Expected Term Structures

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Abstract

This paper studies the properties of bond risk premia in the cross-section of subjective expectations. We exploit an extensive dataset of yield curve forecasts from financial institutions and document a number of novel findings. First, contrary to evidence presented for stock markets but consistent with rational expectations, the relation between subjective expectations and future realizations is positive, and this result holds for the entire cross-section of beliefs. Second, when predicting short term interest rates, primary dealers display superior forecasting ability when compared to non-primary dealers. Third, we reject the null hypothesis that subjective expected bond returns are constant. When predicting long term rates, however, primary dealers have no information advantage. This suggests that a key source of variation in long-term bonds are risk premia and not short-term rate variation. Fourth, we show that consensus beliefs are not a sufficient statistics to describe the cross-section of beliefs. Moreover, the beliefs of the most accurate agents are those most spanned by a contemporaneous cross-section of bond prices. This supports equilibrium models and Friedman's market selection hypothesis. Finally, we use ex-ante spanned subjective beliefs to evaluate several reduced-form and structural models. We find support for heterogeneous beliefs models and also uncover a number of statistically significant relationships in favour of alternative rational expectations models once the effect of heterogeneous beliefs is taken into account.

Keywords: Rational Expectations, Cross-Section of Beliefs, Bond Risk Premia, Spanning, Expectation Formation.

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I. Introduction

A large asset pricing literature finds compelling evidence of predictability in several asset markets. A stream of the literature interprets this result as evidence of a time-varying risk premium that can be understood in the context of rational general equilibrium models. A second stream of the literature, on the other hand, argues that several characteristics of this predictability are more likely due to the existence of behavioral biases affecting the dynamics of subjective beliefs, informational frictions, or both. In this paper, we use a detailed data set of investors' forecasts about future interest rates to obtain a direct measure of subjective expectations on long-term bond returns and short-term interest rates. We use their time-series and cross-sectional features to study the properties of bond risk premia as revealed by agents, as opposed to infer bond risk premia from projections of future return realizations on lagged state variables.

The existing literature that uses macroeconomic survey expectations argues that survey data indeed contain useful information about future GDP and inflation.[1] However, Greenwood and Schleifer (2014) report that forecasts about tradeable market variables, such as stock returns, not only are inaccurate but they are even negatively correlated with future actual realizations. Koijen, Schmeling, and Vrugt (2015) find similar results in the context of global equities, currencies and fixed income markets across different countries. Both these studies argue that this result is difficult to reconcile with rational expectation models. In contrast, we focus on a dataset that provides us with the forecasters identity. This unique feature allows us to examine several new questions that cannot be addressed when data are available only at the aggregate level. We show that the use of consensus expectations to proxy for the expectations of the marginal investor is misleading and does not reveal important properties. Moreover, we focus on bond markets to explore the time dimension of predictability (short-term versus long-term yields). This allows us to study the potential source (if any) of bond return predictability, which could originate either from short-term interest rate predictability or time-variation in bond risk premia, and alternative models of formation of expectations.[2]

We begin by constructing measures of subjective bond risk premia (EBR) from professional market participants' expectations regarding future yields. Specifically, we use Treasury coupon bond yield forecasts at the agent specific level to obtain a set of constant maturity 1-year zero-coupon bond yield expectations. Individual agent expected excess bond returns (EBRs) are then obtained by subtracting the date t observable risk free rate from expected price changes. With these measures at hand we document a number of novel findings.

First, we document a large unconditional heterogeneity in the cross-section of EBR point

[1] See e.g. Ang, Bekaert, and Wei (2007) and Aioli, Capistran, and Timmermann (2011).

[2] Other studies that investigate the dynamics of private sector expectations about interest rates and the corresponding forecast errors include Cieslak and Povala (2012) for fed fund rate forecasts and Piazzesi, Salomao, and Schneider (2015) for bond risk premia.

forecasts. The median (Q2) forecaster EBRs is 1.06% for 10-year bonds. However, the median of the first quartile (Q1) EBR is -1.66%, which implies that these agents believe long-term bonds are hedges against economic shocks (growth and inflation) while the median of the third quartile (Q3) is $+3.57\%$, which is consistent instead with beliefs of long-term bonds being risky bets on future economic states. We also find clear evidence of persistence in agents expected bond risk premia. For example, a forecaster in the first quartile of the cross-sectional distribution of 2-year EBR has a probability of about 75% to stay in the first quartile the following month, and this probability is about 74% for the 10-year EBR. This is about three times what it should be under the null hypothesis of no persistence. Finally, we find evidence against the null hypothesis that the cross-sectional properties of expectations can be summarized by the consensus value. This raises important questions about the common assumption of identifying the marginal investor with the agent with average (consensus) expectations. Notwithstanding the previous heterogeneity, overall expectations about bond returns display significant elements of rationality. They are positively related to future bond returns and are consistent - at the individual level - with same agents' forecasts about GDP and inflation.

Second, we find evidence of predictability in short-term interest rates and the accuracy of the best forecasters is persistent over time. When we examine in detail predictions conditioning on the identity of the forecaster, we find that banks and broker-dealer that act as primary dealers and trade directly with the Federal Reserve System are more likely to be between the top forecasters of the short-term interest rate.[3] The superior forecasting ability of primary dealers is not only statistically but also economically significant. We simulate a fictitious trading account of primary dealers if they were trading against non-primary dealers institutions on the basis of their ex-ante forecasts using a simple duration based trading strategy. We find that primary dealers would have been able to persistently accumulate significant profits. We also find that the greatest relative accuracy (profit opportunity) occurs during periods in which the Fed changes its stance and aggressively reduces short-term rates. While this takes by surprise all agents, whose expected excess bond returns are downward biased in these subperiods,[4] the bias is smaller for primary dealers. This is consistent either with primary dealers having superior information about Fed's implementation of monetary policy or, more simply, with an information flow advantage originating from their role as market makers in Treasury bonds. The result is quite important given that the top 5 primary dealers hold about 50% of all Treasuries.[5]

Third, we study the properties of long-term expected bond risk premia and strongly reject

[3]Primary dealers are trading counterparties of the New York Fed in its implementation of monetary policy. They are also expected to make markets for the New York Fed on behalf of its official accountholders as needed, and to bid on a pro-rata basis in all Treasury auctions at reasonably competitive prices.

[4]This is consistent with the findings in Cieslak and Povala (2012) who analyze survey forecast expectations of the fed fund rate and show that the largest errors are negative and occur during and after NBER recessions.

[5]Statistics are available in the Primary Dealers section of the New York Fed website: www.newyorkfed.org/markets/primarydealers.

the hypothesis that bond risk premia are constant. We find that expected bond excess returns are time varying across all deciles of the cross-sectional distribution of forecasters. However, agents who have an edge in forecasting short term rates do not have a persistent edge in predicting long term bond returns. Banks that act as primary dealers are not better than others in forecasting long-term bonds returns. This is interesting since it shows that the main determinant of long-term bond returns predictability is not the predictability of short-term interest rates. Rather, the results suggest the importance of time variation in bond risk premia. In the context of these results, we also find that the slope coefficient of predictive regressions of bond excess returns on their ex-ante subjective expectations is always positive, contrary to what Greenwood and Schleifer (2014) document in the context of the stock market.[6] This suggests that subjective expectations are much less irrational than previously thought.

An important set of questions relates to the properties of the marginal agent who sets bond prices in equilibrium. While a working hypothesis of several models is that the representative agent holds consensus beliefs, the heterogeneous beliefs literature with short-selling constraints argue that the representative agent has to be an optimist in terms of expected returns (Hong, Sraer, and Yu (2013)). If pessimists cannot sell short, bond prices should reflect the beliefs of optimists. Another set of models, finally, argue that an intrinsic property of competitive markets is market selection (see, e.g., Friedman (1953) and Alchian (1950)). Trading markets eventually punish irrationality and those agents that are consistently more accurate than others accumulate more economic weight in the pricing kernel. Thus, their beliefs, rather than the consensus ones, should be the one more tightly revealed (spanned) by bond prices. We use our rich panel dataset on beliefs to address this question by testing which beliefs are spanned by contemporaneous bond prices. We find that the beliefs of the most accurate agents are on average better spanned by current bond prices. For example, for the 10-year bond, regressions of EBR for portfolios of agents ranked on the basis of past accuracy on the principal components of the yield curve produce an R-squared of around 52% for the most accurate portfolio of agents and only 23% for the least accurate one. This result is consistent with the market selection hypothesis in competitive markets. Indeed, while optimists are on average more accurate in our sample and more spanned, the spanning result is reversed when the pessimists are most accurate. Thus, this result is not supportive of models with short selling constraints (as in Hong, Sraer, and Yu (2013)).

Fourth, an extensive literature in bond markets uses the properties of bond risk premia to propose economic models that are consistent with the data. The empirical evaluation of

[6]Koijen, Schmeling, and Vrugt (2015) also find that survey expectations of returns negatively predict future returns in the time series in three major asset classes: global equities, currencies, and global fixed income. However, instead of looking at the slope coefficient of predictive regressions, they show this by building a survey-based portfolio strategy. The strategy goes a dollar long or short in country i in month t when the consensus forecast is above or below a certain threshold, which is set to be equal to the middle value World Economic Survey respondents can select.

these models often accepts as approximations to agents expectations econometric projections of future realized returns on lagged state variables. We revisit this approach and instead of using methodologies based on econometric projections, we use subjective expectations as directly revealed in real time by agents to learn the merits of alternative economic models. We find that the out-of-sample performance of the survey-implied bond risk premia are highly competitive in forecasting future realized excess returns relative to some popular reduced form models. Indeed, in some cases subjective bond risk premia significantly outperform projections implied by either Cochrane and Piazzesi (2005) or Ludvigson and Ng (2009) forecasting factors, for all bond maturities. These findings suggests that surveys can indeed be used to build reliable measures of bond risk premia, thus avoiding the forward looking bias which often affects traditional predicting regressions methods. However, instead of the consensus, a better measure of subjective expectation should build on the beliefs of the most spanned agent. Therefore, we use the spanned measure of EBR to evaluate a series of structural and reduced-form models, in conjunction with belief heterogeneity.

We show that both disagreement and sentiment matter for EBR. For a given level of disagreement, negative sentiment increases the price of risk but reduces the quantity of risk. Empirically, the net effect is hump-shaped in sentiment and dominated by the quantity of risk channel. For very negative values of sentiment and low disagreement the fitted value of EBR switches sign and can become negative. At the same time, as predicted by heterogeneous models when bonds are risky assets, negative sentiment amplifies the marginal impact of disagreement. The interaction between disagreement and sentiment is negative so that in periods with negative sentiment (aggregate relative pessimism), positive shocks to disagreement further increase expected bond risk premia. The opposite is true in periods when sentiment is positive. Moreover, we document that the start of recession periods is often characterized by larger values of disagreement and negative sentiment. This is consistent with large positive bond risk premia in these states of the world.

Finally, taking the effects of heterogeneity into account, we find supporting evidence for rational expectation explanations of expected bond returns using a set of risk factor signals. In most cases, the empirical sign of the factor loading is consistent with predictions from theory. This result stands in contrast to the findings of Greenwood and Schleifer (2014) in the context of equity markets and suggests that rational expectation models cannot be dismissed so easily.

The paper proceeds as follows. Section II summarizes the empirical questions we aim to address and presents the data. Section III discusses the empirical properties of subjective expected term structures. In Section IV we study the forecasting properties of expected short-term interest rates. Section V discusses the dynamics of the expected bond excess returns (EBR), the predicting power of EBR for future realized excess returns and the cross-sectional variations in the forecast accuracy. Section VI analyzes the link between EBR and statistical and structural models of expected bond risk premia proposed in the literature. Section VII discusses the results and concludes.

II. Framework, Questions and Data

Given information on individual expectations about future interest rates, we compute individual subjective risk premia as follows. Let p_t^n be the logarithm of the time-t price of a risk-free zero-coupon bond that pays one unit of the numeraire n-years in the future. Spot yields and forward rates are then defined as $y_t^n = -\frac{p_t^n}{n}$ and $f_t^n = p_t^n - p_t^{n-1}$, respectively. The realized holding period bond return in excess of the one year yield is $rx_{t+1}^n = r_{t+1}^n - y_t^1$, with the gross return being defined as $r_{t+1}^n = p_{t+1}^{n-1} - p_t^n$.

The individual expected bond excess return (EBR) of agent i at one-year horizon for a bond maturity n is defined as $erx_{i,t}^n \equiv E_t^i\left[rx_{t+1}^n\right]$. Using survey forecasts on $E_t^i\left[y_{t+1}^{n-1}\right]$ we can compute the implied cross-section of EBR as $erx_{i,t}^n = E_t^i\left[p_{t+1}^{n-1}\right] - p_t^n - y_t^1$. Indeed, from the surveys we directly observe $E_t^i\left[y_{t+1}^{n-1}\right]$, so that:

$$erx_{i,t}^n = -(n-1) \times \underbrace{E_t^i\left[y_{t+1}^{n-1}\right]}_{\substack{\text{Survey Yield} \\ \text{Forecasts}}} + ny_t^n - y_t^1. \tag{1}$$

Forecasts on future long-term interest rates depend on both expectations on future short-term interest rates $E_t^i\left[y_{t+s}^1\right]$ and future bond risk premia $erx_{i,t}^n$. We use a panel data of named forecasts on both short-term and long-term yields to address a number of questions that have been of great relevance in the financial economics literature, which we formalize in the following four main questions.

First, a common assumption in the literature is the existence of a representative agent with rational expectations. While agents' expectations may be wrong, this assumption implies that they are not systematically biased and are internally consistent. Our first set of tests study the following question:

Q_1 : *Are subjective expectations of bond returns unbiased and what is the extent to which the cross section of individual expectations can be approximated by the consensus belief?*

We start by investigating the extent to which consensus beliefs summarize the cross section of expectations. Then, we test for the existence of a drift in forecasting errors and whether it is time-varying is a systematic way. These two properties have direct implications for a large literature that studies equilibrium models with heterogeneous beliefs and speculation. Indeed, the empirical predictions of these models depend on the significance of biases in beliefs aggregation. In these economies the equilibrium stochastic discount factor is affected by both sentiment and disagreement,[7] thus equilibrium interest rates and bond risk premia can potentially deviate from those implied by traditional Lucas tree models by amounts that depend directly on these two components of the distribution of beliefs (see Buraschi and Whelan (2010) for a detailed discussion in the context of bond markets). Finally, we investigate whether expectations on interest rates are internally consistent with the same agent expectations on future economic fundamentals (i.e. GDP growth and inflation). This is of relevance in the context of the current debate between rational and behavioral models about whether agents expectations are (un)correlated with prime properties of fundamentals under the physical measure.

Second, an extensive empirical literature argues about the existence of bond returns predictability. This may originate from either predictability of future short-term interest rates or time-variation in bond risk premia. Our second set of tests studies these two channels using data on real time individual expectations and addresses the following question:

Q_2: *Can professional forecasters predict short-term interest rates? Are those agents who are better in predicting future short-term rates also better in predicting long-term bond returns?*

Since our dataset provides the specific identity of each forecasters, we can altogether avoid issues related to data aggregation and can conduct an agent-specific study. Moreover, since we are already provided with their expectations, we can avoid assumptions about the models they use to form their expectations. We first investigate and rank the accuracy of each forecasters over time. For short-term rates, we distinguish between primary dealers and other financial institutions to study whether their status with the U.S. Federal Reserve Bank gives them an information advantage. We use the answer to the first question to address a second important question in the literature. Long-term bond returns can be predictable either because short term interest rates are predictable or because of time variation in risk premia. Thus, we compare the ranking in accuracy of short and long-term interest rates and study the extent to which agents who appear to do better in forecasting short-term rates also have an advantage in forecasting long-term bond returns.

Third, an important debate in the asset pricing literature relates to the spanning properties of market prices. A common working hypothesis of single agent models is that the representative agent holds consensus beliefs. However, in economies with frictions (such as short-selling constraints) markets prices may temporarily span the characteristics of those agents with are less affected by these frictions, even if they hold irrational beliefs. In frictionless and competitive markets, on the other hand, the market selection hypothesis (see, e.g., Friedman (1953) and Alchian (1950)) suggests that inaccurate agents eventually lose economic weight and their

[7] Sentiment relates to the difference between the (potentially biased) wealth-weighted average of beliefs and the (unbiased) expectation under the true physical measure; disagreement relates to the cross-sectional dispersion in beliefs.

influence on the stochastic discount factor. Thus, the beliefs of the most accurate agents, rather than consensus ones, are more tightly revealed (spanned) by bond prices.

Q_3: *Consistent with the market selection hypothesis in competitive markets, do bond prices span the beliefs of the most accurate agents?*

Fourth, we compare the dynamics of EBR to statistical and structural models of risk premia that have been proposed in the literature. Our fourth set of tests investigates the following set of questions:

Q_4: *Do existing rational expectation models explain the dynamics of EBR with the correct slope coefficient; are properties of beliefs, such as sentiment and disagreement, important state variables in the dynamics of EBR; and, finally, are reduced form models known to perform well in fitting realized bond excess return also successful in explaining EBR?*

The last part of the paper proposes an alternative assessment of existing fixed income models. While it is tradition to evaluate these models on the basis of their predictive power for future *realized* returns, we use direct measures of (subjective) *expected* returns. On the right hand side, we consider several specifications of bond risk premia arising from well known structural rational expectation models. Are model-implied bond risk premia consistent with observed subjective EBR? As part of these tests, we also study the importance of belief heterogeneity on bond risk premia. Indeed, general equilibrium models with heterogeneous beliefs and speculation predict that EBR depends on both sentiment and disagreement (see, among others, Buraschi and Whelan (2010)). Thus, we control for single-agent specifications of bond risk premia and test the role of expectation biases and heterogeneity on EBR.

A. The Data

This section briefly introduces the data and provides a description of subjective bond excess returns. All data are monthly, from January 1988 to July 2015.

We construct measures of expected bond risk premia (EBR) directly from professional market participants' expectations regarding future yields. The BlueChip Financial Forecasts (BCFF) is a monthly survey providing extensive panel data on the expectations of professional economists working at leading financial institutions about all maturities of the yield curve and economic fundamentals, such as GDP and inflation.[8] The contributors are asked to provide point forecasts at horizons that range from the end of the current quarter to 5 quarters ahead (6 from January 1997).

[8]In our analysis we use agent specific forecasts for the Federal Funds rate, Treasury bills with maturities 3-months/6-months/1-year, Treasury notes with maturities 1,2,5,10-years, and the 30-year Treasury bond.

BCFF represents the most extensive dataset currently available to investigate the role of expectations formation in asset pricing. It is unique with respect to alternative commonly studied surveys along at least four dimensions. First, the dataset is available at a monthly frequency, while other surveys, such as the Survey of Professional Forecasters' (SPF) is available only at quarterly frequency. This increases the power of asset pricing tests. Second, the number of participants in the survey is large and stable over time. In our sample it is 42 on average, with a standard deviation of about 2.3. Moreover, it never falls below 35, and even considering only the forecasters who contribute to the sample for at least 5 years (60 monthly observations) the number of participants is always above 30. On the other hand, in the SPF the distribution of respondents displays significant variability: the mean number of respondents is around 40, the standard deviation is 13 and in some years the number of contributors is as low as 9. While in the early 70s the number of SPF forecasters was around 60, it decreased in two major steps in the mid 1970s and mid 1980s to as low as 14 forecasters in 1990.[9] Third, Bluechip has always been administered by the same agency, while other surveys, such as SPF, have been administered by different agencies over the years. Moreover, SPF changed some of the questions in the survey, and some of these changes crucially affected the forecasting horizon.[10] Fourth, the survey is conducted in a short window of time, between the 25th and 27th of the month and mailed to subscribers within the first 5 days of the subsequent month. This allows the empirical analysis to be unaffected by biases induced by staleness or overlapping observations between returns and responses.

To obtain curves of expected zero coupon discount rates we uses the Svensson (1994) method, which is widely used in the estimation of realized zero coupon discount rates. The Svensson (1994) model assumes that the instantaneous forward rate is given by a 5-factor parametric function. To estimate the set of parameters we minimize the weighted sum of the squared deviations between actual and model-implied prices.[11] We calculate the term structures using all available maturities (including 30-year Treasury yield forecasts) and obtain a monthly panel data of expected constant time-to-maturity zero coupon (continuously compounded) discount rates. The holding period is quarterly up to 1.25-years and the maturities are evenly spaced between 1 and 10-years (we disregard maturities greater than 10-years). Over the whole sample there are 97 forecasters for which we can compute the whole expected term structure of zero-coupon yields and on average they contribute to the cross-section for about 138 months. Of this

[9]If one restricts the attention to forecasters who participated to at least 8 surveys, this limits the number of data points considerably.

[10]For a detailed discussion on the issues related to SPF, see D'Amico and Orphanides (2008) and Giordani and Soderlind (2003).

[11]Specifically, we search for the parameters which solve $b_t^j = \arg\min_b \sum_{h=1}^{H_t^j} \left[\left(P^h(b) - P_t^h \right) \times \frac{1}{D_t^h} \right]^2$,where H_t^j denotes the number of bonds available by forecaster j in month t, $P^h(b)$ is the model-implied price for bond $h = 1, ..., H_t^j$, P_t^h is its expected bond price, and D_t^h is the corresponding Macaulay duration. We also impose the following set of parameter restrictions: $\beta_0 > 0, \beta_0 + \beta_1 > 0$, $\tau_1 > 0$, and $\tau_2 > 0$.

97 forecasters, 84 participate to the panel for at least 5 years, and on average they contribute to the cross section for about 154 months.

For realized bond data we use zero-coupon bond yields provided by Gürkaynak, Sack, and Wright (2006) which are available from the Federal Reserve website.

III. The Cross Section of Expected Term Structures

A. *Subjective Expectations and Bond Risk Premia*

Figure 1 gives a first look at the data. Each panel plots quartiles (Q1, Q2(median) and Q3) of the 1-year cross-sectional distribution of expectations.[12] If we focus on the top left panel, which reports subjective expected excess returns on a 10-year bonds, we find that, consistent with the predictions of many structural models, subjective bond risk premia are counter-cyclical: they are negatively correlated with expectations about real growth. For example, expected returns are increasing in the early part of the sample, decreasing in the high growth rate years between the dot-com bubble and the financial crisis, and spiking again around Lehman Brother collapse. Moreover, as we compare macro versus short rate expectations, subjective expectations appear consistent with a Taylor rule relationship. For example, between the years 1988 and 1990 agents expected inflation to increase. At the same time forecasters expected the Federal Reserve to increase short term rates and that this policy would have a contractionary effect on the real economy (GDP growth).

[Insert Figure 1 here.]

At the same time, we document large unconditional heterogeneity in the cross section of EBR forecasts. Table I provides summary statistics for the median, the first quartile, and the third quartile of the (1-year) EBR distribution for the 2, 5 and 10-year bonds. The median (Q2) forecaster EBR is 1.06% for 10-year bonds. However, the first and third quartiles (Q1 and Q3) are -1.66% and +3.57% for the same maturity, respectively. This implies that while there is consensus belief of a positive risk premium, a significant fraction of investors believe in a negative bond risk premium. Moreover, the spread between the Q1 and Q3 unconditional expected excess bond returns is increasing with the bond maturity.

The conditional properties of the cross-sectional distribution of EBR display rich dynamics in the time series. The top left panel of Figure 1 shows the Q1, median, and Q3 of the cross-sectional distribution of EBR for 10-year maturity bonds. There exists significant time-varying heterogeneity around the consensus forecast. Given the wide use of consensus (average) expectations both in the literature and in the financial industry, it is interesting to test more

[12] 1-year average expectations are computed from 4 and 5 quarter ahead projections.

formally the null hypothesis that the cross-sectional properties of expectations can indeed be summarized by the consensus. In order to do this, we compute the interquartile range (IQR) of the cross-sectional distribution of EBR, as the difference between Q3 and Q1, for all bond maturities $n = 2, \ldots, 10$, and then regress it on the consensus forecast for the corresponding bond maturity. The slope coefficients of these regressions are positive, and statistically significant for all maturities, but the variations in the consensus forecasts explain only around 3% of the variation in the IQR. Moreover, we can strongly reject the hypothesis that the IQR is constant. In fact, the slope coefficient of a regression of IQR on its 1-year lag is significantly different from zero, for all maturities and at all levels. Therefore, the dispersion in beliefs varies over time and it is not merely a scaled version of the consensus: the mean is not a sufficient statistics for the cross section of expectations.

The top panel of figure 2 highlights the time variation in heterogeneity by plotting the cross-sectional standard deviation of EBR standardized by the full sample mean EBR, for bond maturities 2, 5 and 10-year. The figure also shows that the dispersion in beliefs is state-dependent: it tends to rise at the onset of recessionary periods and drop again as the economy recovers.[13] It is interesting to note that disagreement about long term EBRs is more than ten times larger than disagreement about short rates or disagreement about the macro economy (bottom panel of Figure 2). However, disagreement is non-monotonic in maturity displaying a 'hump shape' around the 5-year maturity. These findings motivate a rigorous study of whether the assumption that the marginal investor has average (consensus) expectation, as often assumed in the literature, is innocuous.

[Insert Table I and Figure 2 here.]

B. *Belief Persistence*

Figure 2 also demonstrates that disagreement about short rates, bond returns, and the macro economy are all persistent. This raises an interesting question: is disagreement a result of dogmatic beliefs and/or information friction? In order to address this question we first rank all forecasters according to whether in a given month t their forecast is in the first, second, third or fourth quartile of the cross-sectional distribution. We repeat this exercise for all months in the sample and compute transition probabilities: the probability that forecasters in a given quartile at time t stay in that particular quartile in $t + 1$ or move to a different quartile of the distribution. We do this first for short rates and macro expectations. If views are not persistent, all the entries in these transition matrices should be approximately equal to 25%. Instead, we find that the diagonal elements are significantly higher than 25%, in particular for

[13]The counter cyclicality of the dispersion in beliefs is consistent with the empirical evidence in Patton and Timmermann (2010) and Buraschi, Trojani, and Vedolin (2014), among others.

the most extreme quantiles, Q1 and Q4 where they are always above 70%.[14]

[Insert Table II here.]

The question of belief persistence is particularly important in the context of bond pricing models since whether agents are persistently optimistic or pessimistic about bond risk premia is related to agents' perception about bonds being hedging assets or rather risky bets on consumption (inflation) risk. In the first case, bonds should earn a negative risk premium, in the second expected bond risk premia should be positive. Thus, we estimate the extent to which individual forecasters are persistently in one particular quartile of the cross-sectional distribution of subjective $EBRs$.

Figure 3 plots the time series average of seven individual forecasters' positions in the cross-sectional distribution of subjective expected bond returns, for maturities between 2 and 10 years. This plot shows that agents are consistently optimistic or pessimistic across maturities. Indeed, in absence of persistence the time series average of the percentiles should be close to 0.5, for all forecasters. Instead, we see in Figure 3 that some institutions, like Goldman Sachs, have been persistent in their forecasts about larger than average excess bond returns at all maturities; others have been persistent in their forecasts of negative excess bond returns. Table III addresses this question more formally by computing transition probabilities matrices for subjective excess returns. The results suggest that forecasters have persistent beliefs about bond risk premia, relative to consensus excess returns. For example, a forecaster in the first quartile of the cross-sectional distribution of 2-year EBR has a probability of 75% to stay in the first quartile the following month, and this probability is 74% for the 10-year EBR, which is about three times what it should be under the null hypothesis of no persistence. In all cases, the probability of remaining in the same quartile is significantly higher than 25% at a level of 5%.

[Insert Figure 3 and Table III here.]

C. Internally Consistent Beliefs

Some readers may interpret the previous results as prima-facie evidence of either irrationality in the formation of beliefs or of dogmatic priors in agents' models. We address this conjecture by investigating whether expected term structures are consistent with agents' expectations about future economic fundamentals. Since we know the identity of each forecaster on both future interest rates and future state of the economy (GDP growth and inflation), we can ask whether these are mutually consistent.

[14]This result is striking and even stronger than what Patton and Timmermann (2010) document for macroeconomic forecasts using data from the Consensus Economics Inc, at a quarterly frequency.

We find that agents who are marginally more optimistic or pessimistic about macroeconomic variables are consistently in one particular quartile of the cross-sectional distribution of short term interest rates, as shown in Table IV. If one focuses on the corners of this table, we find that analysts who forecast lower short-term interest rates are also those forecasting lower GDP growth and, at the same time, lower CPI inflation. For instance, 35% of those who are in the first quartile of the distribution of future short-term interest rate forecasts are also in the first quartile of the distribution for GDP growth forecasts; similarly, 41% of those who are in the first quartile of the distribution of future short-term interest rate forecasts are also in the first quartile of the distribution for CPI inflation forecasts. This relation between forecasts at the individual level is consistent with the idea that good states of the economy are generally characterised by increasing yields, at least at short maturity. At the same time, the pattern is not deterministic, suggesting that beliefs on interest rates and the macroeconomy (GDP and inflation) are not driven by a single factor.

Table V repeats this exercise for long term bond returns. Agents who are in the highest quartiles of the distribution of forecasts for inflation and GDP are also in the highest quartiles of the distribution of forecasts of returns. This suggests that agents beliefs are broadly consistent with the rational expectation requirement that agents forecast interest rates in accordance to the sign of the correlation between short term rates and macro economic variables.

[Insert Tables IV and V here.]

In order to investigate the drivers of this disagreement (being them behavioral or not) we directly study the dynamics and accuracy of these beliefs. In this context, it is useful to distinguish between beliefs about short-term interest rates and bond risk premia. This is the topic of the next two sections, which are cast in the predictability regression framework used in the classical bond literature.

IV. The Short Rate

A. Predictive regressions

We initially explore this question in the context of simple predictive regressions for the three-month Treasury yield. Due to its persistence, we run predictive regression in differences where the dependent variable is specified as future realized monthly changes in 3-month rate and the independent variables are the corresponding expected changes according to survey beliefs for each decile $i = 0.10, \ldots, 0.90$ of the cross-sectional distribution of three-month yield forecasts:

$$\Delta y_{t+1}^{3m} = \alpha_i^{3m} + \beta_i^{3m} \left[E_t^i \left(y_{t+1}^{3m} \right) - y_t^{3m} \right] + \epsilon_{i,t+1}^{3m}, \tag{2}$$

where $\Delta y_{t+1}^{3m} = y_{t+1}^{3m} - y_t^{3m}$. Figure 4 shows the cross section of regression coefficients and R^2 of regression (2) for each decile. The intercepts, α_i^n, are monotonically decreasing and insignificant up to the third decile; the slope coefficients are positive and significant for all deciles of the distribution. The values are very close to one and in five cases are not significantly different from one. The R^2 vary between 8% and 13%, and they are highest for the intermediate deciles. The consensus agent has a slightly larger predictive power but a biased forecast (the alpha is negative), while the low deciles, which correspond to the pessimistic agents in terms of interest rates (optimistic in terms of bond returns) are almost unbiased but have a slightly lower R-squared. These findings document that expectations of future yields are indeed positively correlated with future realizations across the distribution of beliefs. However, there is a large heterogeneity in the degree of accuracy.

[Insert Figure 4 here.]

To investigate the characteristics of this heterogeneity, we use a unique advantage offered by our dataset which provides forecasters' identities. Then, we revisit the previous regression (2), but where i denotes each single contributor to the BCFF panel. For robustness, we focus on contributors with at least 5 years (60 months) of forecasts. Figure 5 shows the distribution of regression coefficients and R^2 for each forecaster. While the overall results confirm the previous findings of a substantial heterogeneity in predictive performances, two characteristics of these results emerge as striking.

First, with the exception of few forecasters, most estimated slope coefficients are positive and statistically significant. This suggests that professional forecasters do a relatively good job in predicting future short rates. Second, a few forecasters are extremely accurate, with slope coefficients larger than 0.5 and R^2 in excess of 10%, with some agents producing an R^2 in excess of 30%. This is contrary to the evidence based on retail individuals and non-professional forecasters.

At the same time, a very intriguing property of the regression coefficients is that the cross-sectional distribution of intercepts is largely skewed towards negative values: α_i^{3m} is negative for 79 of the 84 forecasters and significantly different from zero for slightly less than half of the forecasters. This suggests that the average forecaster has been surprised by the extended decline in short term interest rates over our sample period.

[Insert Figure 5 here.]

Figure 6 shows this bias explicitly by plotting the cumulative 3-month yield forecast errors over time for the average forecaster:

$$U_i^{3m}(t) = \sum_{s=0}^{t} u_i^{3m}(s), \tag{3}$$

for $t = 1, \ldots, T$ and where $u_i^{3m}(t) = y_{t+1}^{3m} - E_t^i\left[y_{t+1}^{3m}\right]$, and i is the consensus agent. Indeed, $U_i^{3m}(t)$ is not a martingale and has a negative drift, which is reflected in the negative α in the predictive regression (2). Figure 6 summarizes the results from which three observations emerge. First, cumulative errors increase quite significantly in the early 90s, in the early 2000s, and during the recent financial crisis. These three periods happen to coincide with the largest GDP contractions in our sample. Second, we compare the drift in survey forecast errors to that of forecasts of an econometrician who estimates a VAR model in real-time using a 10 year rolling window (pink line). We find very different results: out-of-sample cumulative forecast errors are significantly larger than professional forecasters in the first half of the sample but subsequently revert. The VAR econometrican makes persistent negative forecast errors followed by persistent positive forecast errors and the drift is not systematically correlated with business cycles. Third, we use the in-12m for-3m forward rate to compute market expectations about the 3 month future interest rates 12 months from now. The black line in Figure 6 plots the implied cumulative forecast errors. In absence of an interest rate risk premium, forward rates should be unbiased forecasts of future spot rates. If the interest rate risk premium is constant, the black line should have a constant negative slope. We find that the slope of the black line is negative, consistent with a significant forward rate risk premium, and time varying. The red line highlights the time-variation in the forward bias by subtracting from the black line the rolling historical spread between forward rates and three month yields. This is hardly surprising and is consistent with an extensive literature documenting deviations from the expectation hypothesis. The surprising result is the remarkable correlation between the bias in surveys and the forward spread. Times when the forward premium is the largest are also times when subjective expectations have the largest bias. It appears as if agents are not forecasting under an (unbiased) physical measure but rather under a (subjective) measure which is biased towards the risk neutral one.

[Insert Figure 6 here.]

This is consistent with a large literature that studies economies with agents holding heterogeneous subjective beliefs in which the equilibrium stochastic discount factor and interest rates are affected by a belief aggregation bias, as discussed in Buraschi and Whelan (2010), Jouini and Napp (2006), and references therein. Indeed, in these models average optimism/pessimism enters directly the stochastic discount factor even in absence of non-information frictions, such as short-selling constraints. To investigate this property, we construct a measure of ex-ante *bias* in survey forecasts $\mathcal{S}_t$, that we call *sentiment*, which is defined as the difference between the average subjective (survey-based) expectation of the 3-month yield and the physical expectation of an econometrician:

$$\mathcal{S}_t = E_t^i\left[y_{t+1}^{3m}\right] - E_t^P\left[y_{t+1}^{3m}\right], \qquad i = \text{consensus}$$

To obtain proxies for $E_t^P\left[y_{t+1}^{3m}\right]$, we consider different econometric models. We summarize the results obtained using a unit-root model since this is often argued to be an accurate and efficient expectation of the short rate, due to the significant persistence of short rates. Figure 7 compares $\mathcal{S}_t$ with the in-12m for-3m forward spread (the forward risk premium).[15] The correlation between the two is striking, at around +60%. When agent's beliefs are biased with respect to the measure of the econometrician, and the consensus agent is more optimistic about short term rates, the forward spread is also high. This is observed during economic downturns which, in our sample, correspond to the recessions of the early 1990s, early 2000s and with the recent 2008-09 financial crisis.[16] We find the results to be robust to different specifications for the forecasting model, and the link between sentiment and forward risk premium holds also looking at longer bond maturities (see right panels of Figure 7).

[Insert Figure 7 here.]

In consumption-based models with heterogeneous beliefs, sentiment (or bias) in short-rate expectations is directly linked to sentiment in endowment growth. Therefore, we compute an alternative measure of sentiment based on GDP growth forecasts, and we compare it to the short-rate sentiment $\mathcal{S}_t$ constructed above. To do this, we borrow from the empirical macro-finance literature and compute one-year forecasts under the econometrician measure using a time-series $AR(4)$ model using quarterly realized GDP growth (see, for instance, Marcellino (2008) and references therein). Our measure of GDP growth sentiment is given by the difference between the subjective expectation of the average agent (see Figure 8) and the physical expectation of an econometrician about GDP growth.[17]

[Insert Figure 8 here.]

Clearly, the two measures of sentiment are highly correlated, which is consistent with theoretical models in which the source of the ex-ante expectation bias is driven by sentiment in the endowment growth. While GDP growth sentiment might be more intuitively linked to the consumption growth sentiment of these models, we will focus on the short-rate sentiment $\mathcal{S}_t$ as an explanatory variable for bond risk premia in the last part of the paper, since it is available monthly instead of quarterly. It is also important to note the persistence in the sentiment measures in Figure 8, which derives directly from the persistence in the underlying beliefs highlighted in the previous section.

[15]The forward spread is computed as the difference between the $12M \to 15M$ forward rate and the spot 3-month yield.

[16]These results are related to the work of Cieslak (2016), who shows that "entering recessions, agents systematically overestimate the future real rate and underestimate unemployment. These forecast errors induce a predictable component in realized bond excess returns".

[17]GDP growth sentiment is available at a quarterly frequency since realized GDP growth is quarterly.

B. Forecast accuracy

The previous results document a bias in consensus beliefs. Does this property carry over also to the distribution of forecasters more generally? How accurate is the distribution of short rate survey expectations with respect to a credible benchmark, such as a unit root process for the 3-month yield? Since the panel is unbalanced, as forecasters do not participate in the same periods, we compare the relative performance of each forecaster with respect to the naive benchmark for the matching period. Given the RMSE of each individual forecaster i, defined as $RMSE_i^{3m}(Surv) = \sqrt{\frac{1}{T_i - t_{0,i}+1}\sum_{t=t_{0,i}}^{T_i}\left(y_{t+1}^{3m} - E_t^i\left[y_{t+1}^{3m}\right]\right)^2}$, we calculate the relative accuracy $\mathcal{A}_i$ of each forecaster as the ratio between the $RMSE$ of each forecaster's expectation and the RMSE of a unit root benchmark:

$$\mathcal{A}_i = \frac{RMSE_i^{3m}(Surv)}{RMSE^{3m}(UnitRoot)}.$$

Figure 9 displays the distribution of $\mathcal{A}_i$ for the 84 contributors with at least 5 years of monthly forecasts. Noticeably, a significant mass of individual forecasters have $\mathcal{A}_i$ between 0.90 and 1.10, suggesting that several agents are as good as the unit-root benchmark (and significantly better than a simple VAR model). Moreover, some agents are extremely precise with $\mathcal{A}_i < 0.90$, suggesting that some professional forecasters can provide reasonably good measures of expected bond returns. At the same time, some agents are very poor forecasters with $\mathcal{A}_i > 1.20$.

[Insert Figure 9 here.]

Is it possible to identify a subset of forecasters who are especially good at predicting short-term interest rates? Since forecasters contribution to the survey can occur at different time periods, we compute the squared forecast error at each time t, and the percentiles of these squared errors for each forecaster, that we call *accuracy ranking* percentiles, $\mathcal{R}_{i,t}$. Then we compute the time average $\mathcal{R}_i$ of these percentiles. Low percentiles correspond to greater accuracy. As in previous tests, we focus on forecasters with at least 5 years of data. The best forecasters in terms of average percentiles of squared forecast errors are summarized in the following table:

1	Goldman Sachs
2	J.P. Morgan
3	BMO Capital Markets
4	Nomura Securities Inc.
5	Bank of America
6	Georgia State University
7	Crestar Financial Corp.
8	US Trust Company
9	Chase Manhattan Bank
10	Woodworth Holdings

Interestingly, the first five institutions in this list (and 7 out of the first 10), are currently primary dealers, or have been primary dealers at least once in our sample period, even if overall only 24 of the 84 financial institutions with at least 5 years of forecasts are or have been primary dealers.[18] Primary dealers are trading counterparties of the Fed in its implementation of monetary policy and they are also expected to make markets for the Fed on behalf of its official account holders, and to bid on a pro-rata basis in all Treasury auctions at reasonably competitive prices. Their superior performance is consistent either with primary dealers superior information about the Fed's implementation of monetary policy or, more simply, with an information flow advantage originating from their role as market makers in Treasury bonds. In either case, the result is quite important given that the top 5 primary dealers hold about 50% of outstanding Treasuries.

In order to investigate the null hypothesis that primary dealers have a comparative advantage in forecasting the short rate, we compare the accuracy of this subset of forecasters, i.e. primary dealers, with respect to the other institutions in the panel of survey contributors. The list of primary dealers changes over time, and looking at accuracy percentiles at every time t instead of RMSE allows us to take this into account as well. At each month t, we compute the fraction of primary dealers (who are actually primary dealers and contributors to BCFF during that specific month) that are in the first, second and third tercile of the squared forecast error distribution and then average them over time. On average 43% of the primary dealers are in the first tercile, 29% in the second and 28% in the third.

Overall, the results above seem to show that primary dealers have better predictive performance for the short rate. While this holds unconditionally, it is interesting to understand whether the increased accuracy of primary dealers is generated in specific periods. Figure 10 shows the time series of average accuracy percentiles for primary dealers (PD) versus all other contributors (NPD), smoothed by computing a 12-month moving average of the monthly accu-

[18]The list of primary dealers at every point in time can be obtained from the Federal Reserve Bank website.

racies. It is clear that PD have a comparative advantage, and this advantage seems indeed to be stronger in specific time periods. The following subsection addresses this issue more formally by analyzing the conditional individual forecast accuracy.

[Insert Figure 10 here.]

C. Conditional forecast accuracy

It is clear from Figure 10 that the average expectation errors for PDs and NPDs diverge significantly in the early 90s, in the early 2000s and during the recent financial crisis. These periods are all characterized by a change of monetary policy in which the Fed has aggressively reduced the short term rate. While these decisions seem to take by surprise the consensus agent, whose expected short rates are biased upward in these subperiods, primary dealers are significantly more accurate, and this is especially true during the recent financial crisis.

To investigate these differences rigorously, we split the sample in two parts to capture persistent periods of increasing and decreasing interest rates, respectively. We compute the exponential moving average of the monthly change in the fed fund rate over the previous 12 months.[19] Considering the whole sample, there are 195 months in which this exponential moving average of changes is negative and 113 in which it is positive. We then recompute the average accuracy percentiles for each individual forecaster explicitly distinguishing these two time periods and we compare the distribution of accuracy percentiles for PDs and NPDs using a Kolmogorov-Smirnov test. The null hypothesis of the Kolmogorov-Smirnov test is that the accuracy percentiles PDs and NPDs are drawn from the same distribution. Unconditionally (considering the full sample), the p-value of the test is 15%, which implies that we cannot reject the null hypothesis. However, in the subperiod in which the Fed has been more active in conducting a dovish policy on the short term rate, the p-value of the test is 1.61%. In these sub-periods we can strongly reject the hypothesis that accuracy percentiles of PDs and NPDs are drawn from the same distribution. On the other hand, the p-value of the test in periods of increasing fed fund rate is 47.75%, suggesting that the distribution of accuracy for PDs and NPDs is very similar in these periods.

A Mann-Whitney U-test for the difference in medians between the accuracy percentile distributions yields similar results: Unconditionally the p-value is 4.98%, in periods of increasing rates it is 58.99%, and in periods of decreasing rates it is 0.80%.

In general we find evidence that primary dealers are much better during inflection points, that are turns of business cycles when the Fed turns dovish by reducing the interest rate. During other periods, expectations of the two sets of forecasters, as well as forecast errors, are very similar.

[19] Results are robust to the choice of time periods for the moving average.

D. Economic significance

The greater accuracy of PDs' expectations on the short rate during periods of decreasing rates is highly statistically significant. Is it also economically significant? In order to test this, we design a fictitious trading strategy based on agents' expectations.

To trade their view about about the 3-month yield in 12 months, we assume that agents replicate the forward rate in 12 months for 3 months, using available Treasury bonds with corresponding maturities. Thus, an agent that expects a relatively low short rate with respect to consensus would go long the 15-month bond and short the 12-month bond. We approximate this trading strategy by using the 2-year bond as a substitute of the 15-month bond, since the constant maturity 15-month bond yield is not directly available. In other words, we assume that agents expecting a relatively high short term rate in a year will sell the 2-year bond and buy the 1-year bond.

Every month, we stratify agents according to their beliefs relative to the consensus view about the 3 month rate. Then, we compute the return of a rolling trading strategy in which agents take positions every month and hold these positions until maturity (i.e. one year). We record this fictitious return for every agent and in every month in which the agent is contributing to the panel, and then average over time. The average of the mean returns for primary dealers is 0.13%, and it is -0.026% for non primary dealers. The difference in cumulative returns is summarized in Figure 11. If both groups started with one dollar in January 1988, by the end of the sample the average PD would have accumulated around 1.6 dollars and the average NPD would be left with 0.88, and the ratio between their wealth would be around 1.81.[20]

Even if the difference in expectations and in forecast errors may not appear particularly large between the two categories and is present only in specific periods, PDs are able to accumulate (theoretical) profits that are economically very significant.

Notice that the mean return of this strategy across all forecasters is slightly positive but close to zero, at 0.029%. This is suggestive that this cross-section of expectations is representative of the whole population. This also shows the limits of aggregating expectations using consensus beliefs.

[Insert Figure 11 here.]

E. Economic Interpretation

The finding that primary dealers have an advantage in predicting the short term rate in periods of monetary easing has three potential explanations:

[20]Note that because there are more NPDs than PDs, their total initial wealth is different and therefore the percentage increase for PDs is higher then the percentage decrease for NPDs.

First, these sub-period correspond to bad states for the U.S. economy. Primary dealers might have better information about future economic growth. To the extent that interest rate policy is endogenous to economic growth, PDs are more accurate in anticipating monetary policy.

Second, due to their role as intermediaries in the Treasury market, PDs have better knowledge about market demand for Treasury bonds. Thus, they can form more accurate forecasts about the directions of short term interest rates. A potential limit of this hypothesis, however, is that the superior accuracy of PDs manifests itself mainly during periods of aggressive dovish change in the stance of the monetary policy.

Third, PDs are able to collect information that is not easily available to the market (potentially private) about changes to the stance of the monetary policy.

We test the first hypothesis by comparing the accuracy of PDs and NPDs about future real economic growth and inflation. Figure 12 shows that primary dealers do not perform better than other agents in forecasting the inputs of the Taylor rule, i.e. inflation and GDP growth.[21] In fact, if anything, the accuracy of PDs' inflation expectations is lower, with an average accuracy ranking of 0.58 against 0.48 for NPDs. The GDP growth accuracy is on average very similar for PDs and NPDs, at 0.52 and 0.50, respectively. However, despite the time variation, PDs are virtually never more accurate than NPDs in forecasting future growth, except in the late '90s.

We can formally test the difference between the accuracy distribution of PDs and NPDs as above using a Kolmogorov-Smirnov test. Considering the full sample, the p-value of the tests is 6.5% for inflation and 62.7% for GDP growth, which implies that we cannot reject the null hypothesis in both cases at a level of 5%. However, the distributions of inflation forecast accuracy for PDs and NPDs are significantly different at a level of 10%, and these conclusions do not change if we look at subsamples of increasing and decreasing fed fund rates. Therefore, we cannot reject that the growth forecast accuracy of primary dealers and other institutions come from the same distribution. Actually, the best macro forecasters on average are institutions like Action Economics and ClearView Economics, while big primary dealers as Goldman Sachs, J.P. Morgan and Nomura are consistently in the worst half of growth and inflation forecaster accuracy.

[Insert Figure 12 here.]

[21]Note that realized GDP growth is available only quarterly. Therefore, the time series of GDP growth accuracy is also quarterly.

V. Long-term Rates and Bond Risk Premia

In this section we focus on two questions: First, given a direct subjective measure of expected bond risk premia $erx^n_{i,t}$, we revisit the literature on the time-varying properties of risk premia. This literature plays an important role in the interpretation of the rejection of the expectation hypothesis in bond markets. Second, we quantify the extent of accuracy of professional forecasters. Does the superior predictive ability of primary dealers on short-term rates lead to an advantage for long-term bonds? Since long-term bond returns are affected by both changes in short-term interest rates and bond risk premia, if the first component were to be dominant we should find that primary dealers conserved the edge in forecasting long-term returns. This is, therefore, an indirect test of the importance of the dynamics of bond risk premia for the dynamics of long-term bond returns.

A. Time-varying risk premia

An extensive literature in fixed income studies the properties of bond risk premia and argues that these are time varying. Empirical proxies of conditional bond risk premia usually either require the specification of a model or they use ex-post data on bond returns. The limit of arguments based on the central limit theorem is of course the lack of sufficiently long data samples. For this reason, some studies have argued that the results are not statistically convincing. Our data allows us to study bond risk premia directly using the dynamics of expectations that are obtained in a model independent way. Given the time series of subjective bond risk premia $erx^n_{i,t+1}$, we run regressions for different quartiles of the cross-sectional distribution for 2, 5 and 10-year zero-coupon bonds on a constant and their own lag at the 1-year horizon:

$$erx^n_{i,t+1} = \alpha^n_i + \beta^n_i erx^n_{i,t} + \epsilon^n_{i,t+1}. \tag{4}$$

The results are summarized in Table VI and show that the slope coefficients are significantly different from zero for all quartiles i at any traditional statistical levels. We can easily reject the null hypothesis that bond risk premia are constant. The results are very strong and support the hypothesis that expected excess bond returns are indeed time varying. Moving from the first to the fourth quartile, for all bond maturities, the autocorrelation coefficient is monotonically increasing. Those agents who believe bonds are hedges (e.g. EBR pessimists) have less persistent and less predictable (in the R^2 sense) expected bond returns.

[Insert Table VI here.]

To summarize, these results offer direct evidence in support of the interpretation of the existence of predictability due to time variation in expected excess bond returns.

B. *Predictive regressions*

To asses the accuracy of these surveys and the degree of heterogeneity, we first run a simple predictive regression of realized excess returns on the subjective EBR, for each single contributor to the BCFF panel, focusing on the contributors with at least 5 years (60 months) of forecasts:

$$rx_{t+1}^{n} = \alpha_i^n + \beta_i^n erx_{i,t}^{n} + \epsilon_{i,t+1}^{n}. \tag{5}$$

Figure 13 shows the distribution of regression coefficients and R^2 of regression (5) for each forecaster. The results show that notwithstanding heterogeneity in accuracy, a few forecasters are extremely accurate with slope coefficients close to one and R^2 larger than 20%. The correlation between expectations and future realization of excess bond returns is positive for 69 out of 84 forecasters.

[Insert Figure 13 here.]

This *positive* relation between expectations and realizations is the opposite to what Greenwood and Schleifer (2014) document in the context of the stock market, and to what Koijen, Schmeling, and Vrugt (2015) find in the context of global equities, currencies and global fixed income returns across countries.[22] This may be due either to issues related to the aggregation in those data sets or to differences between professional and non-professional forecasters. Our results show that agents beliefs are substantially more rational than previously thought.

C. *Forecast accuracy*

We study forecast accuracy at the level of each individuals forecaster i by computing the root mean squared errors ($RMSE_i^n$) for bond maturity $n = 10$, as

$$RMSE_i^n(Surv) = \sqrt{\frac{1}{T_i - t_{0,i} + 1} \sum_{t=t_{0,i}}^{T_i} \left(rx_{t+1}^n - erx_{i,t}^n \right)^2}.$$

They range between 7.5013 and 15.8325. Since individual forecasters may appear in the sample at different times, we assess their accuracy relative to a model. In the case of long term bonds, two models that have gained significant popularity in the literature: Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009).

[22] Koijen, Schmeling, and Vrugt (2015) also find that survey expectations of returns negatively predict future returns in the time series in three major asset classes: global equities, currencies, and global fixed income. However, instead of looking at the slope coefficient of predictive regressions, they show this by building a survey-based portfolio strategy. The strategy goes a dollar long or short in country i in month t when the consensus forecast is above or below a certain threshold, which is set to be equal to the middle value World Economic Survey respondents can select.

- The Cochrane and Piazzesi (2005) return forecasting factor is a tent-shaped linear combination of forward rates that has been shown to be a powerful predictor of future bond returns. It has been argued to subsume information contained in the level, slope and curvature of the term structure. However, the in-sample predictive content of the Cochrane-Piazzesi factor relies on estimates of factor loadings that were not available in real time. For example, the coefficients of the 'tent-shaped' factor used to forecast returns in the 1990s uses information available during the 2000s. In real time the shape of the factor loadings on the forward curve displays time variation (see, for example, Bauer and Hamilton (2015)). We construct a real-time version of the CP factor as follows. We initialise the factor loadings with 5-years of data from January 1983 to January 1988. Then, using an expanding window we estimate factor loadings used to construct a date t predicting factor, $CP(t)$, using realized returns available 1-year ago.

- The Ludvigson and Ng (2009) real macro factor is a broad based summary time-series based on a panel of macro economic variables capturing the level of economic activity. However, predictive return regressions based on such panels potentially overstate the information set available to investors in real time. To compare the real time forecast accuracy of macro versus survey based predictability we follow Ghysels, Horan, and Moench (2014) who argue proper tests of macro predictability should be based on vintage first release data. We obtain this data from the Archival Federal Reserve Economic Database (ALFRED) at the Federal Reserve Bank of St. Louis. We build a real-time macro predictability factor recursively from the first principle component of a vintage macro panel and denote this time factor LN.[23]

The in-sample $RMSEs$ of these two models are 7.3857 and 7.7758, respectively. When we compare these values to those obtained from the surveys, these models outperform even some of the best forecasters in-sample. However, this comparison is potentially unfair since the model $RMSEs$ are in-sample and affected by a look-ahead bias, as some information is not available to the forecasters in real time. The difference is potentially important. In the context of equity returns, Goyal and Welch (2008) document significant differences of in-sample versus out-of-sample performances of several well-known models. Accordingly, we proceed with an out-of-sample assessment: we initialize both models in January 1998 and obtain model-implied expectations recursively using expanding windows. We compare these to survey forecasts, which are out-of-sample by construction. Then, we compute a measure of relative performance $\mathcal{A}_i^n$:

$$\mathcal{A}_i^n = \frac{RMSE_i^n(Survey)}{RMSE^n(Model)}.$$

[23]Our data set broadly covers the same economic categories as Ghysels, Horan, and Moench (2014) which is chosen to match Ludvigson and Ng (2009) as close as possible. The final dataset comprises of a real time panel of 98 economic time series that are transformed into stationary growth rates.

Values smaller than one imply better performance under the subjective measure.

Out-of-sample, we find that an important fraction of survey forecasters perform better than both models. For example, relative to both the CP factor model and the LN-factor model, the relative accuracy on the 10-year bond of survey forecasters, $\mathcal{A}_i^{10}$, is less than one for about 21% of the individual agents, and $\mathcal{A}_i^{10}$ is between around 0.55 and 1.5 for all forecasters, and similar results hold for the LN factor.[24] These findings suggest that survey-implied bond risk premia are highly competitive in forecasting future realized excess returns relative to popular reduced form models.

In fact, not only there is evidence of accuracy in the cross-section, but this accuracy tends to be persistent. To quantify the persistence, we rank all forecasters according to their accuracy in month t within the distribution of all forecasters at that moment. Namely, we calculate the percentile of squared forecast errors of bond excess returns. We repeat this exercise for all months in the sample and compute transition probabilities, defined as the probability that forecasters in a given quartile at time t stay in that particular quartile in $t+1$ or move to a different quartile of the distribution. If accuracy is not persistent, all the entries in Table VII should be approximately equal to 25%. If, on the other hand, accuracy is persistent, we expect the diagonal elements to be significantly higher than 25%. We find that the accuracy of the most extreme quantiles, Q1 and Q4, is very persistent. For example, a forecaster in the first quartile of the cross-sectional distribution of 10-year EBR accuracy has a probability of 58% to stay in the first quartile of accuracy the following month. This probability is 70% for the 4^{th} quartile, which contains the worst forecasters, suggesting that a bad forecasting performance is more persistent than a good one. In all cases, the probability of remaining in the same quartile is significantly higher than 25% at a level of 5%.

[Insert Table VII here.]

This confirms two conclusions. First, expectations of a significant fraction of professional forecasters are far from being irrational. Second, surveys can be used to build reliable measures of bond risk premia. However, one needs to be mindful of the heterogeneity in the distribution of beliefs. The assumption that consensus can be used as a sufficient statistics of the panel and can proxy the beliefs of the marginal agents are not supported by our results.

D. Primary Dealers

The previous section documents that primary dealers have a comparative advantage in predicting the short rate. Does their superior predictive power for the short rate lead also to superior

[24] We also find that the out-of-sample RMSE of the models is quite sensitive to the sample period considered and to the choice of the starting date for the out-of-sample period. For robustness, we also require the survey forecasters to have at least 3 years of monthly observations in the out-of-sample period.

predictive power on the long rate? This question is important for several reasons. First, if the answer was positive one could conclude that long-term bond returns are mainly driven by short rates over the life of the bond. A rejection of this hypothesis, on the other hand, would suggest that the dynamics of long-term bond returns are dominated by other components, such as bond risk premia. In this case, knowing the dynamics of short-term rates may not suffice to earn extra returns when trading long-term bonds.

To test this hypothesis, we compute the accuracy percentiles on the 10-year excess bond returns for each individual forecaster by squaring forecast errors at each month t, rank them, and average across time periods. Finally, we compare these long-term accuracy percentiles with the corresponding accuracy on the short rate. The two rankings are highly correlated, in fact a regression of the 10-year accuracy percentiles on the 3-month accuracy has a significant slope coefficient of 0.42 and an adjusted R-squared of 21%. However, the link is less strong if we focus on the subsample of primary dealers: the regression coefficient is 0.37 and it is only marginally significant, with an adjusted R-squared of 15%. Thus, the greater accuracy of primary dealers on the short-end of the term structure is not reflected in a greater accuracy on long-term bond excess returns. The best forecasters in terms of average percentiles of squared forecast errors for the 10-year bond are summarized below:

1	Thredgold Economic Assoc.
2	UBS
3	Goldman Sachs
4	Huntington National Bank
5	RidgeWorth Capital Management
6	Fleet Financial Group
7	DePrince & Associates
8	The Northern Trust Company
9	GLC Financial Economics
10	J.W. Coons & Associates

Contrary to our findings for the short rate, only two of the top ten forecasters for the 10-year bond returns are primary dealers. To analyze the performance of primary dealers on the long end of the term structure more formally, we compute, at each month t, the fraction of primary dealers (who contribute to BCFF during that specific month) that are in the first, second and third tercile of the squared forecast error distribution and then average them over time. For the 10-year yield, on average 36% of the primary dealers are in the first tercile, 30% in the second and 34% in the third. The results contrast with those for the 3-month yield for which the primary dealers are overrepresented in the best accuracy tercile.

Panel A of Table VIII displays the joint distribution of forecast accuracy for the 10-year EBR and 3-month yield, that is the probability of being in a given tercile of the 3-month yield accuracy percentile distribution *and* a given tercile of the 10-year EBR accuracy percentile distribution, at the same time.

The elements on the diagonal show that there is a link between accuracy at the short and at the long end of the term structure, which is not surprising given that, for example, the correlation between realized 3-month and 10-year yield, at the monthly frequency, is around 86%, and the correlation between the 3 month yield and the slope of the term structure (computed as the difference between the 10 and the 1-year yield) is -74%. However, the correlation between the accuracy on the 3-month yield and on the 10-year EBR is far from perfect.

When we focus on primary dealers, see Panel B of Table VIII, the evidence is different and intriguingly so: the fraction of primary dealers who are accurate in both dimensions is slightly higher than for all forecasters, but there is an asymmetry between the 3-month yield and the 10-year EBR accuracies. We test directly the null hypothesis that the accuracy percentiles of PDs and NPDs for the 10-year excess return are drawn from the same distribution using a Kolmogorov-Smirnov test. Unconditionally (considering the full sample), the p-value of the test is 68.2%. Even after distinguishing periods of increasing and decreasing rates or using the Mann-Whitney test, we cannot reject the null hypothesis with p-values larger than 50%. Overall, primary dealers have a significantly better predictive performance only for the short rate.

[Insert Table VIII here.]

This suggests that the dynamics of expected excess bond returns at longer maturities might indeed be dominated by a bond risk premium component. Moreover this risk premium is time varying.

Since risk premia are time varying and accuracy is quite heterogeneous, it is natural to ask whether the most accurate forecasters are also those whose beliefs are more spanned. This question is important in the context of the correct aggregation of beliefs and it is the topic of the following section.

VI. Subjective Risk Premia and Rational Expectation Models

A. Spanning properties

It is common in the empirical literature to use consensus expectations as a proxy of subjective beliefs. In some cases, the choice is forced by data limitations. In the context of asset pricing, this is tantamount to assuming that the marginal agent holds consensus beliefs. Different streams of the literature, however, study equilibrium models in which the beliefs of the marginal agent deviate from consensus. For instance, the behavioral finance literature argues that in presence of short-selling constraints marginal agents ought to be those holding optimistic beliefs about expected returns (see e.g. Scheinkman and Xiong (2003) and Hong, Sraer, and Yu (2013)). Since pessimists cannot short-sell, their beliefs are not revealed (spanned) by equilibrium asset prices. The general equilibrium literature that studies economies where agents speculate on their (heterogeneous) beliefs argues, on the other hand, that in absence of short-selling constraints irrational agents eventually lose economic weight to the benefits of less biased agents. What matters is not agent's optimism but rather their accuracy. The superior accuracy of rational agents allows them to accumulate economic importance in the Pareto weights of the representative agent (as in Basak (2005), Buraschi and Jiltsov (2006), Jouini and Napp (2006), Xiong and Yan (2010), Chen, Joslin, and Tran (2012), Buraschi and Whelan (2010), Ehling, Gallmeyer, Heyerdahl-Larsen, and Illeditsch (2015), among others). This argument, consistent with the original "market selection hypothesis" by Friedman (1953) and Alchian (1950), implies that bond prices should span the beliefs of the most accurate agents (i.e. closest to the actual physical probability). As Alchian (1950) argues, "*Realized profits [...] are the mark of success and viability. It does not matter through what process of reasoning or motivation such success was achieved. The fact of its accomplishment is sufficient. This is the criterion by which the economic system selects survivors: those who realize positive profits are the survivors; those who suffer losses disappear.* " If some agents have been consistently more accurate than others, they would have been accumulating more economic weight in the pricing kernel. Thus, these beliefs, rather than the consensus ones, should be the one spanned by bond prices.

We use information on agents beliefs from both the time series and the cross section to address the question of whether the beliefs of the most accurate agents are more spanned by current bond prices. First, we sort agents according to the level of their accuracy up to that date. Specifically, at every month t we consider agents present in the panel in the previous 12 months and compute the average squared forecast errors up to a period straddling month t, based on previous year expectations. The forecast errors based on the EBR reported 12 months before is already realized, but the remaining EBRs are unrealized. However, they still affect the accumulation of wealth of the agents up to time t. For example, the EBR reported 6-months ago will be in profit or loss based on the path of realised bond returns over the period $t-6$ to t.

Next, we rank agents by their average accuracy at each time t and form tercile portfolios. Then, we compute the average EBR within each tercile. This procedure provides us with a cross section of beliefs with different levels of accuracy, that allows us to test the hypothesis that a superior accuracy is correlated with a larger Pareto weight, and therefore a larger degree of spanning. Figure 14 displays measures for the most accurate tercile EBR_1 at each point in time based on ranking the sum of the previous years squared forecast errors. The top plot displays the survey implied expected excess returns on a 2-year bond compared to the ex-post realised returns. The bottom plot is for the 10-year bond.

[Insert Table 14 here.]

Finally, we decompose the yield curve up to 10 years maturity in a small number of (orthogonal) principle components.[25]

To test the spanning hypothesis we run regressions of 10-year $EBRs$ for different terciles of the accuracy distribution onto the first five principal components of the term structure, which efficiently summarize the cross section of bond prices:

$$erx_{i,t}^{n} = \beta_{i,0}^{n} + \sum_{j=1}^{5} \beta_{i,j}^{n} PC_{j,t} + \epsilon_{i,t}^{n}. \tag{6}$$

Table IX reports the results of this regressions where EBR_1 denotes the most accurate and EBR_3 the least accurate beliefs. We find a monotonic link between accuracy and degree of spanning, measured as the adjusted R-square of the regression.[26] Consistent with the general equilibrium literature with disagreement and no frictions, accurate investors expectations are well spanned by the cross-section of bond prices, while for the least accurate investors the degree of spanning is much smaller.

[Insert Table IX here.]

For comparison, we run the spanning regression (6) also for the consensus beliefs and we find an adjusted R^2 of about 44%, versus 52% of the most accurate agents. As an additional benchmark, we run the same regressions using ex-post realized returns as a proxy for ex-ante bond risk premia and we find an R^2 of only 31%. On the basis of ex-post realized returns, one might be tempted to conclude that the amount of spanning is somewhat limited. On the other hand, when one considers direct measures of subjective expected returns of accurate agents, there is strong evidence that the variation in subjective bond risk premia is largely spanned by date t yield factors.

Taken together, we conclude that the beliefs of forecasters who have been on average more accurate appear better spanned by contemporaneous prices than the beliefs of the least rational agents. This result is intriguing and consistent with "market selection hypothesis" in competitive markets by Friedman (1953) and Alchian (1950).

[25]The first three factors are often labelled in the literature as level, slope, and curvature, based on how shocks to these factors affect the shape of the yield curve (see, for example, Litterman and Scheinkman (1991), Dai and Singleton (2003), or Joslin, Singleton, and Zhu (2011)). We consider the first five factors, which explain around 99.9999% of the overall variation in yields.

[26]The shape of the link between accuracy and spanning is qualitatively robust to the number of accuracy portfolios considered, i.e. if we use quartiles or deciles of the accuracy distribution instead of terciles.

B. Rational expectation models vs subjective risk premia

The empirical evaluation of rational expectation models is traditionally conducted by approximating expected risk premia by sample averages of future returns. $E(rx_{t,t+T})$ is often proxied by $\frac{1}{T}\sum_{s=t}^{t+T-1} rx_{s,s+1}$ and conditional expectations $E_t(rx_{t,t+T}|\mathcal{F}_t)$ by sample projections of future realizations $rx_{s,s+1}$ onto observables with respect to the information set $\mathcal{F}_t$. This is potentially problematic for at least three reasons. First, sample projections based on future realizations can be quite different from true investors expectations. We have a clear example of this in the context of our data when we find that, at the individual level, erx_t^i are more persistent than what a pure rational model would imply. Second, long horizon predictability regressions give rise to overlapping errors which affect the estimators properties. While it is possible to cure the asymptotic properties of projection coefficients using well-known correction methods, these solutions do not address the inevitable challenge of the reduced number of genuinely independent observations. A regression of 5 year holding period returns on a 10 year sample has two truly independent observations, even when the data is sampled daily. Finally, traditional predicting regressions with dependent variables constructed from future return realizations always raise the question of the extent to which in-sample results can be extended out-of-sample. At the same time, if in-sample regressions are plagued by look-ahead bias, out-of-sample regressions are typically exposed to the excess flexibility critique: the results are sensitive to the specific way the experiment is designed.[27]

Direct measures of subjective expectations can address these three problems. They provide a useful way to assess alternative structural and reduced-form models of bond risk premia. Under the assumption that erx_t measure expectations of bond excess returns accurately, alternative models of risk premia can be ranked based on their ability to explain the dynamics of erx_t, as opposed to sample averages (or projections) of rx_{t+1}. Indeed, previous results confirm that, out-of-sample, survey-implied bond risk premia are highly competitive in forecasting future realized excess returns relative to some popular reduced form models. In our setting we can directly address all these issues by running regressions of our direct measure of risk premia on alternative model-implied specifications of risk premia.

The second dimension we investigate relates to the cross-sectional and time-series characteristics of beliefs. Previous sections document both the existence of significant heterogeneity and the presence of time-varying sentiment. Are the properties of this heterogeneity helpful in describing the dynamics of bond risk premia above and beyond homogeneous models? The heterogeneous beliefs literature in fact shows how theoretically bond risk premia are affected by the interaction of both, see e.g. Buraschi and Whelan (2010) and Jouini and Napp (2006). Buraschi and Whelan (2010) derive expressions for expected bond risk premia under the mea-

[27]Examples include the length of the training period, the start of the out-of-sample period, the use of fixed versus time-varying parameters, the out-of-sample horizon, etc.

sure of an unbiased econometrician endowed with the knowledge of the true data generating process. They show that "bond risk premia are equal to the product of two terms. The first term is given by the price of risk, which is equal to the sum of the traditional risk premium emerging in an homogeneous Lucas economy plus a term equal to the wealth-weighted belief sentiment bias. The second term is the sensitivity of bond prices to consumption shocks, i.e. the quantities of risk." Formally, in their economy if g_t is the true endowment growth rate and $E^i(g_t)$ is the subjective expectation of agent $i = a, b$, the instantaneous bond risk premium $\mu_B(t) - r_f$ is given by

$$
\begin{aligned}
\mu_B(t) - r_f &= \underbrace{\left[\gamma\sigma_c - \frac{1}{\sigma_c}\mathcal{S}_t\right]}_{\text{Price of Risk}} \times \underbrace{\sigma_B(DiB_t, \mathcal{S}_t)}_{\text{Quantity of Risk}} \qquad (7) \\
\mathcal{S}_t &= \textit{Sentiment Bias} = (\omega_t^a E^a(g_t) + \omega_t^b E^b(g_t)) - g_t \\
DiB_t &= \textit{Disagreement} = (E^a(g_t) - E^b(g_t))/\sigma_g
\end{aligned}
$$

where σ_c and σ_B are the volatility of endowment and bond returns, respectively, and ω_t^a are the relative wealth weights of the two agents. When long-term bonds are risky assets, in these economies bond volatility σ_B is increasing in disagreement DiB_t.[28] Thus, bond risk premia can switch sign depending on the level of sentiment $\mathcal{S}_t$ and are larger when sentiment $\mathcal{S}_t$ is negative: sentiment drives the effect of disagreement in a non-linear way. Buraschi and Whelan (2010) notice, moreover, that while the Lucas term $\gamma\sigma_c \longrightarrow 0$ when the volatility of consumption $\sigma_c \longrightarrow 0$, the term due to sentiment is inversely proportional to σ_c are is potentially very large when σ_c is small. This is important given the well known difficulty of homogeneous consumption-based models to reproduce bond risk premia due to the empirically low observed values of σ_c. To empirically investigate this property, we run a two-stage regression. First, we estimate the bond return volatility $\hat{\sigma}_B(t)$ for different bond maturities using daily data on bond returns. Then we regress $\hat{\sigma}_B$ onto DiB_t and $\mathcal{S}_t$, to obtain $\hat{\sigma}_B(DiB_t, \mathcal{S}_t)$ and in the second stage we follow the model-implied specification (7) and run the regression

$$
erx_t^* = a_0 + (a + b\mathcal{S}_t)\hat{\sigma}_B(DiB_t, \mathcal{S}_t) + \epsilon_t. \qquad (8)
$$

We obtain measures for $erx_{i,t}^*$ by using the forecasts of the agents with greatest spanning properties (i.e. the most accurate, EBR_1 in the previous subsection and in Table IX), which should reveal more closely the beliefs of the marginal agent in competitive markets. To obtain a proxy of disagreement DiB_t, we compute the interquartile range of the distribution of short rate forecasts, to be consistent with our construction of the sentiment measure $\mathcal{S}_t$, defined in Section

[28]Long term bonds are risky assets when their price dynamics is positively correlated with endowment shocks. This occurs when bond factor loading $\sigma_B(DiB_t)$ is positive.

IV.A, which is also based on the 3-month yield survey forecasts. Notice that we avoid using proxies for sentiment based on bond return expectations to avoid the possibility of spurious results. Then, we run the regression:

$$erx_t^* = a_0 + (a + b\mathcal{S}_t)\hat{\sigma}_B(DiB_t, \mathcal{S}_t) + c\mathcal{M}_t^j + \epsilon_t, \tag{9}$$

to help understanding the relative contribution of sentiment and disagreement. We control for four traditional specifications of bond risk premium $\mathcal{M}_t^j$ proposed in a series of well known rational expectation equilibrium models with homogeneous agents.

Specifications for $\mathcal{M}_t^j$:

- In economies with external habit preferences, such as Campbell and Cochrane (1999), time variation in risk compensation arises because of an endogenously time-varying price of risk. Shocks to the current endowment affect the wedge between consumption and habit, i.e. the consumption surplus, which induces a time-varying expected returns. To obtain a proxy of risk premium $\mathcal{M}_t$, we follow Wachter (2006) and calculate consumption surplus ($Surp$) using a weighted average of 10 years of monthly consumption growth rates: $Surp = \sum_{j=1}^{120} \phi^j \Delta c_{t-j}$, where the weight is set to $\phi = 0.97^{1/3}$ to match the quarterly autocorrelation of the P/D ratio in the data.[29]

- In long-run risk economies with recursive preferences (see e.g. Bansal and Yaron (2004)), time variation in risk compensation arises from economic uncertainty (second moments) of the conditional growth rate of fundamentals. To obtain a proxy for economic uncertainty we adapt the procedure of Bansal and Shaliastovich (2013). First, we use our survey data on consensus expectation of GDP growth and inflation and fit a bivariate $VAR(1)$. In a second step, we compute a GARCH(1,1) process on the VAR residuals to estimate the conditional variance of expected real growth ($LRR(g)$) and expected inflation ($LRR(\pi)$).

- Finally, Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009) have proposed two influential reduced-form factors that are found to explain a significant proportion of realized excess bond returns. The first is based on a combination of forward rates; the second is based on principal components of a large panel data of economic variables. As discussed above, we construct real time versions of these return forecasting factors denoting them CP and LN, respectively.

Results:

Table X summarizes the first and second stage regression results of regression (8), when using the most accurate tercile of forecasters expectations erx_t^*, and before controlling for traditional

[29]For consumption data we obtain seasonally adjusted, real per-capita consumption of nondurables and services from the Bureau of Economic Analysis.

model-implied specification of bond risk premia. Panel A shows that the first stage coefficients (quantity of risk) for the 2 and 5 year bonds are statistically strongly significant. For the 2 year bond, DiB_t and $\mathcal{S}_t$ have *t-stat* equal to 7.73 and 3.21, respectively, and an R^2 equal to 25%. The slope coefficient are both positive, suggesting that larger values of both disagreement and sentiment increase subjective monthly erx_t^* volatility. The second stage estimates show that expected risk premia are increasing in $\hat{\sigma}_B(DiB_t, \mathcal{S}_t)$ with *t-stats* that range between 6.43 and 7.17. The slope coefficient for the interaction term $\mathcal{S}_t \times \hat{\sigma}_B(DiB_t, \mathcal{S}_t)$ is negative, suggesting that negative sentiment $\mathcal{S}_t$ has an amplification effect on the impact of disagreement on the quantity of risk $\hat{\sigma}_B$. The *t-stats* for $\hat{b}$ range between -4.39 and -6.25 with an R^2 equal to 14% for the 2 year bond.[30]

[Insert Table X here.]

It is interesting to notice that, at the estimated parameter values, expected bond returns $(\hat{a}+\hat{b}\mathcal{S}_t)\hat{\sigma}_B(DiB_t, \mathcal{S}_t)$ can switch sign. This is potentially important given Duffee (2002) observation that completely affine models cannot explain negative expected bond returns due to the fact that in these models bond risk premia are proportional to interest rate volatility. The top panel of Figure 15 plots the fitted surface of EBR, defined as $\hat{a}_0 + (\hat{a} + \hat{b}\mathcal{S}_t)\hat{\sigma}_B(DiB_t, \mathcal{S}_t)$, for a 10 year bond over the range of values for DiB_t and $\mathcal{S}_t$ observed within our sample period. We find that fitted $EBRs$ can range between -6% and $+10\%$. The surface shows that since sentiment $\mathcal{S}_t$ affects both the quantity and price of risk, and with opposite signs, the effect of sentiment is non-linear and non-monotonic. For a given level of disagreement, DiB, negative sentiment increases the price of risk and reduces the quantity of risk. Empirically, the net effect is hump-shaped in sentiment and dominated by the quantity of risk channel. For very negative values of sentiment and low disagreement the fitted value of EBR switches sign and can become negative. At the same time, as predicted by heterogeneous models when bond are risky assets, negative sentiment amplifies the marginal impact of disagreement. The slope coefficient on $\mathcal{S}_t \times DiB_t$ is negative so that in periods with negative sentiment (aggregate relative pessimism), positive shocks to disagreement further increase expected bond risk premia. The opposite is true in periods when sentiment is positive. The largest bond risk premia are obtained for mildly negative sentiment $\mathcal{S}_t$ and large disagreement DiB_t. The bottom panel of Figure 15 shows a scatter plot of actual economies as they have been historically observed in terms of DiB_t (y-axis) and $\mathcal{S}_t$ (x-axis). The size of each dot corresponds to the size of the risk premium: black dots highlight negative $EBRs$. Green dots correspond to EBRs forecasted in the preceding 12 months prior to the start of NBER-dated recessions, while blue dots correspond to EBRs forecasted in the following 12 months after the start of NBER-dated recessions. The bottom

[30] Disagreement matters on its own with a positive slope coefficient. The larger the disagreement the larger the expected bond risk premium erx_t^*. When we run separate regressions of $erx_{i,t}^n$ on DiB_t and $\mathcal{M}_t$, in periods of positive and negative sentiment, we confirm the previous result.

panel of Figure 15 shows that negative $EBRs$ are observed for very low absolute values of both disagreement $\mathcal{S}_t$ and sentiment DiB_t. Moreover, the start of recession periods are often associated with larger values of disagreement and negative sentiment. This is consistent with larger values of expected long-term bond risk premia. Exception to the rule are seven months in which one can observe extremely large $EBRs$ without the economy entering a recession.[31]

[Insert Figure 15 here.]

The second set of questions relates to the link between erx_t^* and traditional specifications for bond risk premia that would arise in homogeneous rational expectations models $\mathcal{M}_t$. The novelty in these regressions with respect to previous empirical studies is the use of the subjective measure (most spanned representative agent) for the identification of the endogenous variable. Table XI summarizes the results of regression (9) for bond maturities of 5 and 10 years, from which four interesting implications emerge.

First, controlling for these alternative specifications never decreases the significance of the interaction of disagreement and sentiment that we discussed earlier.

Second, proxies of economic uncertainty $LLR(g)$ inspired by long-run risk models are strongly statistically significant and produce a total R^2 of 16%. Larger values of real long-run risk are correlated with greater subjective expected bond risk premia. This is consistent, for instance, with the model discussed in Bansal and Yaron (2004) in which greater real GDP uncertainty raises interest rates, lowers bond prices and increases future expected bond returns. However, only real uncertainty enters with a positive loading. The second class of structural models we investigate relates to Campbell and Cochrane (1999), Wachter (2006), and Buraschi and Jiltsov (2007). When agents have habit preferences, the price of risk is state-dependent and negatively related to the consumption surplus ratio. Table XI shows that the slope coefficient of $Surp$ is strongly significant with *t-stats* of -3.56 and -4.41 for the 10 and 5 year bond, respectively.

Third, we find that for both proxies of (structural) models, the signs of the slope coefficients on $Surp$ and $LLR(g)$ are consistent with the theory behind these factors. Moreover, the empirical proxies implied by the models perform significantly better in explaining the dynamics of subjective $EBRs$ than future realized bond excess returns. This was not obvious ex-ante to us, as both these results contrast with previous studies for equity returns which argue that equilibrium models generate implied risk premia that correlate negatively with empirical risk premia (see, for instance, Greenwood and Schleifer (2014)).

Fourth, when we consider reduced-form predictive models of bond returns (Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009)), we find a statistically significant relationship

[31] The six large red dots in top left of Figure 15 correspond to December '88, March to June '89, October '89 and July '90. The nine large green dots in the plot correspond to September to November '89 and January to July '90.

between erx_t^* and both CP and LN. However, their importance in explaining the time variation in EBR is not overwhelming, and the marginal contribution to R^2 of these predicting factors is somewhat smaller than in the original papers and does not exceed 17%. This is due to two reasons. Both these two variables are not identical to their original counterparts and, different than in the original papers, they are constructed using real-time information to remove any potential look-ahead bias. Thus, at time t, both $CP(t)$ and $LN(t)$ do not depend on any observations made at time $T > t$. The second reason is that the endogenous variable is defined as the contemporaneous subjective bond risk premia.

[Insert Table XI here.]

To summarize, for equity market Greenwood and Schleifer (2014) find a negative correlation between model-implied equity risk premia and survey expectations of stock market returns. They interpret their result as clear evidence of a rejection of rational expectations models: "*We can reject this hypothesis with considerable confidence. This evidence is inconsistent with the view that expectations of stock market returns reflect the beliefs or requirements of a representative investor in a rational expectations model.*" On the other hand, we find significant positive correlation between some rational expectation models and empirical proxies of erx_t^* of the most accurate (most spanned) agents. Both models of economic uncertainty and habit formation capture different characteristics of bond risk premia, once the properties of belief heterogeneity are carefully taken into account. Moreover, we find clear supporting evidence for equilibrium models of speculation that account for heterogeneous beliefs and in which negative sentiment increases the marginal impact of disagreement.

VII. Conclusion

This paper studies the expectations of bond returns taken directly from survey data and compares them to traditional measures of bond risk premia measured from ex-post realizations. Our analysis reveals a number of interesting results.

First, we find that individual risk premia are largely heterogeneous and the consensus does not subsume the information contained in the distribution of forecasts. We find a significant amount of persistence in agents beliefs on bond excess returns and in the degree of optimism/pessimism relative to consensus. However, overall expectations about bond returns display significant elements of rationality. In fact, individual expectations of bond returns are consistent with agents' forecasts about GDP and inflation.

Secondly, we find evidence of predictability in short-term interest rates and we show that the accuracy of the best forecasters is persistent over time. In particular, we find that primary dealers are more likely to be between the top forecasters of the short-term interest rate, and their superior forecast accuracy is both statistically and economically significant. This is consistent either with primary dealers superior information about Fed's implementation of monetary policy or, more simply, with an information flow advantage originating from their role as market maker in Treasury bonds. The result is quite important given that the top 5 primary dealers hold about 50% of all Treasuries.

Third, we study the properties of long-term expected bond risk premia and strongly reject the hypothesis that bond risk premia are constant. Moreover, we show that agents who are more accurate in forecasting short term rates do not have a persistent edge in predicting long term bond returns. This finding supports the idea that time variation in bond risk premia plays an important role in long-term bond predictability. Overall, results for long-term bond returns strengthen the evidence of rationality in the cross-section of survey forecasters, since the slope coefficient of predictive regressions of bond excess returns on their ex-ante subjective expectations is positive for a large fraction of forecasters, contrary to what Greenwood and Schleifer (2014) document in the context of the stock market.

Fourth, expectations of bond risk premia are largely spanned by the current term structure of bonds prices and the degree of spanning is substantially larger than when using sample averages of future excess returns as proxies of bond risk premia. Even more importantly, the degree of spanning greatly differs in the cross-section of agents beliefs. Indeed, there is a strong positive relation between spanning and forecasting accuracy in the cross-section: the beliefs of agents who have been more accurate in their forecasts in the preceding months are more spanned by the term structure of bond yields. This is consistent with the predictions of general equilibrium heterogeneous agents models with speculative trading and no frictions. In these models, the pricing kernel is a stochastic weighted average of agents beliefs, where relative weights depends on the wealth accumulation generated by belief-based trading.

These findings suggests that surveys can indeed be used to build reliable measures of bond risk premia in real time and thus avoid issues related to in-sample versus out-of-sample model fitting, as long as we rely on the beliefs of the most spanned, i.e. most accurate, agents instead of just looking at the consensus. Therefore, we use the spanned measure of EBR to evaluate a series of structural and reduced-form models. We focus on testing the effect on risk premia of belief heterogeneity, and we evaluate the marginal contribution of other factors implied by rational expectation models with homogeneous economies. We show that disagreement always matters, but only conditional on sentiment, consistent with the idea that disagreement increases risk premia in periods of pessimism, as predicted by standard models with heterogeneous beliefs. Moreover, we find supporting evidence for several rational expectation explanations of risk premia, when we explicitly take into account the effect of disagreement.

References

Aioli, M., C. Capistran, and A. Timmermann, 2011, *The Oxford handbook of economic forecasting* (Oxford: Oxford University Press).

Alchian, A., 1950, Uncertainty, evolution and economic theory, *Journal of Political Economy* 58, 211–221.

Ang, A., G. Bekaert, and M. Wei, 2007, Do macro variables, asset markets, or surveys forecast inflation better?, *Journal of Monetary Economics* 54, 1163–1212.

Bansal, R., and I. Shaliastovich, 2013, A long-run risks explanation of predictability puzzles in bond and currency markets, *Review of Financial Studies* 26, 1–33.

Bansal, R., and A. Yaron, 2004, Risks for the long run: A potential resolution of asset pricing puzzles, *The Journal of Finance* 59, 1481–1509.

Basak, S., 2005, Asset pricing with heterogeneous beliefs, *Journal of Banking and Finance,* 29, 2849–2881.

Bauer, Michael D, and James D Hamilton, 2015, Robust bond risk premia, *Available at SSRN 2666320.*

Buraschi, A., and A. Jiltsov, 2006, Model uncertainty and option markets with heterogeneous beliefs, *The Journal of Finance* 61, 2841–2897.

———, 2007, Habit formation and macroeconomic models of the term structure of interest rates, *Journal of Finance* 62, 3009 – 3063.

Buraschi, A., F. Trojani, and A. Vedolin, 2014, Economic Uncertainty, Disagreement, and Credit Markets, *Management Science* 60, 1281–1296.

Buraschi, Andrea, and Paul Whelan, 2010, Term structure models and differences in beliefs, *Working paper.*

Campbell, J.Y., and J.H. Cochrane, 1999, By force of habit: A consumption-based explanation of aggregate stock market behavior, *Journal of political Economy* 107, 205–251.

Chen, H., S. Joslin, and N. Tran, 2012, Rare disasters and risk sharing with heterogeneous beliefs, *Review of Financial Studies* 25, 2189–2224.

Cieslak, A., 2016, Short-rate expectations and unexpected returns in treasury bonds, *Working paper, Duke University, Fuqua School of Business.*

——— , and P. Povala, 2012, Expecting the Fed, *Working paper, Kellogg School of Management.*

Cochrane, J.H., and M. Piazzesi, 2005, Bond risk premia, *American Economic Review* 95, 138–160.

Dai, Qiang, and Kenneth Singleton, 2003, Term structure dynamics in theory and reality, *Review of Financial Studies* 16, 631–678.

D'Amico, S., and A Orphanides, 2008, Uncertainty and Disagreement in Economic Forecasting, Discussion paper, Divisions of Research & Statistics and Monetary Affairs, Federal Reserve Board.

Duffee, G.R., 2002, Term premia and interest rate forecasts in affine models, *The Journal of Finance* 57, 405–443.

Ehling, Paul, Michael Gallmeyer, Christian Heyerdahl-Larsen, and Philipp Illeditsch, 2015, Disagreement about inflation and the yield curve, *Working paper. University of Pennsylvania.*

Friedman, M., 1953, *Essays in Positive Economics* (University of Chicago Press, Chicago).

Ghysels, Eric, Casidhe Horan, and Emanuel Moench, 2014, Forecasting through the rear-view mirror: Data revisions and bond return predictability, *FRB of New York Staff Report.*

Giordani, P., and P Soderlind, 2003, Inflation forecast uncertainty, *European Economic Review* 47, 1037–1059.

Goyal, A., and I. Welch, 2008, A comprehensive look at the empirical performance of equity premium prediction, *Review of Financial Studies* 21, 1455–1508.

Greenwood, R., and A. Schleifer, 2014, Expectations of returns and expected returns, *Review of Financial Studies* 27, 714–746.

Gürkaynak, Sack, and Wright, 2006, The u.s. treasury yield curve: 1961 to the present, *Federal Reserve Board Working Paper Series.*

Hong, H., D. Sraer, and J. Yu, 2013, Reaching for maturity, Discussion paper, Princeton University.

Joslin, S., K. J. Singleton, and H. Zhu, 2011, A new perspective on gaussian dynamic term structure models, *Review of Financial Studies* 24, 926–970.

Jouini, E., and C. Napp, 2006, Heterogeneous beliefs and asset pricing in discrete time: An analysis of pessimism and doubt, *Journal of Economic Dynamics and Control* 30, 1233–1260.

Koijen, R., M. Schmeling, and E. Vrugt, 2015, Survey expectations of returns and asset pricing puzzles, Discussion paper, London Business School, Cass Business School and VU University Amsterdam.

Litterman, R., and J. Scheinkman, 1991, Common factors affecting bond returns, *The Journal of Fixed Income* 1, 54–61.

Ludvigson, Sydney C., and Serena Ng, 2009, Macro factors in bond risk premia, *Review of Financial Studies* 22, 5027–5067.

Marcellino, M., 2008, A linear benchmark for forecasting gdp growth and inflation, *Journal of Forecasting* 27, 305–340.

Patton, A. J., and A. Timmermann, 2010, Why do Forecasters Disagree? Lessons from the Term Structure of Cross-Sectional Dispersion, *Journal of Monetary Economics* 57, 803–820.

Piazzesi, M., J. Salomao, and M. Schneider, 2015, Trend and cycle in bond premia, Discussion paper, Stanford, NBER and University of Minnesota.

Scheinkman, J.A., and W. Xiong, 2003, Overconfidence and speculative bubbles, *Journal of Political Economy* 111, 1183–1220.

Svensson, Lars, 1994, Estimating and interpreting forward interest rates: Sweden 1992-1994, Discussion paper, National bureau of economic research.

Wachter, J.A., 2006, A consumption-based model of the term structure of interest rates, *Journal of Financial Economics* 79, 365–399.

Xiong, W., and H. Yan, 2010, Heterogeneous expectations and bond markets, *Review of Financial Studies* 23, 1433–1466.

VIII. Tables

Q1	2 Year	5 Year	10 Year
Mean	−0.03	−0.95	−1.66
Std Dev	0.00	0.02	0.03
Min	−0.01	−0.06	−0.10
Max	0.01	0.03	0.11
Skew	−0.06	−0.09	0.01
Kurtosis	2.49	2.67	3.17
1st Lag Auto	0.79	0.75	0.74
Q2	2 Year	5 Year	10 Year
Mean	0.28	0.34	1.06
Std Dev	0.00	0.02	0.03
Min	−0.01	−0.04	−0.08
Max	0.02	0.04	0.12
Skew	0.05	−0.06	−0.03
Kurtosis	2.34	2.70	3.07
1st Lag Auto	0.82	0.75	0.76
Q3	2 Year	5 Year	10 Year
Mean	0.56	1.46	3.57
Std Dev	0.01	0.02	0.04
Min	−0.01	−0.03	−0.05
Max	0.02	0.06	0.15
Skew	0.23	−0.02	0.04
Kurtosis	2.11	2.51	2.68
1st Lag Auto	0.86	0.78	0.79

Table I. Summary Statistics

Summary statistics of the first (Q1), second (Q2) and third (Q3) quartiles of the distribution of subjective expected excess bond returns, for maturities of 2, 5 and 10 years, and forecast horizon of 1 year. Sample period is January 1988 to July 2015 (331 observations).

	3M				GDP				CPI			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Q1	72%	21%	5%	1%	74%	19%	5%	2%	79%	16%	4%	1%
Q2	22%	51%	23%	4%	20%	54%	21%	5%	17%	62%	19%	3%
Q3	5%	21%	54%	19%	6%	21%	55%	17%	5%	19%	61%	16%
Q4	2%	5%	22%	71%	3%	7%	20%	70%	2%	4%	19%	76%

Table II. Transition Probabilities Short Rates and Macro
This table presents the probability of a forecaster transitioning from a given quartile of the cross-sectional distribution of 3-month yield (left), GDP (middle) and CPI (right) forecasts to another quartile in the following month.

	2-year bond				10-year bond			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Q1	75%	19%	4%	2%	74%	18%	5%	2%
Q2	20%	51%	23%	5%	21%	52%	22%	5%
Q3	4%	23%	52%	20%	5%	23%	52%	20%
Q4	1%	5%	22%	71%	1%	5%	22%	71%

Table III. Transition Probabilities Subjective Excess Returns
This table presents the probability of a forecaster transitioning from a given quartile of the cross-sectional distribution of forecasts to another quartile in the following month, for bond maturities of 2 and 10 years.

	GDP				CPI			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Q1	35%	26%	22%	16%	41%	26%	21%	11%
Q2	26%	27%	28%	19%	26%	30%	28%	16%
Q3	22%	26%	29%	23%	20%	23%	31%	27%
Q4	20%	22%	25%	33%	15%	20%	26%	39%

Table IV. Conditional Probabilities Short Rates vs Macro

This table presents the probability of a forecaster being in a given quartile of the cross-sectional distribution of Macro forecasts given that the forecaster is in a particular quartile of the cross-sectional distribution of 3 month yield forecasts.

		2-year bond				10-year bond			
		Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
GDP	Q1	19%	21%	27%	33%	19%	23%	27%	32%
	Q2	22%	28%	26%	23%	24%	26%	27%	23%
	Q3	28%	27%	27%	18%	27%	28%	26%	19%
	Q4	37%	25%	20%	18%	37%	22%	21%	20%
		Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
CPI	Q1	14%	21%	27%	38%	14%	19%	27%	40%
	Q2	20%	27%	30%	23%	20%	27%	30%	23%
	Q3	32%	28%	23%	18%	29%	30%	25%	16%
	Q4	43%	23%	21%	13%	46%	23%	17%	14%

Table V. Conditional Probabilities Returns vs Macro

This table presents the probability of a forecaster being in a given quartile of the cross-sectional distribution of Macro forecasts (GDP in top panels and CPI in the bottom panels), given that the forecaster is in a particular quartile of the cross-sectional distribution of EBR forecasts, for bond maturities of 2 (left panels) and 10 years (right panels).

Maturity	Q1	Q2	Q3	Q4
2-year	0.33	0.41	0.48	0.50
	(3.22)	(4.17)	(4.84)	(4.51)
5-year	0.29	0.35	0.42	0.40
	(2.81)	(3.42)	(4.29)	(3.25)
10-year	0.26	0.33	0.41	0.43
	(2.72)	(3.41)	(4.22)	(3.79)

Table VI. Autoregressive Regression

Slope coefficients of the regressions of the quartiles (Q1 to Q4) of the cross-sectional distribution of subjective excess returns of 2, 5, and 10-year zero-coupon bonds on a constant and their own lag at the 1-year horizon. t-statistics, reported in parentheses below the point estimates, are Newey-West corrected.

	Q1	Q2	Q3	Q4
Q1	58%	27%	11%	4%
Q2	25%	44%	24%	7%
Q3	9%	22%	47%	21%
Q4	5%	7%	19%	70%

Table VII. Transition Probabilities Accuracy

This table presents the probability of a forecaster transitioning from a given quartile of the cross-sectional distribution of forecasts' accuracy to another quartile in the following month, for bond maturity of 10 years.

Panel A:		**10y EBR Acc**		
All Forecasters		Good	Average	Bad
	Good	15%	11%	8%
3m Yield Acc	Average	11%	13%	9%
	Bad	8%	9%	16%
Panel B:		**10-y EBR Acc**		
Primary Dealers		Good	Average	Bad
	Good	19%	13%	10%
3-m yield Acc	Average	11%	10%	9%
	Bad	6%	7%	15%

Table VIII. Joint Accuracy: 10-year vs 3-month

Panel A displays the joint distribution of forecast accuracy for the 10-year EBR and 3-month yield considering all forecasters. Panel B considers only the primary dealers.

	PC1	PC2	PC3	PC4	PC5	$\overline{R}^2$
EBR_1	0.00	0.02	−0.02	0.06	−0.15	52%
	(8.52)	(11.94)	(−2.62)	(1.91)	(−1.22)	
EBR_2	0.00	0.01	−0.02	−0.02	0.07	45%
	(10.68)	(8.32)	(−3.43)	(−0.53)	(0.58)	
EBR_3	0.00	0.01	−0.02	−0.07	0.16	23%
	(6.68)	(4.08)	(−2.18)	(−1.71)	(0.92)	

Table IX. Spanning of Ex-Ante Accurate Subjective 10-year Bond Return Terciles

This table reports estimates from regressions of spanning regression of terciles of ex-ante accurate subjective expected excess returns on 10-year bonds on the first 5 principle components of the nominal term structure. PC2 is rotated such that a positive shock to this factor implies the slope of the term structure becomes steeper. Terciles are constructed at each point in time based on ranking the sum of the previous years sum of squared forecast errors. EBR_1 denotes the most accurate forecasters while EBR_3 denotes the least accurate forecasters. t-statistics, reported in parentheses below the point estimates, are Newey-West corrected. Adjusted R-squared of the regressions are reported in the last column. The sample period is from January 1989 to July 2015.

Panel A:	**First Stage: Quantity of Risk**		
Maturity	DiB_t	$\mathcal{S}_t$	$\overline{R}^2$
2-year	4.12	1.09	25%
	(7.73)	(3.21)	
5-year	1.89	1.01	11%
	(4.36)	(3.53)	
10-year	0.66	0.67	3%
	(1.64)	(2.82)	
Panel B:	**Second Stage: Risk Premia**		
Maturity	$\hat{\sigma}_B(DiB_t, \mathcal{S}_t)$	$\mathcal{S}_t \cdot \hat{\sigma}_B(DiB_t, \mathcal{S}_t)$	$\overline{R}^2$
2-year	0.20	-6.97	14%
	(6.43)	(-4.39)	
5-year	1.35	-29.19	11%
	(6.55)	(-5.69)	
10-year	9.19	-105.86	14%
	(7.17)	(-6.25)	

Table X. Link Between Risk Premia and Heterogeneous Beliefs

Panel A reports estimates from regressions of the bond return volatility, for 2, 5 and 10-year bonds, on sentiment $\mathcal{S}_t$ and disagreement DiB_t, to obtain $\hat{\sigma}_B(DiB_t, \mathcal{S}_t)$. Panel B, reports the results of the regression:

$$erx^n_{i,t} = a_0 + (a + b\mathcal{S}_t)\hat{\sigma}_B(DiB_t, \mathcal{S}_t) + \epsilon^n_{i,t},$$

using $erx^n_{i,t}$ of the agents with greatest spanning properties (the most accurate at time t), as a proxy for the marginal agent. t-statistics, reported in parentheses below the point estimates, are Newey-West corrected. Adjusted R-squared of the regressions are reported in the last column. The sample period is from January 1988 to July 2015.

Panel A:	5-year bond maturity						
$\hat{\sigma}_B(DiB_t, \mathcal{S}_t)$	$\mathcal{S}_t \cdot \hat{\sigma}_B(DiB_t, \mathcal{S}_t)$	$Surp$	$LRR(g)$	$LRR(\pi)$	LN	CP	$\overline{R}^2$
0.63	−0.66	−0.28					17%
(7.09)	(−6.20)	(−4.41)					
0.38	−0.43		0.28	−0.07			16%
(4.70)	(−4.47)		(4.01)	(−1.22)			
0.88	−0.75				0.14	0.30	17%
(6.61)	(−6.16)				(2.28)	(4.21)	
Panel B:	**10-year bond maturity**						
$\hat{\sigma}_B(DiB_t, \mathcal{S}_t)$	$\mathcal{S}_t \cdot \hat{\sigma}_B(DiB_t, \mathcal{S}_t)$	$Surp$	$LRR(g)$	$LRR(\pi)$	LN	CP	$\overline{R}^2$
1.08	−1.03	−0.24					19%
(7.35)	(−6.45)	(−3.56)					
0.75	−0.68		0.24	0.02			19%
(5.63)	(−4.76)		(3.69)	(0.39)			
0.92	−0.89				0.23	0.12	18%
(5.37)	(−4.59)				(3.25)	(1.56)	

Table XI. Determinants of Ex-Ante Accurate Subjective 10-year Bond Returns
This table reports estimates from regressions of the subjective expected excess returns on 5-year bonds (Panel A) 10-year bonds (Panel B) and for good forecasters on a set of explanatory variables:

$$erx^n_{i,t} = a_0 + (a + b\mathcal{S}_t)\hat{\sigma}_B(DiB_t, \mathcal{S}_t) + b^n_i \mathcal{M}^j_t + \epsilon^n_{i,t}.$$

These factors are discussed in detail in the main body of the paper, and all variables are standardized. t-statistics, reported in parentheses below the point estimates, are Newey-West corrected. Adjusted R-squared of the regressions are reported in the last column. The sample period is from December 1988 to December 2014.

IX. Figures

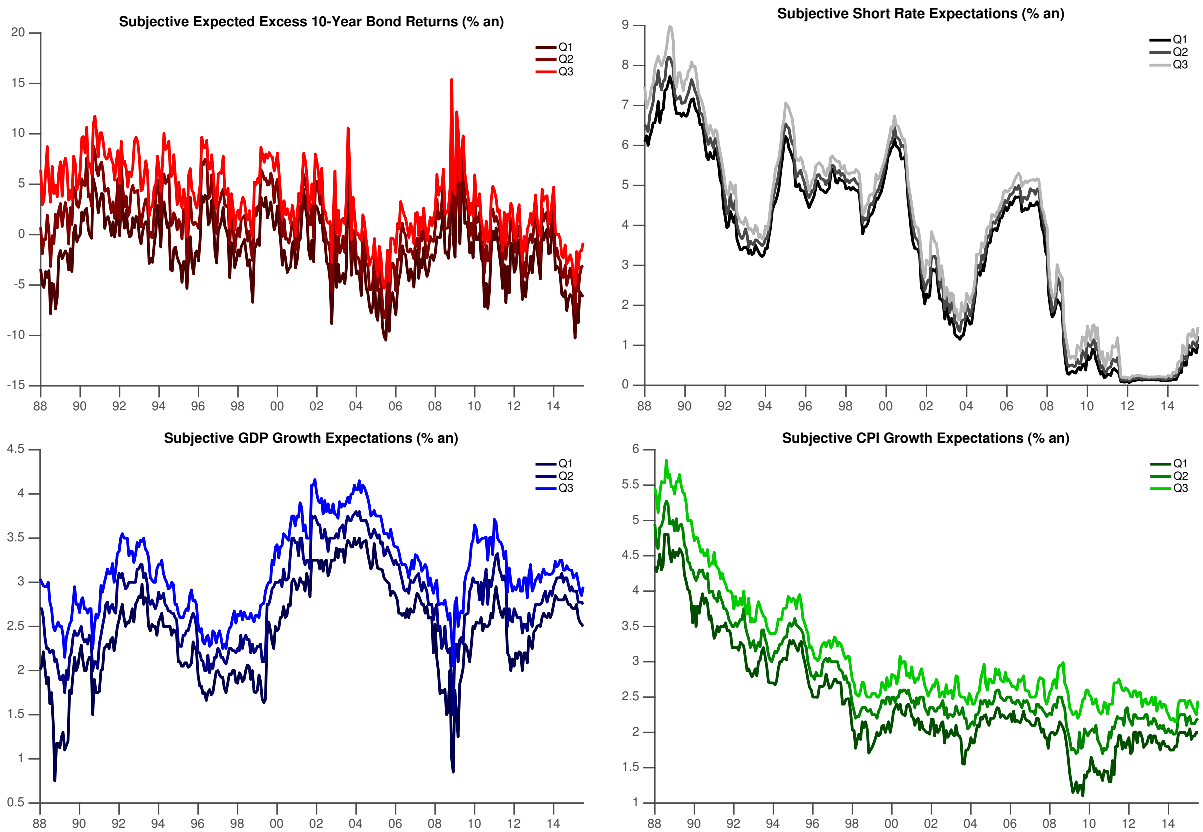


Figure 1. Subjective Expectations

Each panel plots quartiles (Q1, Q2(median) and Q3) of the cross-sectional distribution of expectations. Top Left: 1-year subjective excess returns for 10-year maturity bonds. Top Right: subjective 3-month Treasury yield expectations. Bottom Left: subjective GDP growth expectations. Bottom Right: subjective CPI growth expectations.

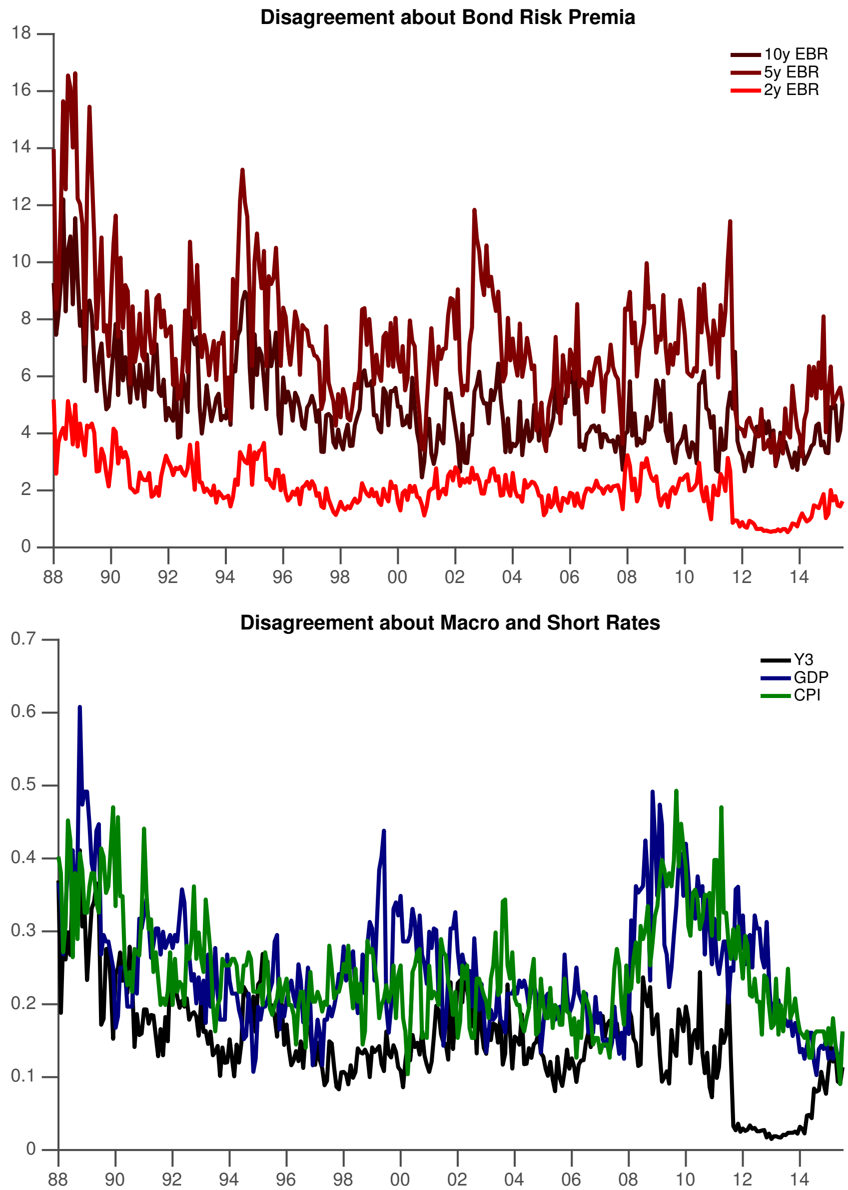


Figure 2. Disagreement about Returns vs Short Rates vs Macro

Top panel plots disagreement about expected bond returns for maturities 2 , 5 and 10-year. Bottom panel plots disagreement about 3-month Treasury yields, GDP and CPI growth. Disagreement is defined as the cross-sectional interquartile range of subjective expectations standardized by the full-sample consensus expectation.

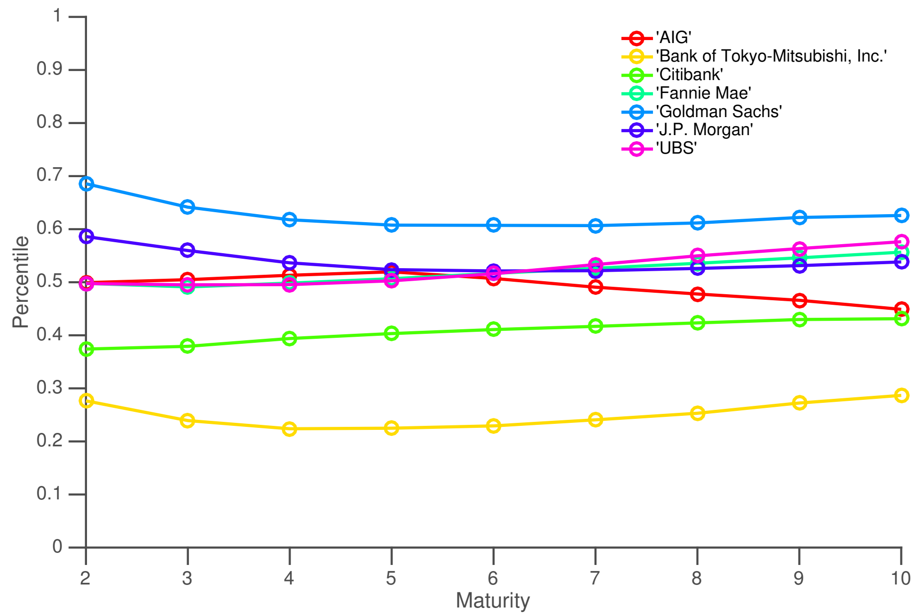
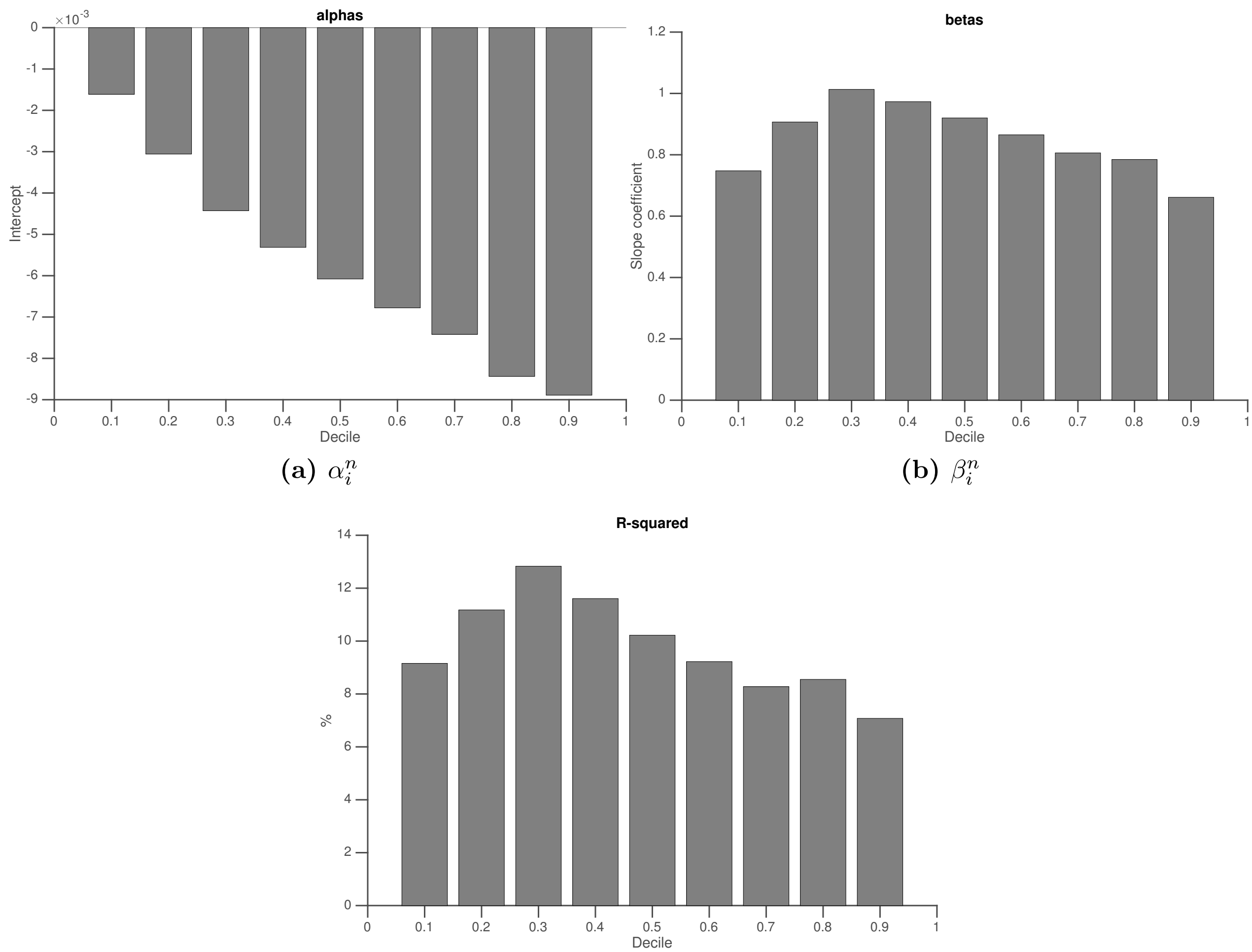


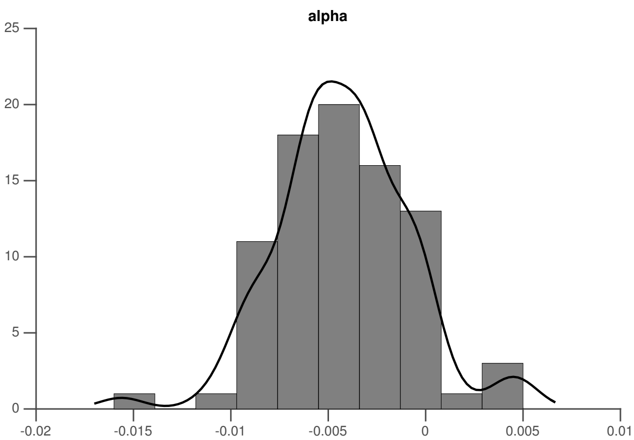
Figure 3. Selected Forecasters' Average Positions

Average position in the cross-sectional distribution of forecasters of seven selected forecasters, for bond maturities between 2 and 10 years.

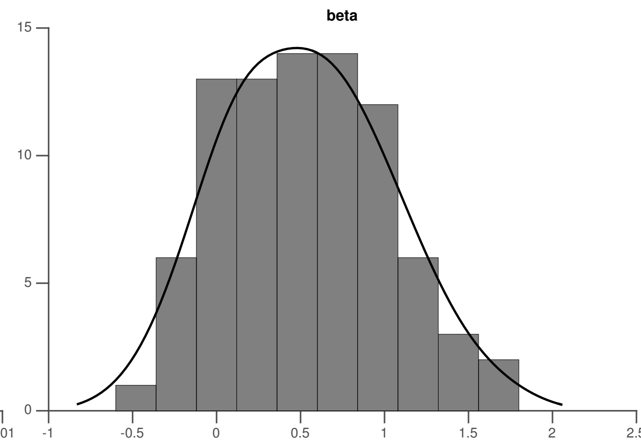


(a) α_i^n **(b)** β_i^n **(c)** R^2

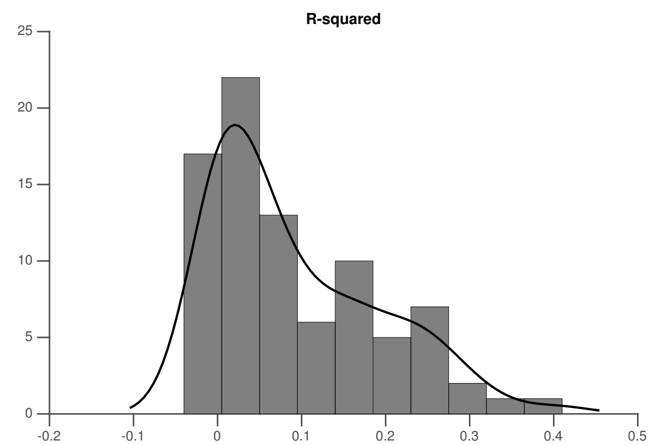
Figure 4. Cross-Section of Short Rate Predictive Regressions
Estimated regression coefficients and adjusted R^2 of regressions of the change in realized 3-month yield on the expected change in 3-month yield for percentile i of the cross-sectional distribution of expectations.



(a) α_i^n



(b) β_i^n



(c) R^2

Figure 5. Short Rate Predictive Regressions: Individual Forecasters
Estimated regression coefficients and adjusted R^2 of regressions of the change in realized 3-month yield on the expected change in 3-month yield for all individual contributors with at least 60 months of forecasts. Solid lines denote kernel density estimates of the cross-sectional distributions.

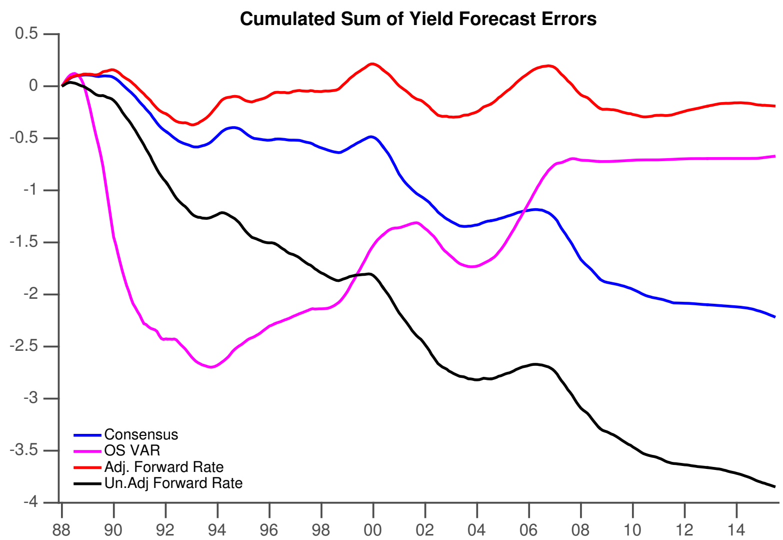


Figure 6. Cumulative 3-month Yield Forecast Errors

Cumulative 3-month yield forecast errors for the average forecaster, i.e. the consensus, an out-of-sample VAR, the forward rate, and the forward rate adjusted by the past average spread between forward rates and realized yields.

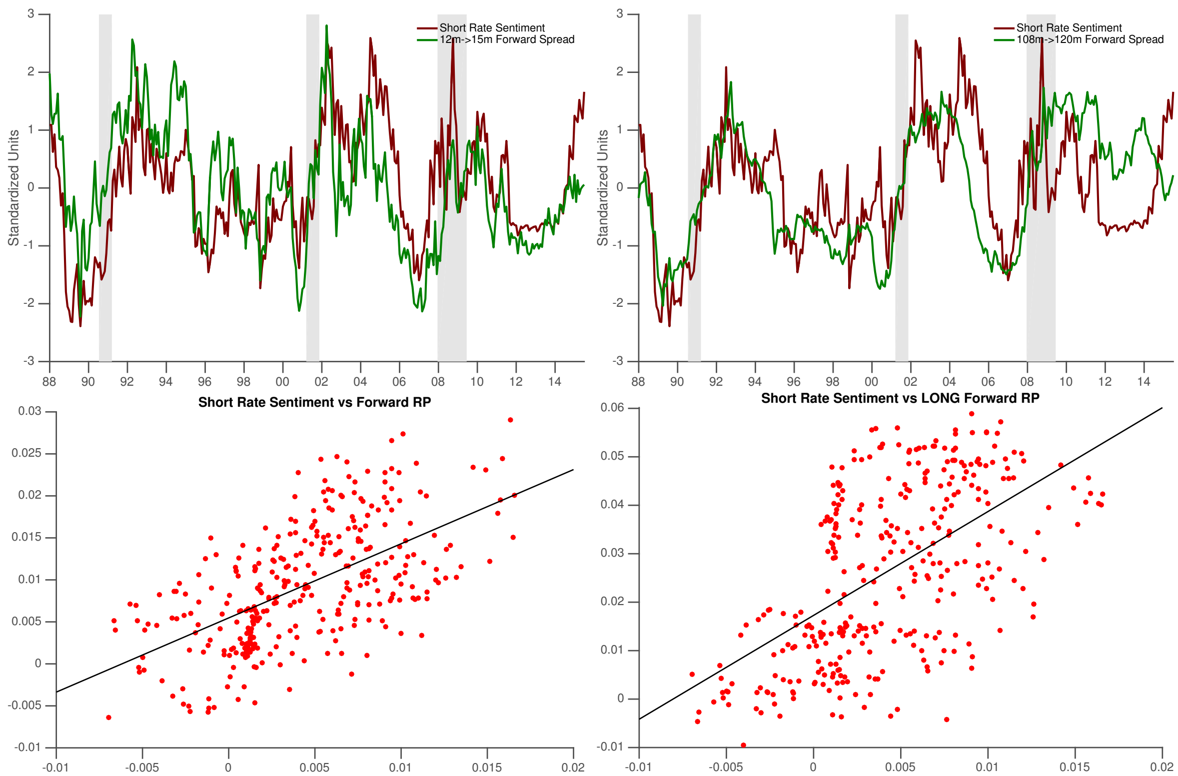
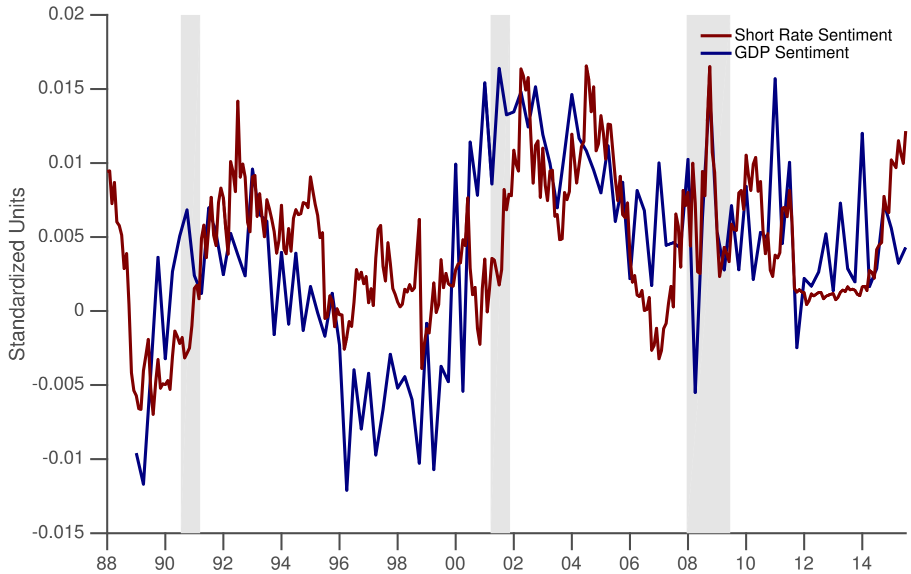


Figure 7. Short Rate Sentiment vs Forward Spread

The blue line is a measure of short rate sentiment, computed as the difference between the consensus 3-month yield forecast and a unit-root forecast. The red lines are forward spreads. The top left plot displays a short term forward spread computed as the difference between the $12M \rightarrow 15M$ forward rate and the current 3-month rate. The top right plot is a long term forward spread computed as the difference between the $108M \rightarrow 120M$ forward rate and the current 1-year yield. For comparison purposes, all time series are standardized to be zero mean and unit variance. The bottom left panel is a scatter plot corresponding to the time series in the top left plot. The bottom right plot is a scatter plot corresponding to the time series in the top right plot.



GDP Sentiment vs Short Rate Sentiment

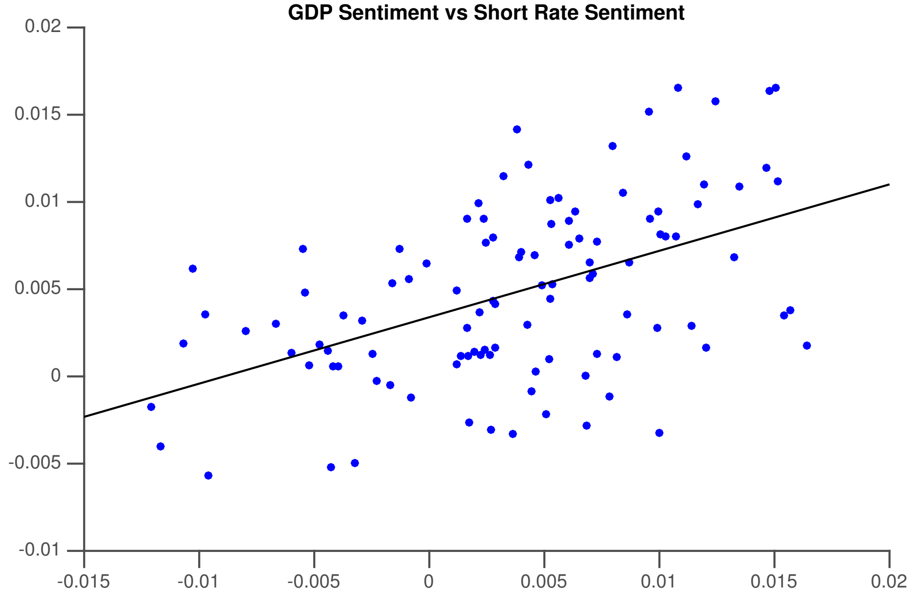


Figure 8. Sentiment Measures

The red line denotes the *Sentiment* measure, computed as the difference between the simple average of expected short-rate from surveys and the expected short-rate implied by a unit-root forecast at 1-year horizon. The blue line is an equivalent measure of sentiment on GDP growth expectations, where the physical expectation is computed from an AR(4) projection of quarterly realized GDP growth. Bottom is a scatter plot corresponding to the time series in the top plot.

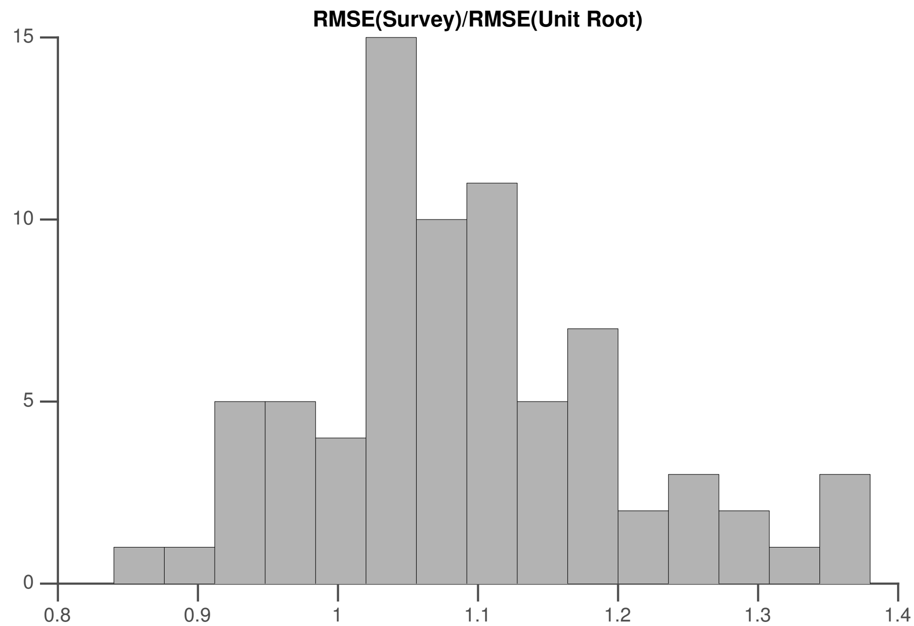


Figure 9. Relative Accuracy

Histogram of the relative accuracy $\mathcal{A}_i$ of each forecaster, that is the ratio between the RMSE of each individual forecaster and the RMSE of a unit root benchmark, for the period in which the forecaster is in the panel:

$$\mathcal{A}_i = \frac{RMSE_i^{3m}(Surv)}{RMSE^{3m}(UnitRoot)}$$

We consider only the contributors with at least 60 months of forecasts, for a total of 84 insitutions.

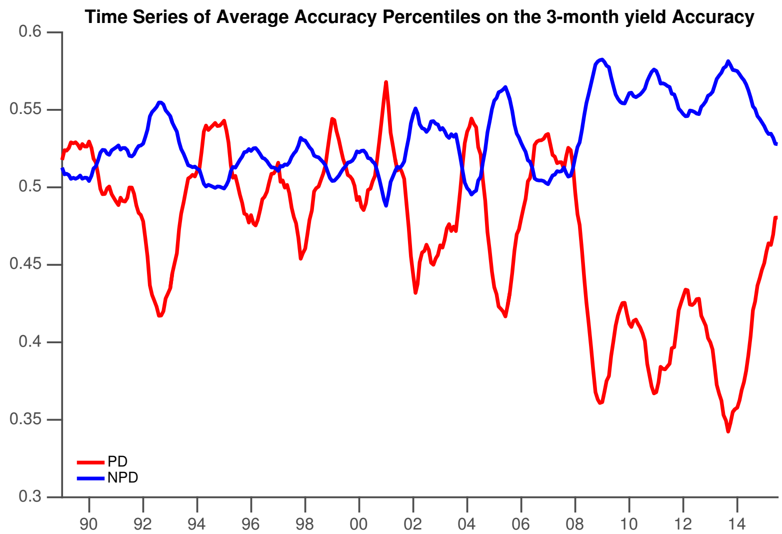


Figure 10. Time Series of Short Rate Accuracy Percentiles for PD vs NPD
Time series of average accuracy percentiles for 3 month Treasury yields for primary dealers (PD) and all other agents (NPD).

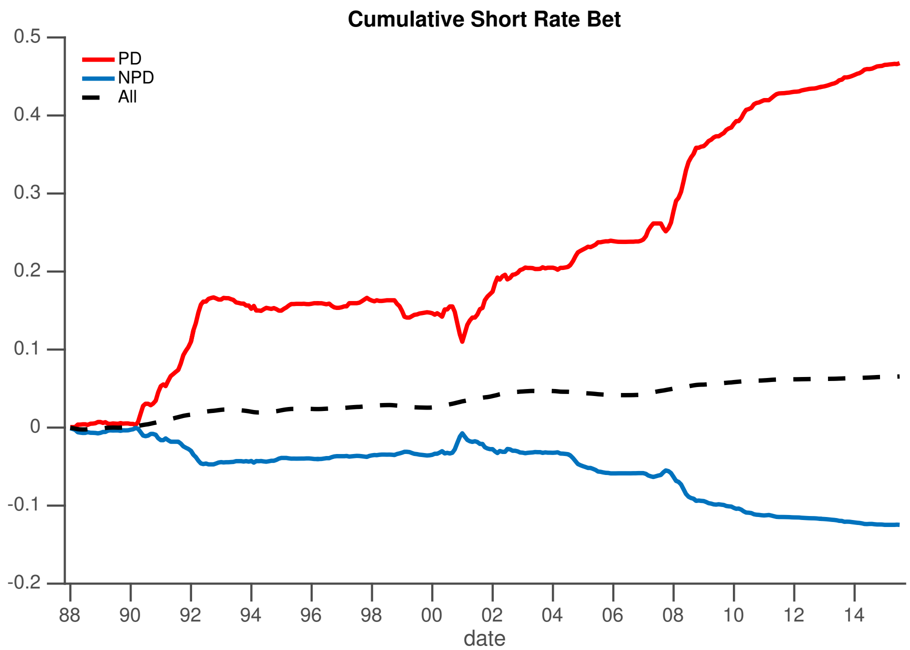


Figure 11. Cumulative Returns on Short Rate Bet for PDs vs NPDs
Cumulative returns on a short rate bet for the average primary dealer (PD) and non primary dealer (NPD). Every month, agents in the left tail of the distribution of 3-month yield expectations go long the 2-year bond and short the 1-year bond, and hold the position for a year. Agents in the right tail of the distribution of 3-month yield expectations do the opposite. We average the returns over PDs and NPDs and plot their cumulative returns assuming a bet is placed every month. The dashed black line denote the cumulative returns on a short rate bet for the average forecaster.

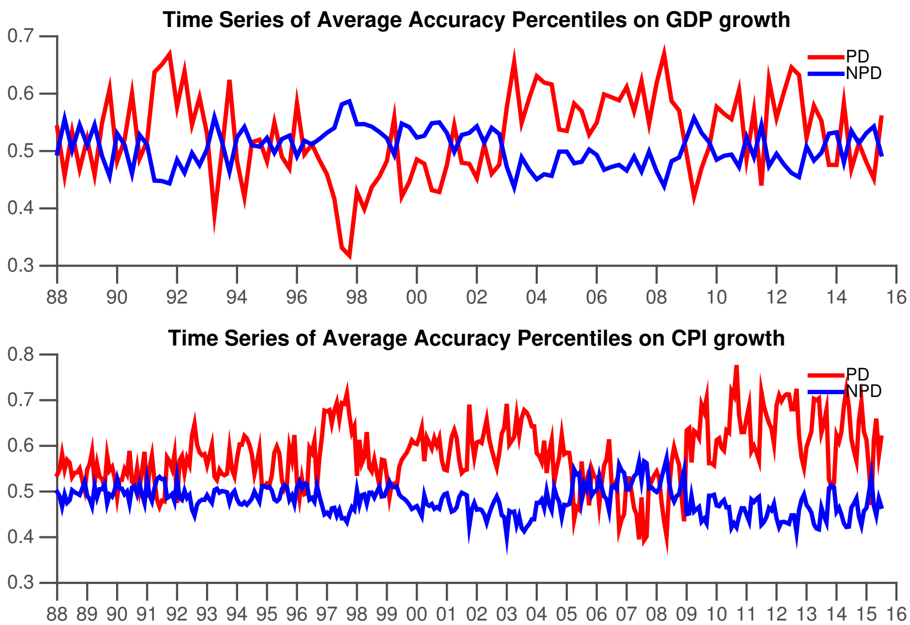
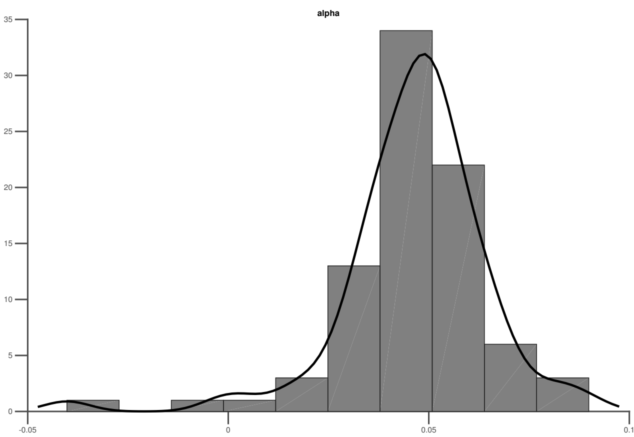
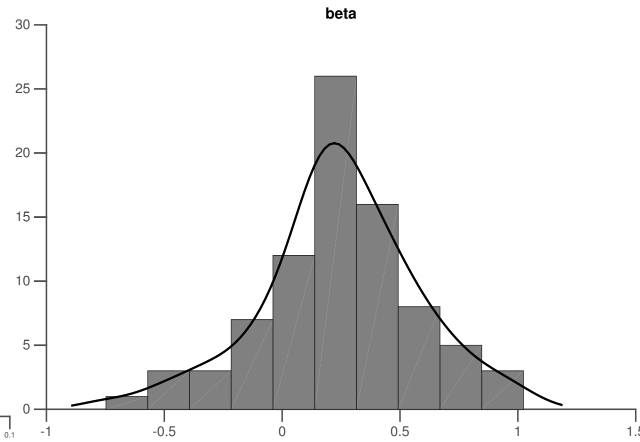


Figure 12. Time Series of Macro Accuracy Percentiles for PD vs NPD

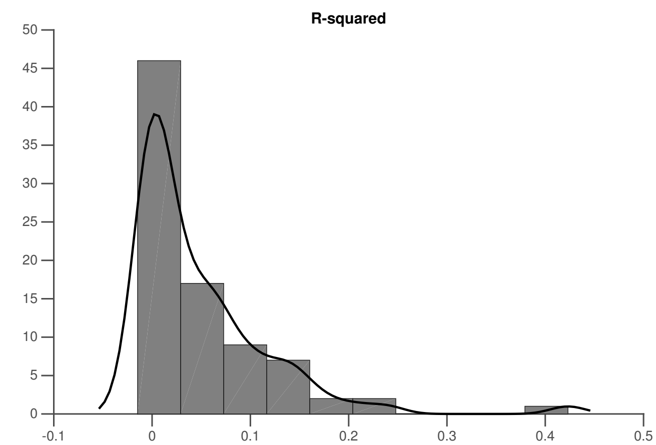
Time series of average accuracy percentiles on the Real GDP growth (upper panel) and CPI growth (bottom panel), for primary dealers (PD) and all other agents (NPD).



(a) α_i^n



(b) β_i^n



(c) R^2

Figure 13. Predictive Regressions Individual Forecasters

Estimated regression coefficients and adjusted R^2 of regressions of the realized excess 10-year bond returns on the expected excess bond returns for all individual contributors with at least 60 months of forecasts:

$$rx_{t+1}^{10} = \alpha_i^{10} + \beta_i^{10} erx_{i,t}^{10} + \epsilon_{i,t+1}^{10}.$$

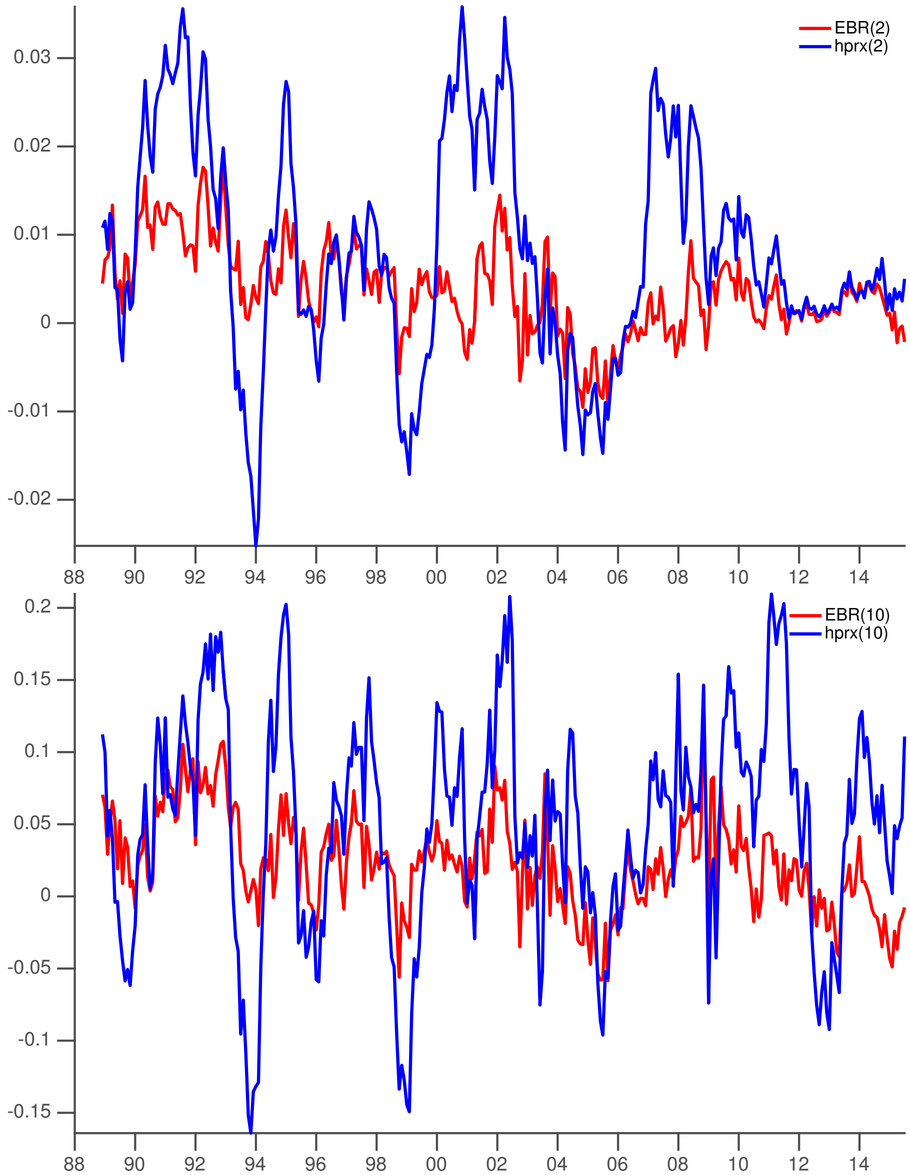
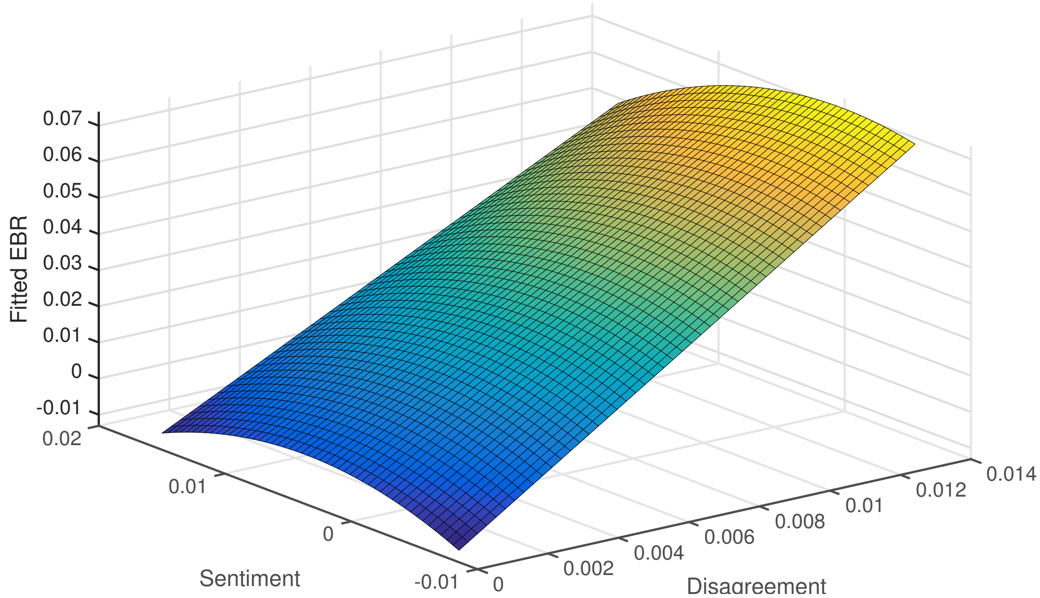


Figure 14. Most Spanned Subjective Expected Returns

We obtain measures for erx_t^* at each point in time based on ranking the sum of the previous years sum of squared forecast errors. The top plot displays the survey implied expected excess returns on a 2-year bond compared to the ex-post realised returns. The bottom plot is for the 10-year bond.



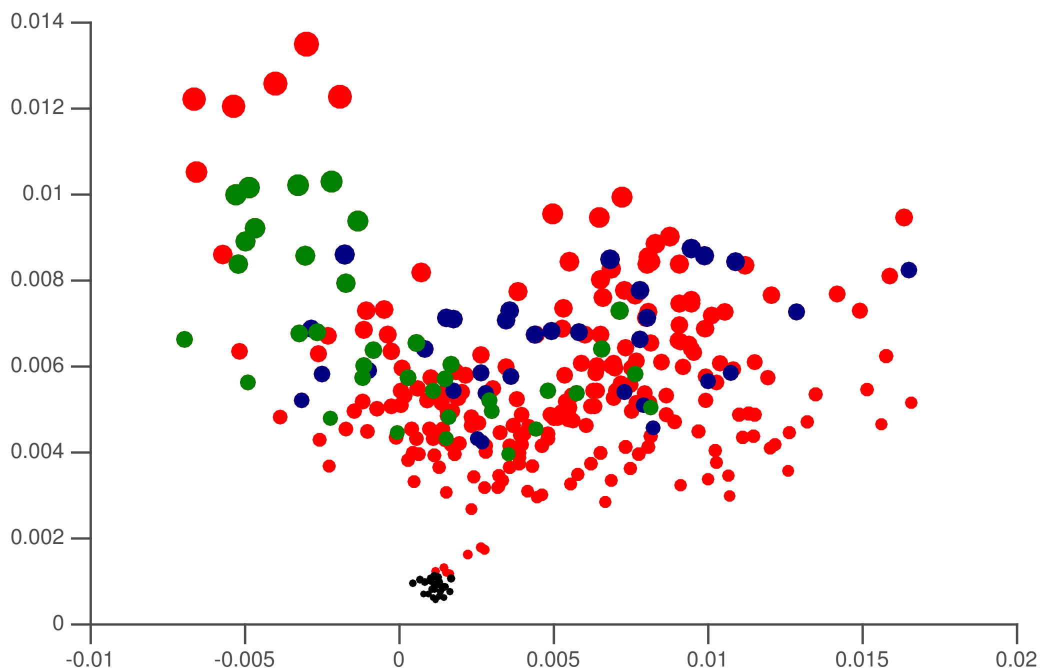


Figure 15. Fitted Subjective Bond Returns

This top figure displays plots the fitted surface of EBR, defined as $\hat{a}_0 + (\hat{a} + \hat{b}\mathcal{S}_t)\hat{\sigma}_B(DiB_t, \mathcal{S}_t)$, for a 10 year bond over the range of values for DiB_t and $\mathcal{S}_t$ in the range observed within our sample period. The bottom panel shows a scatter plot of actual economies as they have been historically observed in terms of DiB_t (y-axis) and $\mathcal{S}_t$ (x-axis). The size of each dot corresponds to the size of the fitted bond risk premium. Black dots highlights negative $EBRs$. Green dots correspond to EBRs forecasted in the preceding 12 months prior to the start of NBER-dated recessions. Blue dots correspond to EBRs forecasted in the following 12 months after the start of NBER-dated recessions.