Expecting the Fed

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We study private sector expectations about the short-term interest rate. We uncover persistent differences between the ex-ante real rate perceived by agents in real-time and its full-sample counterpart estimated by the econometrician. Entering recessions, agents systematically overestimate the real rate, and underestimate future unemployment and the degree of monetary easing. These forecast errors induce persistence in identified monetary policy shocks and cause the econometrician to overstate the variation in Treasury risk premia. Our evidence offers a new interpretation of the unspanned factors phenomenon in the yield curve, emphasizing the key role of information rigidities for the dynamics of real interest rates.

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I. Introduction

Using survey data and information from asset prices, we study expectations of the short-term interest rate formed by the private sector. Separating short rate expectations from risk premia in interest rates is of importance for policy makers and for understanding the economic determinants of the yield curve. Such decomposition provides insights about market's perceptions of the future course of monetary policy, economic activity, inflation and their associated risks, upon which agents base their economic choices. It is also informative about the channels—risk premium versus expectations—through which monetary policy could influence the economy.[1] While recent academic research has extensively studied bond risk premia, relatively little is known as to how investors form expectations about the future path of the short rate. This focus is justified in light of the common assumption of full-information rational expectations (FIRE). Based on this premise, one interprets predictive regressions of bond returns on various conditioning variables as a way to capture the time-varying risk premium. In this paper, we show that the frictionless view of expectations is inconsistent with the observed behavior of interest rates. We document a particular role of deviations from the FIRE for the real rate dynamics.

We start with the observation that lagged information, spanning length of the business cycle, improves econometrician's predictions of future short-rate changes relative to conditioning on the current yield curve alone. This is surprising given that today's cross-section of yields reflects risk-adjusted expectations and therefore, absent additional restrictions, should subsume all information relevant for forecasting. We use this fact to study the degree to which expectations that shape the yield curve are indicative of expectations frictions faced by agents in real time. To directly disentangle the risk premium from short rate expectations, we rely on survey data containing private sector's forecasts of the federal funds rate (FFR)—the conventional US monetary policy tool—as well as forecasts of longer maturity yields and inflation.

While survey-based expectations of the short rate match almost one for one the contemporaneous behavior of short-term yields and fed fund futures, these expectations are poor predictors of future short rates except at very short horizons. We show that with hindsight it is relatively easy to identify variables that improve upon agents' real-time forecasts of the short rate. Specifically, we find a persistent discrepancy between the real short rate implied by real-time expectations and one

[1] See for instance the speeches of the Fed governor Kohn and Chairman Bernanke on the importance of this distinction for policy making (Kohn, 2005; Bernanke, 2006).

that an econometrician constructs with access to the full sample. This wedge becomes large at the start of NBER-dated recessions and during monetary easings, reaching up to -200 basis points, which suggests that in those periods agents tend to overestimate the real rate relative to the FIRE benchmark. Relatedly, we find that in the last three decades agents' forecast errors about the short rate comove closely with errors they make when forecasting unemployment (correlation in excess of -0.7), and much less so—inflation. Building on these facts, we construct a variable that traces the discrepancy between the investors' and the statistical measures of the ex-ante real rate. We label it as the real rate wedge and denote with $MP_t^{\perp}$.

We study the implications of these findings for the measurement of bond risk premia with predictive regressions. We find that two factors, with an economically distinct interpretation, span the predictable variation in realized bond returns across maturities. The real rate wedge, $MP_t^{\perp}$, is nearly uncorrelated with contemporaneous yields, and predicts bond excess returns separately from measures of the risk premium extracted from the yield curve, such as the Cochrane and Piazzesi (2005) factor. Its effect is the strongest at short maturities and subsides for longer-term bonds. With help of survey data on longer-maturity yields, we obtain a model-free decomposition of annual excess bond returns into an expected return (risk premium) and an ex-ante unexpected component. The unexpected return on a two-year bond moves in lockstep with the negative of FFR forecast errors with a correlation above 0.9. Around 30% of its variation can be predicted ex-post by $MP_t^{\perp}$. We find that several conditioning variables used in predictive regressions of bond returns, especially variables related to the real activity, predict the *unexpected* return component. While these variables comove with $MP_t^{\perp}$, they are essentially uncorrelated with measures of bond risk premia, either subjective (i.e., extracted from surveys) or statistical (i.e., estimated from the yield curve). By establishing a link with short-rate forecast errors, these results contribute new evidence to the discussion in the recent literature that highlights the so-called unspanned or hidden factors in the term structure of interest rates—factors that have forecasting power for bond excess returns while not being spanned by the current cross-section of yields (e.g., Duffee, 2011; Joslin, Priebsch, and Singleton, 2013).

Several forms of information rigidities may interact to produce our results, which we collectively term as expectations frictions. We document that the predictability of the short-rate forecast errors can be partially, but not entirely, rationalized with rigidities such as sticky or noisy information. We also investigate an alternative scenario that involves agents' learning about the parameters of the economy and the Fed's reaction function. In a simulation, we show that such a setup could deliver the full-sample predictability of forecast errors in the magnitude found in the data.

Our results are related to the identification of monetary policy shocks. We find that the real rate wedge $MP_t^{\perp}$ is highly correlated with the low-frequency variation in monetary policy shocks constructed from the fed funds futures (e.g., Kuttner, 2001; Gürkaynak, Sack, and Swanson, 2005). At an annual horizon, $MP_t^{\perp}$ predicts up to 50% of variation in surprises to the Fed policy target realized during the subsequent year. This observation suggests that while the Fed delivers persistent surprises to the public in real time, an econometrician working under the FIRE assumption would classify these shocks as anticipated policy actions. Moreover, studying the short-rate forecasts prepared by the Fed staff, so-called Greenbook forecasts, we find that they are qualitatively very similar to these of the public.

There are at least two concerns about the validity of our results, which are related to the use of survey data. First, it can be that surveys are noisy, which would make survey-based forecasts inaccurate. Using various statistical models with different degree of sophistication, from a simple random walk through a time-varying parameters Bayesian VAR, we find that none is able to outperform surveys in generating more precise real-time predictions. This fact speaks against the hypothesis that noise prevents inference using surveys but it does not address the second concern. Namely, forecasters may simply anchor their predictions to the current market rates reporting risk-adjusted rather than physical expectations. Thus, what we identify as expectations frictions could arise from a pure risk premium variation. While we find a close overlap between survey expectations and the fed fund futures or short-term Treasury yields, it is unlikely that forecasters report risk-adjusted predictions for several reasons. For the risk premium to account for our results, one would need to accept that investors charge a highly volatile and implausibly large risk premium (on the scale of several hundred basis points) when investing in short-term and safe interest rate instruments. While the bulk of our results relies on professional forecasts of the FFR from the Blue Chip Financial Forecasts survey, we uncover analogous results in the Survey of Professional Forecasters comprising different panelists and T-bill rate predictions, and in the Greenbook forecasts of the FFR. Finally, we find the same expectations frictions that drive the predictability of the FFR forecast errors to be also present in expectations of unemployment, which are not influenced by the risk premium considerations.

Related literature

Our work is motivated by the recent developments in the term structure literature combined with the research in macroeconomics that emphasize the role of deviations from the FIRE (see Mankiw and Reis (2011) and Woodford (2012) for overview). A growing area of macro research focusses on information rigidities. Coibion and Gorodnichenko (2011a, 2012) and Andrade and Le Bihan (2013) provide evidence that survey expectations of macro variables require models that relax the FIRE assumption. Fuster, Laibson, and Mendel (2010) introduce natural expectations—the idea that while macroeconomic variables may have complex dynamics, agents forecast the future using simple models. On the theoretical front, several authors stress the relevance of imperfect knowledge in modeling monetary policy (e.g. Orphanides and Williams, 2005; Woodford, 2010; Angeletos and La'O, 2012; Wiederholt and Paciello, 2012). We use the bond market as a laboratory to provide an empirical assessment of the degree of expectations frictions faced by agents, their economic sources, and relevance for describing the dynamics of interest rates. In particular, our results point to a nontrivial role of real information rigidities in shaping the yield curve. As such, they provide empirical support to the key assumption of Angeletos and La'O (2012) who focus on incomplete information as a source real frictions driving firms' employment, investment and production decisions.

We also build on the literatures dealing with bond risk premia and extracting market-based expectations of monetary policy from asset prices. Motivated by the failure of the expectations hypothesis of the term structure, a large body of work has focussed on exploring the dynamics of bond risk premia (Campbell and Shiller, 1991; Fama and Bliss, 1987; Cochrane and Piazzesi, 2005). A common approach to measuring the risk premium variation is through predictive regressions, i.e. a projection of realized bond returns on a variety of conditioning variables, including the yield curve slope, a set of forward rates and macro variables. A subject of active discussion in this line of research is the observation that future bond returns are predictable by variables that have a weak contemporaneous correlation with the cross section of yields. This observation has given rise to the study of hidden or unspanned factors, and has been formalized as a component driving bond risk premia in Duffee (2011), Barillas and Nimark (2012), Joslin, Priebsch, and Singleton (2013), and Joslin, Le, and Singleton (2013). We show empirically that unspanned factors can arise as a consequence of the expectations formation at the short end of the yield curve. Specifically, documenting the wedge between the agents' and econometricians' expectations of the real short-rate, we are able to reconcile our results with the empirical evidence in the earlier literature.

A parallel literature studies the properties of monetary policy expectations extracted from asset prices (e.g. Rudebusch, 1998; Kuttner, 2001; Cochrane and Piazzesi, 2002; Ferrero and Nobili, 2009). Sack (2004) argues for a time varying but overall small risk premium in the fed fund and eurodollar futures. On the other hand, Piazzesi and Swanson (2008) show that realized excess returns on the fed funds futures are strongly predictable with real variables, implying large countercyclical risk premia on these assets. We link their results to the predictability of ex-post forecast errors about the short rate.

Survey data have been before used to study expectations formation in financial markets. In the foreign exchange market, Frankel and Froot (1987) explain the forward premium puzzle with expectations errors, and find that these errors are predictable with past information. Bacchetta, Mertens, and van Wincoop (2009) extend this evidence to other asset classes including stocks and bonds. Using survey data on bond yields in the 1969–1985 period, Froot (1989) shows that predictable forecast errors contribute to the violations of the expectations hypothesis for long-maturity bonds. Piazzesi and Schneider (2011) reach a similar conclusion with more recent data. They argue that risk premia implied by the surveys are more persistent than those obtained with statistical approaches such as the Cochrane-Piazzesi regressions. While these papers focus on extracting subjective bond risk premia using survey data, our focus is different in that we identify a predictable element of realized bond returns, related to short rate dynamics, that is orthogonal to either subjective or statistical premia.

Deviations from the FIRE have recently gained prominence in studies of other major asset markets. Singleton (2014) emphasizes the distinctive role of informational frictions in the commodities market to explain the pricing of oil. Using micro-survey data on expectations about inflation, stock returns and house prices, Nagel (2012) relates biases in expectations such as overextrapolation to the life-time macroeconomic experiences of individuals. Similarly, Greenwood and Shleifer (2014) draw on responses from equity investor surveys and flows to confirm the presence of extrapolation in the way investors form expectations about future stock returns. They highlight a negative relationship between the statistical and survey-based equity premia.

II. Short-rate expectations

II.A. Survey data

Our primary source for short rate expectations of the public are the forecasts of the federal funds rate (FFR) from the Blue Chip Financial Forecasts (BCFF) survey. To argue that these data are a good description of actual expectations of market participants, in Section VI, we use fed fund futures and alternative survey sources. The BCFF survey contains monthly forecasts by about 45 leading financial institutions. Our sample starts from its inception in March 1983 through December 2010, spanning a relatively homogenous period in the US monetary policy, during which the FFR was the main operating tool of the Fed.[2] Forecasters predict quarterly averages of the effective FFR for the current quarter, the next quarter, out to four quarters ahead. Also from BCFF, we obtain forecasts of all-items CPI inflation at the same horizons. The inflation survey is available from June 1984 through December 2010. We use the median forecast across panelists, because a simple combination of models/forecasters are known to increase the forecast precision (e.g. Stock and Watson, 1998; Timmermann, 2006).[3] Our subsequent results are essentially unchanged if we use the mean forecast.

Figure 1 plots the time series of survey-based FFR forecasts. Panel *a* aligns the forecasts for different horizons with the realized FFR at the time when the forecasts are formed, showing that expectations trace fairly closely the current FFR. Panel *b* displays the same information in form of conditional term structures of forecasts. The gap between realized and expected rate indicates that agents systematically underestimate both the degree of monetary tightening and easing. We define the forecast error of the median forecaster at horizon h as:

$$FE_{t,t+h}^{FFR} = FFR_{t+h} - E_t^s(FFR_{t+h}), \tag{1}$$

[2] The forecasts are published on the first day of each month, but the survey itself is conducted over a two-day period, usually between the 23rd and 27th of each month. The exception is the survey for the January issue which generally takes place between the 17th and 20th of December. BCFF does not publish the precise dates as to when the survey was conducted.

[3] We confirm this result in our data by studying the persistence in individual forecasters' ability to outperform the median FFR forecast. We find that very few forecasters are able to beat the median forecast consistently across different forecast horizon and over longer time spans. Our data allows us to identify a forecaster (institution contributing to the survey) and trace them over time. To study the persistence in forecast accuracy, we require a forecaster to contribute at least 36 consecutive months to the survey (the samples differ among forecasters). There are 33 contributors who survive this filter. For each forecaster, we measure the ratio of their RMSE relative to the RMSE of the median forecaster. We find that 21% of forecasters are able to achieve a ratio below 1, but only one of them is below 0.95. The distribution of RMSE ratios is strongly skewed to the right with more than 68% of the panelists achieving a ratio of 1.05 or worse.

where $E_t^s(FFR_{t+h})$ denotes the median survey expectation of the FFR. Panel c of Figure 1 shows that forecast errors are on average negative during monetary easings and positive during tightenings. The most pronounced errors are negative and typically occur during and after NBER recessions as forecasters largely fail in predicting the extent of subsequent monetary easing. At a one-year horizon, the average error reaches -1.43% and 0.60% in easing and tightening episodes, respectively, with standard deviations of 1.37% and 0.88% (more details are provided in Table C-XII of the Appendix). Despite an increased transparency of the Fed throughout our sample, forecast errors do not seem to decrease over time, as suggested by a regression (not reported) of absolute forecast errors on a time trend.[4]

II.B. *Predicting short-rate forecast errors with lagged information*

Through the paper, we measure time in years. To assess the fraction of future changes in the short rate that is anticipated by the public we estimate the following regression:

$$\Delta FFR_{t,t+1} = \underbrace{\gamma_2}_{-0.63\ [-2.34]} + \underbrace{\gamma_3}_{1.06\ [3.36]} [E_t^s(FFR_{t+1}) - FFR_t] + \varepsilon_{t+1}, \quad \bar{R}^2 = 0.18, \tag{2}$$

where $\Delta FFR_{t,t+1} = FFR_{t+1} - FFR_t$ is the annual change in the FFR, and Newey-West t-statistics are reported in brackets. The estimates show that more than 80% of annual changes in the short rate is unexpected by the public. Table I.A reports analogous results for other forecast horizons, indicating that forecasters are relatively more precise at short horizons.[5]

If expectations of the public support the FIRE assumption, no addition information available at time t should improve upon regression (2). Looking for candidate predictors of short rate changes, we focus on the lagged values of the nominal term spread (slope) for the following reason: To the extent that the Fed's inflation target is highly persistent, the short-term changes in the policy rate $\Delta FFR_{t,t+1}$ should mainly reflect the dynamics of real variables. A variable that predicts

[4]In our sample, there have been several operational changes that increased the transparency of the Fed. First, in 1994 the Fed started issuing a statement following each FOMC meeting. Starting in March 2002, votes of the committee members are public. Sellon (2008) finds that the transparency of the monetary policy decreased the prediction errors at short horizons while the prediction errors at longer horizons (one year and more) have not changed.

[5]While we cannot reject the null hypothesis that $\gamma_3 = 1$, we observe significantly negative γ_2 which is due to the zero-lower bound hit in 2008. Excluding the 2008–2010 period gives an insignificant γ_2 and γ_3 close to one (not reported).

real activity is therefore also likely to contain information about future changes in the FFR.[6] This intuition suggest the lagged yield curve slope as a candidate predictor of $\Delta FFR_{t,t+1}$, given its well-documented forecasting power for real activity several quarters ahead (Estrella and Hardouvelis, 1991; Harvey, 1989; Bernanke and Blinder, 1992). Unlike macro variables that are revised, the slope is easily observable by agents in real time and is minimally subject to measurement issues. Thus, we project the one-year change in the FFR on today's and lagged slope:

$$\Delta FFR_{t,t+1} = \alpha_0 + \underbrace{\alpha_1}_{-0.07\ [-0.74]} S_t + \underbrace{\alpha_2}_{0.79\ [6.13]} S_{t-1} + \varepsilon_{t+1}, \quad \bar{R}^2 = 0.37, \tag{3}$$

where $S_t = y_t^{(20)} - y_t^{(3m)}$, and $y_t^{(20)}$ and $y_t^{(3m)}$ is the 20-year and three-month yield, respectively.[7] For ease of interpretation, we include only one-year lag of the slope, S_{t-1}. The predictability implied by the estimates in (3) is almost entirely driven by the lagged slope, and significantly higher than the one attained with the survey forecasts in (2). The positive sign of α_2 means that high past slope (steep yield curve) is a signal that FFR will increase in the future, possibly as growth prospects of the economy improve as well.

To verify whether agents perceive the dynamics of the short rate in real time in the same way as an econometrician can observe it ex-post, we test if their expectations subsume the lagged slope:

$$\Delta FFR_{t,t+1} = \alpha_3 + \underbrace{\alpha_4}_{0.52\ [2.25]} [E_t^s(FFR_{t+1}) - FFR_t] + \underbrace{\alpha_5}_{0.52\ [4.31]} S_{t-1} + \varepsilon_{t+1}, \quad \bar{R}^2 = 0.35. \tag{4}$$

The estimates in (4) strongly reject this null hypothesis that $\alpha_5 = 0$. Thus, from the perspective of the econometrician, forecast errors of the public are ex-post predictable:

$$FE_{t,t+1}^{FFR} = \delta_0 + \underbrace{\delta_2}_{0.40\ [3.36]} S_{t-1} + \varepsilon_{t+1}, \quad \bar{R}^2 = 0.15. \tag{5}$$

In Table I, we report results of regressions (4) and (5) for other forecast horizons. Private sector forecasts are quite accurate at short horizons but deteriorate as the horizon increases. This feature

[6]Indeed historically, annual changes in the FFR have comoved strongly with the contemporaneous annual changes in the rate of unemployment with a correlation of -60% in the 1954–2010 period, which strengthened to nearly -70% post Volcker.

[7]We use the 20-year yield as the longest available maturity over our sample period. Using the ten-year maturity as the long-term yield or a six-month/one-year maturity as the short-term yield only minimally affects the results. While allowing for more lags in regression (3) improves information criteria, the improvement is marginal relative to the specification with just one lag and does not significantly alter our conclusions.

is visible in panel C, where the economic and statistical significance of S_{t-1} for predicting forecast errors increases with the horizon. In the table, we additionally augment the above regressions with five principal components extracted from the yield curve at time t, which is motivated by the fact that current yields reflect risk-adjusted market expectations of the short rate. Including this information does not drive out the significance of the lagged slope, suggesting that the predictability of forecast errors in not a simple artifact of the quality of survey data. We address the question of survey quality in Section VI in more detail.

II.C. FIRE versus real-time expectations: The real rate wedge

The predictability of the FFR forecast errors with the lagged term spread raises the question about economic variables, real or nominal, that drive the difference between what agents expect ex-ante and what an econometrician finds ex-post. In this section, we document that there is a persistent discrepancy between the ex-ante real short rate measured using surveys and one estimated with access to full-sample information. We introduce a measure of expectations frictions, which we call $MP_t^{\perp}$, that focuses on this aspect of the short-rate dynamics.

We define the ex-post real rate as $r_{t+1} = FFR_{t+1} - \Delta CPI_{t+1}$,[8] where $\Delta CPI_{t+1} = \ln\left(CPI_{t+1}/CPI_t\right)$ is the annual inflation, and CPI_t is the price level, or in an ex-ante form:

$$r_t^e = E_t(FFR_{t+1}) - E_t(\Delta CPI_{t+1}). \tag{6}$$

We consider two approaches to estimating (6). The first approach, assuming constant parameters and rational expectations, uses linear full-sample projections of r_{t+1} on time-t variables; the second approach relies on survey expectations of the FFR and of inflation. In the latter case, we make the assumption that the median survey response coincides with the market consensus, which we verify in Section VI. Therefore, under FIRE, we regress r_{t+1} on a set of instruments:

$$\hat{r}_t^{e,FIRE} = E_t\left[r_{t+1} \middle| \, \text{Instruments}_t\right], \tag{7}$$

where $\text{Instruments}_t = \left(y_t^{(3m)}, \Delta UNE_t, S_t, S_{t-1}, \Delta CPI_t\right)$, $y_t^{(3m)}$ is the three-month T-bill rate and ΔUNE_t is the annual change in the rate of unemployment. None of the instruments is revised or

[8] This definition has been adopted in the literature by, for instance, Laubach and Williams (2003) or Clark and Kozicki (2004).

contains forward-looking information.[9] The fitted value from (7) is what we refer to as the FIRE version of the ex-ante real FFR, denoted $\hat{r}_t^{e,FIRE}$.

In the second approach, we construct the ex-ante real FFR directly from the survey forecasts:

$$r_t^{e,surv} = E_t^s(FFR_{t+1}) - E_t^s(\Delta CPI_{t+1}). \tag{8}$$

The survey data, described in Section II.A, allow us to obtain $r_t^{e,surv}$ at a monthly frequency for the sample period 1984:06–2010:12.

One should note that the real rate r_{t+1} differs from the definition of the ex-post real rate that is usually adopted in the literature, i.e.:

$$\widetilde{r}_{t+1} = y_t^{(1)} - \Delta CPI_{t+1}, \tag{9}$$

where $y_t^{(1)}$ is the one-period nominal interest rate. The ex-ante real rate is then obtained from full-sample projections of $\widetilde{r}_{t+1}$ on a set of time-t instruments (e.g. Fama, 1975; Mishkin, 1981; Yogo, 2004),[10] as a way to extract the unobserved inflation expectations from ΔCPI_{t+1}. However, by using the current nominal yield in (9), this approach takes as given expectations about the real rate embedded in $y_t^{(1)}$. As such, it does not draw a distinction between the real-rate expectations formed by the public and under FIRE, which we are interested in.

Panel A1 of Table II reports projection (7) using the full set of instruments as well as gradually expanding the set of instruments by one variable at a time. The results suggest that the inclusion of lagged information such as the lagged slope and the past year's change in unemployment rate contain information about the dynamics of r_{t+1}. For comparison, panel A2 of Table II displays analogous projections for $\widetilde{r}_{t+1}$ defined in equation (9). Unlike in panel A1, the same lagged variables do not contain additional predictive power for $\widetilde{r}_{t+1}$, indicating that they are mainly relevant for predicting the future real rate component of the short rate rather than inflation.

[9] We obtain vintage data from the Philadelphia Fed. The online documentation to the data sets indicates that unemployment and CPI inflation are subject to very minor revisions. For instance, annual changes in real time unemployment and its current vintage have a correlation above 0.99; the root mean squared difference between real time and final vintage of unemployment is less than 10 basis points. CPI series are considered to be unrevised (Croushore and Stark, 1999). Using final or real time data we obtain essentially identical estimates. Thus, our results not driven by revisions to macroeconomic series.

[10] The set of instruments typically contains CPI_t, FFR_t, or other short-term interest rate and the term spread.

To gauge the difference between the two approaches in (7) and (8), we define a variable that measures the wedge between the full-sample and the real-time estimates:

$$MP_t^{\perp} = \hat{r}_t^{e,FIRE} - r_t^{e,surv}. \tag{10}$$

Under FIRE, both measures of the ex-ante real rate should coincide, or differ just by a noise component. However, the empirical properties of $MP_t^{\perp}$ deviate from this benchmark. Panel a of Figure 2 superimposes $\hat{r}_t^{e,FIRE}$ and $r_t^{e,surv}$; panel b plots their difference. The plots show that the survey-based expectations systematically lag behind those of the econometrician. The real rate wedge $MP_t^{\perp}$ is persistent, declines ahead of NBER-dated recessions bottoming at around -200 basis points, and recovers after the recessions, i.e. during recessions agents expect a higher real rate compared to the estimates of an econometrician. As a result, $MP_t^{\perp}$ predicts a significant part of the variation in ex-post forecast errors:

$$FE_{t,t+1}^{FFR} = \delta_0 + \underbrace{\delta_1}_{0.87\ [4.1]} MP_t^{\perp} + \varepsilon_{t+1}, \quad \bar{R}^2 = 0.29. \tag{11}$$

Panel B1 of Table II compares forecast errors predictability corresponding to different specifications of $MP_t^{\perp}$ that vary by the set of instruments included in (7). The explained variation increases dramatically from 5% with only T-bill as instrument to 25% when change in unemployment is also added.

Panel B2 of Table II replicates the results assuming that the econometrician estimates the ex-ante real rate following the definition of $\widetilde{r}_{t+1}$ in equation (9). The real rate wedge constructed with this alternative approach, denoted as $\widetilde{MP}_t^{\perp}$ in the table, and using the full set of instruments, predicts about 6% of variation in the forecast error with an insignificant coefficient (t-statistic=1.5). The differences between the estimates based on r_{t+1} and $\widetilde{r}_{t+1}$ are consistent with the intuition that the ex-post predictability of FFR forecast errors is primarily driven by the expectations of the real component of the short rate.

These results suggest that the real rate wedge, $MP_t^{\perp}$, captures information that is not contained in the time-t information set of the forecasters. Thus, we expect it to be weakly related to the contemporaneous yield curve, which is shaped by the time-t expectations of agents. Table II.C reports a projection of $MP_t^{\perp}$ on the principal components (PCs) of yields with maturities from one through 20 years. While three and five PCs account for 17% and 26% of the variance of $MP_t^{\perp}$

when the regressions are run in levels, the explained variance is zero in monthly changes.[11] After orthogonalizing $MP_t^{\perp}$ with respect to the yield PCs, we find a somewhat stronger predictability of the forecast errors relative to (11), as indicated by an increase in $\bar{R}^2$ and by information criteria in panel C2 of Table II. This evidence points to an interpretation of $MP_t^{\perp}$ as an unspanned factor in the yield curve. We explore this link below in Section III.D.

II.D. Expectations of macro variables

To verify that the above results are primarily driven by frictions in real rate expectations, we show that $MP_t^{\perp}$ does not predict inflation forecast errors, but it contains substantial predictive power for forecast errors about the output gap. Following the intuition from New Keynesian models, the latter can be linked directly to the real rate forecast errors through the IS equation. Because public expectations of output gap are not easily observable, we use survey forecasts of unemployment instead, based on the fact that output gap and unemployment have a historical correlation of -0.95 (Gali, Smets, and Wouters, 2011).

Table III.A, displays unconditional correlations of forecast errors. FFR errors are relatively weakly correlated with errors about inflation ($FE_{t,t+h}^{CPI}$), but they comove strongly negatively with those about unemployment ($FE_{t,t+h}^{UNE}$). The comovement strengthens with the forecast horizon.[12] Projections of macro forecast errors on $MP_t^{\perp}$, presented in Table III.B, confirm both the lack of predictability of inflation forecast errors, and a large predictable element in unemployment forecast errors. These results hold true across forecast horizons from one through four quarters ahead.

Starting from a simple Taylor rule, according to which monetary policy reacts to current inflation and unemployment, we can relate the FFR forecast errors to macro variables:

$$FE_{t,t+h}^{FFR} = \gamma_0 + \gamma_1 FE_{t,t+h}^{UNE} + \gamma_2 FE_{t,t+h}^{CPI} + \varepsilon_{t,t+h}. \qquad (12)$$

[11]While in the level regressions five PCs are jointly significant (p-value=1%), the result is driven by PC5, and we find it not to be stable across different data sets of zero-coupon yields and across sample periods. This can be explained by the fact that higher-order PCs are likely to be subject to a sizeable measurement error. For instance, we find that PC5 constructed using Fama-Bliss zero-coupon yields has no correlation with PC5 constructed with Gürkaynak, Sack, and Wright (2006) zero-coupon yields.

[12]Since the BCFF survey does not provide unemployment forecasts, the public expectations of macro variables are obtained from the quarterly Survey of Professional Forecasters (SPF), which contains the term structure of forecasts at horizons corresponding to those for the FFR in the BCFF survey.

Equation (12) cannot be estimated with OLS because macro forecast errors are likely to be correlated with the innovations $\varepsilon_{t,t+h}$. Therefore, we estimate (12) with instrumental variables, using contemporaneous oil shock and lagged values of the Chicago Fed National Activity Index (CFNAI) as instruments.[13]

Table III.C summarizes the instrumental variables regressions at horizons h of three and four quarters ahead. We consider two sample periods: the full sample for which we have the data (1983–2010) and the sample ending in 2006 to make sure that the results do not depend on the spike in the unemployment during the 2007/09 crisis. $FE^{CPI}_{t,t+h}$ is only marginally significant in the pre-crisis sample and is a small contributor to the overall variation in $FE^{FFR}_{t,t+h}$, while $FE^{UNE}_{t,t+h}$ is significant at the 1% level across both samples and forecast horizons. More than 40% of the sample variation in the FFR forecast errors at a four-quarter horizon can be related to macro sources. Thus, expectation errors about the short rate arise, at least partially, from public's errors in forecasting the path of unemployment, and real activity more generally.

III. Implications for bond return predictability

This section studies the implications of the above findings for the interpretation of bond risk premia in the US Treasury market. While the common approach to measuring risk premia is through predictive regressions of future realized returns on a set of conditioning variables, our results suggest that part of variation identified in this way may stem from the ex-post forecast errors about the short rate. It is important to distinguish between the two sources of return predictability. In standard asset pricing models, risk premia are driven by the preferences and reflect the compensation *expected* by investors for facing the covariance risk of Treasury returns with their marginal utility. Expectations frictions, instead, are manifest in the predictability of *unexpected* returns after the risk premium has been controlled for.

First, we show that the real rate wedge, $MP^{\perp}_t$, has predictive power for the realized excess bond returns. Then, we further decompose the realized return into an expected and unexpected part, and study their properties. We find that, at short maturities, up to a half of the predictable variation in realized bond returns comes from a component that is ex-ante unexpected. The contribution

[13] Following Coibion and Gorodnichenko (2011a), we define the oil shock as the residual from an AR(2) model estimated on the four quarter changes in the oil price. The data is obtained from the FRED database. This variable is a valid instrument since it is uncorrelated with the lagged information and orthogonal to shocks to the monetary policy forecast errors.

of forecast error predictability to the overall return predictability is strongest at the short end of the yield curve, and subsides as the maturity increases. We link these results to the notion of unspanned term premium factors in the yield curve that have been studied in the recent literature.

III.A. Predictive regressions of bond excess returns

We estimate standard predictive regressions of bond excess returns:

$$rx_{t+1}^{(n)} = \delta_0 + \delta_1 RP_t + \delta_2 MP_t^{\perp} + \varepsilon_{t+1}^{(n)}, \tag{13}$$

where $rx_{t+1}^{(n)}$ is the annual holding period excess return on a Treasury bond with n years to maturity, $rx_{t+1}^{(n)} = (n-1)y_{t+1}^{(n-1)} - ny_t^{(n)} - y_t^{(1)}$ and $y_t^{(n)}$ is the n-year yield. RP_t is an empirical measure of the bond risk premium, i.e. of the *expected* return. Since the risk premium is itself not directly observable, we use two proxies for RP_t from the literature. Our first measure is the linear combination of forward rates proposed by Cochrane and Piazzesi (2005), CP_t; the second one is the cycle factor $\widehat{cf}_t$ from Cieslak and Povala (2013). The CP_t is a commonly used in-sample benchmark for the time-varying bond risk premium. Cieslak and Povala (2013) show that $\widehat{cf}_t$ subsumes the information in CP_t and can be constructed in quasi real-time, having stable out-of-sample properties.[14] We report the results using both measures to ensure that our conclusions are robust to risk premium measurement issues.

Table IV summarizes the results of return forecasting regressions for bonds with maturities of two, three, five, ten and twenty years.[15] Due to overlapping data, we report t-statistics based on Hodrick's reverse regression (rows "t(H)") as well as the Newey-West t-statistics (rows "t(NW)"). Panels A, B1 and C1 report univariate regressions using $MP_t^{\perp}$, and the two risk premium proxies, respectively, as predictors. The main observation is that $MP_t^{\perp}$ is a significant predictor of realized excess returns (panel A), and that predictive power comes mainly from its component that is orthogonal to the contemporaneous yield curve (last row of panel A). The predictive power of $MP_t^{\perp}$ is most significant, economically and statistically, at short maturities. In contrast, for the risk premium proxies, the significance of coefficients increases with maturity. The negative sign

[14] Cieslak and Povala (2013) decompose the yield curve into long-horizon inflation expectations and maturity-related interest rate cycles. Then, the term structure of cycles is used to separate the risk premium variation from the business cycle variation in short rate expectations.

[15] We obtain zero-coupon yields from the constant maturity Treasury (CMT) rates provided by the Fed Board.

of the $MP_t^{\perp}$ coefficient is consistent with lower $MP_t^{\perp}$ anticipating lower yields (higher returns) in the future. Panels B2 and C2 report estimates of bivariate regressions (13). In the presence of $MP_t^{\perp}$, the significance of the RP_t proxies remains nearly unchanged, in line with the idea that $MP_t^{\perp}$ captures a source of return predictability that is independent of the standard risk premium.

To account for statistical biases that arise with long-horizon returns, overlapping data, and artificially splined zero-coupon yield curves, in Appendix (Table C-XIII) we repeat the predictive exercise with monthly excess returns on actual bond portfolios from CRSP. The estimates confirm our above conclusions. Specifically, $MP_t^{\perp}$ has a negative and highly significant loading, and it dominates the other two predictors in forecasting returns of portfolios with short maturities.

III.B. Factor structure in realized bond returns

These results suggest that realized bond returns move on two factors whose predictability stems from largely independent sources. To illustrate this fact, we use two orthogonal factors to span variation in bond excess returns across maturities. Since long-term bonds are highly informative about the risk premium, as the first factor, we use the realized excess return on a 20-year bond, $rx_{t+1}^{(20)}$. We construct the second factor $rx_{t+1}^{(2)\perp(20)}$ as the return on the short-term bond (two-year maturity) that is orthogonal to $rx_{t+1}^{(20)}$. Jointly, $rx_{t+1}^{(20)}$ and $rx_{t+1}^{(2)\perp(20)}$ explain more than 94% of variation in contemporaneous excess returns at different maturities. The contribution of the short-term component monotonically declines, while the contribution of the long-term component increases with the maturity (see Appendix, Table C-XIV). Using this two-factor decomposition, in Table IV.D, we find that the short-term component of returns $rx_{t+1}^{(2)\perp(20)}$ is strongly predictable by our measure of expectations frictions $MP_t^{\perp}$, but it is unrelated to the risk premium proxies. For $rx_{t+1}^{(20)}$ the reverse holds true. These results are consistent with the intuition that the effect of frictions in short-rate expectations should be most pronounced for bonds with short maturities.

III.C. Decomposing realized bond returns

To directly decompose the realized bond returns into an expected (risk premium) and ex-ante unexpected (forecast error) component, we rely on survey forecasts of interest rates from the BCFF survey available from December 1987 through December 2010. The survey contains private sector's predictions of interest rates at different maturities and for horizons of one through four quarters ahead. The panel of participants is the same as for the FFR survey forecasts. We focus on the two-year bond return because the BCFF data allow us to construct directly a survey-based expected excess return for one-year holding period. Moreover, this maturity captures the segment of the yield curve for which we expect the effect of expectations frictions to be most relevant.

Using survey forecasts of the one-year yield one year ahead, we have:

$$rx^{(2)}_{t,t+1} = \underbrace{\left[f^{(2)}_t - E^s_t(y^{(1)}_{t+1})\right]}_{\substack{\text{risk premium} \\ E^s_t(rx^{(2)}_{t+1})}} - \underbrace{\left[y^{(1)}_{t+1} - E^s_t(y^{(1)}_{t+1})\right]}_{\substack{\text{unexpected return} \\ rx^{(2)}_{t+1} - E^s_t(rx^{(2)}_{t+1})}}. \tag{14}$$

where $f^{(2)}_t$ is the one-year forward rate, $f^{(2)}_t = 2y^{(2)}_t - y^{(1)}_t$. The unexpected return equals the (negative of) agents' forecast error about the one-year rate at the one-year horizon, $-\left[y^{(1)}_{t+1} - E^s_t(y^{(1)}_{t+1})\right] = rx^{(2)}_{t,t+1} - E_t(rx^{(2)}_{t+1})$. Empirically, it is strongly correlated with the FFR forecast error $FE^{FFR}_{t,t+1}$, with a correlation of -0.93.

In Table V.A, we regress each term on the RHS of (14) on $MP^{\perp}_t$ and other time-t predictors. For comparison, we perform a similar exercise using $FE^{FFR}_{t,t+1}$ as the dependent variable on a sample starting in 1987, which corresponds to the available survey forecasts of the one-year yield.

The main conclusion is that $MP^{\perp}_t$ predicts a significant fraction of unexpected returns and of the FFR forecast errors, but has no explanatory power for the survey-based expected return. These regressions are in column (1) of each subpanel of Table V. Columns (2)–(4) run regressions allowing for separate loadings on $\hat{r}^{e,FIRE}_t$ and $r^{e,surv}_t$: alone, each term contributes little to predicting the unexpected return, but jointly both become highly significant. In particular, the free coefficient loadings are very close to the $(1, -1)$ restriction that we impose when constructing $MP^{\perp}_t$ in (10). Finally, column (6) shows that while $\widehat{cf}_t$ has a strong correlation with survey-based expected return on the two-year bond, it shows no predictability of the unexpected return and of $FE^{FFR}_{t,t+1}$ supporting its interpretation as a risk premium proxy that we relied upon in the previous section.

III.D. Link to unspanned factors

We connect the above results to substantive empirical evidence suggesting that variables which are weakly correlated with contemporaneous yields, so-called uspanned or hidden factors, contain predictive information about future bond returns. This observation has been surprising given that yields are conditional expectations of future short rates and excess returns, and therefore, the current yield curve should contain all information useful for forecasting returns.[16] While the economic interpretation of unspanned factors is still debated, this section discusses how expectation frictions can be useful in reconciling the empirical predictability results with the benchmark yield curve intuition.

Let us consider a realized one-period excess return on a two-period zero coupon bond:

$$rx_{t+1}^{(2)} = -y_{t+1}^{(1)} + 2y_t^{(2)} - y_t^{(1)}, \tag{15}$$

where $y_t^{(2)}$ denotes a continuously compounded two-period yield, and $y_t^{(1)}$ is a one-period (short) rate. Rearranging (15), the two-period yield can be expressed as:

$$y_t^{(2)} = \frac{1}{2}\left(y_t^{(1)} + y_{t+1}^{(1)}\right) + \frac{1}{2}rx_{t+1}^{(2)}. \tag{16}$$

Equation (16) is a tautology that follows from the definition of bond returns. Since it holds ex-post realization-by-realization it also holds ex-ante:

$$y_t^{(2)} = \frac{1}{2}F_t\left(y_t^{(1)} + y_{t+1}^{(1)}\right) + \frac{1}{2}F_t\left(rx_{t+1}^{(2)}\right), \tag{17}$$

where $F_t(\cdot) = F(\cdot|I_t)$ is an expectations operator, conditional on all information available at time t, I_t. Importantly, (17) holds for any model of expectations formation and for any conditioning information set (e.g., Fama and Bliss, 1987; Fama, 1990).

Most term structure models and tests of the expectations hypothesis assume that $F_t(\cdot)$ is formed under FIRE, i.e. the realized future short rate equals $y_{t+1}^{(1)} = F_t(y_{t+1}^{(1)}) + v_{t+1}$, where the forecast error v_{t+1} is unpredictable by information available at time t. Since the contemporaneous yield curve reflects such expectations, it also summarizes all information relevant for forecasting future interest rates. Thus, a variable can forecast future returns without visibly affecting today's yields only when it impacts expectations of the short rate and the risk premium in an exactly offsetting manner. Such a cancelation argument has been used to justify why variables that are weakly related to the contemporaneous yield curve can predict future bond returns beyond information that is contained in yields themselves (e.g., Duffee, 2011).

[16] Duffee (2012) gives a recent comprehensive survey of this literature.

An alternative interpretation of the empirical fact, one whose relevance we explore in this paper, builds on the idea that the FIRE may not hold exactly in the data. We note that the identities (16) and (17) jointly imply:

$$y_{t+1}^{(1)} - F_t(y_{t+1}^{(1)}) = -\left[rx_{t+1}^{(2)} - F_t(rx_{t+1}^{(2)})\right], \tag{18}$$

where the left-hand side measures agents' forecast error about the short rate, and the right-hand side—the unexpected return. Through equation (17), any forecast error that agents make when predicting the short rate must cancel with unexpected returns that they earn ex-post.[17] A variable that predicts forecast errors will by construction have a zero net effect on the current yield curve because it is not in agent's time-t information set. It is possible that both effects, i.e. the cancelation of factors within the yield curve and ex-post predictable forecast errors, coexist in the data. Our evidence shows that the latter has an empirical merit and could account for the observed predictability patterns.

As we argue in Section II.C, the wedge variable $MP_t^{\perp}$ can be thought of as an unspanned factor induced by the real short-rate dynamics. It is worth establishing a link between $MP_t^{\perp}$ and macro variables that have been documented to forecast returns. Beginning with Cooper and Priestley (2009) and Ludvigson and Ng (2009), many authors find that real activity variables help predict excess bond returns beyond the predictability attained with yields or forward rates. This literature also recognizes that real variables are only weakly spanned by the cross section of yields.[18]

In Table V.B, we regress each term on the right-hand side of equation (14) on two measures of real activity: CFNAI and the annual change in unemployment (ΔUNE_t), respectively.[19] The main observation is that while neither of the real variables has explanatory power for the risk premium part, both are strongly significant predictors of unexpected returns and monetary policy forecast

[17]This argument also holds for an n-period bond, for which:

$$\sum_{j=0}^{n-2}\left[y_{t+1+j}^{(1)} - F_t(y_{t+1+j}^{(1)})\right] = -\sum_{j=0}^{n-2}\left[rx_{t+1+j}^{(n-j)} - F_t(rx_{t+1+j}^{(n-j)})\right]. \tag{19}$$

[18]The common approach to show the lack of spanning is to project a macro variable on yields with different maturities. For real activity measures, the R^2 from this regressions is typically low, suggesting that the cross-section of yields does not span the macro information.

[19]CFNAI is essentially indistinguishable from the real activity factor constructed in Ludvigson and Ng (2009) with correlation above 99%, and is a version of the common real factor proposed by Stock and Watson (1999) to aggregate information from a large cross-section of real activity measures. The real-time CFNAI is available only from January 2001, and therefore for a large part of our sample it uses revised data.

errors. The estimates of bivariate regressions using real activity proxies jointly with $MP_t^{\perp}$ support a weak relationship of those variables with expected returns, but a strong relationship with the forecast errors and unexpected returns.

IV. Sources of forecast error predictability

A broad class of models implies that forecast errors can be predictable without agents' being irrational. Agents are likely to face frictions such as noisy information as in Woodford (2003) or information stickiness as in Mankiw and Reis (2002). They also may not know the exact monetary policy reaction function but rationally learn about its parameters (Friedman, 1979), which themselves can evolve over time. Alternatively, faced with complex underlying dynamics, they may base their forecasts on simpler intuitive models that deviate from the truth in a significant way but still imply a small utility loss (Cochrane, 1989; Fuster, Laibson, and Mendel, 2010). Below, we show that under these scenarios an econometrician with an access to full-sample information would find ex-post predictability of forecast errors, as we do empirically.

IV.A. Testing information rigidities

We test whether the predictability of ex-post forecast errors can be explained within models with information rigidities such as sticky or noisy information. These models assume that agents know the structure and the parameters of the economy but the information they receive about the state of the economy is imperfect. Coibion and Gorodnichenko (2011a) show that in such models, the average (across agents) ex-post forecast error should be predictable by the average forecast revision at the corresponding horizon. The baseline test can be performed by estimating:

$$FE_{t,t+h}^{FFR} = \beta_0 + \beta_1 \left[E_t^s(FFR_{t+h}) - E_{t-1/4}^s(FFR_{t+h})\right] + \varepsilon_{t+h}, \tag{20}$$

where in presence of information frictions $\beta_1 > 0$. The results of estimating (20) are reported in column (1) of Table VI.A, for horizons h from one through three quarters.[20] The coefficient β_1 is positive and statistically significant, supporting the hypothesis that forecasters act under

[20] For the FFR we report estimates of (20) using forecast errors and forecast revisions of the median forecaster to be consistent with the previous results. We verify that the results are essentially identical when using means. The mean and median forecast errors and updates are more than 0.99 correlated with each other at corresponding horizons.

information frictions. Forecast updates alone explain up to 17% of the variation in ex-post forecast errors, and their statistical significance is the strongest at the shortest horizon.

Models of information frictions summarized by (20) imply that forecast updates should account for the entire predictable variation in ex-post forecast errors. In columns (2) and (3) of Table VI.A, we augment regression (20) with variables that we have found to contain information about the FFR forecast errors, the real rate wedge $MP_t^{\perp}$ and the lagged slope S_{t-1}, respectively:

$$FE_{t,t+h}^{FFR} = \beta_0 + \beta_1 \left[E_t^s(FFR_{t+h}) - E_{t-1/4}^s(FFR_{t+h}) \right] + \beta_X X_t + \varepsilon_{t+h}, \tag{21}$$

where $X_t = \{MP_t^{\perp}, S_{t-1}\}$ and β_X is the corresponding loading. The results of the extended test indicate that the additional variables have explanatory power beyond forecast updates, which increases with the forecast horizon. For instance, at the three-quarter horizon, $MP_t^{\perp}$ raises the $\bar{R}^2$ from 17% to 41% relative to the baseline case (20), and is highly statistically significant (t-statistic=5.9). Similar results pertain to the lagged term structure slope.[21]

One way to assess whether frictions that we document reflect a more general feature of expectations formation is to study their explanatory power for forecast errors about macro variables other than the FFR. To this end, we estimate regressions analogous to (20) and (21) for the forecasts of unemployment and CPI inflation. In constructing both, we use unrevised data and the SPF survey. The evidence in favor of expectations frictions is particulary strong for unemployment, confirming the conclusions from Section II.D. $MP_t^{\perp}$ is statistically and economically significant beyond forecast updates, contributing 13% to the explained variation at the horizon of three quarters.

In sum, the results suggest that information rigidities such as sticky or noisy information are an important but not the only source of the forecast error predictability in the short rate.

IV.B. Time-varying parameters and learning

Many authors have documented a significant time-variation in the parameters of the Fed reaction function (Primiceri, 2005; Boivin, 2006; Ang, Boivin, Dong, and Loo-Kung, 2011; Coibion and Gorodnichenko, 2011b; Coibion, 2012). To study the implications of a structural change and agents' learning about the parameters for the ex-post predictability of forecast errors, we rely on vector

[21] The lower significance of the slope is consistent with the fact that the slope also reflects risk premium variation which should not predict forecast errors.

autoregressions in CPI inflation, unemployment and FFR, in which we allow for time-varying parameters.

In Table VII.A, we consider two scenarios. In the first scenario, we assume that agents estimate a time-varying parameters Bayesian VAR (BTVP-VAR) in the spirit of Primiceri (2005); in the second one, they use constant-gain learning (CG-VAR) as in Branch and Evans (2006) with the gain parameter, γ, equal to 0.01 or 0.05.[22] In both cases, we estimate a VAR(2) recursively on an expanding window to obtain the forecasts of the short rate that agents could have formed in real time. We then ask whether an econometrician could predict their forecast errors ex-post with lagged variables, i.e. we estimate the regression:

$$FE_{t,t+h}^{FFR,VAR} = \gamma_0 + \gamma_1' Y_t + \gamma_2' \Delta Y_{t-1,t} + \varepsilon_{t+h}, \tag{22}$$

where $Y_t = (\Delta CPI_t, UNE_t, FFR_t)'$ are the variables included in the VAR, and $\Delta Y_{t-1,t}$ is their one-year change.

Table VII.A presents the forecast error predictability for horizons of one and four quarters ahead. The results show that at the one-year horizon an econometrician can predict up to 40% of the forecast error variation, finding significant coefficients on the lagged macro variables (the level and change of unemployment in particular). While we compare the quality of survey forecasts with a variety of statistical models in Section VI below, we note that the predictability of the VAR-based forecast errors is stronger than that implied by survey expectations.

The true data generating process for the short rate is likely to be more complex than the VAR we posit above. Thus, we conduct a Monte Carlo simulation to quantify the effect of learning separately from model misspecification and from the role of time-varying parameters. We simulate VAR(2) models at the parameters calibrated to the historical data.[23] We assume that the agent takes into account the possibility of a structural change, and estimates the parameters using constant-gain learning (with gain $\gamma = 0.01$). This assumption is motivated by the fact that such a specification gives the lowest RMSE for FFR forecasts in the data, among models presented in panel A. We

[22] By discounting past observations at a rate $(1-\gamma)$, constant gain learning is considered robust to structural change. Evans, Honkapohja, and Williams (2010) show that constant gain learning algorithm is the maximally robust estimator in settings with uncertainty about the true data generating process. Similar to Branch and Evans (2006), we assume that agents use an equal gain for all variables included in the VAR.

[23] In the time-varying parameters version, we assume that the parameters follow a random walk, which is a standard assumption in the literature.

consider two scenarios for the data generating process allowing either for time-varying or constant parameters. Additionally, as a simple way to accommodate misspecification, we compare forecast error predictability when agents estimate the correct model (VAR(2)) and a misspecified model (VAR(1)).

Table VII.B presents the distribution of the statistics from equation (22) estimated on the simulated data. The main observations from the simulation are as follows: In samples of the size consistent with our empirical analysis (upper panel), an econometrician can predict ex-post more than 20% of the one-year-ahead forecast errors made by agents in real time, even if agents know the structure of the true model. The results are similar whether or not the data generating process is characterized by time-varying parameters, thus the effect can be mostly ascribed to learning. With an access to the full sample of data, more than 70% of times an econometrician would conclude that lagged information is statistically significant (t-statistics above 2 in absolute value), and about 50% of times they would reject the null that all regressors in (22) are jointly zero at the 10% level.

The econometrician's advantage over the real-time forecaster is particularly large in small samples, and dissipates as the sample size increases. However, even with 1000 quarterly observations, we still find ex-post forecast error predictability. These results suggest that agents' learning about the unknown parameters of the economy could explain an important part our empirical results.[24]

V. Relationship with monetary policy shocks

The discussion so far leaves open the question about the extent to which predictable errors of the public could be induced directly by the actions of the Fed, or are a feature of the business cycle more generally. To cast light on this question, we proceed in two steps. First, we study the properties of monetary policy shocks that have been identified in the literature, separating them into shocks to the actual FFR target and shocks to expectations about the future monetary policy path. Second, we ask whether internal forecasts prepared by the Fed staff share the same characteristics as the forecasts of the public.

[24]In a related way, the consequences of agents' learning about the true data generating process of fundamentals have been emphasized by Timmermann (1993) in the context of predictability of equity returns.

V.A. Persistent component in monetary policy shocks

We focus on shocks extracted from the fed fund futures at the frequency of the FOMC meetings. This is motivated by the evidence that these shocks are less likely to be contaminated by measurement noise or omitted information compared to monetary VARs, and by the risk premia (e.g. Gürkaynak, Sack, and Swanson, 2005; Piazzesi and Swanson, 2008; Thapar, 2008). Moreover, they are innovations relative to the time-t information set of investors rather than that of the econometrician. We consider shocks from Kuttner (2001), Barakchian and Crowe (2013, BC), Gürkaynak, Sack, and Swanson (2005, GSS) and Campbell, Evans, Fisher, and Justiniano (2012, CEFJ). These papers differ in the range of futures' maturities that they use and in details of the identification strategy.[25] The identified shocks fall into two categories: shocks to the Fed's target and shocks to the future policy path which, following Gürkaynak, Sack, and Swanson (2005), provides a way to distinguish between the effects of Fed actions versus the effects of its communication. GSS and CEFJ separate these two components explicitly, Kuttner captures dominantly the target shocks, and BC shock is a linear combination of both. Shock summary statistics are included in Table VIII.C.

To establish whether our results uncover a persistent factor in identified monetary policy shocks, we analyze the predictability of these shock by the real rate wedge, $MP_t^{\perp}$. In Table VIII.A, we project shocks observed in month $t+\frac{1}{12}$ and denoted $\varepsilon^{MP}_{t+1/12}$ on previous months' value of $MP_t^{\perp}$. Given that $MP_t^{\perp}$ is constructed at an annual horizon, in Table VIII.B we also consider predictive regressions of cumulative shocks realized over the course of the following year, $\sum_{i=1}^{12} \varepsilon^{MP}_{t+i/12}$. The results point to a significant degree of predictability. For instance, $MP_t^{\perp}$ predicts above 7% of variation in next month Kuttner's shocks, and 51% in the cumulative shocks over the following year. Widening of the real rate wedge from zero to -50 basis points forecasts the cumulative monetary policy shock of -18 basis points over the next year (t-statistic=5.7). While similar estimates pertain also to GSS and CEFJ target shocks, they are somewhat weaker (still statistically significant) for BC shocks, and become insignificant for GSS and CEFJ path shocks. To illustrate their comovement, Figure 3 superimposes the time series of cumulative Kuttner and BC shocks with $MP_t^{\perp}$.

These results imply that there is a persistent element in surprise target changes by the Fed (Fed actions) that is related to the real rate and is not impounded into expectations of the public

[25] We thank Christopher Crowe, Alejandro Justiniano and Eric Swanson for sharing their shock series with us, and Kenneth Kuttner for making the series available online.

in real time. At the same time, the lack of correlation between $MP_t^{\perp}$ and shocks to the policy path suggests that the Fed's communication itself is not responsible for the persistent discrepancy between expectations and subsequent realizations of the short rate.

V.B. Expectations by the Federal Reserve's staff

To test whether the persistent component in monetary policy shocks is a specific feature of the expectations of the public, we study the properties of the expectations formed by the staff at the Federal Reserve Board (FRB). Before each FOMC meeting, the FRB staff prepares their own forecasts of the FFR from the current quarter up to five quarters ahead. The forecasts are published in the Greenbook and available to the public with a five-year lag.[26] The Greenbook has several useful characteristics. First, when forming their projections, the FRB staff has extensive access to economic data flowing in from the regional Feds. The publication lag together with the Fed's ability to observe the current expectations of the market participants, and their possibly better understanding of the policy rule can lead to information asymmetries between the private sector and the policy makers (Romer and Romer, 2000). Second, forecasts of the FRB staff are unlikely to be influenced by subjective, worst-case scenario considerations that characterize the forecasts of the FOMC members (Romer and Romer, 2008; Ellison and Sargent, 2010). Thus, one could argue that forecasts of the FRB staff provide an upper bound on the FFR predictability.

We evaluate the quality of FRB staff's forecasts of the FFR compared to those of the public.[27] In Table IX, panels A and B, we implement the test proposed in Romer and Romer (2000) by regressing either the level of the FFR or its changes jointly on the forecasts of the public and the staff. The test indicates that forecasts of the staff are superior in that they drive out the private sector expectations. We note, however, that this advantage weakens with the forecast horizon: the correlation between forecast errors of the staff and the public increases and the relative precision of the public forecasts (as measured by the RMSE ratio) improves with the horizon. At four quarters ahead, public forecasts contribute economically (and marginally statistically) significant information about the future FFR changes. In Table IX.C, we project the FFR forecast errors

[26] The data are obtained from the Philadelphia Fed website for the period 1981:01–2007:12.

[27] This question has been extensively studied for inflation and real activity (Romer and Romer, 2000; Faust, Swanson, and Wright, 2004), but we are not aware of studies that evaluate the potential information advantage of Fed forecasters for FFR. We merge the data so that a given Greenbook forecast is matched with the latest monthly BCFF survey available to the FRB staff at the time of their forecast.

of the staff on the real rate wedge, $MP_t^{\perp}$. Even though the predictability of the staff's errors is somewhat weaker as measured by the predictive $\bar{R}^2$, the results are strikingly similar to those for the private sector forecasts reported earlier.

This suggests that expectations frictions that we document pertain to different groups of agents with potentially different access to information. The increasing alignment of the expectations of the public and the FRB staff at longer horizons points to a more general feature of expectations formation over the business cycle rather than a direct effect of actions by policy makers. Analyzing these relationships in a general equilibrium setting with various forms of nominal and real informational rigidities is a promising avenue for future research.

VI. Evidence on the quality of survey expectations

In this section, we provide robustness analysis of the quality of survey forecasts. We ask how easy it is to outperform survey forecasts of the FFR with statistical models estimated in real time. We also compare surveys with market-based forecast of the FFR from the fed fund futures.

VI.A. Do statistical models outperform surveys in real time?

We compare forecast accuracy of surveys with several statistical models of the short rate estimated in real time. The main results are collected in Table X.A. Given evidence that simple methods of forecasting interest rates often work best in real time (e.g. Duffee, 2009; Wright, 2011), we compare statistical models with different level of sophistication. We report forecasts assuming that FFR follows: a random walk (row 2); an AR(2) (row 3); an AR(p) allowing up to 16 quarterly lags which are selected dynamically with the BIC from all possible lag combinations (row 4); a recursive VAR(2) estimated with OLS (row 5); VAR(2) estimated with constant-gain learning fixing the gain $\gamma = 0.01$ for all variables (row 6); a homoscedastic Bayesian VAR(2) with time varying parameters in the spirit of Primiceri (2005) (row 7). The VARs are second-order and include three variables: CPI inflation, unemployment and the FFR. The two final specifications are those we have considered in Section IV.B. The models are estimated on an expanding window with a burn-in period of 73 quarters. The out-of-sample forecasts are constructed for the period of 1983:Q1 through 2010:Q4, corresponding to when private sector's FFR surveys are available.

Across all forecast horizons, surveys provide the lowest RMSE by a wide margin (row 1), followed by the autoregressive model with a fixed number of lags (AR(2)), and by the random walk. For instance, the relative error made by survey forecasters ranges from 63% at one-quarter horizon to 92% at four quarters of the forecast error from the AR(2) model. Importantly, also more sophisticated methods, including time-varying Bayesian VARs, fail to match the precision of the FFR survey forecasts in real time. These results for the FFR resonate well with the finding that, at least in the recent data, surveys tend to outperform statistical forecasting methods out of sample, as documented by, e.g., Ang, Bekaert, and Wei (2007) and Faust and Wright (2011) for inflation, or Del Negro and Schorfheide (2013) for output and FFR.[28]

VI.B. Market-based forecasts from the fed funds futures

In Table X.B, we compare forecast errors made by the median survey panelist to the ones implied by the fed fund futures. Historical futures data are available from Bloomberg starting from 1988:12 for contract horizons up to six months. We match end-of-month futures data with the monthly survey forecasts.[29] Clearly, futures-based forecasts of the FFR differ from the statistical forecasts by the presence of a risk premium. Using surveys, we obtain an estimate of the premium that is on average four basis points for the six-month contract with a standard deviation of 16 basis points. Given the small magnitude of the risk premium, the forecast errors implied from the futures (i.e. the negative of the realized futures returns) are highly correlated with these from the surveys, with correlation coefficient of 0.89 at a three-month horizon and 0.93 at a six-month horizon. The futures-based RMSEs for the three- and six-month ahead forecasts are marginally lower relative to

[28] While surveys forecasts of the short-term interest rate (here: FFR) are hard to beat with statistical models, it is possible to outperform survey forecasts of longer maturity yields (two years and above). This is consistent with the evidence that statistical models estimated in real time predict excess returns on bonds with long maturities better than surveys. For instance, at a forecast horizon of one-quarter a dynamic affine term structure model with three factor generates lower RMSEs than surveys at maturities of two years and above (the outperformance is marginal for the two-year bond, and increases with the maturity). However, at the forecast horizon up to four quarters, surveys produce uniformly lower forecast errors for all maturities, and their outperformance is most visible at the short end of the yield curve, which is the particular focus of our paper. We thank Ken Singleton for making this point.

[29] The comparison of survey and futures forecasts is necessarily imperfect because futures are settled based on the average FFR that prevails during the contract month, while the forecasters predict average quarterly FFR rates. To make the setup comparable, we use monthly data, and calculate the survey forecast error with respect to the monthly average of the FFR that prevails at time 3, 6, 9 and 12 months from the time of the forecast. Survey forecast errors when using either quarterly or monthly FFR averages are very highly correlated, with correlations 0.94, 0.98, 0.99 and 0.99 for one through four quarters ahead, respectively.

the surveys, by three and two basis points respectively, but for the six-month horizon we fail to find a statistically significant difference between these two sources of FFR predictions.

One interpretation of these results is that the median survey response represents quite well market-wide expectations of the short rate. Another interpretation, more problematic for our conclusions, could be that survey respondents simply anchor their forecasts at the current market rates, and thus report risk-adjusted rather than physical expectations.[30] In that case, interpreting forecast error predictability as evidence of expectations frictions becomes invalid, as it may reflect the risk premium variation. However, this latter hypothesis is unlikely to hold true for several reasons. First, the evidence above tells us that in real time it is hard to beat survey forecasts with statistical models of the physical short-rate dynamics. Therefore, the risk premium that forecasters potentially include when forming their expectations, if any, should not be a significant confounding factor. Second, we obtain very similar estimates of risk premia in short-term interest rates to those in the fed fund futures when using expectations of different survey respondents (SPF) and for other interest rates (three-month T-bill). These estimates confirm that risk premia at the short end of the yield curve are small relative to the overall variation in short-term rates, and are volatile around zero. They also systematically decline before and at the beginning of recessions, consistent with the role of short-maturity Treasury bonds in liquidity and safety provision. In contrast, to interpret our forecast error predictability as risk premium, one would need to accept that, in recessions, short-term Treasury bonds earn a large positive risk premium in the magnitude of several hundred basis points. Finally, Section II.D shows that unemployment forecast errors, which are unaffected by the variation in risk premium, display similar predictability patterns as forecast errors of the FFR. Altogether, this evidence points to expectations frictions being an important determinant of predictable variation in short-term interest rates.

VII. Conclusions

This paper studies how agents form expectations about the short-term interest rate. We show that lagged variables forecast future short rate changes beyond information embedded in today's cross section of yields or in survey expectations. In particular, we document systematic differences

[30]Private conversations with some of the prominent survey participants suggest that forecasters understand very well the difference between the physical and risk neutral dynamics and do not anchor their forecast to the latter, but rather use sophisticated models and judgement to form their predictions.

between the ex-ante real rate perceived by agents in real time and its counterpart estimated by an econometrician who works under the assumption of rational expectations and full information.

These findings are important for understanding the information content of the yield curve as a reflection of risk premia and agents' expectations about the economy. In particular, by referring to expectations frictions, our results both support and cast light on the observation in the literature that information not contained in the current yield curve helps predict future yields and bond returns. Constructing a proxy for such expectations rigidities, we show that they induce predictable dynamics of bond returns that are distinct from the statistical and survey-based measures of bond risk premia.

More generally, our evidence highlights the relevance of real information rigidities for explaining the interest rate dynamics. As such, we lend support to the recent theoretical work of Angeletos and La'O (2012) who allow information frictions to influence not only price setting decision but also real production decisions of firms. Our results suggest that such real rigidities could have played a major role in shaping the business cycle during the last three decades. Modeling the term structure of interest rates in a general equilibrium setting with both nominal and real information rigidities is a promising avenue for future research.

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A. Figures

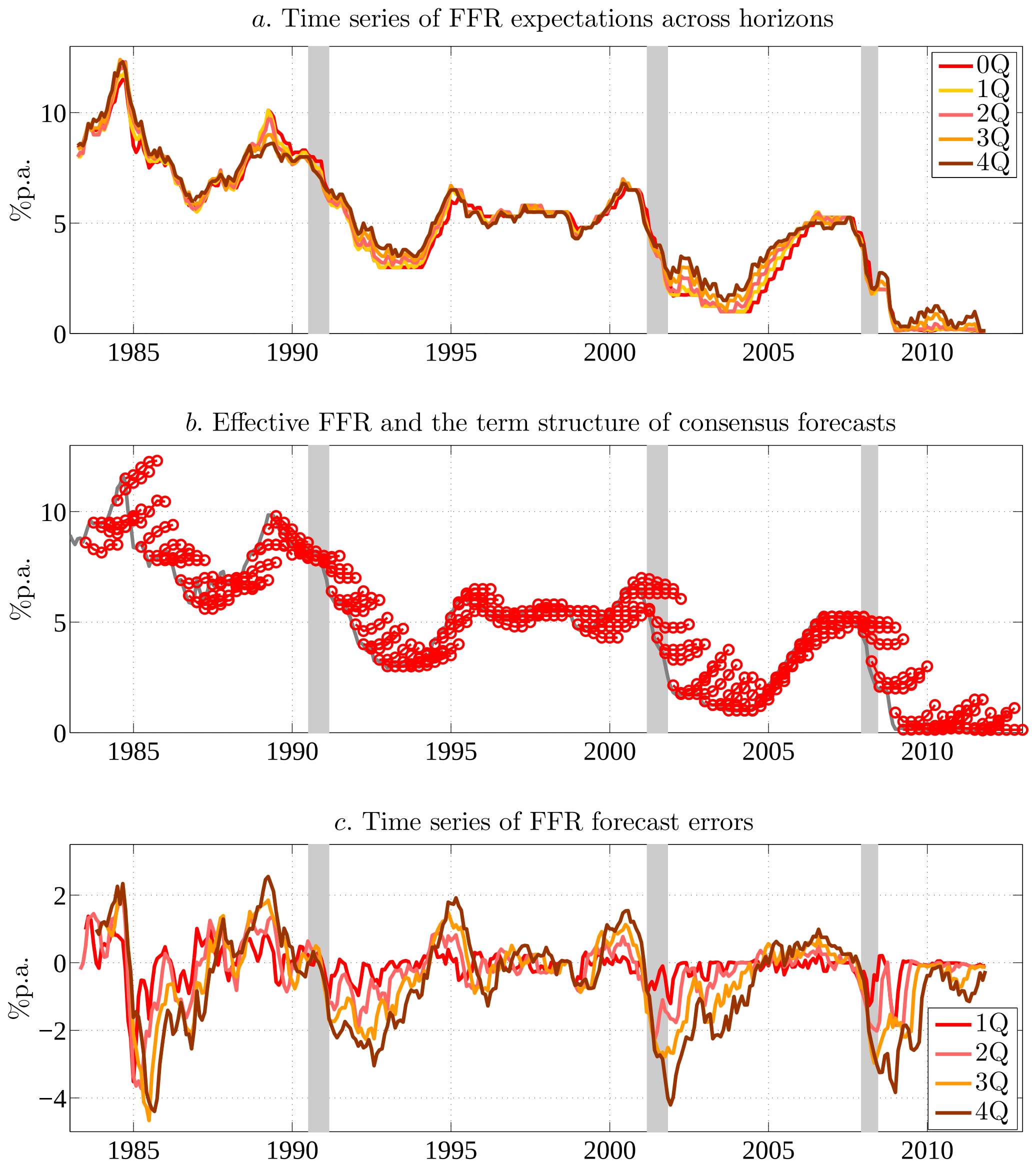

Figure 1: Short rate expectations

Panel *a* plots the time series of FFR forecasts from the BCFF survey. The forecasts are for the current quarter up to four quarters ahead. Panel *b* plots the term structures of forecasts. For clarity, while the forecasts are given monthly, the plot shows those made in the middle of each quarter, i.e. February, May, August and November. Panel *c* displays the time series of forecast errors for horizons from one through four quarters ahead. The shaded areas are NBER-dated recessions.

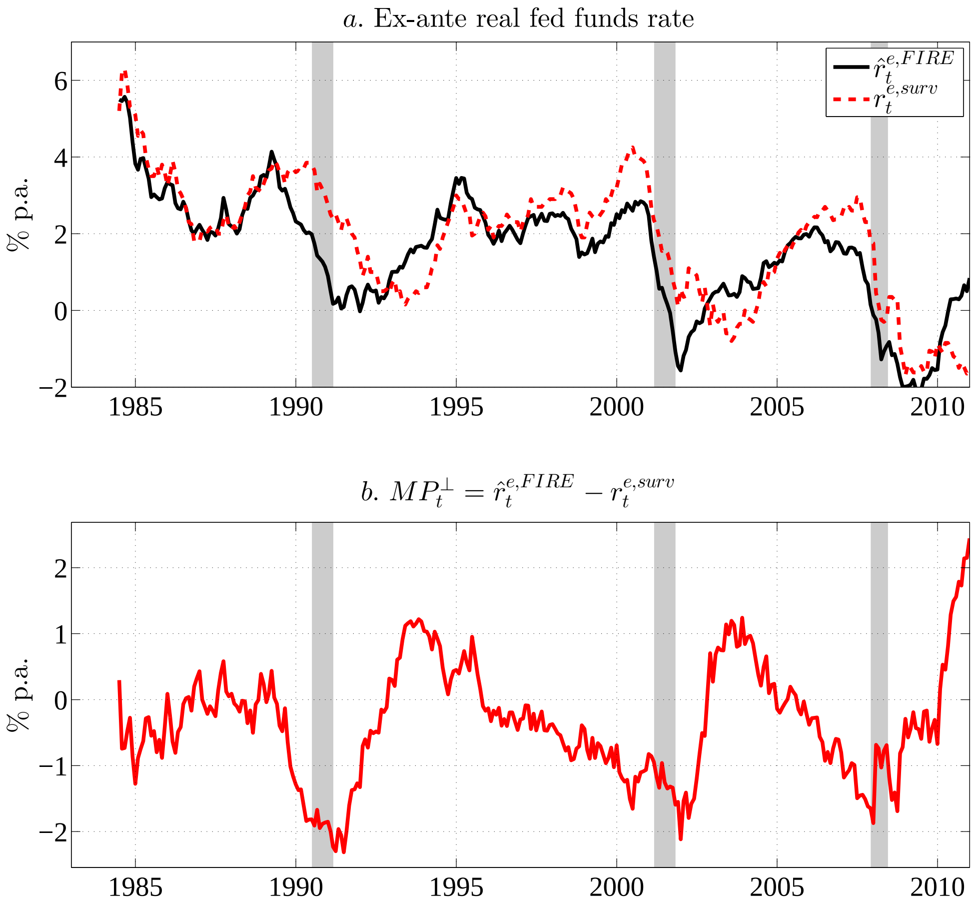

Figure 2: Wedge between the FIRE and survey-based real FFR

Panel *a* plots two versions of ex-ante real FFR: $\hat{r}_t^{e,FIRE}$ is obtained using instrumental variables in full-sample projections; $r_t^{e,surv}$ is constructed using survey forecasts. Panel *b* shows their difference, $MP_t^{\perp} = \hat{r}_t^{e,FIRE} - r_t^{e,surv}$.

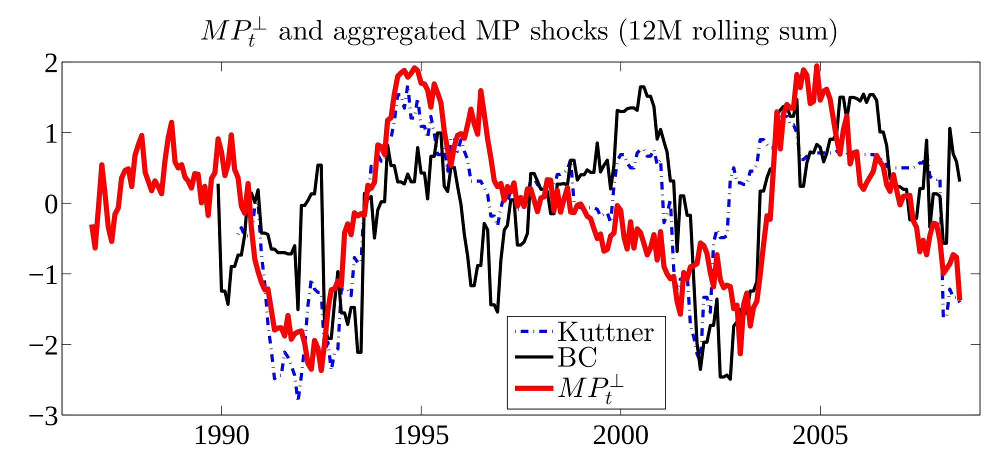

Figure 3: Moving averages of monetary policy shocks

Figure compares $MP_t^{\perp}$ with twelve-month rolling sums of monetary policy shocks obtained from fed fund futures by Kuttner (2001) and Barakchian and Crowe (2013, BC). The timing of the series is such that the sum of monetary policy surprises from time $t + \frac{1}{12}$ to time $t+1$ is aligned with time t value of $MP_t^{\perp}$. All variables are standardized.

B. Tables

Table I: Private sector's expectations of the short rate

Panel A reports predictive regressions of the future FFR changes from time t to $t+h$ on the change expected at time t by forecasters in the BCFF survey. Panel B augments the predictive regression with additional information; explanatory variables are the survey-based expected FFR change and the lagged term structure slope at time $t-1$ (upper section) and only the lagged slope only (bottom section). Panel C reports regressions of the FFR forecast errors on the lagged slope. Time subscripts and horizons are expressed as the fraction of the year, i.e. S_{t-1} is lagged by one year. The RHS in panels B and C use as additional regressors five principal components (PCs) of the yield curve at time t. The data is monthly in the period 1983:03–2010:12. T-statistics are Newey-West adjusted with 15 lags.

	$h=1Q$	$h=2Q$	$h=3Q$	$h=4Q$
A. Predictability of short-rate changes: $\Delta FFR_{t,t+h} = \gamma_2 + \gamma_3\left[E_t^s(FFR_{t+h}) - FFR_t\right] + \varepsilon_{t+h}^{FE}$				
const.	-0.09	-0.24	-0.44	-0.63
	(-1.53)	(-1.96)	(-2.27)	(-2.34)
$E_t^s(FFR_{t+h}) - FFR_t$	0.83	0.94	1.05	1.06
	(4.68)	(3.01)	(3.23)	(3.36)
$\bar{R}^2$	0.25	0.19	0.19	0.18
t-stat ($\gamma_2 = 0$)	(-1.53)	(-1.96)	(-2.27)	(-2.34)
t-stat ($\gamma_3 = 1$)	(-0.95)	(-0.20)	(0.14)	(0.18)

	$h=1Q$	$h=2Q$	$h=3Q$	$h=4Q$	$h=1Q$	$h=2Q$	$h=3Q$	$h=4Q$
	w/o yield PCs controls				*with yield PCs controls*			
B. Predictability of short rate changes $\Delta FFR_{t,t+h}$ with lagged slope								
const.	-0.00	-0.01	-0.01	-0.02	0.00	0.01	0.01	0.01
	(-2.46)	(-2.87)	(-3.58)	(-4.25)	(0.93)	(1.25)	(1.24)	(0.78)
$E_t^s(FFR_{t+h}) - FFR_t$	0.83	0.76	0.64	0.52	0.67	0.61	0.50	0.26
	(5.27)	(2.45)	(2.09)	(2.25)	(3.81)	(2.00)	(1.53)	(0.88)
S_{t-1}	0.06	0.17	0.33	0.52	0.09	0.24	0.42	0.61
	(2.02)	(2.41)	(3.17)	(4.31)	(2.31)	(3.49)	(4.56)	(5.99)
$\bar{R}^2$	0.32	0.29	0.31	0.35	0.34	0.35	0.39	0.41
yield PCs$_t$	N	N	N	N	Y	Y	Y	Y
const.	-0.00	-0.01	-0.01	-0.02	0.00	0.01	0.01	0.01
	(-3.36)	(-3.81)	(-4.26)	(-4.59)	(1.79)	(1.54)	(1.49)	(0.91)
S_{t-1}	0.14	0.30	0.47	0.64	0.17	0.33	0.50	0.65
	(3.34)	(3.85)	(4.43)	(4.97)	(3.89)	(4.88)	(5.75)	(6.49)
$\bar{R}^2$	0.12	0.20	0.26	0.32	0.24	0.31	0.37	0.41
yield PCs$_t$	N	N	N	N	Y	Y	Y	Y
C. Predictability of forecast errors $FE_{t,t+h}^{FFR}$ with lagged slope								
const.	-0.00	-0.01	-0.01	-0.02	0.00	0.01	0.01	0.01
	(-2.32)	(-2.99)	(-3.48)	(-3.85)	(0.67)	(1.11)	(1.07)	(0.51)
S_{t-1}	0.04	0.13	0.25	0.40	0.05	0.18	0.34	0.50
	(1.41)	(2.15)	(2.74)	(3.36)	(1.50)	(2.84)	(3.95)	(4.94)
$\bar{R}^2$	0.01	0.05	0.09	0.15	0.02	0.12	0.19	0.23
yield PCs$_t$	N	N	N	N	Y	Y	Y	Y

Table II: Linear full-sample projections of the ex-post real rate

Panel A reports the projections of ex-post real rate on a set of time-t instruments that are listed in the rows of the table. Panel A1 defines the ex-post real rate as $r_{t+1} = FFR_{t+1} - \Delta CPI_{t+1}$. Panel A2 defines the ex-post real rate as $\widetilde{r}_{t+1} = y_t^{(1)} - \Delta CPI_{t+1}$. Newey-West adjusted (15 lags) t-statistics are reported in parentheses. Panel B shows the predictability of forecast errors with $MP_t^{\perp}$ constructed with instruments corresponding to columns in panel A. Standard errors in panel B are adjusted for generated regressors with GMM. Panel C1 reports the results from contemporaneous regression of $MP_t^{\perp}$ on three and five PCs of yields. $MP_t^{\perp}$ corresponds to column (5) of panel A1, i.e. using the full set of instruments. The regressions are run in levels and in monthly changes. Column "Wald" reports the Wald test that all coefficient loadings on the PCs are zero, "pval" is the corresponding p-value. Column "corr($MP_t^{\perp}$, $MP_t^{\perp PC}$)" is the correlation between $MP_t^{\perp}$ and the residual from its projection on the yield PCs, denoted $MP_t^{\perp PC}$. Panel C2 compares the predictability of FFR forecast errors, $FE_{t,t+1}^{FFR}$, obtained using $MP_t^{\perp PC}$ relative to the predictability with the baseline $MP_t^{\perp}$. Column ΔBIC reports the change in BIC when using the $MP_t^{\perp PC}$ relative to the baseline $MP_t^{\perp}$. Column $\Delta \bar{R}^2$ reports the change in the predictive $\bar{R}^2$, $\Delta \bar{R}^2 > 0$ means that $MP_t^{\perp PC}$ gives a higher predictability of forecast errors compared to the baseline. The sample is monthly, 1984:6–2010:12.

	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
A. Projections of the ex-post real rate on instruments										
	A1. $r_{t+1} = FFR_{t+1} - \Delta CPI_{t+1}$, $\hat{r}_t^{e,FIRE} = \text{Proj}(r_{t+1}\vert\text{Instr}_t)$					A2. $\widetilde{r}_{t+1} = y_t^{(1)} - \Delta CPI_{t+1}$, $\hat{\widetilde{r}}_t^{e,FIRE} = \text{Proj}(\widetilde{r}_{t+1}\vert\text{Instr}_t)$				
$y_t^{(3M)}$	0.52	0.34	0.43	0.41	0.70	0.65	0.63	0.62	0.61	1.08
	(6.29)	(3.63)	(4.22)	(3.56)	(3.41)	(12.09)	(9.55)	(9.61)	(8.78)	(14.55)
ΔUNE_t		-0.80	-0.60	-0.57	-0.41		-0.12	-0.13	-0.13	0.13
		(-2.69)	(-2.07)	(-1.99)	(-1.52)		(-0.87)	(-0.88)	(-0.81)	(1.64)
S_{t-1}			0.27	0.31	0.31			-0.02	-0.01	-0.02
			(1.75)	(2.04)	(2.27)			(-0.26)	(-0.13)	(-0.46)
S_t				-0.11	0.06				-0.02	0.24
				(-0.76)	(0.35)				(-0.26)	(2.84)
ΔCPI_t					-0.51					-0.79
					(-1.44)					(-7.09)
$\bar{R}^2$	0.43	0.56	0.60	0.60	0.62	0.84	0.84	0.84	0.84	0.90
B. Forecast errors predictability										
	B1. $FE_{t,t+1}^{FFR} = \alpha + \beta MP_t^{\perp} + \varepsilon_{t+1}$, $MP_t^{\perp} = \hat{r}_t^{e,FIRE} - r_t^{e,surv}$					B2. $FE_{t,t+1}^{FFR} = \alpha + \beta \widetilde{MP}_t^{\perp} + \varepsilon_{t+1}$, $\widetilde{MP}_t^{\perp} = \hat{\widetilde{r}}_t^{e,FIRE} - r_t^{e,surv}$				
β	0.54	0.90	0.80	0.84	0.87	0.49	0.73	0.72	0.76	0.71
	(1.57)	(3.76)	(3.51)	(3.65)	(4.05)	(1.11)	(1.75)	(1.71)	(1.80)	(1.53)
$\bar{R}^2$	0.05	0.25	0.26	0.28	0.29	0.03	0.07	0.07	0.07	0.06

C. Spanning of the real rate wedge $MP_t^{\perp}$ by the cross-section of yields ($MP_t^{\perp}$ as in column (5) of panel A1)

	C1. Projection of $MP_t^{\perp}$ on yield PCs				C2. Predictability of $FE_{t,t+1}^{FFR}$ with part of $MP_t^{\perp}$ orthogonal to yield PCs	
	Wald	pval	$\bar{R}^2$	corr ($MP_t^{\perp}$, $MP_t^{\perp PC}$)	ΔBIC	ΔR^2
PC 1–3						
levels	2.57	0.11	0.17	0.91	-0.11	0.07
changes	0.52	0.47	-0.01	0.91		
PC 1–5						
levels	7.13	0.01	0.26	0.86	-0.17	0.11
changes	0.12	0.73	-0.01	0.73		

Table III: Macro expectations

Panel A reports the unconditional correlations between forecast errors at different horizons. Panel B reports the predictability of macro forecast errors with $MP_t^{\perp}$. Panel C reports the regressions of FFR forecast errors on the errors about CPI inflation and unemployment. As instruments, we use the contemporaneous oil shock and past CFNAI lagged by one quarter. Oil shock is the residual from an AR(2) estimated on the oil price change. For both instruments we report the first stage estimates. Row labeled "Weak (size, 10%)" displays the Stock-Yogo test for the bias in standard errors. "No" indicates that we reject the null that significance level is smaller than at least 10% when the desired level is 5%, i.e. we fail to find evidence of biased standard errors due to the presence of weak instruments. T-statistics (in parentheses) use Newey-West adjustment.

A. Unconditional correlations of forecast errors at different horizons

	$FE^{FFR}_{t,t+h}, FE^{UNE}_{t,t+h}$	$FE^{FFR}_{t,t+h}, FE^{CPI}_{t,t+h}$	$FE^{UNE}_{t,t+h}, FE^{CPI}_{t,t+h}$
$h = 1Q$	-0.46	0.28	-0.19
$h = 2Q$	-0.57	0.25	-0.19
$h = 3Q$	-0.62	0.24	-0.17
$h = 4Q$	-0.66	0.28	-0.13

B. Forecast error predictability

	$FE^{UNE}_{t,t+h}$				$FE^{CPI}_{t,t+h}$			
	$h = 1Q$	$h = 2Q$	$h = 3Q$	$h = 4Q$	$h = 1Q$	$h = 2Q$	$h = 3Q$	$h = 4Q$
$MP_t^{\perp}$	-0.18	-0.32	-0.44	-0.55	0.34	0.37	0.39	0.41
	(-3.87)	(-4.59)	(-4.53)	(-4.23)	(1.38)	(1.51)	(1.63)	(1.74)
$\bar{R}^2$	0.19	0.25	0.25	0.24	0.01	0.01	0.01	0.01

C. IV regressions

2nd stage regressions of forecast errors, $FE^{FFR}_{t,t+h}$

	Sample: 1983:Q1–2010:Q4				Sample: 1983:Q1–2006:Q4			
	$h = 3Q$		$h = 4Q$		$h = 3Q$		$h = 4Q$	
	LS	IV	LS	IV	LS	IV	LS	IV
$FE^{CPI}_{t,t+h}$	0.08	0.00	0.14	0.07	0.17	0.15	0.22	0.15
	1.36	-0.02	2.33	0.75	3.17	2.07	3.42	1.84
$FE^{UNE}_{t,t+h}$	-0.96	-0.94	-1.01	-0.96	-1.52	-1.81	-1.62	-1.99
	-3.55	-2.43	-3.76	-2.54	-8.39	-6.77	-9.73	-5.90
$\bar{R}^2$	0.39	0.37	0.47	0.45	0.54	0.52	0.61	0.58
Weak (size, 10%)	—	No	—	No	—	No	—	No

First stage

	$FE^{CPI}_{t,t+h}$		$FE^{UNE}_{t,t+h}$		$FE^{CPI}_{t,t+h}$		$FE^{UNE}_{t,t+h}$	
	$h = 3Q$	$h = 4Q$	$h = 3Q$	$h = 4Q$	$h = 3Q$	$h = 4Q$	$h = 3Q$	$h = 4Q$
Oil shock$_{t+h}$	0.12	0.12	—	—	0.17	0.17	—	—
	5.50	5.49	—	—	6.57	6.69	—	—
CFNAI$_t$	—	—	-0.55	-0.65	—	—	-0.39	-0.46
	—	—	-4.50	-4.25	—	—	-5.10	-4.31
$\bar{R}^2$	0.29	0.27	0.37	0.34	0.22	0.21	0.22	0.21

Table IV: Forecasting annual excess Treasury bond returns

The table presents the predictive regressions of realized excess bond returns across maturities n of two, three, five, ten and 20 years. $rx_{t+1}^{(n)}$ is excess return with an annual holding period. The explanatory variables are two empirical measures of bond risk premium: the cycle factor, $\widehat{cf}_t$, of Cieslak and Povala (2013) (LHS panels) and CP factor, CP_t, of Cochrane and Piazzesi (2005) (RHS panels), as well as the proxy for expectations frictions $MP_t^{\perp}$. Panel A reports the univariate regression of excess returns on $MP_t^{\perp}$. The row "$\bar{R}^2$ (orth.)" displays the $\bar{R}^2$ form the same predictive regressions but with $MP_t^{\perp}$ orthogonalized with respect to five yield PCs. Panel D compares the predictability of long- and short-maturity factors in returns by $MP_t^{\perp}$ and the risk premium measures, RP_t. $rx_t^{(2)\perp(20)}$ is the two-year bond return orthogonalized with respect to the 20-year excess return. In all panels, both left- and right-hand variables are standardized. The data is monthly and covers the period 1984:6–2010:12. T-statistics in parentheses in rows denoted "t(NW)" use Newey-West standard errors adjusted with 15 lags; t-statistics in rows denoted "t(H)" are based on Hodrick's reverse regressions delta method extended by Wei and Wright (2013).

A. $rx_{t+1}^{(n)} = \delta_0 + \delta_1 MP_t^{\perp} + \varepsilon_{t+1}$

	$rx^{(2)}$	$rx^{(3)}$	$rx^{(5)}$	$rx^{(10)}$	$rx^{(20)}$
$MP_t^{\perp}$	-0.55	-0.50	-0.39	-0.23	-0.08
t(NW)	(-5.69)	(-4.73)	(-3.48)	(-2.22)	(-0.86)
t(H)	[-3.26]	[-3.11]	[-2.74]	[-2.10]	[-1.17]
$\bar{R}^2$	0.30	0.25	0.15	0.05	0.00
$\bar{R}^2$ (orth.)	0.28	0.26	0.18	0.09	0.03

B. $RP_t = \widehat{cf}_t$

	$rx^{(2)}$	$rx^{(3)}$	$rx^{(5)}$	$rx^{(10)}$	$rx^{(20)}$
B1. $rx_{t+1}^{(n)} = \delta_0 + \delta_1 RP_t + \varepsilon_{t+1}$					
$\widehat{cf}_t$	0.49	0.54	0.63	0.72	0.70
t(NW)	(4.02)	(4.91)	(6.27)	(7.70)	(6.98)
t(H)	[2.28]	[2.70]	[3.26]	[3.88]	[4.09]
$\bar{R}^2$	0.24	0.29	0.39	0.51	0.49
B2. $rx_{t+1}^{(n)} = \delta_0 + \delta_1 RP_t + \delta_2 MP_t^{\perp} + \varepsilon_{t+1}$					
$\widehat{cf}_t$	0.47	0.52	0.61	0.71	0.70
t(NW)	(4.41)	(5.53)	(6.83)	(7.85)	(7.04)
t(H)	[2.26]	[2.68]	[3.22]	[3.82]	[4.05]
$MP_t^{\perp}$	-0.52	-0.48	-0.36	-0.20	-0.05
t(NW)	(-4.99)	(-4.05)	(-2.88)	(-1.64)	(-0.42)
t(H)	[-3.20]	[-3.03]	[-2.66]	[-1.99]	[-1.04]
$\bar{R}^2$	0.51	0.52	0.52	0.55	0.49

C. $RP_t = CP_t$

	$rx^{(2)}$	$rx^{(3)}$	$rx^{(5)}$	$rx^{(10)}$	$rx^{(20)}$
C1. $rx_{t+1}^{(n)} = \delta_0 + \delta_1 RP_t + \varepsilon_{t+1}$					
CP_t	0.35	0.35	0.41	0.47	0.51
t(NW)	(2.21)	(2.10)	(2.44)	(2.76)	(2.90)
t(H)	[0.68]	[1.00]	[1.47]	[1.87]	[2.01]
$\bar{R}^2$	0.12	0.12	0.17	0.22	0.26
C2. $rx_{t+1}^{(n)} = \delta_0 + \delta_1 RP_t + \delta_2 MP_t^{\perp} + \varepsilon_{t+1}$					
CP_t	0.39	0.39	0.44	0.49	0.52
t(NW)	(3.23)	(3.03)	(3.19)	(3.16)	(3.02)
t(H)	[1.26]	[1.56]	[1.97]	[2.17]	[2.12]
$MP_t^{\perp}$	-0.57	-0.53	-0.42	-0.27	-0.11
t(NW)	(-4.68)	(-3.97)	(-2.94)	(-1.89)	(-0.89)
t(H)	[-3.23]	[-3.10]	[-2.81]	[-2.26]	[-1.48]
$\bar{R}^2$	0.45	0.40	0.35	0.29	0.27

D. Predictive regressions for the short- and long-term return components

	$RP_t = \widehat{cf}_t$		$RP_t = CP_t$	
	$rx_{t+1}^{(2)\perp(20)}$	$rx_{t+1}^{(20)}$	$rx_{t+1}^{(2)\perp(20)}$	$rx_{t+1}^{(20)}$
RP_t	0.06	**0.70**	0.10	**0.52**
t(NW)	(0.59)	**(7.04)**	(1.19)	**(3.02)**
t(H)	[-0.45]	**[4.05]**	[-0.49]	**[2.12]**
$MP_t^{\perp}$	**-0.61**	-0.05	**-0.62**	-0.11
t(NW)	**(-5.95)**	(-0.42)	**(-5.83)**	(-0.89)
t(H)	**[-3.85]**	[-1.04]	**[-3.72]**	[-1.48]
$\bar{R}^2$	0.38	0.49	0.38	0.27

Table V: Expected returns versus predictable forecast errors

We regress components of the realized return on a two-year bond between time t and $t+1$ on time t variables. In panel A, as the dependent variables, we use the unexpected return $rx^{(2)}_{t+1} - E^s_t(rx^{(2)}_{t+1}) = -(y^{(1)}_{t+1} - E^s_t(y^{(1)}_{t+1}))$, private sector's forecast error about the FFR four quarters ahead $FE^{FFR}_{t,t+1} = FFR_{t+1} - E^s_t(FFR_{t+1})$, and the expected return component $E^s_t(rx^{(2)}_{t+1}) = f^{(2)}_t - E^s_t(y^{(1)}_{t+1})$. In panel B, we regress the same dependent variables on two macro factors: the year-over-year change in the rate of unemployment and the CFNAI. The data is monthly and covers the period 1987:12–2010:12; the beginning of the sample is dictated by the availability of the one-year yield forecast in the BCFF survey.

A. Regressions of components of realized returns on $MP^{\perp}$

	Unexpected return, $rx^{(2)}_{t+1} - E^s_t(rx^{(2)}_{t,t+1})$						Expected return, $E^s_t(rx^{(2)}_{t,t+1})$						Forecast error, $FE^{FFR}_{t,t+1}$					
Regressor	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
$MP^{\perp}_t$	-0.66						0.00						0.62					
	(-6.20)						(0.02)						(5.68)					
$r^{e,FIRE}_t$		-1.16	-0.29					0.16	0.24					1.13	0.32			
		(-6.92)	(-2.53)					(0.63)	(2.35)					(6.90)	(2.43)			
$r^{e,surv}_t$		1.06		0.11				0.10		0.23				-0.99		-0.06		
		(5.63)		(0.77)				(0.35)		(2.04)				(-5.13)		(-0.47)		
S_{t-1}					-0.50						-0.08						0.49	
					(-4.08)						(-0.44)						(4.04)	
$\widehat{cf}_t$						0.17						0.48						-0.10
						(1.22)						(4.33)						(-0.78)
$\bar{R}^2$	0.43	0.45	0.08	0.01	0.25	0.02	0.00	0.06	0.06	0.05	0.00	0.23	0.39	0.42	0.10	0.00	0.23	0.01

B. Regressions of components of realized returns on macro variables

	Unexpected return, $rx^{(2)}_{t+1} - E^s_t(rx^{(2)}_{t+1})$				Expected return, $E^s_t(rx^{(2)}_{t,t+1})$				Forecast error, $FE^{FFR}_{t,t+1}$			
Regressor	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
CFNAI_t	-0.39		-0.16		0.17		0.19		0.42		0.22	
	(-2.43)		(-1.70)		(1.49)		(1.94)		(2.08)		(1.50)	
ΔUNE_t		0.42		0.19		-0.05		-0.06		-0.42		-0.20
		(2.63)		(1.70)		(-0.47)		(-0.56)		(-2.27)		(-1.43)
$MP^{\perp}_t$			-0.60	-0.58			-0.07	-0.02			0.54	0.54
			(-5.17)	(-4.68)			(-0.42)	(-0.13)			(4.44)	(4.03)
$\bar{R}^2$	0.15	0.18	0.45	0.46	0.02	0.00	0.03	0.00	0.17	0.18	0.43	0.42

Table VI: Tests of information frictions

Panel A, column (1) denoted "Baseline", reports estimates of test (20) from Coibion and Gorodnichenko (2011a), i.e. forecast errors are regressed on the corresponding forecast update. Columns (2)–(3) augment this regression respectively with: $MP_t^{\perp}$ in column (2), and S_{t-1} in column (3). Panels B and C perform the same test for forecast errors about unemployment and CPI inflation, respectively. FFR forecasts are from the BCFF survey; unemployment and CPI forecasts are from the SPF survey. The RHS variables are standardized. The data is quarterly and spans the sample period 1984:Q3–2010:Q4. T-statistics use Newey-West adjustment with 6 quarterly lags.

	A. FFR			B. Unemployment			C. CPI		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Coeff.	Baseline	$MP_t^{\perp}$	S_{t-1}	Baseline	$MP_t^{\perp}$	S_{t-1}	Baseline	$MP_{t-1}^{\perp}$	S_{t-1}
Horizon, $h = 1Q$									
β_0	-0.04	-0.09	-0.09	-0.04	-0.04	-0.04	-0.05	-0.05	-0.05
	(-1.03)	(-2.84)	(-2.68)	(-1.03)	(-1.16)	(-1.14)	(-0.69)	(-0.68)	(-0.69)
β_1	0.28	0.13	0.14	0.15	0.13	0.14	0.22	0.22	0.22
	(6.54)	(4.87)	(4.55)	(2.55)	(2.26)	(2.48)	(3.01)	(3.00)	(3.00)
β_X		0.14	0.08		-0.07	-0.05		0.06	0.01
		(3.46)	(2.36)		(-2.98)	(-1.92)		(0.74)	(0.09)
$\bar{R}^2$	0.14	0.24	0.17	0.20	0.24	0.22	0.03	0.03	0.02
Horizon, $h = 2Q$									
β_0	-0.14	-0.24	-0.24	-0.02	-0.02	-0.02	-0.13	-0.13	-0.13
	(-1.39)	(-3.36)	(-2.96)	(-0.25)	(-0.28)	(-0.27)	(-1.05)	(-1.05)	(-1.06)
β_1	0.46	0.22	0.25	0.24	0.21	0.23	-0.01	-0.02	-0.01
	(4.92)	(3.68)	(3.61)	(3.22)	(2.72)	(2.98)	(-0.09)	(-0.11)	(-0.07)
β_X		0.32	0.20		-0.14	-0.12		0.06	0.03
		(4.60)	(2.79)		(-3.84)	(-2.24)		(0.66)	(0.25)
$\bar{R}^2$	0.13	0.30	0.19	0.23	0.31	0.28	0.00	0.00	0.00
Horizon, $h = 3Q$									
β_0	-0.26	-0.41	-0.41	0.02	0.02	0.02	-0.22	-0.22	-0.22
	(-1.71)	(-3.86)	(-3.29)	(0.22)	(0.25)	(0.24)	(-1.66)	(-1.67)	(-1.67)
β_1	0.75	0.36	0.39	0.30	0.24	0.25	0.01	0.01	0.02
	(5.17)	(4.28)	(4.16)	(3.21)	(2.45)	(2.62)	(0.15)	(0.12)	(0.20)
β_X		0.53	0.35		-0.26	-0.24		0.04	0.10
		(5.94)	(3.39)		(-4.07)	(-2.55)		(0.34)	(0.90)
$\bar{R}^2$	0.17	0.41	0.27	0.17	0.30	0.27	0.00	0.00	0.00

Table VII: Predictability of FFR forecast errors in VARs

Panel A reports the predictability of forecast errors from a VAR(2) model which includes annual CPI inflation, unemployment and FFR. The VAR is estimated recursively on an expanding sample and quarterly data. The out-of-sample period over which we construct forecasts is 1983:Q2–2010:Q4. Column "BTVP" denotes results from the time-varying parameters homoskedastic VAR (TVP-VAR) estimated with Bayesian MCMC algorithm. Columns denoted "CG" are for a VAR estimated with constant gain recursive least squares algorithm; we consider two values for the constant gain parameter $\gamma = 0.01$ and $\gamma = 0.05$, respectively. The first row shows the RMSE for the FFR forecasts (in percentages) obtained from each model. The subsequent rows provide full-sample estimates from a regression of the FFR forecast errors $FE^{FFR}_{t,t+h}$ on time-t variables included in the VAR and their lagged year-on-year changes, as in equation (22):

$$FE^{FFR,VAR}_{t,t+h} = \gamma_0 + \gamma_1' Y_t + \gamma_2' \Delta Y_{t-1,t} + \varepsilon_{t+h}, \quad \text{where} \quad Y_t = (\Delta CPI_t, UNE_t, FFR_t)', \quad h = \{1/4, 1\} \text{ years.} \quad (*)$$

Panel B presents a Monte Carlo simulation to study the properties of the above regression. All simulated models are VAR(2) and are calibrated to the historical data. We consider VARs with constant parameters (TVP=0) and time-varying parameters (TVP=1). In all simulations, agents use constant gain recursive least squares to estimate the model parameters in real time (gain $\gamma = 0.01$). Rows denoted with VAR(2) indicate that the agent estimates the correct statistical model; rows denoted VAR(1) indicate cases where the agent estimates VAR(1) while the true dynamics is VAR(2). The table reports the distribution of predictive $\bar{R}^2$ in regression ($*$) for $h = 1$ year estimated by an econometrician with access to the full sample. Column "Joint at 10%" shows the frequency of a rejection at the 10% level of the null hypothesis that all coefficients in (*) are jointly significant (excluding constant). Column "Indiv. $|t| \geq 2$" gives the frequency at which at least one regressor in ($*$) has a t-statistics above 2 in absolute value. All simulations are based on 1000 repetitions. T-statistics in both panels are Newey-West adjusted.

A. Data (quarterly, 1983:2–2010:4)

	$h = 1Q$			$h = 4Q$		
	BTVP	CG ($\gamma = 0.01$)	CG ($\gamma = 0.05$)	BTVP	CG ($\gamma = 0.01$)	CG ($\gamma = 0.05$)
RMSE	0.56	0.57	0.65	1.76	1.70	1.90
ΔCPI_t	-0.08	-0.08	0.00	-0.68	-0.82	-0.55
	(-0.86)	(-0.83)	(0.05)	(-2.48)	(-2.82)	(-1.71)
UNE_t	0.08	0.06	0.09	0.45	0.31	0.58
	(1.93)	(1.58)	(1.85)	(2.30)	(1.62)	(3.13)
FFR_t	0.05	0.05	-0.01	0.25	0.26	-0.05
	(1.36)	(1.31)	(-0.31)	(2.12)	(2.10)	(-0.41)
$\Delta^2 CPI_{t-1,t}$	-0.08	-0.06	-0.09	0.07	0.14	0.17
	(-1.28)	(-0.93)	(-1.23)	(0.30)	(0.63)	(0.68)
$\Delta UNE_{t-1,t}$	-0.08	-0.03	-0.24	-0.58	-0.51	-1.08
	(-0.98)	(-0.31)	(-2.05)	(-3.15)	(-2.56)	(-4.29)
$\Delta FFR_{t-1,t}$	0.06	0.05	-0.04	0.12	0.14	-0.09
	(1.41)	(1.15)	(-0.63)	(0.96)	(1.08)	(-0.51)
$\bar{R}^2$	0.17	0.10	0.07	0.40	0.36	0.29

B. Monte Carlo simulation: Predictability of FFR forecast errors in a CG-VAR, $h = 4Q$

	Distribution of $\bar{R}^2$					Significance	
	Mean	Std	p5	p50	p95	Joint at 10%	Indiv. $\lvert t\rvert \geq 2$
Small sample, 112 obs							
TVP=0, VAR(2)	0.27	0.18	0.03	0.24	0.62	0.49	0.81
TVP=1, VAR(2)	0.25	0.16	0.03	0.23	0.57	0.48	0.75
TVP=0, VAR(1)	0.41	0.20	0.10	0.38	0.78	0.58	0.92
TVP=1, VAR(1)	0.40	0.19	0.09	0.40	0.72	0.57	0.89
Large sample, 1000 obs							
TVP=0, VAR(2)	0.05	0.06	0.00	0.03	0.19	0.47	0.77
TVP=1, VAR(2)	0.04	0.04	0.00	0.04	0.12	0.39	0.68
TVP=0, VAR(1)	0.16	0.08	0.07	0.14	0.34	0.56	1.00
TVP=1, VAR(1)	0.11	0.07	0.02	0.10	0.25	0.59	0.91

Table VIII: Predictability of monetary policy shocks

The table reports the predictability of monetary policy shocks by the real rate wedge $MP_t^{\perp}$. Monetary policy shocks are from Kuttner (2001), Barakchian and Crowe (2013, BC), Gurkaynak, Sack and Swanson (2005, GSS), and Campbell, Evans, Fisher and Justininiano (2012, CEFJ). Shocks are identified from fed funds futures at the FOMC meeting frequency and converted into monthly frequency by assigning a zero if there was no meeting in a given month. Panel A reports predictability of monthly shocks realized in month $t+1/12$ by $MP_t^{\perp}$, panel B reports the predictability of shocks accumulated over the following year from $t+1/12$ to $t+1$. T-statistics in parentheses are Newey-West adjusted with 12 lags. Panel C reports the summary statistics for each monthly (i.e. non-cumulative) shock in basis points.

	(1) Kuttner 1989:6–2008:12	(2) BC 1988:12–2008:6	(3) GSS target 1990:2–2004:12	(4) GSS path 1990:2–2004:12	(5) CEFJ target 1990:02–2010:12*	(6) CEFJ path 1990:02–2010:12*
A. Monthly shocks: $\varepsilon^{MP}_{t+1/12} = \alpha + \beta MP_t^{\perp} + u_{t+1/12}$						
α	-1.082	0.443	0.702	0.126	0.679	-0.0241
	(-2.42)	(0.98)	(2.04)	(0.21)	(1.47)	(-0.06)
β	0.0312	0.0101	0.0165	0.00416	0.0224	-0.00132
	(4.44)	(2.47)	(3.66)	(0.59)	(3.78)	(-0.28)
$\bar{R}^2$	0.073	0.007	0.044	-0.004	0.055	-0.004
Obs.	235	235	179	179	217	217
B. Cumulative 12-month shocks: $\sum_{i=1}^{12} \varepsilon^{MP}_{t+i/12} = \alpha + \beta MP_t^{\perp} + \bar{u}_t$						
α	-13.60	3.234	9.405	4.113	12.22	-1.292
	(-3.63)	(0.77)	(2.73)	(0.71)	(3.13)	(-0.39)
β	0.360	0.111	0.214	0.104	0.255	0.0579
	(6.37)	(3.00)	(4.93)	(1.85)	(5.07)	(1.57)
$\bar{R}^2$	0.550	0.147	0.475	0.078	0.458	0.052
Obs.	223	223	167	167	192	192
C. Summary stats for the shocks, ε_t^{MP} in bps Stats for $MP_t^{\perp}$ (bps, 1984:6–2010:12): mean=-35.4; std=86.4; min=-231.3; max=244.4; obs.=319						
mean	-2.57	0.00	0.05	-0.04	0.00	0.00
std	9.94	8.15	7.02	10.04	8.93	8.81
min	-84.00	-55.40	-48.15	-40.50	-49.40	-40.06
max	17.00	38.31	14.44	43.82	22.91	28.47

* with breaks, the shocks are available for the subsamples 1990:2–2004:12 and 2007:8–2010:12.

Table IX: Test of Fed's additional information

This table tests additional information of the Fed staff about the FFR relative to the public. The test follows Romer and Romer (2000). The data are at the frequency of FOMC meetings. The sample period is 1983:5–2007:12 (panels A and B). Sub- and superscripts "F" and "P" refer to the Greenbook and BCFF forecasts, respectively. Panel A reports the original test proposed in Romer and Romer (2000) run in levels. Panel B reports an analogous test in changes. Row "corr(FE^F, FE^P)" provides unconditional correlations between the Greenbook and the BCFF forecast errors at the corresponding horizons. Row "RMSE ratio F/P" shows the ratio of the RMSEs for the forecast errors of the Fed relative to the public. A number less than one indicates a smaller RMSE of the Fed forecasts. Panel C displays the regressions of Greenbook FFR forecast errors on $MP_t^{\perp}$. The sample is 1984:6–2007:12, as determined by the availability of the data used in constructing $MP_t^{\perp}$. Row "$\Delta\bar{R}^2(F-P)$" is the difference in $\bar{R}^2$ when predicting the private and Greenbook forecast errors; both regressions are run on the same sample. T-statistics are Newey-West adjusted with 12 lags.

	$h=1Q$	$h=2Q$	$h=3Q$	$h=4Q$
A. $FFR_{t+h} = \alpha + \gamma_F E_t^F(FFR_{t+h}) + \gamma_P E_t^P(FFR_{t+h}) + \varepsilon_{t+h}$				
α	0.09	0.27	0.47	0.71
	(0.84)	(0.97)	(1.02)	(1.16)
γ_F	1.07	0.95	0.83	0.78
	(5.56)	(5.02)	(4.56)	(3.78)
γ_P	-0.11	-0.04	0.01	0.01
	(-0.52)	(-0.19)	(0.06)	(0.03)
$\bar{R}^2$	0.98	0.90	0.79	0.67
B. $\Delta FFR_{t,t+h} = \alpha + \gamma_F\left[E_t^F(FFR_{t+h}) - FFR_t\right] + \gamma_P\left[E_t^P(FFR_{t+h}) - FFR_t\right] + \varepsilon_{t+h}$				
α	-0.10	-0.28	-0.46	-0.67
	(-2.07)	(-2.23)	(-2.26)	(-2.43)
γ_F	1.03	0.97	0.85	0.84
	(5.14)	(5.17)	(4.54)	(3.35)
γ_P	-0.06	0.26	0.50	0.66
	(-0.25)	(0.65)	(1.27)	(2.04)
$\bar{R}^2$	0.38	0.26	0.21	0.19
corr(FE^F, FE^P)	0.78	0.85	0.87	0.89
RMSE ratio F/P	0.77	0.90	0.95	0.98
C. $FE_{t,t+h}^{FFR,F} = \alpha + \beta MP_t^{\perp} + \varepsilon_{t+h}$				
α	-0.06	-0.13	-0.18	-0.19
	(-1.02)	(-1.16)	(-0.99)	(-0.80)
β	0.15	0.39	0.67	1.00
	(3.91)	(4.55)	(5.38)	(6.02)
$\bar{R}^2$	0.05	0.13	0.21	0.30
$\Delta\bar{R}^2(F-P)$	-0.04	-0.08	-0.09	-0.10

Table X: Comparison of survey and statistical real-time forecasts

Panel A reports the root mean squared error (RMSE) in percent per annum for the out-of-sample forecasts of the FFR at horizons from one to four quarters ahead. We consider the following models: (1) the survey-based private sector forecast from BCFF, (2) random walk, (3) univariate AR(2), (4) univariate AR(p) with lags selected dynamically using BIC (UDLS), (5) VAR(2) estimated recursively by OLS, (6) VAR(2) estimated with constant gain recursive learning scheme with gain parameter $\gamma = 0.01$ (CG-VAR), (7) time-varying parameters homoscedastic Bayesian VAR(2) (TVP-VAR). All models are estimated recursively with a burn-in period of 73 quarters. The data is quarterly. The out-of-sample period is 1983:Q1–2010:Q4, i.e. it coincides with the availability of survey forecasts. Panel B compares the RMSEs of forecast errors from the survey and from the fed fund futures. The sample starts in 1988:12, when the fed fund futures become available. T-statistics test for the difference between the respective MSEs; the correlation is between the survey and futures-based forecast errors.

	$h = 1Q$	$h = 2Q$	$h = 3Q$	$h = 4Q$
A. RMSE of forecast errors (% p.a.) from different models				
(1) FFR survey	0.33	0.75	1.12	1.47
(2) RW	0.54	0.95	1.31	1.63
(3) AR(2)	0.52	0.95	1.29	1.60
(4) UDLS	0.55	0.97	1.30	1.61
(5) VAR(2) OLS	0.55	0.93	1.30	1.64
(6) CG-VAR(2)	0.57	0.98	1.37	1.70
(7) TVP-VAR(2)	0.56	1.00	1.40	1.76
B. RMSE for surveys and fed fund futures (% p.a.), 1988:12-2010:12				
Fed fund futures RMSE	0.33	0.70	–	–
FFR survey RMSE	0.36	0.72	–	–
t-stat (diff MSEs = 0)	2.49	0.86	–	–
correlation	0.89	0.93	–	–

Appendix

For online publication

C. Survey data

To test for potential biases in the FFR forecasts, we regress future $t+h$ realizations of the FFR on the time-t forecasts, for h ranging from one to four quarters ahead, $FFR_{t+h} = \alpha + \beta E_t^s(FFR_{t+h}) + \varepsilon_{t,t+h}$. An unbiased forecast implies that $\alpha = 0$ and $\beta = 1$ (Mincer and Zarnowitz, 1969). Table C-XI summarizes the results. We fail to reject the null at all horizons suggesting the private sector reports unbiased forecasts of the future FFR.

Table C-XI: Testing for survey bias

Table reports the Mincer-Zarnowitz test for survey bias for four forecasting horizons: one (h = 1Q) through four (h = 4Q) quarters. The joint null hypothesis is $\alpha = 0, \beta = 1$. The standard errors are obtained by Newey-West adjustment with 12 lags.

$FFR_{t+h} = \alpha + \beta E_t^s(FFR_{t+h}) + \varepsilon_{t,t+h}$				
	h=1Q	h=2Q	h=3Q	h=4Q
α	-0.14	-0.28	-0.47	-0.52
	(-1.90)	(-1.54)	(-1.47)	(-1.07)
β	1.01	1.01	1.01	0.99
	(62.84)	(27.39)	(16.09)	(10.47)
pval ($\beta = 1$)	0.25	0.40	0.42	0.54
$\bar{R}^2$	0.98	0.92	0.82	0.68

Table C-XII: Forecast errors across monetary policy regimes

The table reports the means and standard deviations of the forecast errors. We condition on the monetary policy regime: easing, tightening and neutral. The regimes are identified on a daily frequency using changes in the FFR target: easing (tightening) episode is defined as the time from the day on which the target FFR has increased (decreased) to the next monetary policy move. Neutral regime is when there has been no monetary policy action for longer than the span between two FOMC meetings. We identify 75 months as tightening, 94 months as easing and 140 months as neutral. From the daily data we construct the end of month series.

	h=Q1	h=Q2	h=Q3	h=Q4
Tightening, $N = 75$ months				
mean (μ_T)	0.18	0.40	0.49	0.60
std	0.32	0.56	0.78	0.88
Easing, $N = 94$ months				
mean (μ_E)	-0.32	-0.77	-1.14	-1.43
std	0.51	0.73	1.04	1.37
Neutral, $N = 140$ months				
mean (μ_N)	-0.09	-0.23	-0.41	-0.62
std	0.19	0.47	0.76	1.13
Z-test ($\mu_E = \mu_T$)	3.94	9.15	12.78	15.89
pval	0.00	0.00	0.00	0.00

C.1. Do survey forecasts match the yield curve dynamics?

We test whether FFR forecasts are a good approximation to the market-wide consensus about the path of the short rate that is reflected in the yield curve. A yield on a zero coupon bond is a sum of the average short rate that is expected to prevail until the maturity of the bond and a risk premium. Therefore, we can decompose one-year nominal yield $y_t^{(1)}$ into short rate expectations and risk premia by averaging the available FFR forecasts over the current quarter through four quarters ahead:

$$y_t^{(1)} = \underbrace{\gamma_0}_{-6e^{-4}\ [-0.74]} + \underbrace{\gamma_1}_{0.99\ [62.62]} \frac{1}{5}\sum_{k=0}^{4} E_t^s(FFR_{t+\frac{k}{4}}) + \nu_t, \quad \bar{R}^2 = 0.99, \tag{23}$$

where $E_t^s(FFR_{t+h})$ denotes the time-t survey-based forecast of the FFR at horizon h (expressed in years). T-statistics (in brackets) are Newey-West adjusted with 12 monthly lags. Note that the regression jointly tests the accuracy of survey data and decomposes $y_t^{(1)}$ into short rate expectations and risk premia comprised in ν_t. Hence, $\nu_t = RP_t + \gamma_1\epsilon_t$ where ϵ_t represents the survey inaccuracies, and RP_t measures the variation in the risk premium. The estimates suggest that the median survey responses at different horizons quite accurately represent market expectations about the future path of the monetary policy, as we cannot reject the hypothesis that $\gamma_0 = 0$ and $\gamma_1 = 1$ at the standard significance levels. Moreover, since expectations explain nearly all variation in the one-year yield, the risk compensation and/or survey inaccuracies can be assumed to be small.

Table C-XIII: Forecasting monthly Treasury bond portfolio excess bond returns

The table presents predictive regressions of realized excess returns of bond portfolios. For instance, $rx^{(<12m)}_{t,t+1/12}$ is excess return with a monthly holding period on a portfolio of bonds whose maturities are below 12 months. Returns are in excess of the one-month Tbill rate. All returns and Tbill data is from CRSP. The explanatory variables are two empirical measures of bond risk premium: the cycle factor of Cieslak and Povala (2011) (LHS panels) and CP factor of Cochrane and Piazzesi (2005) (RHS panels), as well as the proxy for expectations frictions $MP^{\perp}_t$. For ease of comparison, both left- and right-hand variables are standardized. The data is monthly and covers the period 1984–2010. T-statistics in parentheses use Newey-West standard errors adjusted with 15 lags.

	$rx^{(<12m)}$	$rx^{(<24m)}$	$rx^{(<36m)}$	$rx^{(<60m)}$	$rx^{(<120m)}$
			A. $rx^{(n)}_{t,t+1/12} = \delta_0 + \delta_1 MP^{\perp}_t + \varepsilon_{t,t+1/12}$		
$MP^{\perp}_t$	-0.20	-0.16	-0.13	-0.09	-0.06
	(-4.15)	(-3.51)	(-2.84)	(-1.91)	(-1.34)
$\bar{R}^2$	0.04	0.02	0.01	0.00	0.00

	$rx^{(<12m)}$	$rx^{(<24m)}$	$rx^{(<36m)}$	$rx^{(<60m)}$	$rx^{(<120m)}$		$rx^{(<12m)}$	$rx^{(<24m)}$	$rx^{(<36m)}$	$rx^{(<60m)}$	$rx^{(<120m)}$
			$RP_t = \widehat{cf}_t$						$RP_t = CP_t$		
B1. $rx^{(n)}_{t,t+1/12} = \delta_0 + \delta_1 RP_t + \varepsilon_{t,t+1/12}$						C1. $rx^{(n)}_{t,t+1/12} = \delta_0 + \delta_1 RP_t + \varepsilon_{t,t+1/12}$					
$\widehat{cf}_t$	0.18	0.22	0.22	0.23	0.24	CP_t	0.15	0.19	0.18	0.16	0.16
	(1.78)	(2.63)	(3.01)	(3.68)	(3.89)		(1.54)	(2.38)	(2.40)	(2.51)	(2.50)
$\bar{R}^2$	0.03	0.05	0.04	0.05	0.05	$\bar{R}^2$	0.02	0.03	0.03	0.02	0.02
B2. $rx^{(n)}_{t,t+1/12} = \delta_0 + \delta_1 RP_t + \delta_2 MP^{\perp}_t + \varepsilon_{t,t+1/12}$						C2. $rx^{(n)}_{t,t+1/12} = \delta_0 + \delta_1 RP_t + \delta_2 MP^{\perp}_t + \varepsilon_{t,t+1/12}$					
$\widehat{cf}_t$	0.17	0.21	0.21	0.22	0.23	CP_t	0.17	0.21	0.19	0.17	0.16
	(1.74)	(2.66)	(3.06)	(3.73)	(3.95)		(1.82)	(2.84)	(2.89)	(2.92)	(2.76)
$MP^{\perp}_t$	-0.19	-0.15	-0.12	-0.08	-0.05	$MP^{\perp}_t$	-0.21	-0.18	-0.15	-0.10	-0.07
	(-3.62)	(-2.95)	(-2.27)	(-1.42)	(-0.90)		(-3.72)	(-3.09)	(-2.52)	(-1.80)	(-1.38)
$\bar{R}^2$	0.06	0.07	0.06	0.05	0.05	$\bar{R}^2$	0.06	0.06	0.05	0.03	0.02

Table C-XIV: Factors in realized Treasury bond returns

The table reports contemporaneous projections of annual bond excess returns on two orthogonal components of returns. The short-term component, $rx^{(2)\perp(20)}_{t+1}$, is a residual from a projection of the two-year excess return, $rx^{(2)}_{t+1}$, on the excess return on the 20-year bond, $rx^{(20)}_{t+1}$. Newey-West t-statistics are with 15 lags.

			Contemporaneous regressions of returns on long- and short-term components				
	$rx^{(2)}_{t+1}$	$rx^{(3)}_{t+1}$	$rx^{(5)}_{t+1}$	$rx^{(7)}_{t+1}$	$rx^{(10)}_{t+1}$	$rx^{(15)}_{t+1}$	$rx^{(20)}_{t+1}$
$rx^{(2)\perp(20)}_{t+1}$	0.80	0.70	0.55	0.41	0.30	0.15	0.00
	–	(36.90)	(21.66)	(18.30)	(10.94)	(6.27)	–
$rx^{(20)}_{t+1}$	0.60	0.69	0.80	0.88	0.93	0.97	1.00
	–	(22.85)	(16.42)	(20.38)	(19.11)	(27.82)	–
$\bar{R}^2$	1.00	0.97	0.94	0.95	0.95	0.97	1.00