the return predictor $FE10Y_t$, which is defined as the realized forecast error of the 10-year Treasury yield. Panel B plots the realized and in-sample fitted average one-year excess bond returns. The fitted values are from a univariate predictive regression using $FE10Y_t$. The grey shaded areas are NBER-dated recessions.

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Appendix A Derivation and Additional Results

A.1 FE-on-FR regression coefficient in commonly-used models of expectations

Suppose that the underlying variable z_t follows an AR(1) process:

$$z_{t+1} = \rho z_t + \varepsilon_{t+1}, \quad \varepsilon_t \sim \mathcal{N}\left(0, \sigma^2\right).$$

The forecaster's one-period ahead forecast in time t is denoted as $F_t(z_{t+1})$. Below I derive coefficients of Coibion and Gorodnichenko (2015, CG) regression, which regresses forecast errors on forecast revisions, as predicted by several commonly-used models of expectations.

1. Backward-looking extrapolative expectations

In backward-looking extrapolative expectations, the forecast is defined as

$$\begin{aligned} F_t z_{t+1} &= z_t + \phi\left(z_t - z_{t-1}\right) \\ &= \left(1+\phi\right) z_t - \phi z_{t-1}, \end{aligned}$$

where $\phi > 0$ captures degree of extrapolation and is unrelated to the autocorrelation of the true process. The forecast error (FE) and forecast revision (FR) are defined as

$$FE_{t+1} = z_{t+1} - F_t z_{t+1},$$

and

$$FR_{t+1} = F_t z_{t+1} - F_{t-1} z_{t+1}.$$

The covariance between FE and FR, which is the numerator of CG regression can be calculated as

$$\begin{aligned} \mathcal{C} &= \operatorname{Cov}\left(FE_{t+1}, FR_{t+1}\right) \\ &= \operatorname{Cov}\left(z_{t+1} - F_t(z_{t+1}), F_t(z_{t+1}) - F_{t-1}(z_{t+1})\right) \\ &= \operatorname{Cov}\left(\rho z_t + \varepsilon_{t+1} - \left(1+\phi\right) z_t + \phi z_{t-1}, \left(1+\phi\right) z_t - \phi z_{t-1} - \left\{\left(1+\phi\right) z_{t|t-1} - \phi z_{t-1}\right\}\right) \\ &= \frac{\left(\theta+1\right)\left(-\rho^2\theta + \rho\left(\theta^2+\theta+1\right) - \left(\theta+1\right)^2\right)}{\rho+1}\sigma^2. \end{aligned}$$

The sign of $\mathcal{C}$ depends on the true autocorrelation of the process ρ and the extrapolation parameter ϕ. If $\rho \to 1$, as is the case for interest rates, and $\phi > 0$, we obtain $\mathcal{C} < 0$. The sign of $\mathcal{C} < 0$ indicates that forecaster with backward-looking extrapolative belief *overreact* to new information for the underlying process.

2. Extrapolative expectations with exponential weights ($k \geq 0$ case)

Another form of extrapolative beliefs, perhaps a more widely-used one, posits that people's expectation is a weighted average of the past realized values, where the weights on the past observations are positive and larger for more recent ones.

$$F_t\left(z_{t+1}\right) = X_t \equiv (1-\theta)\sum_{k=0}^{t-1}\theta^k\left(z_{t-k}\right) + \theta^{t-1}X_1$$
$$X_t = \theta X_{t-1} + (1-\theta)\, y_t = X_{t-1} + (1-\theta)\left(y_t - X_{t-1}\right)$$

The two-period-ahead extrapolative expectations can be calculated as

$$\begin{aligned}
F_{t-1}\left(z_{t+1}\right) &= F_{t-1}\left(F_t\left(z_{t+1}\right)\right)\\
&= F_{t-1}\left(X_t\right)\\
&= F_{t-1}\left(\theta X_{t-1} + (1-\theta)\, z_t\right)\\
&= \theta X_{t-1} + (1-\theta)\, F_{t-1}\left(z_t\right)\\
&= \theta X_{t-1} + (1-\theta)\, X_{t-1}\\
&= X_{t-1},
\end{aligned}$$

where the first line assumes that the law of iterated expectations holds. Since this model of extrapolative expectations does not take into account true properties of the underlying process, time t forecasts for different horizons are the same, i.e. $F_t\left(z_{t+i}\right) = X_t\ \forall i > 0$. I define forecast error and forecast revision as follows

$$FE_{t+1} = z_{t+1} - F_t(z_{t+1}) \qquad\qquad = (\rho+\theta-1)\, z_t - \theta X_{t-1} + \varepsilon_{t+1},$$

and

$$FR_{t+1} = F_t(z_{t+1}) - F_{t-1}(z_{t+1}) = X_t - X_{t-1} = (1-\theta)\left(z_t - X_{t-1}\right)$$

The covariance of FE and FR can be calculated as

$$\begin{aligned}
\mathcal{C} &= \mathrm{Cov}\left(FE_{t+1}, FR_{t+1}\right)\\
&= \mathrm{Cov}\left(z_{t+1} - F_t(z_{t+1}), F_t(z_{t+1}) - F_{t-1}(z_{t+1})\right)\\
&= \mathrm{Cov}\left((1-\theta)\left(z_t - X_{t-1}\right), (\rho+\theta-1)\, z_t - \theta X_{t-1} + \varepsilon_{t+1}\right)\\
&= (1-\theta)(\rho+\theta-1)\,\mathrm{Var}\left(z_t\right) + (1-\theta)\,\theta\mathrm{Var}\left(X_{t-1}\right) - (1-\theta)\left[\rho+2\theta-1\right]\mathrm{Cov}\left(z_t, X_{t-1}\right).
\end{aligned}$$

To determine the sign of the covariance, we need to obtain unconditional variance of z_t, unconditional variance of X_t and covariance between z_t and X_{t-1}. The unconditional variance of X_t can be expressed as a sum of variance terms and covariance terms:

$$\begin{aligned}
\mathrm{Var}\left(X_t\right) &= \mathrm{Var}\left((1-\theta)\sum_{k=0}^{t-1}\theta^k\left(z_{t-k}\right)\right)\\
\frac{\mathrm{Var}\left(X_t\right)}{(1-\theta)^2} &= \text{Variances} + 2\times\text{Covariances},
\end{aligned}$$

The variance terms can be calculated as

$$\text{Variances} = \left(1 + \theta^2 + \theta^4 + ... + \theta^{2(t-1)}\right) \sigma_z^2 = \frac{1-\theta^{2t}}{1-\theta^2} \frac{\sigma^2}{1-\rho^2},$$

and the covariance terms can be calculated as

$$\begin{aligned}
\frac{\text{Covariances}}{\sigma_z^2} \cdot \frac{1-\theta\rho}{\theta\rho} &= \left(1 - (\theta\rho)^{t-1}\right) + \theta^2 \left(1 - (\theta\rho)^{t-2}\right) + \theta^4 \left(1 - (\theta\rho)^{t-3}\right) + ... + \theta^{2t-4} (1 - \theta\rho) \\
&= 1 + \theta^2 + \theta^4 + ... + \theta^{2t-4} \\
&\quad - \left[(\theta\rho)^{t-1} + \theta^2 (\theta\rho)^{t-2} + \theta^4 (\theta\rho)^{t-3} + ... + \theta^{2t-4} (\theta\rho)\right] \\
&= A - B,
\end{aligned}$$

where

$$\begin{aligned}
A &= \frac{1-\theta^{2t-2}}{1-\theta^2}, \\
B &= \frac{\rho\left((\theta\rho)^{t-1} - \theta^{2t-2}\right)}{\rho - \theta}.
\end{aligned}$$

The the sum of the covariance terms are

$$\text{Covariances} = \frac{\theta\rho}{1-\theta\rho} \left[\frac{1-\theta^{2t-2}}{1-\theta^2} - \frac{\rho\left((\theta\rho)^{t-1} - \theta^{2t-2}\right)}{\rho-\theta}\right] \frac{\sigma^2}{1-\rho^2}.$$

We therefore obtain unconditional variance of X_t as

$$\text{Var}(X_t) = \frac{\sigma^2}{1-\rho^2} \left\{\frac{1-\theta^{2t}}{1-\theta^2} + \frac{2\theta\rho}{1-\theta\rho} \left[\frac{1-\theta^{2t-2}}{1-\theta^2} - \frac{\rho\left((\theta\rho)^{t-1} - \theta^{2t-2}\right)}{\rho-\theta}\right]\right\}$$

When time t is far enough from the initial time, i.e., $t \to \infty$, we have

$$\lim_{t\to\infty} \text{Var}(X_t) = \frac{\sigma^2}{1-\rho^2} \frac{1}{1-\theta^2} \frac{1+\theta\rho}{1-\theta\rho}.$$

Next, we calculate the covariance between z_t and X_{t-1} as

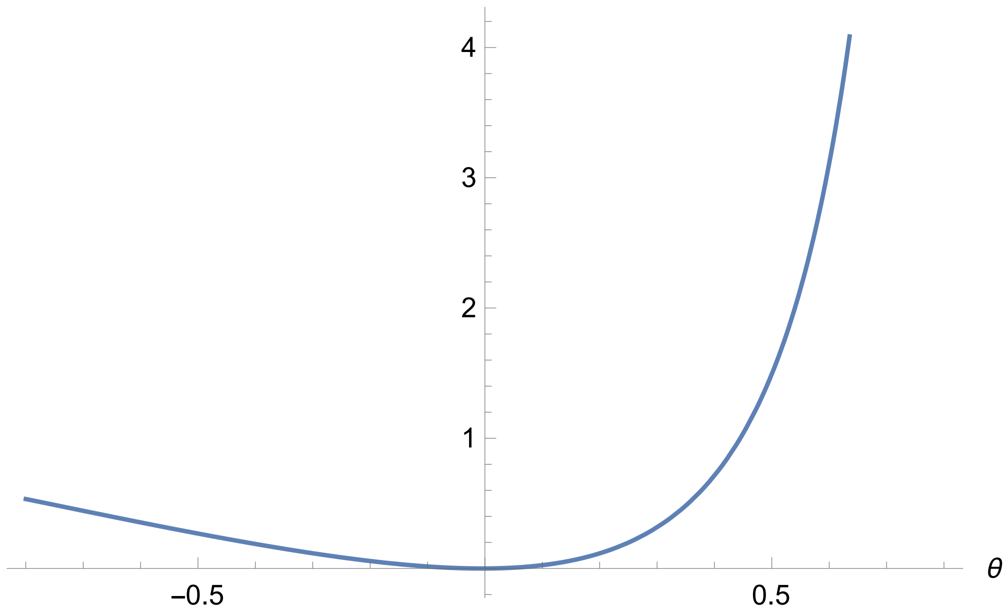
$$\begin{aligned}
\text{Cov}(z_t, X_{t-1}) &= \text{Cov}\left(z_t, (1-\theta) \sum_{k=0}^{t-2} \theta^k (z_{t-1-k})\right) \\
&= \frac{(1-\theta)\sigma^2\rho}{1-\rho^2} \frac{1-(\theta\rho)^{t-1}}{1-\theta\rho} \\
\lim_{t\to\infty} \text{Cov}(z_t, X_{t-1}) &= \frac{(1-\theta)\sigma^2\rho}{(1-\theta\rho)(1-\rho^2)}.
\end{aligned}$$

Similarly assume that t is large enough and we obtain the covariance between FE and FR as

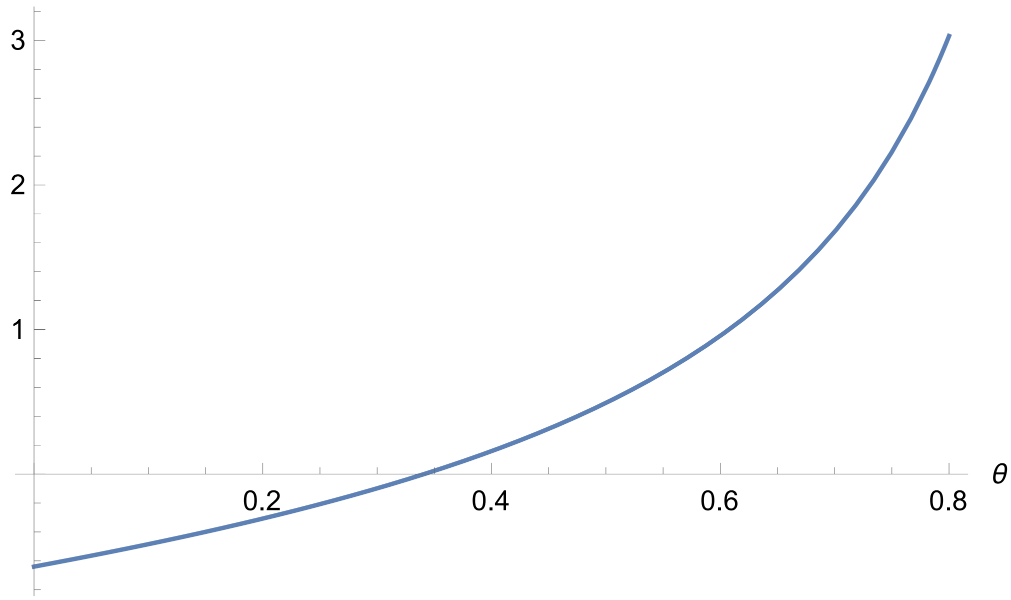
$$\mathcal{C} = (1-\theta)\frac{\sigma^2}{1-\rho^2}\left[(\rho+\theta-1) + \frac{\theta}{1-\theta^2}\frac{1+\theta\rho}{1-\theta\rho} - \frac{(1-\theta)\,\rho}{(1-\theta\rho)}(\rho+2\theta-1)\right].$$

The sign of $\mathcal{C}$ is determined as follows:

- For very a persistent process z_t (i.e., $\rho \to 1$) such as the interest rate for a certain maturity, the sign of $\mathcal{C}$ is always positive. The covariance $\mathcal{C}$, as a function of the degree of extrapolation θ, is ploted in the following figure.



- For a non-persistent process z_t (i.e., $\rho \to 0$) such as a typical asset return, the sign is negative for smaller degree of extrapolation θ. The following figure plots $\mathcal{C}$ for the non-persistent case.



3. Sticky expectations

See Coibion and Gorodnichenko (2015) Section I for detailed derivations.

4. Diagnostic expectations

See Bordalo et al. (2019b) Proposition 2 and proofs for detailed derivations.

A.2 Motivating "autocorrelation averaging" using "slow" learning

In section 3, I explicitly assume that the forecaster anchors her subjective autocorrelation to the default and simple model, which uses the average autocorrelation across a number of time series. The motivation of the choice of the simple model stem from the limited cognitive or institutional processing power in light of many demanding tasks such as correctly estimate the autocorrelations of short rate and term premium components for each interest rate in real time.

Alternatively, the "autocorrelation averaging" behavior can be motivated using supervised learning. The forecaster assumes that all autocorrelations are drawn from the same distribution with mean $\bar{\rho}$. Suppose she has the following prior with respect to autocorrelations of EH and TP components across M maturities

$$\boldsymbol{\rho} \sim \mathcal{N}\left(\bar{\rho}\mathbb{1}, \boldsymbol{\Sigma}\right), \tag{22}$$

where $\boldsymbol{\rho}$ is a $2M \times 1$ vector of autocorrelations of EH and TP components across maturities, $\mathbb{1}$ is a vector of ones, and the mean autocorrelation $\bar{\rho}$ is the same across maturities. Empirically, $\bar{\rho}$ can be obtained from cross-sectional average of autocorrelations. At each period, the forecaster uses all available data $\boldsymbol{y}_t$ to estimate the autocorrelations with least-squared estimation but penalizes estimation results that deviate too much from her prior

$$\hat{\boldsymbol{\rho}} = \arg\min_{\boldsymbol{\rho}} \left\{ \left(\boldsymbol{y}_t - \boldsymbol{\rho}'\boldsymbol{y}_{t-1}\right)' \left(\boldsymbol{y}_t - \boldsymbol{\rho}'\boldsymbol{y}_{t-1}\right) + \lambda(\boldsymbol{\rho} - \bar{\rho}\mathbb{1})'(\boldsymbol{\rho} - \bar{\rho}\mathbb{1}) \right\}, \tag{23}$$

where λ is the penalty parameter and $(\boldsymbol{\rho}-\bar{\rho}\mathbb{1})'(\boldsymbol{\rho}-\bar{\rho}\mathbb{1})$ is an L_2-norm penalty. This penalized estimation method is essentially a ridge regression. When $\lambda = 0$, we obtain an OLS estimator. The penalty weight is a way to express prior knowledge about autocorrelations. As long as the forecaster has a strong prior and penalizes any deviation from the prior significantly (a high λ), her posterior estimates of the cross section of autocorrelations $\hat{\boldsymbol{\rho}}$ remain close to the mean autocorrelation $\bar{\rho}$, i.e. she learns very "slowly". In doing so, the forecaster exhibits "autocorrelation averaging" behavior, which resembles what we have observed in the survey expectations data.

One testable implication from the "slow learning" behavior is that there shall not be any significant differences in the reactions to new information in early and late periods. I empirically examine this assertion by splitting the sample in halves. I do this in two ways at the individual level: (1) I split the sample at 2003 for all forecasters; (2) I split each forecaster's sample in halves. The results are plotted in Figure A.5 where each panel correspond to one splitting scheme. I also apply the first way to the consensus-level forecasts, the results of which are plotted in Figure A.6. In all plots, the regression coefficients are quantitatively similar among first and second halves, consistent with the "slow learning" behavior.

A.3 Beliefs and Bank Treasury Portfolios

In this section, I move from understanding the survey expectations to building the link between beliefs and the Treasury portfolios of the forecasters.[34] In doing so, I provide further evidence that the survey-participating financial institutions take the survey forecasts seriously, i.e. that they put real money behind these forecasts. Moreover, the link between beliefs and asset allocations offers additional justification for the asset pricing implication documented in the main text. Thanks to the unique feature of the BCFF forecasts that the identity of the forecasters is known, I am able to map bank forecasters' elicited beliefs to the Treasury securities holdings of the institutions that they work for. I first provide some details on how to connect the forecasts to banks' balance sheet data. I then explore the relationship between Treasury yield forecasts and the contemporaneous portfolio holdings of Treasury securities that are closest in maturity. I also extend the analyses to other asset classes that contain similar interest rate risk.

[34] A series of recent papers, starting from Manski (2004), has linked subjective beliefs to investment behavior and portfolio choices (e.g., Vissing-Jorgensen, 2003; Dominitz and Manski, 2007; Kézdi and Willis, 2009; Amromin and Sharpe, 2014; Drerup, Enke, and von Gaudecker, 2017; Choi and Robertson, 2018; Giglio et al., 2019). Most of the literature focuses on the equity market and individual investors. This paper is the first to explicitly connect survey expectations to portfolio allocations at the bank level by manually matching the identities of survey forecasters to granular information about the maturities of banks' assets and liabilities provided by Call Reports.

Bank-level data. A large proportion of the forecasters in the BCFF survey are banks, which enables me to merge the survey forecasts of this subsample of forecasters to details about their balance sheets. The variables of interest are each bank's holdings of Treasury securities of various maturities. The balance sheet information of banks is tracked by the FR Y-9C (at the bank holding company level) and Call Reports (at the commercial bank-level) data from the Federal Reserve. I use the granular and comprehensive information on the maturity of assets and liabilities on banks' balance sheets, which becomes available on the Call Reports starting in 1997Q2. I follow closely two previous papers, namely English et al. (2018) and Drechsler et al. (2017), to extract the bank-level portfolio holding variables. I use the quarterly data obtained from regulatory filings by the BHCs (FR Y-9C forms) and their commercial bank subsidiaries (the Call Reports) available from WRDS and merge them with the survey expectations using manually-matched identifiers from FFIEC.

The Call Reports do not record the holdings of individual securities on banks' balance sheets; instead, they group securities by asset class and by maturity. The maturity ranges the Call Reports use are: less than 3-month, 3-month to 1-year, 1- to 3-year, 3- to 5-year, 5- to 15-year and beyond 15-year. I match these ranges to the yield forecasts with the closest maturity, i.e., to forecasts of 3-month, 1-, 2-, 5-, 10-, and 30-year yields respectively. Though the matching is not perfect, the term structure of interest rates is preserved. This feature is potentially an advantage of the interest rate forecasts over the stock market surveys, which mostly ask for people's expectations of the aggregate stock market.

Beliefs and portfolio allocations. To guide our intuition for the relationship between yield expectations and portfolio holdings of Treasury bonds, I turn to the benchmark model of portfolio choice by Merton (1969). For a power-utility forecaster investing in the Treasury bond market, her portfolio weight in the bond market is determined as

$$w_{i,t} = \frac{1}{\gamma}\frac{\mathbb{E}^S_{i,t}[R_{t+1}] - R_f}{\mathrm{Var}_i[R_t]} = \frac{1}{\gamma}\frac{\mathbb{E}^S_{i,t}\left[ny^{(n)}_t - (n-1)y^{(n-1)}_{t+1} - y^{(1)}_t\right]}{\mathrm{Var}_i[R_t]}, \tag{24}$$

where γ is the coefficient of relative risk aversion and $\mathbb{E}^S_{i,t}\left[y^{(n-1)}_{t+1}\right]$ is the subjective belief studied in the previous sections. Notice that the above formula assumes that there is only a risky bond and a risk-free asset to choose from. Nonetheless, given the high correlations between Treasury yields, we can use the above relationship as an approximation for each maturity separately. The simple frictionless benchmark implies that, all else equal, the portfolio weight or allocation is negatively related to the subjective expectation of the future yield

$$w_{i,t} \propto -\mathbb{E}^S_t(y^{(n)}_{t+1}). \tag{25}$$

Since "portfolio" is not a well-defined concept for a bank, I use the allocation to specific Treasury securities as the main empirical holding-based variable. To estimate the relationship of portfolio allocations to beliefs, I run the following regression:

$$\text{Treasury}(n)_{i,t} = \alpha_i + \beta\mathbb{E}^S_{i,t}(y^{(n)}_{t+h}) + \gamma \cdot X_{i,t} + \varepsilon_{i,t}, \tag{26}$$

where the dependent variable is the dollar amount of Treasury securities with maturity close to n years. β is the coefficient of interest; it measures the sensitivity of portfolio allocations to beliefs, i.e. how much an individual bank's allocation changes in dollars at the end of the quarter for each percentage point change in the one-year expected yield. To account for unobserved heterogeneity at the bank level, I include firm fixed effects in the main specification. $X_{i,t}$ is a placeholder for other potential controls and time fixed effects in alternative specifications. The regression is estimated monthly, in which the quarterly allocation data is assigned to all three months of a quarter. I include all the maturity buckets described previously that are greater than one year.

The results are reported in Table A.16. Panel A, which directly tests equation (24), fixes the forecast horizon h to 4 quarters for ease of interpretation. Panel B obtains slightly stronger results by pooling yield forecasts across horizons (1-4Q) for the right-hand-side beliefs variable. Firm (bank) fixed effects are included in all regressions. A key finding from these regressions is that the sign of the β estimates is negative across all maturities, consistent with the relationship prescribed by Merton's formula. All coefficients except for the 30-year maturity in Panel A are statistically significant. Take the 10-year relationship in Panel A as an example. A one standard deviation increase in the one-year expected yield of the 10-year Treasury yield leads to around a \$1.64 billion decrease in 5- to 15-year Treasury securities held by the average bank in the sample. The absolute value of the effect might not seem large compared with the sheer size of the Treasury market. However, the average bank in the sample holds around \$4 billion in Treasury securities in this maturity bucket. The above effect is a 40% decrease from the average, underscoring the economic importance of the subjective beliefs.

The results not only hold across different maturities in the Treasury market but also in markets where interest rate risk at various maturities is an integral component. Specifically, I conduct a similar analysis for (1) the tradable securities, (2) the residential mortgage-back securities (RMBS), and (3) the total assets at specific maturities. To illustrate the relevance of beliefs to allocations, I use the 10-year Treasury yield forecasts and estimate the following regression:

$$\text{Allocation}(5-15Y)_{i,t} = \alpha_i + \beta \mathbb{E}^S_{i,t}(y^{(10)}_{t+h}) + \varepsilon_{i,t}, \tag{27}$$

where *Allocation* refers to dollar allocations to the Treasuries, assets, securities, and RMBS. Similar to the previous regression, all coefficients, reported in Table A.17, are negative and statistically significant. Since the Treasury yield is a major part of the interest rates of other asset classes with at the same maturity, the same negative link between beliefs about the bond yield and portfolio allocation carries through.

In summary, this section uses the detailed information on the maturity of the securities on banks' balance sheets from the Call Reports, and establishes a statistically robust relationship between the subjective expectations of Treasury yields and portfolio allocation at the bank level. The effect is sizable for an average bank. This evidence further lends support to the effect of subjective beliefs on asset prices documented in the last section. Though it is beyond the scope of the paper to establish a causal link from beliefs to portfolio composition and asset prices, the strong correlation between beliefs and allocation and the importance of the BCFF survey participants in the Treasury market sheds light on the importance and validity of the survey forecast data.

Appendix B Additional Tables and Figures

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

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

	Count	Institution Names
Asset Manager	13	ASB Capital Management, Sanford C. Bernstein, J.W. Coons, ING Aeltus, JPMorgan Chase Wealth Management, Loomis Sayles, Mesirow, Northern Trust, RidgeWorth, Stone Harbor, U.S. 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, U.S. Chamber of Commerce, Georgia State University

Table A.2 Summary statistics of the consensus-level forecasts of interest rates

This table reports the summary statistics of the consensus-level forecast errors and forecast revisions. The observations are pooled across forecast horizons. Panels A1 and A2 report quarterly-frequency statistics and Panels B1 and B2 report monthly-frequency statistics. The underlying variables are the Federal Funds Rate (ffr) and Treasury yields with maturities of 3-month, 1-, 2-, 5-, 10- and 30-years ($tb3m$, $tb1y$, $tn2y$, $tn5y$, $tn10y$ and $tn30y$). The data cover the period 1988 to 2018.

	Count	Mean	SD	Min	p25	p50	p75	Max
Panel A1: Quarterly consensus forecast errors								
ffr	566	-0.29	1.03	-4.48	-0.65	-0.08	0.20	2.82
$tb3m$	566	-0.33	1.06	-4.16	-0.78	-0.14	0.26	2.95
$tb1y$	486	-0.33	1.02	-3.80	-0.82	-0.16	0.20	3.26
$tn2y$	490	-0.41	0.97	-3.35	-0.97	-0.26	0.13	3.06
$tn5y$	490	-0.37	0.85	-2.82	-0.90	-0.33	0.17	2.46
$tn10y$	502	-0.18	0.79	-2.39	-0.67	-0.24	0.30	3.18
$tn30y$	532	-0.23	0.77	-3.70	-0.61	-0.25	0.23	2.55
Panel A2: Quarterly consensus forecast revisions								
ffr	515	-0.16	0.51	-2.28	-0.34	-0.07	0.12	1.39
$tb3m$	515	-0.16	0.49	-1.93	-0.35	-0.09	0.11	1.31
$tb1y$	456	-0.16	0.47	-1.73	-0.32	-0.10	0.10	1.23
$tn2y$	457	-0.16	0.47	-1.58	-0.36	-0.12	0.09	1.28
$tn5y$	457	-0.15	0.44	-1.60	-0.34	-0.13	0.12	1.21
$tn10y$	464	-0.12	0.39	-1.38	-0.38	-0.14	0.10	1.15
$tn30y$	515	-0.12	0.39	-1.62	-0.37	-0.13	0.10	1.59
Panel B1: Monthly consensus forecast errors								
ffr	1696	-0.33	1.11	-4.54	-0.78	-0.09	0.21	2.82
$tb3m$	1696	-0.38	1.13	-4.23	-0.93	-0.16	0.28	2.95
$tb1y$	1458	-0.38	1.09	-4.04	-0.92	-0.18	0.21	3.32
$tn2y$	1464	-0.47	1.02	-3.93	-1.04	-0.31	0.13	3.13
$tn5y$	1468	-0.41	0.89	-3.10	-0.99	-0.37	0.17	2.87
$tn10y$	1504	-0.21	0.83	-2.50	-0.75	-0.26	0.27	3.34
$tn30y$	1596	-0.26	0.81	-3.91	-0.70	-0.28	0.22	2.55
Panel B2: Monthly consensus forecast revisions								
ffr	1666	-0.05	0.22	-1.30	-0.11	-0.02	0.03	0.65
$tb3m$	1666	-0.05	0.21	-1.10	-0.12	-0.02	0.04	0.59
$tb1y$	1449	-0.05	0.20	-1.15	-0.12	-0.03	0.04	0.61
$tn2y$	1449	-0.06	0.21	-1.09	-0.14	-0.03	0.05	0.57
$tn5y$	1456	-0.05	0.21	-1.06	-0.14	-0.03	0.05	0.55
$tn10y$	1487	-0.04	0.19	-1.19	-0.13	-0.034	0.06	0.48
$tn30y$	1666	-0.04	0.19	-1.21	-0.12	-0.031	0.05	0.87

Table A.3 Summary statistics of the individual-level forecasts of interest rates by horizon

This table reports the summary statistics of the individual-level forecast errors and forecast revisions at different forecast horizons. Panels A1 and A2 report statistics at one-quarter horizon and Panels B1 and B2 report statistics at four-quarter horizon. The underlying variables are the Federal Funds Rate (ffr) and Treasury yields with maturities of 3-month, 1-, 2-, 5-, 10- and 30-years ($tb3m$, $tb1y$, $tn2y$, $tn5y$, $tn10y$ and $tn30y$). The data cover the period 1988 to 2018.

	Count	Mean	SD	Min	p25	p50	p75	Max
Panel A1: Quarterly individual forecast errors, $h = 1Q$								
ffr	6714	-0.06	0.59	-4.62	-0.20	-0.01	0.15	2.98
$tb3m$	6610	-0.10	0.67	-3.88	-0.32	-0.05	0.20	3.65
$tb1y$	5338	-0.09	0.68	-2.79	-0.37	-0.03	0.24	2.46
$tn2y$	5830	-0.17	0.70	-2.83	-0.51	-0.08	0.19	4.01
$tn5y$	5813	-0.16	0.69	-2.45	-0.57	-0.12	0.29	3.69
$tn10y$	5984	0.00	0.65	-2.42	-0.44	-0.05	0.44	2.91
$tn30y$	6058	-0.03	0.68	-3.3	-0.43	-0.07	0.41	2.74
Panel A2: Quarterly individual forecast revisions, $h = 1Q$								
ffr	6589	-0.12	0.64	-5.70	-0.30	0.00	0.10	6.30
$tb3m$	6466	-0.14	0.64	-5.00	-0.33	-0.03	0.10	4.20
$tb1y$	5183	-0.13	0.58	-4.70	-0.38	-0.06	0.14	2.40
$tn2y$	5675	-0.14	0.60	-4.10	-0.40	-0.09	0.17	2.50
$tn5y$	5652	-0.13	0.58	-3.00	-0.41	-0.10	0.20	2.30
$tn10y$	5828	-0.12	0.55	-6.00	-0.41	-0.10	0.20	2.31
$tn30y$	6325	-0.12	0.60	-5.90	-0.43	-0.10	0.20	4.70
Panel B1: Quarterly individual forecast errors, $h = 4Q$								
ffr	6376	-0.52	1.48	-7.31	-1.34	-0.24	0.33	5.83
$tb3m$	6298	-0.59	1.49	-7.06	-1.44	-0.35	0.32	4.73
$tb1y$	5160	-0.58	1.42	-4.98	-1.47	-0.39	0.24	4.45
$tn2y$	5484	-0.68	1.32	-5.03	-1.55	-0.56	0.12	3.96
$tn5y$	5470	-0.61	1.11	-3.88	-1.37	-0.62	0.1	3.34
$tn10y$	5636	-0.39	1.02	-3.62	-1.08	-0.46	0.16	5.96
$tn30y$	5922	-0.42	1.04	-6.02	-0.99	-0.41	0.15	4.36
Panel B2: Quarterly individual forecast revisions, $h = 4Q$								
ffr	3755	-0.19	0.60	-5.00	-0.42	0.00	0.05	2.17
$tb3m$	3663	-0.19	0.59	-4.80	-0.40	-0.02	0.10	1.90
$tb1y$	3370	-0.19	0.59	-4.80	-0.40	-0.05	0.10	1.90
$tn2y$	3692	-0.19	0.58	-4.30	-0.40	-0.09	0.10	1.75
$tn5y$	3666	-0.16	0.55	-3.30	-0.40	-0.10	0.10	5.89
$tn10y$	3722	-0.14	0.49	-2.83	-0.40	-0.10	0.10	2.05
$tn30y$	3510	-0.12	0.45	-2.70	-0.36	-0.10	0.10	2.00

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Table A.4 Forecast error on forecast revision regression results for interest rates across maturities: 1982Q4-2018Q4

This table reports the coefficients from the forecast error on forecast revision regression of Coibion and Gorodnichenko (2015) for each interest rate:

$$FE_{i,t}\left(x_{t+h}\right) = \alpha_i + \beta FR_{i,t}\left(x_{t+h}\right) + \epsilon_{i,t,h},$$

where the individual-level forecasts are pooled across horizon h, standard errors are clustered by both forecaster and time, and forecaster fixed effects are included. Panel A reports the baseline results using individual-level forecasts. Panel B reports results for an extended list of short-maturity interest rates. Panel C reports results for an extended list of long-maturity interest rates. The underlying variables are the Federal Funds Rate (ffr), Treasury bill, note and bond yields with maturities of 3-month, 1-, 2-, 5-, 10- and 30-years ($tb3m$, $tb1y$, $tn2y$, $tn5y$, $tn10y$ and $tn30y$), one-month commercial paper rate ($cp1m$), prime bank rate (pr), three-month LIBOR rate ($libor$), Aaa and Baa corporate bond yields (aaa and baa) and home mortgage rate (hmr). The data are quarterly and cover the period 1982Q4 to 2018Q4. *, ** and *** indicate statistical significance at 10, 5, and 1% levels, respectively.

	Dependent variable: $FE_{i,t}\left(x_{t+h}\right)$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Baseline results							
	ffr	$tb3m$	$tb1y$	$tn2y$	$tn5y$	$tn10y$	$tn30y$
$FR_{i,t}\left(x_{t+h}\right)$	0.20**	0.20**	0.20**	0.04	-0.18**	-0.21***	-0.24***
	(0.08)	(0.08)	(0.09)	(0.09)	(0.08)	(0.08)	(0.07)
N	22,808	22,410	18,503	20,079	20,007	20,501	20,934
R^2	0.05	0.06	0.06	0.04	0.06	0.08	0.10
Panel B: Short-maturity interest rates							
	ffr	$tb3m$	$tb1y$	$tn2y$	$cp1m$	pr	$libor$
$FR_{i,t}\left(x_{t+h}\right)$	0.20**	0.20**	0.20**	0.04	0.38***	0.21***	0.29***
	(0.08)	(0.08)	(0.09)	(0.09)	(0.10)	(0.08)	(0.09)
N	22,808	22,410	18,503	20,079	12,134	22,063	18,202
R^2	0.05	0.06	0.06	0.04	0.09	0.06	0.07
Panel C: Long-maturity interest rates							
	$tn5y$	$tn10y$	$tn30y$	aaa	baa	hmr	
$FR_{i,t}\left(x_{t+h}\right)$	-0.18**	-0.21***	-0.24***	-0.17***	-0.25***	-0.16***	
	(0.08)	(0.08)	(0.07)	(0.05)	(0.07)	(0.06)	
N	20,007	20,501	20,934	19,813	10,660	21,147	
R^2	0.06	0.08	0.10	0.11	0.10	0.08	

Table A.5 Forecast error on forecast revision regression results for interest rates across maturities: No fixed effects

This table reports the coefficients from the forecast error on forecast revision regression of Coibion and Gorodnichenko (2015) for each interest rate:

$$FE_{i,t}\left(x_{t+h}\right) = \alpha_i + \beta FR_{i,t}\left(x_{t+h}\right) + \epsilon_{i,t,h},$$

where the individual-level forecasts are pooled across horizon h, standard errors are clustered by both forecaster and time, and *no* fixed effects are included. Panel A reports the baseline results using individual-level forecasts. Panel B reports results for an extended list of short-maturity interest rates. Panel C reports results for an extended list of long-maturity interest rates. The underlying variables are the Federal Funds Rate (ffr), Treasury bill, note and bond yields with maturities of 3-month, 1-, 2-, 5-, 10- and 30-years (*tb3m*, *tb1y*, *tn2y*, *tn5y*, *tn10y* and *tn30y*), one-month commercial paper rate (*cp1m*), prime bank rate (*pr*), three-month LIBOR rate (*libor*), Aaa and Baa corporate bond yields (*aaa* and *baa*) and home mortgage rate (*hmr*). The data are quarterly and cover the period 1982Q4 to 2018Q4. *, ** and *** indicate statistical significance at 10, 5, and 1% levels, respectively.

	Dependent variable: $FE_{i,t}\left(x_{t+h}\right)$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Baseline results							
	ffr	*tb3m*	*tb1y*	*tn2y*	*tn5y*	*tn10y*	*tn30y*
$FR_{i,t}\left(x_{t+h}\right)$	0.38***	0.34***	0.24***	0.08	-0.13	-0.19**	-0.23***
	(0.08)	(0.09)	(0.09)	(0.09)	(0.08)	(0.08)	(0.07)
Constant	-0.20***	-0.27***	-0.30***	-0.40***	-0.40***	-0.25***	-0.25***
	(0.06)	(0.07)	(0.08)	(0.08)	(0.07)	(0.06)	(0.05)
N	20,440	20,041	18,503	20,049	19,976	20,222	19,447
R^2	0.06	0.04	0.02	0.003	0.01	0.02	0.02
Panel B: Short-maturity interest rates							
	ffr	*tb3m*	*tb1y*	*tn2y*	*cp1m*	*pr*	*libor*
$FR_{i,t}\left(x_{t+h}\right)$	0.38***	0.34***	0.24***	0.08	0.42***	0.35***	0.32***
	(0.08)	(0.09)	(0.09)	(0.09)	(0.10)	(0.08)	(0.09)
Constant	-0.20***	-0.27***	-0.30***	-0.40***	-0.32***	-0.16***	-0.20***
	(0.06)	(0.07)	(0.08)	(0.08)	(0.08)	(0.06)	(0.07)
N	20,440	20,041	18,503	20,049	12,134	19,696	18,202
R^2	0.06	0.04	0.02	0.003	0.06	0.05	0.04
Panel C: Long-maturity interest rates							
	tn5y	*tn10y*	*tn30y*	*aaa*	*baa*	*hmr*	
$FR_{i,t}\left(x_{t+h}\right)$	-0.13	-0.19**	-0.23***	-0.14**	-0.19**	-0.15**	
	(0.08)	(0.08)	(0.07)	(0.07)	(0.08)	(0.07)	
Constant	-0.40***	-0.25***	-0.25***	-0.33***	-0.38***	-0.33***	
	(0.07)	(0.06)	(0.05)	(0.06)	(0.07)	(0.06)	
N	19,976	20,222	19,447	17,925	10,660	18,824	
R^2	0.01	0.02	0.02	0.01	0.02	0.01	

Table A.6 Forecast error on forecast revision regression results for interest rates across maturities: Monthly regressions 1988:01-2018:12

This table reports coefficients from the forecast error on forecast revision regression of Coibion and Gorodnichenko (2015) for each interest rate:

$$FE_{i,t}\left(x_{t+h}\right) = \alpha_i + \beta FR_{i,t}\left(x_{t+h}\right) + \epsilon_{i,t,h},$$

where the individual-level forecasts are pooled across horizon h, standard errors are clustered by both forecaster and time, and forecaster fixed effects are included. Different from the main specification of quarterly regressions, this regression is monthly and uses one month forecast revision. Panel A tabulates the baseline results of the Federal Funds Rates and U.S. Treasury yields. Panel B and C include additional short- and long-maturity rates respectively. The underlying variables are the Federal Funds Rate (ffr), the Treasury bill, note and bond yields with maturities of 3-month, 1-, 2-, 5-, 10- and 30-years ($tb3m$, $tb1y$, $tn2y$, $tn5y$, $tn10y$ and $tn30y$), one-month commercial paper rate ($cp1m$), prime bank rate (pr), three-month LIBOR rate ($libor$), Aaa and Baa corporate bond yields (aaa and baa) and home mortgage rate (hmr). The data are monthly and cover the period 1988 to 2018. *, ** and *** indicate statistical significance at 10, 5, and 1% levels, respectively.

	Dependent variable: $FE_{i,t}\left(x_{t+h}\right)$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Baseline results							
	ffr	$tb3m$	$tb1y$	$tn2y$	$tn5y$	$tn10y$	$tn30y$
$FR_{i,t}\left(x_{t+h}\right)$	0.48***	0.35***	0.21**	0.03	-0.19***	-0.27***	-0.33***
	(0.09)	(0.08)	(0.08)	(0.08)	(0.07)	(0.06)	(0.06)
N	66,044	64,835	60,433	64,836	64,882	65,684	63,222
R^2	0.07	0.06	0.06	0.05	0.06	0.07	0.11
Panel B: Short-maturity interest rates							
	ffr	$tb3m$	$tb1y$	$tn2y$	$cp1m$	pr	$libor$
$FR_{i,t}\left(x_{t+h}\right)$	0.48***	0.35***	0.21**	0.03	0.51***	0.31***	0.34***
	(0.09)	(0.08)	(0.08)	(0.08)	(0.11)	(0.10)	(0.09)
N	66,044	64,835	60,433	64,836	37,480	63,710	59,073
R^2	0.07	0.06	0.06	0.05	0.07	0.06	0.06
Panel C: Long-maturity interest rates							
	$tn5y$	$tn10y$	$tn30y$	aaa	baa	hmr	
$FR_{i,t}\left(x_{t+h}\right)$	-0.19***	-0.27***	-0.33***	-0.29***	-0.30***	-0.27***	
	(0.07)	(0.06)	(0.06)	(0.04)	(0.05)	(0.05)	
N	64,882	65,684	63,222	58,340	32,961	61,086	
R^2	0.06	0.07	0.11	0.12	0.11	0.08	

Table A.7 Forecast error on forecast revision regression results for interest rates across maturities: Regression by horizon 1988Q1-2018Q4

This table reports coefficients from the forecast error on forecast revision regression of Coibion and Gorodnichenko (2015) for each interest rate and forecast horizon:

$$FE_{i,t}\left(x_{t+h}\right) = \alpha_i + \beta FR_{i,t}\left(x_{t+h}\right) + \epsilon_{i,t,h}, \quad h \in \{1, 2, 3, 4Q\},$$

where the standard errors are clustered by both forecaster and time, and forecaster fixed effects are included. Each panel corresponds to a certain forecast horizon. The underlying variables are the Federal Funds Rate (ffr) and the Treasury bill, note and bond yields with maturities of 3-month, 1-, 2-, 5-, 10- and 30-years ($tb3m$, $tb1y$, $tn2y$, $tn5y$, $tn10y$ and $tn30y$). The data are quarterly and cover the period 1988 to 2018. *, ** and *** indicate statistical significance at 10, 5, and 1% levels, respectively.

	Dependent variable: $FE_{i,t}\left(x_{t+h}\right)$						
	ffr	$tb3m$	$tb1y$	$tn2y$	$tn5y$	$tn10y$	$tn30y$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: $h = 1Q$							
$FR_{i,t}\left(x_{t+h}\right)$	0.23***	0.21***	0.13	-0.01	-0.15*	-0.13	-0.14*
	(0.05)	(0.08)	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)
N	5,712	5,593	5,151	5,604	5,583	5,652	5,453
R^2	0.09	0.07	0.03	-0.001	0.01	0.01	0.04
Panel B: $h = 2Q$							
$FR_{i,t}\left(x_{t+h}\right)$	0.32***	0.32***	0.22**	0.05	-0.20**	-0.27***	-0.32***
	(0.08)	(0.09)	(0.11)	(0.10)	(0.10)	(0.10)	(0.09)
N	5,645	5,531	5,099	5,535	5,519	5,584	5,393
R^2	0.09	0.09	0.05	0.02	0.04	0.06	0.10
Panel C: $h = 3Q$							
$FR_{i,t}\left(x_{t+h}\right)$	0.42***	0.34***	0.22*	0.05	-0.19*	-0.29***	-0.38***
	(0.10)	(0.11)	(0.11)	(0.11)	(0.10)	(0.09)	(0.09)
N	5,491	5,397	5,014	5,369	5,352	5,415	5,236
R^2	0.10	0.08	0.05	0.04	0.06	0.09	0.15
Panel D: $h = 4Q$							
$FR_{i,t}\left(x_{t+h}\right)$	0.39**	0.27*	0.17	0.05	-0.19	-0.31**	-0.36***
	(0.16)	(0.16)	(0.16)	(0.15)	(0.13)	(0.13)	(0.11)
N	3,592	3,520	3,239	3,541	3,522	3,571	3,365
R^2	0.07	0.05	0.06	0.05	0.07	0.11	0.14

Table A.8 Predicting one-year excess bond returns with forecast revisions

The table presents regressions of one-year bond excess returns on forecast revisions of 10-year Treasury yield $FR_t(y^{(10)}_{t+3Q})$ at the monthly frequency

$$rx^{(n)}_{t+1} = \alpha + \beta FR_t(y^{(10)}_{t+3Q}) + \varepsilon_{t+1},$$

where $rx^{(n)}_{t+1}$ is the one-year holding period excess return of a n-year bond and $\overline{rx}_{t+1}$ is the average excess return weighted by the inverse of bond maturities. Panel A reports monthly frequency regression using one-month forecast revision. Panel B reports monthly frequency regression using three-month forecast revision. Panel C reports quarterly frequency regression using one-quarter forecast revision. T-statistics are reported for two types of standard errors: Newey and West (1987) standard errors with 12 lags (in parentheses) and Hodrick (1992) standard errors obtained from reverse regressions (in brackets). The data cover the period 1988 to 2018. The results for the intercept are omitted.

	$rx^{(2)}_{t+1}$	$rx^{(3)}_{t+1}$	$rx^{(5)}_{t+1}$	$rx^{(7)}_{t+1}$	$rx^{(10)}_{t+1}$	$rx^{(20)}_{t+1}$	$rx^{(30)}_{t+1}$	$\overline{rx}_{t+1}$
Panel A: Monthly regression, $h = 3Q$, 1-month forecast revision								
$FR_t(y^{(10)}_{t+3Q})$	0.01	0.02	0.03	0.05	0.08	0.17	0.24	0.07
	(2.16)	(2.65)	(3.10)	(3.37)	(3.67)	(4.46)	(3.98)	(4.27)
	[1.90]	[2.05]	[2.19]	[2.28]	[2.39]	[2.60]	[2.60]	[2.64]
N	359	359	359	359	359	359	359	359
R^2	0.01	0.01	0.02	0.03	0.04	0.06	0.05	0.05
Panel B: Monthly regression, $h = 3Q$, 3-month forecast revision								
$FR_t(y^{(10)}_{t+3Q})$	0.00	0.01	0.02	0.03	0.05	0.11	0.15	0.05
	(2.57)	(3.07)	(3.41)	(3.62)	(3.86)	(4.38)	(3.94)	(4.29)
	[2.36]	[2.48]	[2.59]	[2.67]	[2.76]	[2.88]	[2.92]	[2.97]
N	357	357	357	357	357	357	357	357
R^2	0.02	0.03	0.05	0.06	0.08	0.11	0.10	0.10
Panel C: Quarterly regression, $h = 3Q$, 1-quarter forecast revision								
$FR_t(y^{(10)}_{t+3Q})$	0.01	0.01	0.03	0.04	0.07	0.13	0.19	0.06
	(2.86)	(3.32)	(3.53)	(3.63)	(3.76)	(4.08)	(3.85)	(4.07)
	[0.27]	[0.36]	[0.46]	[0.47]	[0.45]	[0.77]	[1.45]	[0.89]
N	119	119	119	119	119	119	119	119
R^2	0.03	0.04	0.06	0.08	0.10	0.13	0.13	0.12

Table A.9 Forecast revision and contemporaneous realized forecast errors

This table reports the relationship between forecast revision and contemporaneous realized forecast error of for long-maturity interest rates:

$$FR_t(x_{t+k}) = \alpha + \beta FE_{t-k}(x_t) + \varepsilon_{t+1}.$$

The left part of the table uses $k = 1$ quarter and the right part of the table uses $k = 4$ quarters. The underlying variables are the Treasury bond yields with maturities of 2-, 5-, 10- and 30-years. The data are quarterly and cover the period 1988 to 2018. *, ** and *** indicate statistical significance at 10, 5, and 1% levels, respectively.

	$FR_t(x_{t+k}), k = 1Q$				$FR_t(x_{t+k}), k = 4Q$			
$x =$	$y^{(2)}$	$y^{(5)}$	$y^{(10)}$	$y^{(30)}$	$y^{(2)}$	$y^{(5)}$	$y^{(10)}$	$y^{(30)}$
$FE_{t-k}(x_t)$	0.63***	0.58***	0.56***	0.46***	0.27***	0.28***	0.27***	0.24***
	(17.71)	(15.17)	(14.10)	(11.38)	(9.14)	(7.94)	(6.88)	(6.51)
Intercept	-0.03	-0.04	-0.11***	-0.11***	0.02	0.04	-0.01	-0.00
	(-1.18)	(-1.50)	(-4.80)	(-4.35)	(0.44)	(0.96)	(-0.20)	(-0.15)
N	124	124	124	124	87	87	87	87
R^2	0.72	0.65	0.61	0.50	0.50	0.43	0.36	0.33

Table A.10 Correlations between realized forecast error $FE10Y$ and other bond predictors

This table reports the pairwise correlations between overreaction-motivated predictor $FE10Y$ and other commonly-used bond predictors. Panel A reports the correlations between $FE10Y$, econometrician's realized forecast error $\widehat{FE}10Y$, Cochrane and Piazzesi (2005) factor (CP), the cycle factor (cf) from Cieslak and Povala (2015), the growth factor (GRO) and the inflation factor ($INFL$) from Joslin, Priebsch, and Singleton (2014), and first three yield curve principal components. Panel B reports the correlation between $FE10Y$ and the eight PCs of a large set of macroeconomic variables from Ludvigson and Ng (2009). The data are monthly and cover the period 1988 to 2018.

Panel A: Correlations with other bond predictors

	$FE10Y$	$\widehat{FE}10Y$	CP	cf	GRO	INF	PC1	PC2
$\widehat{FE}10Y$	0.86							
CP	0.24	0.00						
cf	0.57	0.51	0.55					
GRO	0.26	0.23	-0.01	-0.08				
INF	0.55	0.26	0.29	0.49	0.34			
PC1	0.41	0.30	0.34	0.84	0.21	0.82		
PC2	-0.08	-0.01	0.73	0.38	-0.49	0.07	0.00	
PC3	-0.60	-0.73	-0.29	-0.56	-0.27	0.06	0.00	0.00

Panel B: Correlations with Ludvigson and Ng (2009) factors

	f1	f2	f3	f4	f5	f6	f7	f8
$FE10Y$	-0.30	-0.05	-0.05	-0.07	0.14	-0.08	0.00	-0.03

Table A.11 Predicting coupon bond portfolio excess returns with realized forecast errors $FE10Y_t$

This table reports the predictive regressions of actual coupon bond excess returns from CRSP Fama Maturity Portfolios on realized forecast errors $FE10Y_t$ at different investment horizons. The column labels reflect the maturity bin for each bond portfolio: from less than two years to above ten years. The last column is the average excess return across maturities. The returns are in excess of Tbill rates obtained from H.15 Fed table (one-month Tbill for $h < 3$, three-month Tbill for $3 < h < 6$ and six-month Tbill for $h > 6$). T-bill rates are converted to a continuous basis. Each panel corresponds to a certain horizon h. T-stats from Hodrick (1992) reverse regressions are reported in brackets. The data are monthly and cover the period 1988 to 2018. The results for the intercept are omitted.

	$rx < 24m$	$rx < 36m$	$rx < 48m$	$rx < 60m$	$rx < 120m$	$rx > 120m$	$\overline{rx}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: $h = 1m$							
$FE10Y_t$	0.04	0.08	0.12	0.15	0.20	0.42	0.15
	[1.81]	[1.82]	[2.00]	[2.08]	[2.23]	[2.42]	[2.36]
N	359	359	359	359	359	359	359
R^2	0.01	0.01	0.01	0.01	0.01	0.02	0.02
Panel B: $h = 3m$							
$FE10Y_t$	0.16	0.30	0.43	0.55	0.71	1.38	0.51
	[2.87]	[2.89]	[2.96]	[2.96]	[3.03]	[3.03]	[3.21]
N	357	357	357	357	357	357	357
R^2	0.04	0.04	0.05	0.05	0.05	0.06	0.06
Panel C: $h = 6m$							
$FE10Y_t$	0.31	0.59	0.87	1.11	1.46	2.78	1.02
	[3.04]	[3.10]	[3.17]	[3.15]	[3.23]	[3.16]	[3.37]
N	354	354	354	354	354	354	354
R^2	0.07	0.08	0.10	0.10	0.11	0.12	0.12
Panel D: $h = 12m$							
$FE10Y_t$	0.59	1.11	1.57	1.94	2.52	4.60	1.75
	[3.96]	[3.84]	[3.66]	[3.44]	[3.34]	[2.98]	[3.54]
N	348	348	348	348	348	348	348
R^2	0.15	0.16	0.17	0.17	0.20	0.21	0.22

Table A.12 Test of the spanning hypothesis using Bauer and Hamilton (2017) bootstrap procedure

This table reports results of testing whether the predictive power of $FE10Y$ is spanned by current yields using Bauer and Hamilton (2017) bootstrap procedure. The dependent variable is the future one-year holding period excess return averaged across all maturities $\frac{1}{29}\sum_{2}^{30} rx_{t+1}^{(n)}$. Regression model 1 contains only three principal components and model 2 adds proposed predictor $FE10Y$. Panel A reports the model 2 regression coefficients, Newey and West (1987) t-stat and p-value, and Bauer and Hamilton (2017) small sample adjusted critical value and p-value using 5000 bootstrap runs. The column "Wald" reports results for the χ^2 test that $FE10Y$ has no predictive power. Panel B reports R^2 of model 1, 2 and their difference. The first row of reports the in sample R^2 in the data. The following rows report bootstrap mean and 95%-quantiles (in parentheses). The bootstrap imposes the null hypothesis that the additional predictor has no incremental predictive power.

Panel A: Bootstrap inference

	PC1	PC2	PC3	$FE10Y$	Wald
Coefficient	-0.114	2.024	-0.009	7.169	
NW t	-1.013	3.595	-0.003	6.837	46.740
NW p-value	0.312	0.000	0.997	0.000	0.000
Bootstrap 5% C.V.				3.003	9.021
Bootstrap p-value				0.000	0.000

Panel B: Additional R^2 from $FE10Y$

	R_1^2	R_2^2	$R_2^2 - R_1^2$
Data	0.164	0.412	0.247
Bootstrap mean	0.262	0.283	0.021
Bootstrap 95% C.I.	(0.081,0.466)	(0.102, 0.485)	(0.000, 0.103)
Bootstrap p-value			0.000

Table A.13 Predicting one-year excess bond returns with overreaction-motivated predictor $FE10Y$: Controlling for Ludvigson and Ng (2009) bond factors

The table presents regressions of one-year bond excess returns on the overreaction-motivated predictor $FE10Y$ with other commonly-used predictors at the monthly frequency $rx_{t+1}^{(n)} = \alpha + \beta FE10Y_t + \gamma \cdot X_t + \varepsilon_{t+1}$, where $rx_{t+1}^{(n)}$ is the one-year holding period excess return of a n-year bond and $\overline{rx}_{t+1}$ is the average excess return weighted by the inverse of bond maturities. Panel A includes the eight PCs of a large set of macro variables from Ludvigson and Ng (2009). Panel B adds the first three PCs of the yield curve. T-statistics are reported for two types of standard errors: Newey and West (1987) standard errors with 12 lags (in parentheses) and Hodrick (1992) standard errors obtained from reverse regressions (in brackets). The results for the intercept are omitted.

	$rx_{t+1}^{(2)}$	$rx_{t+1}^{(3)}$	$rx_{t+1}^{(5)}$	$rx_{t+1}^{(7)}$	$rx_{t+1}^{(10)}$	$rx_{t+1}^{(20)}$	$rx_{t+1}^{(30)}$	$\overline{rx}_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Ludvigson and Ng (2009) factors								
$FE10Y_t$	-0.19*	-0.55***	-1.47***	-2.41***	-3.58***	-5.90***	-8.49***	-2.88***
	(-1.92)	(-2.82)	(-4.05)	(-4.61)	(-4.76)	(-4.43)	(-4.57)	(-4.67)
	[3.28]	[3.04]	[2.83]	[2.82]	[2.88]	[2.59]	[2.02]	[2.61]
f1	0.02***	0.03***	0.05***	0.05***	0.04***	0.01	0.01	0.03***
	(4.74)	(4.81)	(4.61)	(4.01)	(2.78)	(0.52)	(0.18)	(2.67)
	[1.51]	[0.99]	[0.33]	[0.00]	[-0.17]	[-0.46]	[-0.87]	[-0.48]
f2	0.01*	0.02	0.02	0.03	0.03	0.02	-0.04	0.02
	(1.75)	(1.58)	(1.40)	(1.31)	(1.18)	(0.49)	(-0.64)	(0.85)
	[-0.42]	[-0.33]	[-0.15]	[0.07]	[0.33]	[0.37]	[-0.04]	[0.24]
f3	0.01	0.01	0.01	0.01	0.01	-0.01	-0.08*	0.00
	(1.50)	(1.31)	(1.10)	(0.98)	(0.81)	(-0.32)	(-1.81)	(0.14)
	[-1.23]	[-0.97]	[-0.60]	[-0.38]	[-0.28]	[-0.84]	[-1.82]	[-0.99]
f4	0.01***	0.02**	0.02	0.02	0.03	0.06	0.04	0.03
	(2.74)	(2.07)	(1.32)	(1.10)	(1.19)	(1.37)	(0.52)	(1.39)
	[-1.74]	[-1.84]	[-1.81]	[-1.59]	[-1.25]	[-1.26]	[-1.75]	[-1.48]
f5	0.00	-0.01	-0.02	-0.03*	-0.05*	-0.08*	-0.06	-0.04*
	(0.09)	(-0.60)	(-1.30)	(-1.66)	(-1.96)	(-1.71)	(-0.95)	(-1.71)
	[0.16]	[0.12]	[-0.02]	[-0.18]	[-0.31]	[-0.01]	[0.10]	[-0.03]
f6	0.02***	0.03***	0.03**	0.03*	0.03	-0.01	-0.07	0.01
	(4.14)	(3.40)	(2.44)	(1.75)	(1.00)	(-0.25)	(-0.99)	(0.61)
	[1.77]	[1.22]	[0.64]	[0.26]	[-0.11]	[-0.56]	[-0.66]	[-0.45]
f7	0.01***	0.02***	0.03**	0.03*	0.03	0.01	0.03	0.02
	(2.72)	(2.61)	(2.31)	(1.93)	(1.30)	(0.27)	(0.60)	(1.20)
	[1.46]	[1.57]	[1.94]	[2.09]	[1.91]	[1.03]	[0.81]	[1.18]
f8	0.00	0.01	0.01	0.03	0.06**	0.19***	0.30***	0.07***
	(0.67)	(0.54)	(0.79)	(1.29)	(2.12)	(3.66)	(3.54)	(2.92)
	[0.09]	[-0.09]	[-0.06]	[0.07]	[0.19]	[-0.08]	[-0.52]	[-0.15]
N	357	357	357	357	357	357	357	357
R^2	0.44	0.40	0.35	0.32	0.28	0.22	0.22	0.26

Panel B: Ludvigson and Ng (2009) factors, yield curve PCs

$FE10Y_t$	-0.24**	-0.58***	-1.55***	-2.62***	-4.02***	-7.15***	-10.30***	-3.36***
	(-2.40)	(-2.85)	(-3.69)	(-4.08)	(-4.24)	(-4.33)	(-4.41)	(-4.41)
	[1.03]	[0.81]	[0.76]	[0.99]	[1.41]	[1.92]	[1.56]	[1.76]
f1	0.01***	0.03***	0.04***	0.03***	0.02*	-0.00	-0.00	0.02
	(5.79)	(5.76)	(4.84)	(3.48)	(1.73)	(-0.05)	(-0.04)	(1.53)
	[1.14]	[0.47]	[-0.26]	[-0.51]	[-0.55]	[-0.66]	[-0.94]	[-0.71]
f2	-0.02***	-0.03***	-0.04**	-0.04	-0.03	-0.00	-0.00	-0.02
	(-2.71)	(-2.76)	(-2.20)	(-1.62)	(-0.94)	(-0.00)	(-0.02)	(-0.82)
	[-0.80]	[-0.96]	[-1.08]	[-1.04]	[-0.90]	[-0.83]	[-0.98]	[-0.92]
f3	-0.01***	-0.02***	-0.03**	-0.03*	-0.03	-0.02	-0.05	-0.02
	(-2.83)	(-2.92)	(-2.39)	(-1.85)	(-1.22)	(-0.53)	(-0.83)	(-1.29)
	[-1.33]	[-1.32]	[-1.19]	[-1.06]	[-0.97]	[-1.65]	[-2.48]	[-1.78]
f4	0.01**	0.01	0.01	0.00	0.01	0.03	0.00	0.01
	(2.16)	(1.34)	(0.42)	(0.16)	(0.25)	(0.61)	(0.01)	(0.50)
	[-2.32]	[-2.38]	[-2.29]	[-2.03]	[-1.65]	[-1.69]	[-2.31]	[-1.95]
f5	-0.01***	-0.03***	-0.05***	-0.06***	-0.08***	-0.10*	-0.06	-0.06**
	(-2.66)	(-3.14)	(-3.21)	(-3.09)	(-2.83)	(-1.80)	(-0.81)	(-2.44)
	[-0.33]	[-0.54]	[-0.80]	[-0.95]	[-0.98]	[-0.42]	[-0.02]	[-0.45]
f6	0.02***	0.04***	0.05***	0.04*	0.03	-0.05	-0.15*	0.01
	(5.12)	(4.35)	(2.88)	(1.83)	(0.82)	(-0.79)	(-1.78)	(0.37)
	[0.51]	[0.28]	[0.02]	[-0.11]	[-0.19]	[-0.38]	[-0.61]	[-0.40]
f7	0.00	0.00	0.01	0.01	0.00	-0.01	0.03	0.00
	(0.48)	(0.50)	(0.57)	(0.45)	(0.07)	(-0.29)	(0.48)	(0.08)
	[0.62]	[0.66]	[0.96]	[1.14]	[1.08]	[0.41]	[0.23]	[0.49]
f8	0.01**	0.02**	0.03*	0.04**	0.07**	0.18***	0.27***	0.08***
	(2.25)	(2.03)	(1.96)	(2.14)	(2.54)	(3.30)	(3.05)	(3.13)
	[-0.09]	[-0.15]	[0.03]	[0.25]	[0.48]	[0.32]	[-0.18]	[0.21]
PCs	✓	✓	✓	✓	✓	✓	✓	✓
N	357	357	357	357	357	357	357	357
R^2	0.61	0.55	0.47	0.41	0.35	0.25	0.24	0.31

Table A.14 Comparing the return predictive power of realize forecast errors $FE10Y$ with related measures

This table reports the results that contrast the return predictive power of realize forecast errors $FE10Y$ with related measures. The dependent variable is the average one-year holding period excess return $\overline{rx}$. Panel A adds another related measure in each regression. Panel B uses the error from projecting $FE10Y$ onto another related measure as return predictor. First three yield curve principal components (PC) are included in each regression. T-stats based on Newey and West (1987) standard errors with 12 lags are reported in the parentheses. The data are monthly and cover the period 1988 to 2018. Results for PCs and intercept are omitted.

$Z_t =$	$\widehat{FE}10Y$	$\Delta y_t^{(10)}$	$y_t^{(10)} - E_t^S(y_{t+1}^{(10)})$
	(1)	(2)	(3)
Panel A: $\overline{rx}_{t+1} = a + bFE10Y_t + cZ_t + \gamma \cdot \Gamma_t + \varepsilon_{t+1}$			
b	5.23***	3.68***	3.99***
	(5.28)	(4.00)	(5.94)
c	-2.37**	0.11	-1.69
	(-2.07)	(0.13)	(-1.24)
R^2	0.44	0.42	0.43
Panel B: $\overline{rx}_{t+1} = a + bFE10Y_t \vert Z_t + \gamma \cdot \Gamma_t + \varepsilon_{t+1}$			
b	5.23***	2.98***	3.86***
	(4.74)	(2.94)	(5.70)
R^2	0.39	0.28	0.42
N	348	348	348

Table A.15 Summary statistics of survey and futures-based forecast errors and forecast revisions of the Federal Funds Rate

This table reports the summary statistics of survey-based (denoted with superscript "S") and futures-based (denoted with superscript "FUT") forecast errors and forecast revisions. The last column reports the correlation between survey-based and futures-based measures. The results are pooled across forecast horizons h. The underlying variable is the Federal Funds Rate. The data are quarterly and cover the period 2002 to 2018.

	Count	Mean	SD	Min	p25	p50	p75	Max	$corr(FUT, S)$
Federal funds rate									
FR^S	249	-0.15	0.38	-1.94	-0.21	-0.035	0.017	0.33	
FR^{FUT}	249	-0.24	1.03	-5.59	-0.22	-0.035	0.095	1.64	0.41
FE^S	249	-0.22	0.69	-3.85	-0.29	-0.064	0.075	0.86	
FE^{FUT}	249	-0.26	0.95	-5.59	-0.17	-0.034	0.052	1.23	0.64

Table A.16 Subjective beliefs and banks' Treasury portfolio allocation: Regression by maturity

This table reports results from regressing banks' Treasury allocations on survey forecasts at the monthly frequency.

$$\text{Treasury}(n)_{i,t} = \alpha_i + \beta \mathbb{E}^S_{i,t}(y^{(n)}_{t+h}) + \gamma X_{i,t} + \varepsilon_{i,t}$$

The dependent variables are bank i's dollar allocations to U.S. Treasury with maturities of 1-3 years, 3-5 years, 5-15 years and over 15 years. The independent variables are bank i's yield forecasts with closest maturities. Monthly forecasts within each quarter are matched with quarter-end allocations. Panel A fixes the forecast horizon to 4 quarters, and Panel B pools across forecast horizons. Standard errors are clustered by firm and month. *, ** and *** indicate statistical significance at 10, 5, and 1% levels respectively.

	Dependent variable:			
	Treasury$(1-3Y)$	Treasury$(3-5Y)$	Treasury$(5-15Y)$	Treasury$(>15Y)$
	(1)	(2)	(3)	(4)
Panel A: $h = 4Q$				
$tn2y$	-0.40**			
	(0.18)			
$tn5y$		-0.50*		
		(0.30)		
$tn10y$			-1.31**	
			(0.64)	
$tn30y$				-1.21
				(0.78)
Firm FE	✓	✓	✓	✓
N	2,581	2,570	2,583	2,371
R^2	0.61	0.52	0.57	0.64
Panel B: $h = 1, 2, 3, 4Q$				
$tn2y$	-0.77*			
	(0.46)			
$tn5y$		-0.67**		
		(0.33)		
$tn10y$			-2.27*	
			(1.17)	
$tn30y$				-1.99*
				(1.05)
Firm FE	✓	✓	✓	✓
N	13,342	13,290	13,365	12,289
R^2	0.48	0.55	0.57	0.57

Table A.17 Subjective beliefs and portfolio allocation: Regression by asset class

This table reports results from regressing banks' asset allocations on survey forecasts at the monthly frequency.

$$\text{Allocation}(5-15Y)_{i,t} = \alpha_i + \beta \mathbb{E}^S_{i,t}(y^{(10)}_{t+h}) + \gamma X_{i,t} + \varepsilon_{i,t}$$

The dependent variables are bank i's dollar allocations to U.S. Treasury, total assets, total securities, and RMBS with maturities 5-15 years. The independent variable is bank i's 10-year Treasury yield forecasts $tn10y$. Monthly forecasts within each quarter are matched with quarter-end allocations. Panel A fixes the forecast horizon to 4 quarters, and Panel B pools across forecast horizons. Standard errors are clustered by firm and month. *, ** and *** indicate statistical significance at 10, 5, and 1% levels respectively.

	Dependent variable:			
	Treasury$(5-15Y)$	Assets$(5-15Y)$	Securities$(5-15Y)$	RMBS$(5-15Y)$
	(1)	(2)	(3)	(4)
Panel A: $h = 4Q$				
$tn10y$	-1.31**	-6.87*	-2.15**	-0.84**
	(0.64)	(3.84)	(0.98)	(0.37)
Firm FE	✓	✓	✓	✓
N	2,583	4,734	2,583	2,583
R^2	0.57	0.60	0.59	0.41
Panel B: $h = 1, 2, 3, 4Q$				
$tn10y$	-2.27*	-7.59**	-3.30**	-1.04**
	(1.17)	(3.59)	(1.55)	(0.41)
Firm FE	✓	✓	✓	✓
N	13,365	22,570	13,365	13,365
R^2	0.57	0.65	0.60	0.42

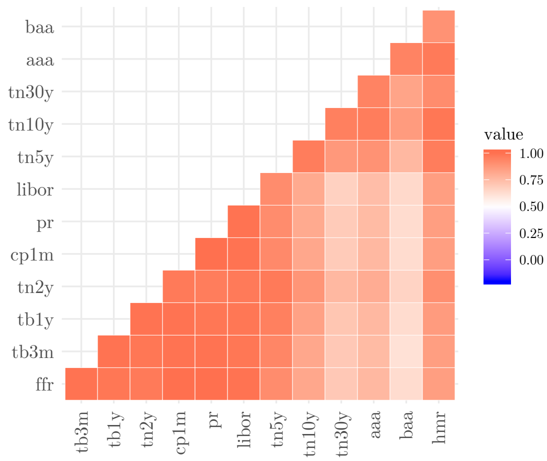
US Quarterly Forecasts
October 2019

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

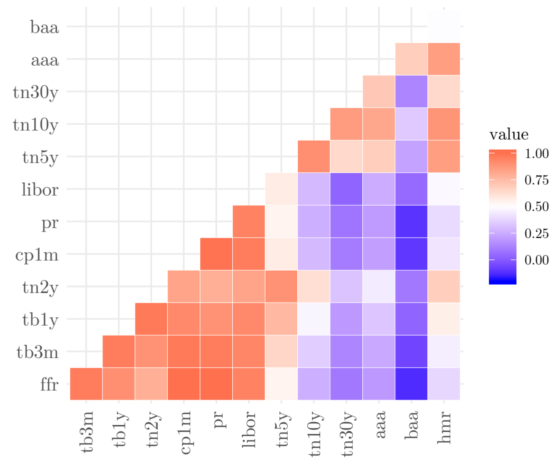
[1] Federal Funds Rate: Charged on loans of uncommitted reserve funds among banks; Federal Reserve Statistical Release (FRSR) H.15
[2] Prime Rate: One of several base rates used by banks to price short term business loans; FRSR H.15.
[3] London Interbank Offered Rate (LIBOR): The interbank offered rate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

Figure A.1 Blue Chip Financial Forecasts sample survey questionnaire

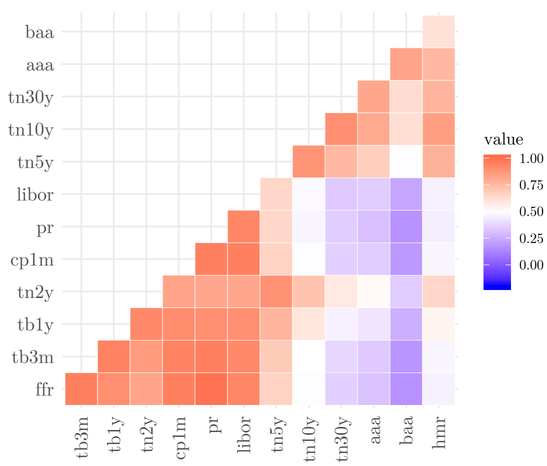
This figure presents a screenshot of the latest iteration of Blue Chip Financial Forecasts survey questionnaire. The definition of each target variable is specified in the footnote.



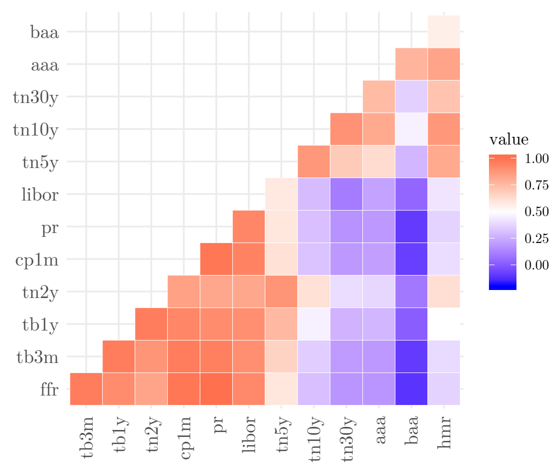
A. Realized Interest Rates



B. One-year Realized Changes



C. Forecast Revisions



D. Forecast Errors

Figure A.2 Cross-sectional correlations between short- and long-maturity interest rates

This figure shows the cross-sectional correlations between short and long-maturity interest rates along the following four dimensions: realized interest rates (Panel A), one-year realized changes (Panel B), individual forecast revisions (Panel C), and individual forecast errors (Panel D). All correlations are calculated using quarterly observations. Red color indicates correlation > 0.5 and blue color indicates correlation < 0.5.

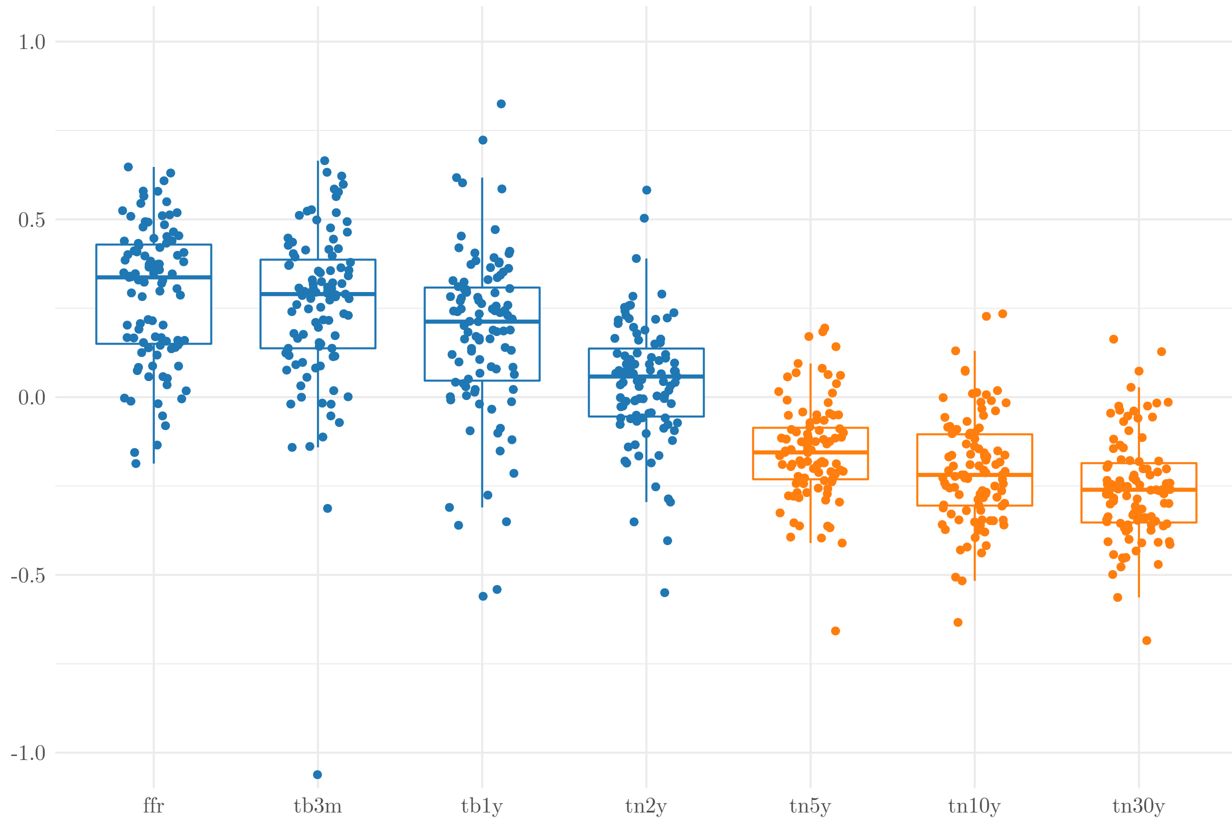


Figure A.3 Forecast error on forecast revision regression coefficients of short- and long-maturity interest rates: Forecaster-by-forecaster regression results

This figure plots the coefficients from the forecast error on forecast revision regression of Coibion and Gorodnichenko (2015) for each interest rate and for each individual forecaster

$$FE_{i,t}\left(x_{t+h}\right) = \alpha_i + \beta FR_{i,t}\left(x_{t+h}\right) + \epsilon_{i,t,h},$$

where the forecasts are pooled across horizon h and the standard errors are calculated following Driscoll and Kraay (1998). The underlying variables are the Federal Funds Rate (ffr), and the Treasury bill, note and bond yields with maturities of 3-month, 1-, 2-, 5-, 10- and 30-years ($tb3m$, $tb1y$, $tn2y$, $tn5y$, $tn10y$ and $tn30y$). The data are quarterly and cover the period 1988 to 2018. The range of each whisker depicts the 95% confidence interval.

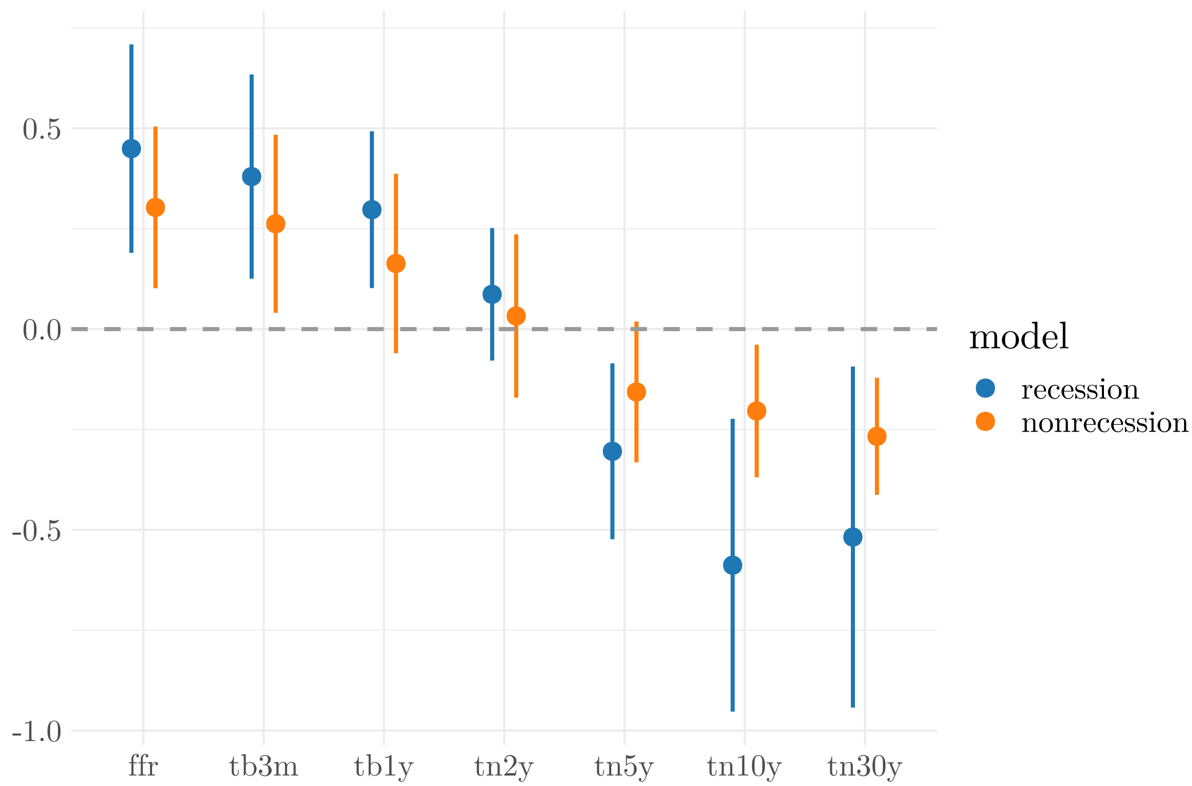
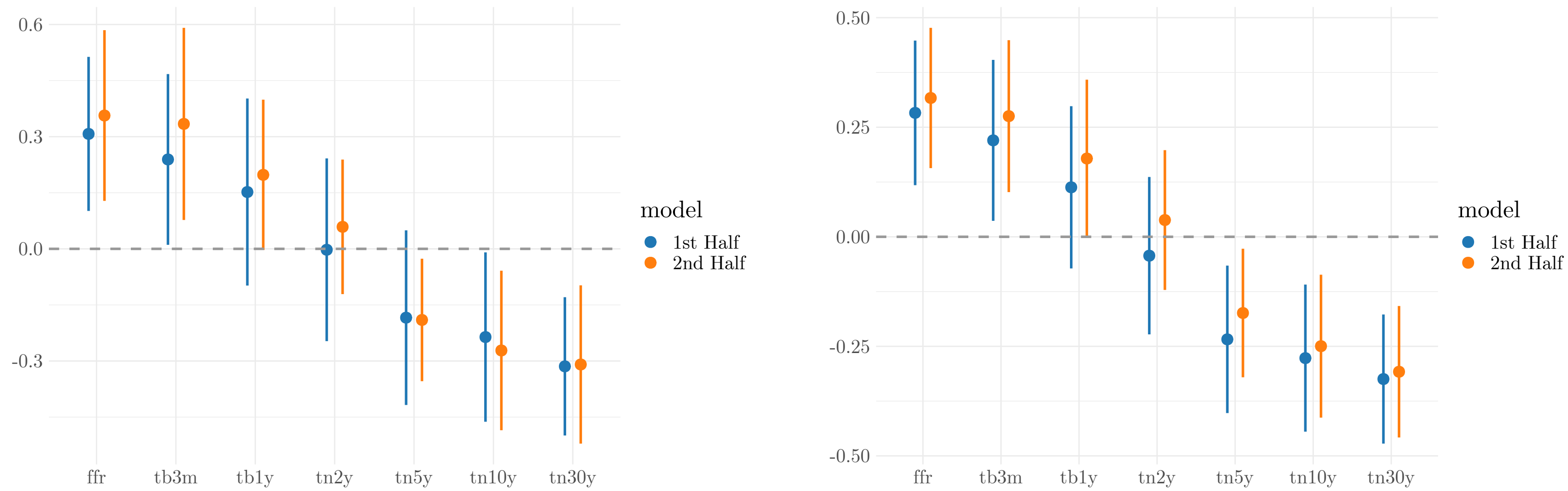


Figure A.4 Forecast error on forecast revision regression coefficients of short- and long-maturity interest rates: Recession vs. non-recession at the individual level

This figure plots the coefficients from the forecast error on forecast revision regression of Coibion and Gorodnichenko (2015) for each interest rate using individual-level forecasts

$$FE_{i,t}\left(x_{t+h}\right) = \alpha_i + \beta FR_{i,t}\left(x_{t+h}\right) + \epsilon_{i,t,h},$$

where the forecasts are pooled across horizon h, the standard errors are clustered by both forecaster and time, and forecaster fixed effects are included. The regressions are estimated separately for recession and non-recession periods. The blue dots represent coefficients from recession-period regressions and the orange dots represent coefficients from non-recession-period regressions. The underlying variables are the Federal Funds Rate (ffr), and the Treasury bill, note and bond yields with maturities of 3-month, 1-, 2-, 5-, 10- and 30-years ($tb3m$, $tb1y$, $tn2y$, $tn5y$, $tn10y$ and $tn30y$). The data are quarterly and cover the period 1988 to 2018. The range of each whisker depicts the 95% confidence interval.



A. Split at 2003

B. Split each forecaster's sample in half

Figure A.5 Forecast error on forecast revision regression coefficients of short- and long-maturity interest rates: Subsample results at the individual level

This figure plots the coefficients from the forecast error on forecast revision regression of Coibion and Gorodnichenko (2015) for each interest rate using individual-level forecasts

$$FE_{i,t}\left(x_{t+h}\right) = \alpha_i + \beta FR_{i,t}\left(x_{t+h}\right) + \epsilon_{i,t,h},$$

where the forecasts are pooled across horizon h, the standard errors are clustered by both forecaster and time, and forecaster fixed effects are included. The regressions are estimated separately for subsamples. In Panel A, I split the entire sample at the midpoint of the date range (end of 2003). In Panel B, I split each forecaster's sample in half. In both panels, the blue dots represent coefficients from first half of the sample and the orange dots represent coefficients from second half of the sample. The underlying variables are the Federal Funds Rate (ffr), and the Treasury bill, note and bond yields with maturities of 3-month, 1-, 2-, 5-, 10- and 30-years ($tb3m$, $tb1y$, $tn2y$, $tn5y$, $tn10y$ and $tn30y$). The data are quarterly and cover the period 1988 to 2018. The range of each whisker depicts the 95% confidence interval.

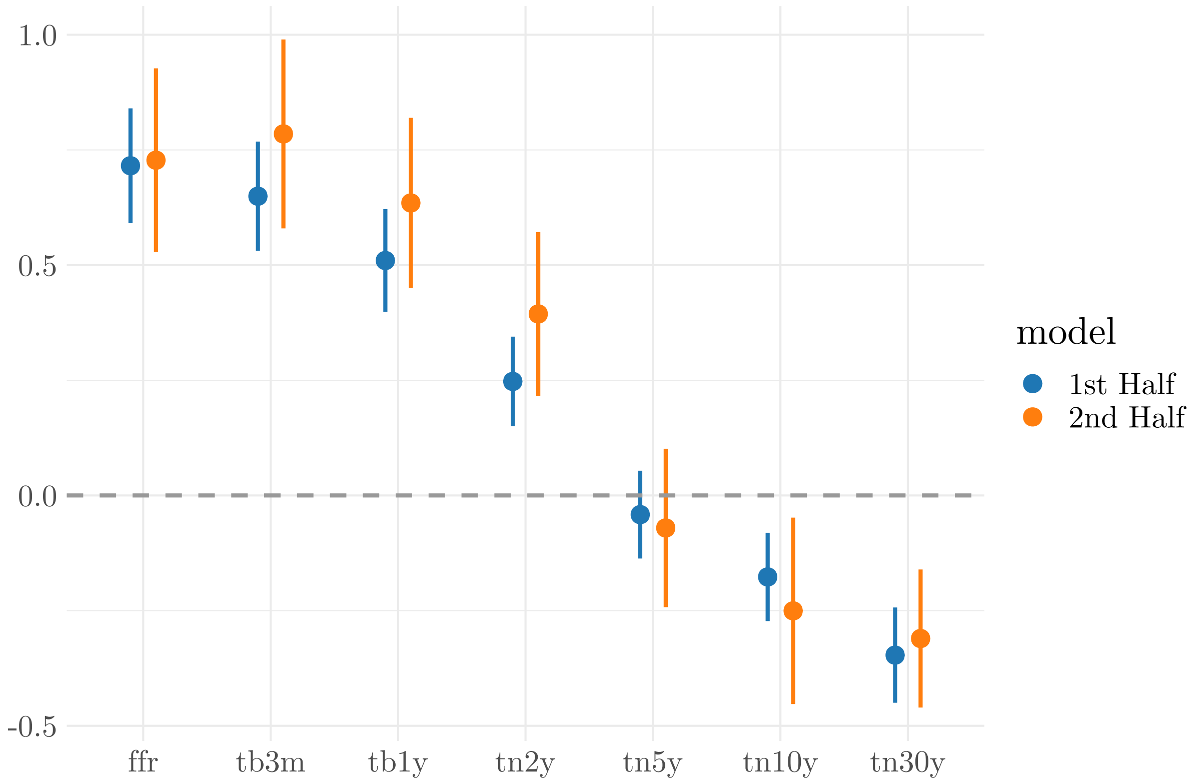


Figure A.6 Forecast error on forecast revision regression coefficients of short- and long-maturity interest rates: Recession vs. non-recession at the consensus level

This figure plots the coefficients from the forecast error on forecast revision regression of Coibion and Gorodnichenko (2015) for each interest rate using consensus-level forecasts

$$FE_t\left(x_{t+h}\right) = \alpha_i + \beta FR_t\left(x_{t+h}\right) + \epsilon_{t,h},$$

where the forecasts are pooled across horizon h, the standard errors are calculated following Driscoll and Kraay (1998). The regressions are estimated separately for subsamples split at the midpoint of the date range (end of 2003). The blue dots represent coefficients from first half of the sample and the orange dots represent coefficients from second half of the sample. The underlying variables are the Federal Funds Rate (ffr), and the Treasury bill, note and bond yields with maturities of 3-month, 1-, 2-, 5-, 10- and 30-years ($tb3m$, $tb1y$, $tn2y$, $tn5y$, $tn10y$ and $tn30y$). The data are quarterly and cover the period 1988 to 2018. The range of each whisker depicts the 95% confidence interval.

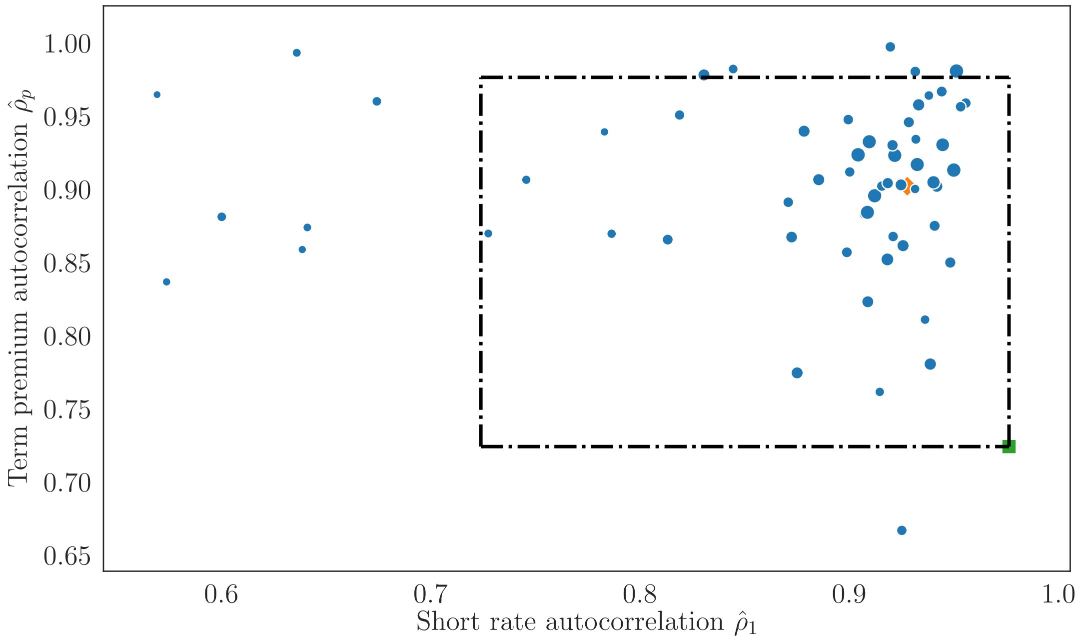


Figure A.7 Forecaster-level median autocorrelation estimates of the short rate and two-year term premium

This figure plots the median autocorrelation estimates of the short rate and two-year term premium. It includes both subjective and actual autocorrelation estimates. Each blue circle represents a forecaster's median subjective autocorrelation estimates of short rate ρ_1^s and term premium ρ_p^s. The size of the circle corresponds to the number of this forecaster's valid autocorrelation estimates. The orange diamond represents the median subjective autocorrelation estimates for the consensus forecasts. The green square at the bottom-right corner represents the median actual autocorrelation estimates of short rate ρ_1 and term premium ρ_p. "Autocorrelation averaging" implies that all subjective autocorrelations should be within the dashed box (i.e., $\rho_p < \rho_1^s, \rho_p^s < \rho_1$). The details of the estimation are in Section 4.3.

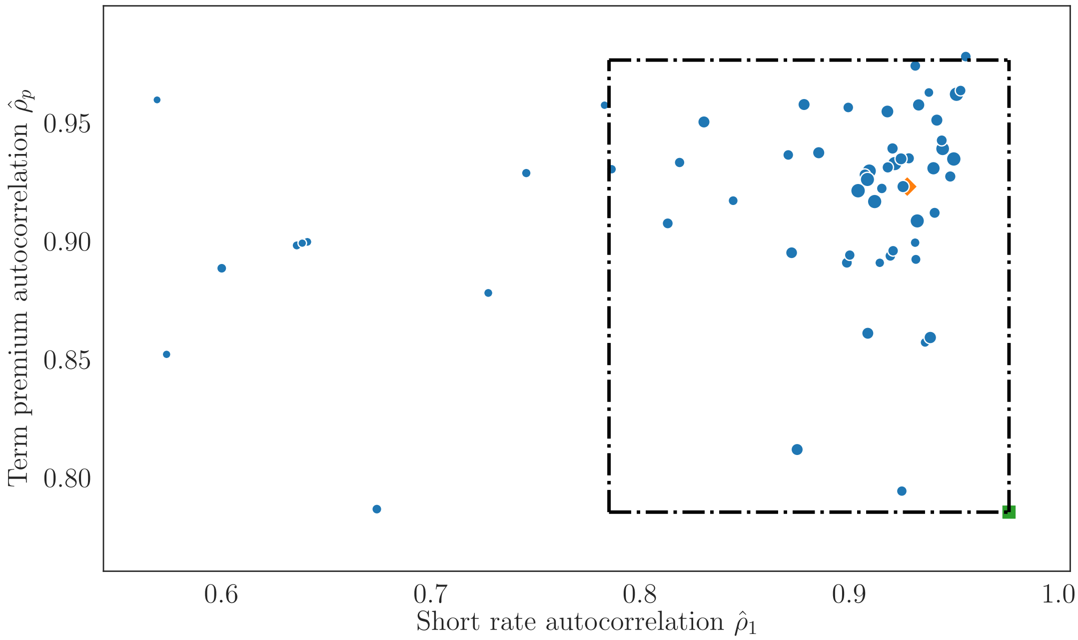


Figure A.8 Forecaster-level median autocorrelation estimates of the short rate and five-year term premium

This figure plots the median autocorrelation estimates of the short rate and five-year term premium. It includes both subjective and actual autocorrelation estimates. Each blue circle represents a forecaster's median subjective autocorrelation estimates of short rate ρ_1^s and term premium ρ_p^s. The size of the circle corresponds to the number of this forecaster's valid autocorrelation estimates. The orange diamond represents the median subjective autocorrelation estimates for the consensus forecasts. The green square at the bottom-right corner represents the median actual autocorrelation estimates of short rate ρ_1 and term premium ρ_p. "Autocorrelation averaging" implies that all subjective autocorrelations should be within the dashed box (i.e., $\rho_p < \rho_1^s, \rho_p^s < \rho_1$). The details of the estimation are in Section 4.3.

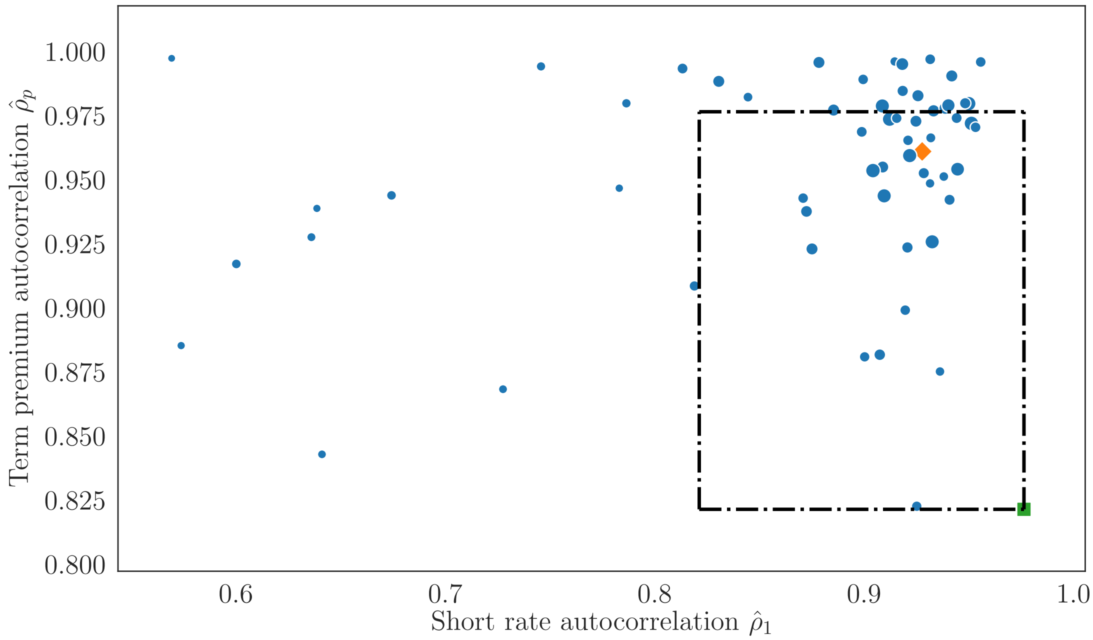


Figure A.9 Forecaster-level median autocorrelation estimates of the short rate and 30-year term premium

This figure plots the median autocorrelation estimates of the short rate and 30-year term premium. It includes both subjective and actual autocorrelation estimates. Each blue circle represents a forecaster's median subjective autocorrelation estimates of short rate ρ_1^s and term premium ρ_p^s. The size of the circle corresponds to the number of this forecaster's valid autocorrelation estimates. The orange diamond represents the median subjective autocorrelation estimates for the consensus forecasts. The green square at the bottom-right corner represents the median actual autocorrelation estimates of short rate ρ_1 and term premium ρ_p. "Autocorrelation averaging" implies that all subjective autocorrelations should be within the dashed box (i.e., $\rho_p < \rho_1^s, \rho_p^s < \rho_1$). The details of the estimation are in Section 4.3.