Expecting the Fed

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— Preliminary and incomplete —

After the creation of the Fed, a few distant lags of the short rate help predict future short rate changes even after conditioning on the information in today's yield curve. We explain this fact with the presence of frictions in short rate expectations formed by the private sector, which we measure using surveys. This expectations channel introduces a wedge between the time series dynamics and the cross section of yields, through which monetary policy delivers persistent surprises to the public. While agents' forecast errors about monetary policy are ex post predictable with lagged information, people do not make obvious mistakes. Fed staff's predictions have similar properties, and sophisticated statistical models fail to beat surveys in real time. In the last three decades, forecasters' errors about the short rate comove strongly with those about unemployment and less so inflation. Real activity proxies that predict realized bond returns, pick up their ex ante unexpected component that is orthogonal to measures of time-varying risk premia in the yield curve.

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I. Introduction

Separating short rate expectations from the risk premia in Treasuries is of key importance for policy makers and those seeking to understand the economics of the yield curve. Such decomposition provides insight about how markets perceive the future course of monetary policy, economic activity, inflation and their associated risks. It is also informative about the channels—risk premium versus expectations—through which monetary policy influences the economy.[1] The recent academic research has significantly improved our understanding and measurement of bond risk premia, but still surprisingly little is known as to how investors form expectations about the future path of monetary policy. This focus can be justified with the common assumption of the full-information rational expectations (FIRE) which stipulates that all predictable variation in bond returns comes from risk premia, with expectations formation being of little independent interest.

We start with the observation that distant lags of the short rate, spanning the length of the business cycle, significantly improve the predictions of future short rate changes, even after conditioning on the current yield curve. This feature of the data emerges after the founding of the Fed, but appears largely absent in the earlier period. This is surprising given that today's cross-section of yields reflects risk-adjusted expectations and therefore, absent strong restrictions, should subsume information relevant for forecasting. We use this observation as a hint to study the properties of private sector's expectations about the future path of monetary policy.

Understanding expectations formation takes on a new importance as central banks around the world embrace the forward policy guidance.[2] Therefore, our objective in this paper is to study how the private sector forms short rate expectations, and to which degree these expectations are consistent with the FIRE or are indicative of informational frictions faced by the agents. To directly disentangle the risk premium from short rate expectations, we rely on comprehensive survey data containing the term structure of private sector's forecasts of the federal funds rate (FFR)—the conventional US monetary policy tool—as well as forecasts of

[1] See for instance the speech of the former Fed governor Kohn on the importance of this distinction for the policy making (Kohn, 2005).

[2] The recent speech of the Fed Chairman Bernanke emphasizes the role of forward policy guidance as means to influence the public's expectations about the future path of policy rates (Bernanke, 2011). Recent papers that stress the role of short rate expectations in shaping the reactions to various monetary policy measures during the financial crisis are Bauer and Rudebusch (2011) and Swanson and Williams (2012).

longer maturity yields. Our results suggest that the view of frictionless rational expectations deviates from the observed behavior of interest rates in important ways.

First, while survey-based short rate expectations match almost one-to-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 (e.g. Rudebusch, 2002). We find that agents, faced with a highly persistent process, fail in real time to appraise the mean reversion in the policy rate that occurs at the business cycle frequency. As such, and for the same reason that lagged short rate matters for forecasting future short rate changes, agents' ex-post forecast errors of the short rate are predictable with past information that captures the mean reversion component. Our evidence suggests that this feature of short rate expectations pertains to an environment with an active central bank that itself might adapt its policy rule over time, and is less likely to characterize the data pre-Fed. In the last three decades, we find that agents' forecast errors about the short rate comove closely (with a negative sign) with the errors they make when forecasting unemployment, and much less so – inflation.

Second, we construct a measure of expectations frictions based on the difference between the observed physical dynamics of the policy rate and the corresponding expectations reflected in the yield curve. This variable reflects the idea that there is information in the time series of monetary policy actions that is not fully impounded in the cross section of yields in real time. We label this variable as $MP_t^{\perp}$. One interpretation is that in the Fed is able to deliver persistent surprises to the market. Accordingly, we show that $MP_t^{\perp}$ picks up the low-frequency movements in the measure of monetary policy surprises identified from high-frequency data (Kuttner, 2001), which the literature has documented to be unaffected by the risk premium (Piazzesi and Swanson, 2008).

With the help of survey data on longer-maturity yields, we obtain a model-free decomposition of excess bond returns into a risk premium and an ex-ante unexpected return component. The unexpected return on a two-year bond moves in lockstep with the (negative of) FFR forecast errors, and one quarter of its variation can be predicted ex-post by $MP_t^{\perp}$. The effect of expectations frictions is the strongest at the short end of the maturity spectrum, most influenced by the monetary policy, and subsides for long-term bonds. Surprisingly, we find that several conditioning variables used to forecast realized bond returns, especially variables related to the real activity, predict *un*expected returns and are essentially uncorrelated with the survey-implied risk premia. These variables feature a high degree of correlation with $MP_t^{\perp}$.

One concern about the validity of these results is that survey expectations of the federal funds rate may not reflect the true market perceptions of the future evolution of the policy rate. It can be that surveys are noisy, and that forecasters simply anchor their predictions to the current market rates reporting risk-adjusted rather than physical expectations. Thus, in case of such circularity between surveys and market yields, what we identify as expectations frictions could arise from a pure risk premium variation. Indeed, we find a close overlap between survey expectations and expectations extracted from the fed fund futures, which represent a market-wide consensus. We also fail to reject the hypothesis that survey expectations are consistent with those shaping the short end of the Treasury curve. This fact speaks against the hypothesis that noise prevents inference using surveys but it does not address the second concern about circularity.

It is unlikely, though, that forecasters report risk-adjusted predictions for several reasons. First, this argument would imply that the risk premium makes survey forecasts less accurate, and forecast errors more predictable, than they otherwise would be. Using various statistical models with different levels 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 forecasts. Moreover, for 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 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 the T-bill rate predictions. Importantly, we also report similar properties of expectation errors in the so-called Greenbook forecasts of the FFR, i.e. forecasts prepared by the staff of the Federal Reserve before FOMC meetings. As a last step, we draw on the evidence from money market funds to find that flows in and out of these funds support the expectations frictions interpretation. After controlling for the flight to safety and liquidity episodes, our measure of expectations frictions explains up to 60% of institutional money market flows and up to 35% of retail flows during a year. Specifically, consistent with the notion that agents struggle to predict the mean reversion in the short rate in real time, the inflows gradually increase after the monetary policy has been tight and peak when it turns out unexpectedly easy. The relationship is symmetric in easing and tightening episodes.

Related literature

Our focus on expectations formation is motivated by the dominant role that expectations play in the yield curve dynamics. In a recent paper, Cieslak and Povala (2011) decompose the Treasury yield curve into three components: long-horizon inflation expectations related to the inflation target, transitory variation in monetary policy expectations, and the bond risk premium. This decomposition reveals the risk premium to be the least persistent component of yields, attributing about 95% of their total variation to short rate expectations.

By studying the role of monetary policy expectations for the yield curve we combine the term structure literature with the recent developments in macroeconomics that emphasize the role of information imperfections and deviations from perfect rational expectations (see Mankiw and Reis (2011) and Woodford (2012) for overview). Our findings are linked to the discussion of the real effects of monetary policy that goes back to Lucas (1972). The question of how (through which friction) models of monetary policy can generate its lasting effect on the real economy is still debated. One promising route and a growing area of macro research has focussed on information rigidities. Coibion and Gorodnichenko (2011a, 2012) provide evidence that information rigidities present in inflation expectations are consistent with models that relax the FIRE assumption. 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). The evidence we collect about the short rate dynamics and expectations is reminiscent of natural expectations introduced by Fuster, Laibson, and Mendel (2010): While many macroeconomic variables have complex hump-shaped dynamics, agents forecast the future using simple models, and thus partially overlook the degree of mean reversion in fundamentals. Building on this literature, our objective is to provide an empirical assessment of expectations frictions faced by bond investors, their link to macroeconomic sources, and relevance for describing the dynamics of yields. Our results have potential implications for the measurement of risk premia and expectations in the curve. Furthermore, they may contribute to the discussion of the channels through which monetary policy impacts the real economy.

Our findings tie together the literatures on measuring bond risk premia and on extracting market-based expectations of monetary policy from asset prices. For one, motivated by a widely reported failure of the expectations hypothesis of the term structure, a large body of work has focussed on exploring the risk premium as the source of this violation (Campbell and Shiller, 1991; Fama and Bliss, 1987; Cochrane and Piazzesi, 2005). Consistent with FIRE, the most 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. Perhaps the most vexing conclusion of the research into bond risk premia is that future bond returns are predictable by variables that have a weak contemporaneous relation with the cross section of yields giving rise to the so-called hidden or unspanned term premia factors. This evidence goes back to Ludvigson and Ng (2009), Cooper and Priestley (2009), and has been formalized in Joslin, Priebsch, and Singleton (2010), Duffee (2011), Barillas and Nimark (2012), and most recently in Joslin, Le, and Singleton (2013).

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 a large degree of countercyclical variation in the risk premia on these assets. Our results suggest that there is a tight link between the hidden factors in the term premia and the predictable variation in returns on short-term interest rate instruments that is induced by the way short rate expectations are formed. In particular, the proxy for expectations frictions that we construct can be characterized as an unspanned monetary policy state.

A closely related strand of research uses survey data 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 reporting that forecast errors on one- through 30-year Treasury yields are predictable both with the term spread and a linear combination of forward rates. They argue that risk premia implied by the surveys, which they describe as subjective, differ significantly from those obtained with statistical VAR approaches. Building on this literature, our contribution is to cast light on the type of frictions underlying these results by relating them to the dynamics and expectations about the short rate and monetary policy. In particular, we document that ex-post there is a wedge between the time series dynamics of the short rate, which is determined by the ex-ante unexpected monetary policy actions, and the cross section of yields which captures perceptions of agents about the future short rate path. We emphasize the distinction between the risk premium, which reflects the ex-ante expected risk compensation on Treasuries, and the predictable variation in the ex-post forecast errors about the policy rate.

Deviations from the FIRE have recently gained prominence in studies of other major asset markets. Singleton (2012) emphasizes the distinctive role of informational frictions and imperfect information 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 of the recent past to the life-time macroeconomic experiences of individuals. Similarly, in a contemporaneous study, Greenwood and Shleifer (2013) 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 the discrepancy between the statistical and survey-based risk premium measures.

II. Background

Substantive empirical evidence suggests that variables other than current bond yields have predictive power for future bond returns and, relatedly, future yields. Such a finding has been surprising given that yields today reflect market's conditional expectations of short rates and excess returns to be realized in subsequent periods, and therefore, the current yield curve should contain all information useful for forecasting.[3] This section discusses how expectations frictions can be useful in reconciling the empirical predictability results with this benchmark logic.

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

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

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

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

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

Equation (2) is a tautology that follows from the definition of bond returns. Since it holds ex post, realization-by-realization, it also holds ex ante:

$$y_t^{(2)} = \frac{1}{2}F_t\left(i_t + i_{t+1}\right) + \frac{1}{2}F_t\left(rx_{t+1}^{(2)}\right), \tag{3}$$

where $F_t(\cdot) = F(\cdot|I_t)$ is an expectations operator, conditional on all information available at time t, I_t. Importantly, (3) 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. Under FIRE, the realized future short rate equals $i_{t+1} = F_t(i_{t+1}) + v_{t+1}$, 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, under FIRE, 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 (Duffee, 2011).

An alternative interpretation of this 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 (2) and (3) jointly imply:

$$i_{t+1} - F_t(i_{t+1}) = -\left[rx_{t+1}^{(2)} - F_t(rx_{t+1}^{(2)})\right], \tag{4}$$

where the left-hand side measures agents' forecast error about the short rate, and the right-hand side—the unexpected return. Through equation (3), any forecast errors that agents make when predicting the short rate must cancel with unexpected returns that they earn ex post. Since the cancelation in (4) is exact, a variable that predicts forecast errors will by construction have a zero net effect on the current yield curve. This argument holds equally for an n-period bond, for which:

$$\sum_{j=0}^{n-2}\left[i_{t+1+j} - F_t(i_{t+1+j})\right] = -\sum_{j=0}^{n-2}\left[rx_{t+1+j}^{(n-j)} - F_t(rx_{t+1+j}^{(n-j)})\right]. \tag{5}$$

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. We draw on evidence from long samples of data, different monetary policy regimes, survey forecasts of the short rate by the private sector and the Fed to show that deviations from the FIRE have an empirical merit and could account for the observed predictability patterns. This does not necessarily mean, however, that people make obvious mistakes. A broad class of models implies that forecast errors can be predictable without people's behavior being irrational. Such a predictability arises under realistic scenarios: Agents are likely to act under imperfect or noisy information (e.g. Woodford, 2003). They also are likely not to know the exact monetary policy reaction function but rationally learn about its parameters (Friedman, 1979), which themselves can evolve over time.[4] 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).

On a methodological level, the wedge between the cross section and the time series of yields introduced by expectations frictions could be interpreted within the term structure framework of Joslin, Priebsch, and Singleton (2010). Their framework assumes the existence of macro factors that have predictive properties for future yields in the time series but are unspanned by their current cross section. Importantly, since a subset of state variables does not enter the bond pricing equation in the first place, the model does not require an explicit cancelation between risk premia and expectations to occur within the yield curve.

III. Short rate dynamics

III.A. Short rate dynamics pre- and post-Fed

We explore the predictability of annual short rate changes in the sample 1875–2011 which spans different monetary policy and institutional settings. Taking the long-term perspective helps to identify robust features of the yield curve across regimes. The goal of this section is to study how predicable short rate changes are by comparing two perspectives: (*i*) a time-series perspective that uses a highly stylized statistical model of short rate dynamics and (*ii*) a cross-sectional perspective that extracts predictive information from the cross-section of yields. Absent time-varying risk premia and/or deviations from the FIRE, the time-series

[4] Indeed, a growing literature documents that the parameters of the monetary policy rule vary over time, e.g. Primiceri (2005), Boivin (2006), Ang, Boivin, Dong, and Loo-Kung (2011), Coibion and Gorodnichenko (2011b).

and cross-sectional predictability should, in general, coincide.[5] We find, however, that the cross-section appears to contain significantly weaker predictive power than the one implied by an unconstrained time-series model. This finding characterizes the data after the founding of the Fed, but not before.

We start with a deliberately simple empirical model in which short rate changes are linear in lagged values of the short rate itself:[6]

$$i_{t+1} - i_t = \alpha_c + \sum_{j \in 0,1,2,4} \alpha_j i_{t-j} + \varepsilon^i_{t+1}, \tag{6}$$

where i_t denotes the short rate and time is measures in years. A formal lag selection procedure (reported in Table C-XIII the Appendix) chooses a low number of lags up to four years back. Accordingly, for simplicity, equation (6) includes four lags up to four years.[7]

We are interested in both the degree of predictability and the stability of this model. To cover different monetary policy regimes, we consider quarterly data from 1875 through 2011, divided into five subperiods marked by important institutional changes: (*i*) pre-Fed (1875–1913), (*ii*) post-Fed – pre-Accord (1914–1951), (*iii*) post-Accord – pre-Volcker (1951–1979), (*iv*) post-Volcker (1984–2011), and (*v*) post-Accord (1951–2011). Our data is obtained from the Global Financial Database and comprises the long-term government yield, y_t^{LT}, and the three-month rate which we use as a proxy for the short rate, i_t.[8]

Panel A of Table I summarizes the results for (6). There are two key observations. First, one-year changes in i_t are highly predictable, except the for special period of interest rate controls and wars (1914–1951). Second, higher-order lags of the short rate carry significant

[5]As we discuss above, this statement does not hold true if there is an exact offsetting between risk premia and expectations within the yield curve—a special case described by Duffee (2011, 2012).

[6]Linear models of the term structure of this type have been studied in the earlier literature (Modigliani and Sutch, 1966, 1967; Sargent, 1972). Modigliani and Shiller (1973); Mishkin (1980) discuss the conditions under which this type of models is consistent with rational expectations.

[7]By selecting a low number of fixed lags, we avoid issues with collinearity. Table C-XIII in the Appendix re-estimates (6) with optimally selected lags using BIC leading to very similar conclusions. Alternatively, we have also implemented a polynomial distributed lag model and found that the it places a statistically and economically significant weight on distant lags.

[8]The short rate is constructed as the three-month commercial paper before 1920 and the three-month T-bill rate afterwards. T-bills become available in 1920 and thus do not cover the period before the Fed. However, using T-bill or commercial paper rate leads to very similar results for the overlapping period, and therefore should not bias the results. In the pre-Fed period commercial paper was considered as safe as government. Following the literature, we use quarterly data by smoothing monthly series with a three-quarter moving average because there is evidence that the short rate was highly seasonal prior to the founding of the Fed in 1914 (e.g. Miron, 1986).

information about future rates relative to a restricted model that excludes lags, increasing the $\bar{R}^2$ by an order of magnitude. This pattern pertains to the period post-Fed Accord, but is largely absent before. For instance, our simple model explains up to 40% of short rate changes in the pre- and post-Volcker samples. The importance of specific lags varies over time.

Switching to the cross-sectional dimension, current yields contain a footprint of real-time market expectations of short rates going forward. In particular, the term structure slope arises as a linear combination of expected short rate changes and time-varying risk premia. The presence of risk premia confounds the direct measurement of short rate expectations as formed by the market. If, however, the model in (6) is a good representation of the physical short rate dynamics, we can use the following projection to decompose the slope into the expected short rate change and the risk premium:

$$S_t = \delta_c + \sum_{j \in 0,1,2,4} \delta_j i_{t-j} + RP_t^S, \tag{7}$$

where the slope is defined as $S_t = y_t^{LT} - i_t$ and RP_t^S is the regression residual.[9]

Panel B of Table I reports the estimates of (7) in different subsamples. The results reveal that a linear combination of past short rates explains a vast fraction of the slope variation, between 68% and 96%.

Assuming that projection (7) is the correct model for extracting short rate expectations embedded in the yield curve, we should observe that: (i) the fitted value $\hat{S}_t$ from the regression predicts future short rate changes and (ii) the fitted residual $\widehat{RP}_t^S$ predicts future excess bond returns but not short rate changes, i.e. all information about future short rates that the slope contains is subsumed in $\hat{S}_t$. To verify the latter, panel C of Table I summarizes predictive regressions of one-year excess return on a ten-year bond[10] using $\hat{S}_t$ and $\widehat{RP}_t^S$. Across subsamples, the only significant predictor of excess returns is $\widehat{RP}_t^S$ which suggests that lags of the short rate distinctly absorb the part of slope variation, $\hat{S}_t$, related to short rate expectations. Note that in the pre-Fed period marked by the Gold standard, bond

[9]Note that due to the data availability, our measure of the slope corresponding to one-year change in the short rate is imperfect. Optimally, one should use the difference between one-year forward rate and the short rate, which are not observed. In using the slope between the long-term and the three-month yields we make the implicit assumption that expectations of short rate changes move on a single mean-reverting factor.

[10]Excess return on a ten-year bond is constructed from total return indices on the ten-year bond and the three-month Tbill, both obtained from the GFD database.

excess returns are not predictable. For comparison, panel C also reports analogous $\bar{R}^2$'s (in brackets) obtained with the Cochrane-Piazzesi (CP) factor in the available 1952-2011 period for which the factor can be constructed. The return predictability by $\widehat{RP}_t^S$ is on par with that of the CP factor.

The key insight from decomposing the slope is that, in the period characterized by an active Fed, the amount of predictable variation in the short rate implied by the cross section is in the range of 2% to 17% (panel D) and is significantly lower than the predictability that can be achieved with the time series model (panel A) of up to 40%.

One immediate criticism of the approach above is that by just using the slope we underrepresent the cross-sectional information in yields. Do distant lags of the short rate continue to matter if we condition on the complete information in today's yield curve? To answer this question, we extend the predictive regression (6) by including up to six principal components (PCs) of yields. We consider the longest possible period 1952-2011 for which we can obtain a cross-section of five zero coupon yields in the Fama-Bliss data. We augment these data with the three-month T-bill rate to capture the variation at the short end of the curve:

$$i_{t+1} - i_t = \beta_0 + \sum_{j=1}^{N} \beta_j PC_t^j + \delta_1 i_{t-\frac{lag1}{4}} + \delta_2 i_{t-\frac{lag2}{4}} + \varepsilon_{t+1}^{PC}, \tag{8}$$

with $lag1$ and $lag2$ selected optimally using the BIC criterion considering all lag combinations up to 16 quarters. Panels A and B of Table II report the results for $N = 3, 6$, respectively. It is clear from comparing column (1) and (2) that adding lags substantially increases the $\bar{R}^2$. The null hypothesis of $\delta_1 = \delta_2 = 0$ is rejected at the 1% level (column 3). In both panels and across different samples, the results indicate that lags of the short rate matter for forecasting even after conditioning on today's yield curve.

The key takeaway is that short rate changes appear ex-post more predictable than the cross-sectional information in yield curve would imply. The slope decomposition suggests that the result is unlikely to be explained away with time varying risk premia, and that expectations frictions also may play a role. The conclusion seems to coincide with the presence of an active central bank. The instability of regression coefficients for lags in different sub-samples is suggestive of learning or imperfect information faced by agents. In the subsequent sections, we more formally study the role of expectations formation in driving the distinction between time-series and cross-sectional dynamics of yields. We focus on the period 1983-2010, the longest for which we can obtain private sector survey forecasts of the FFR, and which allows us to observe expectations directly.

III.B. Slope as a measure of the monetary policy cycle

Before we move on, it is useful to discuss which properties of short rate dynamics are captured with its lags. It is well documented that during the last five decades, interest rates have featured highly persistent dynamics. A growing literature links this persistence to time-varying long-term inflation expectations, and to a slow-moving inflation target of the Fed.[11] This component makes yields close to non-stationary, generating a level factor in the term structure. Consequently, lagged short rates in the time-series regression (6) achieve two things. First, they remove the persistent component.[12] Second, they capture the mean-reversion in the short rate at the business cycle frequency that is informative for predicting short rate changes. Cieslak and Povala (2011) find that the factor in the yield curve that is induced by long-horizon expected inflation is orthogonal to yield variation at the business cycle frequency. Given that the focus of this paper is on the cyclical variation in yields, we remove the persistent variation from the short rate to work with stationary series.

Specifically, we define a variable—labeled as the monetary policy cycle—that captures the variation in the short rate which is unrelated to movements in long-term inflation expectations (and inflation target) and free of the risk premium as:

$$FFR_t^c = FFR_t - \hat{\beta}_{FFR} E_t(\pi_{t+\infty}), \tag{9}$$

where FFR_t is the federal funds rate, $\hat{\beta}_{FFR}$ is the OLS regression coefficient, $\hat{\beta}_{FFR} = 1.26$ (t-statistics = 8.3). $E_t(\pi_{t+\infty})$ is a proxy for the inflation target in the spirit of shifting endpoints (Kozicki and Tinsley, 2001a,b). We measure $E_t(\pi_{t+\infty})$ following Cieslak and Povala (2011) as the discounted moving average of the past core CPI and denote it as τ_t^{CPI}. As an alternative way, we also consider long-term inflation expectations from surveys.[13]

[11] This relationship has been highlighted as a key feature of yield curve data by, e.g., Kozicki and Tinsley (2001a), Bekaert, Cho, and Moreno (2010), Atkeson and Kehoe (2008). The persistence of the inflation target and of inflation expectations has been the focus of a large body of work including **?**, **?**, Stock and Watson (2007), Coibion and Gorodnichenko (2011b).

[12] In sub-samples marked by time-varying persistent component, the regression coefficients sum approximately to zero, a clear indication of removing the persistent component. Quite differently, in the pre-Fed period (Gold Standard) the sum of coefficients is different from zero.

[13] The discounted moving average is computed using the window of 120 months and the gain parameter equal to 0.9868, as discussed in Cieslak and Povala (2011). Similar approach to constructing long-run

Panel a of Figure 1 superimposes FFR_t^c constructed in two ways: using τ_t^{CPI} and using the long-term expected inflation compiled by the Philadelphia Fed from surveys, respectively; their correlation reaches 0.96 in levels and 0.94 in monthly changes. In order to avoid interpolation of survey data, which are available semiannually, our subsequent results rely on τ_t^{CPI}. In a similar fashion to (9), we define the expected monetary policy cycle, $E_t^s(FFR_{t+1}^c)$, by removing τ_t^{CPI} from a survey-based measure of short rate expectations, which we discuss in more details in Section IV below. Note that both FFR_t^c and $E_t^s(FFR_{t+1}^c)$ can be constructed in real time.

We notice that the expected monetary policy cycle, $E_t^s(FFR_{t+1}^c)$, corresponds closely to the fitted value of the slope $\hat{S}_t$, i.e. the part of slope variation attributed to short rate expectations in decomposition (7). Panel b of Figure 1 plots $E_t^s(FFR_{t+1}^c)$ together with $\hat{S}_t$ in the period 1983–2010. The series have a correlation of 0.93.

IV. Short-rate expectations

The previous section has shown that distant lags of the short rate have explanatory power for future short rate changes, even after conditioning on the information in today's yield curve. We investigate frictions in expectations formation process as one possible way to explain this empirical result. Specifically, we rely on a direct measure of short rate expectations from surveys, thus avoiding any assumptions about how short rate expectations are formed.

IV.A. Measuring short rate expectations with surveys

We use private sector forecasts of the federal funds rate, the main operating target of the Fed, from the Blue Chip Financial Forecasts (BCFF) survey. The survey has been conducted from 1983, and contains monthly forecasts of the FFR provided by approximately 45 leading financial institutions. Our sample extends from March 1983 to December 2010 spanning a relatively homogenous period for the US monetary policy, during which the FFR was its main operating tool.[14] The beginning of our sample is determined by the availability of survey

inflation mean has been taken by Orphanides and Wei (2008) and Piazzesi and Schneider (2011), and more recently by Faust and Wright (2011). Alternatively, we also use long-horizon inflation surveys and obtain qualitatively similar results (Figure 1, panel a). Ten-year ahead inflation forecasts are compiled by the Philadelphia Fed from the Livingston and the BCEI surveys but the data is available at a semiannual frequency. Therefore, we use linear interpolation to obtain surveys at the monthly frequency.

[14]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

data. While this is a relatively short period, Section IV.D below replicates our results in a longer sample using the information in yields and additional assumptions. The forecasts are quarterly averages of the FFR for the current quarter, the next quarter out to four quarters ahead. We use the median forecast across the panelists, because a simple combination of models/forecasters, such as the mean or median, is known to increase the forecast precision (e.g. Stock and Watson, 1998). We confirm this result in our data by studying the persistence of individual forecasters' ability to outperform the median forecast. We find that very few forecasters are able to beat the median forecast consistently across different forecast horizon and over longer time spans.[15]

Figure 2 plots the time series of survey-based FFR forecasts from two perspectives: Panel a lines up the forecasts for different horizons with the realized FFR at the time when the forecasts are formed; panel b displays the same information in form of conditional term structures of forecasts. Panel a reveals that forecasts closely trace the current realizations of the FFR, suggesting that there is relatively little mean reversion in expectations, i.e. the market expectations of the short rate are close to but not exactly random walk. Panel b indicates that investors systematically underestimate both the degree of monetary tightening and easing.

Which fraction of future changes in the policy rate is expected? Focusing on annual horizon, we estimate:

$$\Delta FFR_{t,t+1} = \underbrace{\gamma_2}_{-0.63\ [-2.34]} + \underbrace{\gamma_3}_{1.04\ [3.36]} [E_t^s(FFR_{t+1}) - FFR_t] + \varepsilon_{t+1}^{FE}, \quad \bar{R}^2 = 0.18, \tag{10}$$

where $\Delta FFR_{t,t+1} = FFR_{t+1} - FFR_t$ and $E_t^s(FFR_{t+1})$ denotes the survey-based proxy for the expectations about FFR one-year ahead. In Table III, we report analogous results for the forecast horizon h from one quarter to one year. While we cannot reject the null 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

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.

[15] Our data allows us to identify a forecaster (an 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.

reported). Given that we cannot reject $\gamma_3 = 1$, regression (10) can be interpreted as a decomposition with the variation in ε_t^{FE} reflecting the forecast error. Importantly, estimates in (10) show that more than 80% of annual changes in the policy rate is unexpected by the private sector, which aligns well with the previous finding from the statistical model of the short rate (Panel D of Table I). However, while this failure is usually attributed to the time-varying risk premium, our results suggest that even if risk premium is corrected for (as it is likely to happen in (10)), private sector expectations are able to forecast only a relatively small fraction of future short-rate movements.

A forecast error made by the median forecaster about the future policy rate at horizon h is:

$$FE_{t,t+h}^{FFR} = FFR_{t+h} - E_t^s(FFR_{t+h}). \tag{11}$$

Panel c of Figure 2 shows that forecast errors have nontrivial dynamics over the monetary policy cycle: they are on average negative during easings and positive during tightenings. The most pronounced errors are negative and occur during and after the NBER recessions meaning that forecasters fail most significantly in predicting the timing and the magnitude of the easing. In tightening episodes, the forecasters fail to predict the strength and the pace of interest rate increases. The average error reaches -1.43% and 0.60% at the one-year horizon in easing and tightening episodes, respectively, with standard deviations of 1.37% and 0.88%. As such, the private sector predicts a smaller magnitude of monetary policy actions relative to those that are subsequently realized (more details are in Table D-XV in the Appendix). Forecast errors do not seem to be decreasing over time even though the Fed has substantially increased its transparency throughout our sample.[16] A simple regression (not reported) of absolute forecast errors on a time trend confirms that there has been no decline in the errors over time.

IV.B. Expectations and the role of lagged information

Survey-based expectations are useful for understanding the discrepancy between the time series and cross-sectional dynamics of the short rate. In particular, we can analyze the degree

[16] In our sample, there have been several remarkable 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. In April 2011, the Fed introduced a press conference following every second FOMC meeting. 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.

to which agents' expectations incorporate the lagged information in the policy rate that we have documented above. Let us focus on a specific estimate for one-year change in the federal funds rate:

$$\Delta FFR_{t,t+1} = \alpha_0 + \underbrace{\alpha_1}_{-0.15\ [-1.35]} FFR_t^c + \underbrace{\alpha_2}_{-0.60\ [-5.02]} FFR_{t-1}^c + \varepsilon_{t+1}, \quad \bar{R}^2 = 0.46 \tag{12}$$

in the spirit of the estimates in panel A of Table I. For parsimony and for the ease of interpreting the coefficients, we select only one lag FFR_{t-1}^c from one year ago.[17] The predictability implied by the estimates in (12) is surprisingly high, entirely driven by the lagged cycle FFR_{t-1}^c, and significantly higher than the one attained with the survey forecasts in (10). The negative and highly significant α_2 is consistent with the slow mean-reversion of the short rate in the long run.

We can verify whether agents understood the dynamics of the short rate in real time exactly as an econometrician can observe them ex post. To this end, we test if their expectations subsume the information in the lagged monetary policy cycle:

$$\Delta FFR_{t,t+1} = \alpha_3 + \underbrace{\alpha_4}_{0.37\ [1.92]} [E_t^s(FFR_{t+1}) - FFR_t] + \underbrace{\alpha_5}_{-0.59\ [-6.10]} FFR_{t-1}^c + \varepsilon_{t+1}, \quad \bar{R}^2 = 0.46. \tag{13}$$

While under the FIRE, α_5 should not be statistically different from zero, the estimates in (13) strongly reject this hypothesis. We note that in the presence of FFR_{t-1}^c the coefficient on the expected path (the first term in (13)) drops to 0.37 from 1.04 reported in equation (10). This indicates that both regressors have a common component.

IV.C. Measuring expectations frictions

If expectations are formed optimally, forecast errors should not be predictable by lags (and by any variable from time t information set). Strikingly, we find strong evidence that forecast errors are in fact predictable by the lagged monetary policy cycle, indicating that short rate expectations deviate from the FIRE by only partially incorporating the information in past short rates:

[17] While allowing more lags improves model specification in terms of BIC and AIC, the improvement is marginal relative to the specification with just one lag and adding multiple lags does not significantly alter our conclusions.

$$FE^{FFR}_{t,t+1} = \delta_0 + \underbrace{\delta_2}_{-0.46\,[-4.48]} FFR^c_{t-1} + \varepsilon_{t+1}, \quad \bar{R}^2 = 0.26. \tag{14}$$

In Table IV, we report analogous results for different forecast horizons. Private sector forecasts are quite accurate at short horizons but deteriorate rapidly as the horizon increases. This feature is visible in panel B of Table IV, where the economic and statistical significance of FFR^c_{t-1} for predicting forecast errors increases with the horizon.

The fitted value from regression (14) can be interpreted as a measure of expectations frictions. Under FIRE, the $\bar{R}^2$ from this regression should be zero and lags of FFR^c_t should not be significant. The fitted value from (14) indicates by how much past yield curve information can improve upon short rate forecasts embedded in today's yields.

Parameter estimates in equation (13) allow us to contrast past information in the time series with the agents' expectations about short rate changes. We reexpress the predictability of $FE^{FFR}_{t,t+1}$ as:

$$FE^{FFR}_{t,t+1} = \delta_3 + \underbrace{\delta_4}_{0.63\,[5.16]} \left[\Delta FFR_{t-1,t} - E^s_t(FFR^c_{t+1})\right] + \varepsilon_{t+1}, \quad \bar{R}^2 = 0.34. \tag{15}$$

Intuitively, the RHS variable in (15) captures information in the time series dynamics of the short rate ($\Delta FFR_{t-1,t}$) that is not in the cross section of yields ($E^s_t(FFR^c_{t+1})$).[18] Accordingly, we define a measure of expectations frictions:

$$MP^{\perp}_t = \Delta FFR_{t-1,t} - E^s_t(FFR^c_{t+1}). \tag{16}$$

This variable reflects the idea that agents fail in real time to recognize the full extent of lag dependence in the policy rate. Note that if agents perceive that the short rate is exactly a random walk, $MP^{\perp}_t$ collapses to $-FFR^c_{t-1}$. This is because, empirically, $\Delta FFR_{t-1,t} \approx \Delta FFR^c_{t-1,t}$ and $FE^{FFR}_{t,t+1} \approx FE^{FFR^c}_{t,t+1} = FFR^c_{t+1} - E^s_t(FFR^c_{t+1})$, with correlations in both cases in excess of 0.99. This means that the persistent component of inflation τ^{CPI}_t contributes a negligible portion to short rate changes at an annual horizon. When we let $\Delta FFR_{t-1,t}$ and $E^s_t(FFR^c_{t+1})$ enter (15) in an unconstrained way, the data strongly call for an orthogonalization between the two components with offsetting coefficients (see also panel C of Table V below). As such, $MP^{\perp}_t$ represents the part of the information set that ex-post appears to be omitted from expectations. It is important to stress that $MP^{\perp}_t$

[18] We note that we fail to reject that $MP^{\perp}_t$ subsumes the information in FFR^c_{t-1}, i.e. in a joint regression $FE^{FFR}_{t,t+1} = a + b_1 MP^{\perp}_t + b_2 FFR^c_{t-1} + \varepsilon_{t+1}$, we fail to reject that b_2 is zero (pval = 51%).

is closely related to the fitted value from regression (14), their correlation in our sample 1983-2010 is 0.91.

$MP_t^{\perp}$ can be interpreted as an indication that the monetary policy is able to generate persistent surprises relative to the expectations of the public. Therefore, it is useful to compare its dynamics with standard measures of monetary policy shocks. One widely applied measure based on the fed fund futures has been suggested by Kuttner (2001), and further supported by Piazzesi and Swanson (2008) as more robust to the presence of risk premia compared to other alternatives. Kuttner (2001) obtains monetary policy shocks from one-day changes in the fed fund futures around the FOMC announcements. The data is available on his webpage for the period 1989:06–2008:06, which we extend through 2010:12 using the same methodology. Panel a of Figure 4 plots the daily series of monetary policy shocks. An interesting observation is that monetary policy shocks appear in clusters. Specifically, initially negative surprises are followed by more negative surprises resulting in persistent dynamics. In panel b of Figure 4, we superimpose $MP_t^{\perp}$ with the time series of cumulative Kuttner's surprises defined as the moving sum of the daily shocks accumulated over eight consecutive FOMC meetings (an approximate number of meetings per year), thus matching the annual horizon of $MP_t^{\perp}$. The cumulative surprises confirm the persistent nature of monetary policy shocks, and also point to a large degree of their comovement with $MP_t^{\perp}$ with correlation of 63%. The largest discrepancies between the two series occur in the early part of the sample. Indeed, before 1994 the Fed was not explicitly announcing changes to its target, which could complicate the identification of monetary policy shocks in that period (Kuttner, 2003). Overall, however, these results suggest that $MP_t^{\perp}$ is related to the persistent component of monetary policy surprises which is not contained in today's market expectations.

IV.D. Alternative way of constructing a measure of expectations frictions

One constraint faced with the survey data above is a relatively short sample period. To cast light on potential frictions over a longer time span, we follow the logic outlined in Section III.A. We consider the 1954-2010 period, i.e. the longest available sample for which FFR is available, and exploit two empirical observations. The first one relies on the fact that short rate expectations can be well described with a low number of short rate lags. Second, we use the following approximation: $\frac{1}{5}\sum_{k=0}^{4} E_t^s\left(FFR_{t+k/4}\right) \approx y_t^{(1)}$.[19]

In the first step, we exploit the cross-sectional information in yields and project:

$$y_t^{(1)} - FFR_t = \beta_c + \sum_{j\in 0,1,2,4} \beta_j FFR_{t-j} + \varepsilon_t. \tag{17}$$

The fitted value from (17), $E_t(\widehat{\Delta FFR_{t+1}^{CS}})$, is the market expectation of the short rate change. Subsequently, we construct the implied forecast errors denoted by FE_{t+1}^{yld}:

$$FE_{t+1}^{yld} = \Delta FFR_{t,t+1} - E_t(\widehat{\Delta FFR_{t+1}^{CS}}). \tag{18}$$

In the second step, we contrast the cross-sectional prediction with the time series by projecting FE_{t+1}^{yld} on the same lags of the short rate:

$$FE_{t+1}^{yld} = \delta_c + \sum_{j\in 0,1,2,4} \delta_j FFR_{t-j} + \varepsilon_{t+1}^{FE}. \tag{19}$$

The fitted value from (19) is the measure of expectations frictions which we denote by $MP_t^{\perp,yld}$. Panel a of Figure 3 plots $MP_t^{\perp,yld}$ for the sample period 1954-2010.

The intuition for this measure is as follows. Absent time-varying risk premia and expectations frictions, a projection of expected change in the short rate on a set of lagged short rates in equation (17) should imply approximately the same linear combination of lags as the time series projection, i.e. the forecast errors should not be predictable. $MP_t^{\perp,yld}$ measures by how much one can improve on the yield curve-based forecast of one-year change in the short rate by fully exploiting the information in lags of the short rate.

Panel b of Figure 3 compares yield curve-based $MP_t^{\perp,yld}$ with the survey-based $MP_t^{\perp}$ in the overlapping period. Note that even though $MP_t^{\perp,yld}$ is estimated on a long sample (1954-2010) and does not rely on surveys or on FFR_t^c, both measures track each other very closely and their correlation is 0.81. This close relationship is important because it suggests that expectations frictions are a stable feature of the yield curve data. It also helps alleviate the concern about using a relatively short sample for which the survey data are available.

[19] In Appendix D.1, we use FFR surveys at different horizons to show that this approximation is valid. In the 1983-2010 sample, the consensus survey forecast of the short rate explains 99% of the variation in one-year yield. The coefficient loading of $y_t^{(1)}$ on the average expected FFR rate is very close to one (0.99 with t-statistics = 62) suggests that the risk premium component in $y_t^{(1)}$ is small.

V. Risk premia and beliefs

This section studies whether expectations frictions could impact the measurement of bond risk premia. While a common approach to measuring premia is through predictive regressions of realized returns on a set of conditioning variables, our findings suggest that part of the predictable variation identified in this way may come from the ex post predictability of forecast errors. This distinction is important as the two channels are economically different. In standard asset pricing models, risk premia are an equilibrium market outcome, and reflect the compensation expected and required by investors for the covariance risk of Treasury returns with their marginal utility. Expectations frictions, in turn, are manifest in the predictability of unexpected returns after the risk premium has been corrected for.

Below, we study the relative importance of risk premia versus expectations frictions for the predictability of bond excess returns. In a first step, we ask whether our measure of frictions has predictive power for the realized excess bond returns. In a second step, we further decompose the realized return into an expected and unexpected part, and study their respective properties. To summarize the outcome, up to half of the predictable variation in realized bond returns stems from a component that is ex ante unexpected. Importantly, the effect is not uniform across maturities: it is strongest at the short end of the curve, where monetary policy is most potent, and subsides as the maturity increases.

V.A. Predictive regressions of bond excess returns

We estimate standard predictive regressions of bond excess returns across maturities:

$$rx_{t,t+1}^{(n)} = \delta_0 + \delta_1 RP_t + \delta_2 MP_t^{\perp} + \varepsilon_{t,t+1}^{(n)}, \tag{20}$$

where $rx_{t,t+1}^{(n)}$ is the annual realized excess return on a Treasury bond with n years to maturity, and RP_t is an empirical measure of bond risk premia, i.e. the *expected* component of returns. In this and subsequent sections, as RP_t, we use the factor constructed in Cieslak and Povala (2011) because it has several advantages relative to other predictors: it can be constructed in real time by estimating a small number of parameters, it has a stable out-of-sample predictive power, and as we document below, it does not predict ex post forecast errors.[20]

[20] Cieslak and Povala (2011) decompose the yield curve into long-horizon inflation expectations and maturity-related interest rate cycles. Then, the term structure of cycles is used separate the risk premium variation from the business cycle variation in short rate expectations. As a risk premium measure RP_t, we use the factor denoted as $\widehat{cf}_t$ in the original paper.

Table V summarizes the results of forecasting regressions for different bond maturities. Panel A uses RP_t as the only explanatory variable. The regression coefficients and the $\bar{R}^2$ increase with maturity which is in line with the intuition that longer-maturity bonds exhibit more pronounced risk premium variation: The explained return variation at the short maturity is about half of that at the long end.

Panel B reports the estimates of equation (20). The key observation is that $MP_t^{\perp}$ is a significant predictor of realized excess returns, and contrary to RP_t, its predictive power is particularly strong at short maturities: The explained portion of the two-year bond excess return doubles relative to panel A. The negative sign of the δ_2 coefficient is consistent with our earlier interpretation: lower $MP_t^{\perp}$ anticipates higher bond returns and lower yield changes in the future. In the presence of $MP_t^{\perp}$, the significance of the risk premium RP_t remains essentially unchanged, suggesting that the two variables capture economically different sources of predictability.

In panel C, we remove the coefficient restriction imposed when constructing $MP_t^{\perp}$ in (16), and estimate an unconstrained regression: $rx_{t,t+1}^{(n)} = \tilde{\delta}_0 + \tilde{\delta}_1 RP_t + \tilde{\delta}_2 \Delta FFR_{t-1,t} + \tilde{\delta}_3 E_t^s(FFR_{t+1}^c) + \varepsilon_{t,t+1}$. We note that coefficients $\tilde{\delta}_2$ and $\tilde{\delta}_3$ have offsetting signs and are both highly statistically significant for short maturity bonds. Except for the 20-year bond, we cannot reject the null hypothesis that the coefficients satisfy the restriction $\tilde{\delta}_2 + \tilde{\delta}_3 = 0$ at the 10% level. We also note that removing the restrictions only marginally changes the explanatory power of the regression. Finally, in panel D we use the lagged monetary policy cycle FFR_{t-1}^c confirming that the lagged short rate information predicts future returns.

These results imply that realized bonds returns move around on two factors which represent largely independent sources of their predictability. Indeed, we notice that using realized bond returns one can construct two orthogonal factors $(rx_{t+1}^L, rx_{t+1}^{S\perp L})$ that essentially span the entire variation of returns across different maturities. The first factor rx_{t+1}^L is simply the return on the long term bond (20-year maturity), while the second factor $rx_{t+1}^{S\perp L}$ represents a component of the return on the short-term bond (two-year maturity) that is orthogonal to rx_{t+1}^L. Using this two-factor decomposition, we find that $rx_{t+1}^{S\perp L}$ is strongly predictable by our measure of expectations frictions, but is unrelated to RP_t, while for rx_{t+1}^L the reverse holds true. These regressions are not reported in any table for brevity.

V.B. Decomposing realized bond returns

We resort to survey forecasts of interest rates to explicitly decompose bond returns into an expected and ex-ante unexpected component. Interest rate forecasts are from the BCFF survey and are 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.

Interest rate forecasts are useful because they allow us to directly, in a model-free way, separate the expected part (risk premium) and the unexpected part (forecast error) of realized returns. It is convenient to write the excess return on an n-period bond realized over m periods as:

$$rx_{t,t+m}^{(n)} = (n-m)\left[f_t^{(n,m)} - y_{t+m}^{(n-m)}\right], \tag{21}$$

where $f_t^{(n,m)}$ is a forward rate locked in today for m period loans starting at time $t+n-m$.

We focus on the two-year bond return because it captures the segment of the yield curve for which the effect of frictions is potentially the most significant. Using survey forecasts of the one-year yield one year ahead, we can obtain a direct decomposition of the realized excess return into an expected and unexpected component as:

$$rx_{t,t+1}^{(2)} = \underbrace{\left[f_t^{(2)} - E_t^s(y_{t+1}^{(1)})\right]}_{\substack{\text{risk premium} \\ E_t^s(rx_{t,t+1}^{(2)})}} \underbrace{- \left[y_{t+1}^{(1)} - E_t^s(y_{t+1}^{(1)})\right]}_{\substack{\text{unexpected return} \\ rx_{t,t+1}^{(2)} - E_t^s(rx_{t,t+1}^{(2)})}}. \tag{22}$$

In equation (22), the unexpected return is equivalent to agents' forecast error about the evolution of the one-year rate at the one-year horizon (with a minus sign), $-\left[y_{t+1}^{(1)} - E_t^s(y_{t+1}^{(1)})\right] = rx_{t,t+1}^{(2)} - E_t(rx_{t,t+1}^{(2)})$. This variable, in turn, is strongly correlated with the monetary policy forecast errors, $\text{corr}\left(FE_{t,t+1}^{FFR}, \left[rx_{t,t+1}^{(2)} - E_t(rx_{t,t+1}^{(2)})\right]\right) = -0.93$.

In Table VI panel A, we regress each of the two elements on the RHS of (22) on $MP_t^{\perp}$ and other time-t predictors. For comparison, we perform a similar exercise using $FE_{t,t+1}^{FFR}$ as the dependent variable, on a sample starting in 1987. The main conclusion is that $MP_t^{\perp}$ predicts a significant fraction of the variation in *un*expected returns that are subsequently realized ($\bar{R}^2 = 0.35$) and in the monetary policy forecast errors ($\bar{R}^2 = 0.35$), but has no explanatory power for the expected return component. These regressions are in column (1) of each subpanel of Table VI. Columns (2)–(5) confirm the interpretation of $MP_t^{\perp}$ with auxiliary regressions using its components: short rate changes ($\Delta FFR_{t-1,t}$), the cyclical component of short rate expectations ($E_t^s(FFR_{t+1}^c)$) and the lagged monetary policy cycle (FFR_{t-1}^c) as explanatory variables. Finally, column (6) reports that while RP_t has a strong explanatory power for the survey-based expected return on the two-year bond, it shows no predictability of the unexpected return and of $FE_{t,t+1}^{FFR}$ supporting its interpretation as a risk premium factor.

It is useful to link these results to the recent literature has emphasized the role of unspanned (hidden) factors in driving bond risk premia. While various macro variables have been shown to have this feature, especially those related to the real activity, the economic underpinnings of such factors are still debated. Interestingly, our proxy $MP_t^{\perp}$ lends itself for an interpretation as the unspanned monetary policy factor, but rather than to usual notion of risk premia, it points to an existence of expectations rigidities. Indeed, even though we do not impose such a restriction upfront, we find that the cross section of yields, summarized by five PCs of yields, can explain just a small part of $MP_t^{\perp}$ (14%) and somewhat higher part of FFR_{t-1}^c (24%). When we orthogonalize these factors with respect to the information in the yield curve, by projecting them on the contemporaneous five PCs, the resulting factors are highly correlated (with correlation coefficient of 0.92 and 0.85, respectively) with the original ones. Their explanatory power for the forecast error, $FE_{t,t+1}^{FFR}$ increases slightly, by 3% and 6%, consistent with the notion that forecast error predictability must come from variables that are not spanned by the contemporaneous yield curve.

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.[21] How does the finding of unspanned real macro variables relate to our results? We address this question in panel B of Table VI, by regressing each of the components on the RHS of (22) on two measures of real activity: Chicago Fed National Activity Index (CFNAI) and the annual log growth rate of unemployment, respectively. CFNAI is essentially indistinguishable from the real activity factor constructed in Ludvigson and Ng (2009), and is a version of the Stock and Watson (1999) common factor. The key result is that while neither of the real variables has

[21]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 information that a given variable contains.

explanatory power for the risk premium component, both are strongly significant predictors of unexpected returns and monetary policy forecast errors. The estimates of bivariate regressions using real activity proxies jointly with $MP_t^{\perp}$ support a weak relationship of those variables with the expected return component, but a strong relationship with the forecast errors and unexpected returns. It is unclear whether real macro variables contain new information relative to $MP_t^{\perp}$. While it is possible that our measure of information frictions is imperfect, we note that the coefficient loadings on the macro variables interact with $MP_t^{\perp}$. In Figure 5 we superimpose $MP_t^{\perp}$ with ΔUnempl_t and CFNAI_t, showing that there is comovement between the series (correlation of 0.28 and -0.30, respectively), and the troughs in $MP_t^{\perp}$ precede those in real activity.

VI. Additional evidence

In this section, we summarize evidence from additional data sources that provide different angles of assessing the expectations formation process in the yield curve. First, we ask how easy it is to outperform survey forecast of the FFR with statistical models in real time. Second, we compare surveys with market-based forecast of the FFR from the fed fund futures. Third, we analyze whether internal FFR forecasts of the staff at the Federal Reserve Board are subject to expectations frictions similar to these of the private sector. Fourth, we link the FFR forecast errors to errors agents make when forecasting macro variables, i.e. unemployment and inflation. Fifth, we perform statistical tests for the presence of information rigidities in the FFR forecasts consistent with sticky and noisy information models. Finally, we discuss evidence from money market flows.

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

This section compares forecast accuracy of surveys with several statistical models of the short rate estimated in real time. The main results are in panel A of Table VII. Given ample evidence that simple methods of forecasting interest rates often work best in real time (e.g. Duffee, 2009; Wright, 2011), we report naive forecasts assuming the FFR to follow a random walk (row 2), and two univariate specifications: an AR(2) (row 3) and an AR(p) allowing up to 16 quarterly lags which are selected dynamically with the BIC from all possible lag combinations (row 4). We additionally consider three multivariate specifications (rows 5 through 7): a recursive VAR(2) estimates obtained with OLS (row 5), and two Bayesian VARs: a constant parameters VAR(2) with a Minnesota prior (row 6) and a time-varying homoscedastic VAR(2) with time varying parameters in the spirit of Primiceri (2005) (row 7). All VARs are second order and include three variables: CPI inflation, unemployment and the FFR. All models are estimated recursively on an expanding window with a burn-in period of 73 quarters, with the out-of-sample forecasts constructed for the period of 1983:Q1 through 2010:Q4.

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, relative to the forecast error from the AR(2), the relative error made by survey forecasters ranges from 63% at one quarter to 92% at four quarters. 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, as documented for inflation forecasts by Ang, Bekaert, and Wei (2007) using post-1985 out-of-sample period.

VI.B. Market based forecasts

In panel B of Table VII, 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.[22] Clearly, futures-based forecasts of the FFR differ from the physical forecasts by the presence of a risk premium. Using surveys, we obtain an estimate of the futures risk premium that is on average four basis points for the six-month contract, and oscillates around zero 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 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

[22] Futures data have been used in earlier studies by Kuttner (2001), Piazzesi and Swanson (2008), Gurkaynak, Sack, and Swanson (2005), among others. 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.

are marginally lower relative to 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 is that the median survey response represents quite well market-wide expectations of the short rate. Another interpretation is that survey respondents simply anchor their forecasts at the current market rates, and thus report risk-adjusted rather than physical expectations.[23] 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 (Survey of Professional Forecasters, SPF) and for other interest rates (3-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. Interestingly, and contrary to the realized returns, they also systematically decline before and at the beginning of recessions, consistent with the role of short-term rate instruments in liquidity and safety provision.

VI.C. Expectations by the Federal Reserve's staff

Before each FOMC meeting, the staff of the Federal Reserve prepares their own forecasts of the FFR from the current quarter up to five quarters ahead. The forecasts are published in Greenbook with a five year lag and available in the financial assumptions files on the Philadelphia's Fed website. The Greenbook has several useful characteristics. First, the staff at the Fed has extensive access to economic data resources when forming their predictions. 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, the forecasts of the 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). Finally, because the names

[23] 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.

of individual members of the staff are not revealed, reputational concerns are a potentially lesser issue compared with the private sector surveys. In sum, Greenbook forecasts could be viewed as an upper bound on the short rate predictability that agents are able to attain.[24]

In Table VIII we provide cross-correlations between four-quarter ahead forecast errors of the Fed staff and the private sector for the FFR. Despite differences in the characteristics of the forecasters' panel and in their access to information, the FFR forecast errors of the staff and the private sector have a very high correlation reaching 88%.

In Table IX, we revisit the question whether expectations of the Fed staff reflect the long-run dependence in the policy rate. Specifically, we use their forecasts of the FFR at the frequency of the FOMC meetings to replicate the regressions reported in Table IV in the available Greenbook sample 1983–2006. The forecasts of the staff are surprisingly similar to those of the private sector: While the economic and statistical significance of past information is somewhat lower, the lagged values of the short rate cycle FFR^c_{t-1} predict forecast errors, and, in the presence of the Greenbook expectations, continue to be significant predictors of short rate changes. For instance, at the four quarter horizon, FFR^c_{t-1} explains 18% of the variation in the Greenbook forecast errors, with a coefficient loading of -0.39 (t-statistic of -2.57). This evidence indicates that, even with access to extensive information, it is inherently difficult to predict the timing and magnitude of the long-run mean reversion in the policy rate in real time. Moreover, since the Fed's staff is likely to have a more precise knowledge about the policy rule relative to the private sector, the results suggest that the source of the friction lies in dynamics of the macro environment rather than in the private sector's uncertainty about the conduct of the monetary policy.

VI.D. Comovement of forecast errors for FFR and macro variables

It is known that a Taylor-type monetary policy rule that includes inflation and unemployment describes the path of the short rate quite well. Therefore, we expect to attribute at the least part of the FFR forecast errors to the forecast errors that agents make about macro variables themselves. Before we move on, it is important to note the differences apparent in the way agents form expectations about inflation and unemployment, respectively. In Figure 6, we

[24] We abstract here from the fact that the number of staff members preparing the forecasts may be smaller than the number of participants in the private sector surveys, and therefore the Greenbook forecasts may not equally benefit from the forecast errors averaging which tend to increase the forecast precision.

plot the term structures of forecasts for these two variables.[25] Inflation expectations are volatile at the very short end, but they converge quickly to a stable local mean at longer horizons. In contrast, expectations of unemployment one quarter ahead and one year ahead are surprisingly close to each other, implying that agents perceive unemployment as close to a random walk, even though statistical evidence and economic intuition would suggest otherwise.[26] These discrepancies pertain to both forecasts of the private sector and of the Fed staff.

Starting from a basic Taylor rule, according to which monetary policy reacts to inflation and unemployment, we can decompose the monetary policy forecast errors into two components corresponding to the macro variables. To this end, we regress $FE^{FFR}_{t,t+h}$ at a given horizon on the corresponding inflation and unemployment forecast errors, $FE^{CPI}_{t,t+h}$ and $FE^{UNE}_{t,t+h}$:

$$FE^{FFR}_{t,t+h} = \gamma_0 + \gamma_1 FE^{UNE}_{t,t+h} + \gamma_2 FE^{CPI}_{t,t+h} + \varepsilon_{t,t+h}. \tag{23}$$

Private sector expectations of macro variables are obtained from the quarterly Survey of Professional Forecasters (SPF), which provides a term structure of forecasts at horizons corresponding to those for the FFR. Table VIII reports the cross correlations of the variables involved in (23) for the Fed staff and private forecasts. The striking observation is that while the FFR errors are relatively weakly correlated with errors on inflation, they comove strongly (and negatively) with those on unemployment.

To establish a more formal link, equation (23) cannot be estimated with OLS because forecast errors on macro variables are likely to be correlated with the innovations to errors on the FFR. Therefore, we estimate (23) with instrumental variables, using contemporaneous oil shock and lagged values of the CFNAI as instruments.[27]

Table X summarizes the IV regressions for private sector forecasts at horizons three and four quarters ahead. We consider two sample periods: the full sample (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 recent crisis. The key finding is that monetary policy forecast

[25] Additional statistics are reported in the Appendix.

[26] For instance, Fuster, Laibson, and Mendel (2010) show that unemployment like many other real macro variables are characterized by hump-shaped impulse response function.

[27] 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.

errors comove strongly with those on unemployment and much less with those on the CPI inflation. $FE^{CPI}_{t,t+h}$ is only marginally significant in the pre-crisis sample and contributes a small margin 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. The $\bar{R}^2$ from the regressions indicate that about 40% of the sample variation in the monetary policy forecast errors can be related to macro sources. The results also suggest a causal relationship: Private sector expectation errors about monetary policy arise, at least partially, from their errors in forecasting the path of unemployment, and real activity more generally.[28]

VI.E. Testing information frictions

In this section, we test whether the predictability of ex-post FFR forecast errors achieved with lags can be justified within rational models with information rigidities. Specifically, expectations can deviate from the FIRE if rational agents face informational frictions such as noisy information as in Woodford (2003) or information stickiness as in Mankiw and Reis (2002). Coibion and Gorodnichenko (2011a) show that in these models, the average (across agents) ex-post forecast error should be predictable with a positive sign by the average forecast revision at the corresponding horizon. Accordingly, the baseline test can be performed by estimating:

$$FE^{FFR}_{t,t+h} = \beta_0 + \beta_1 \left[E^s_t(FFR_{t+h}) - E^s_{t-1/4}(FFR_{t+h})\right] + \varepsilon_{t+h}, \tag{24}$$

where under information frictions $\beta_1 > 0$. The results of estimating (24) are reported in column (1) of Table XI for horizons h from one through three quarters.[29] The coefficient β_1 is positive and statistically significant across h, supporting the hypothesis that forecasters act under information frictions. Forecast updates alone explain up to 10% of the variation in ex-post forecast errors, and their statistical significance is the strongest at short horizons.

The models of information frictions summarized by (24) imply that forecast updates should account for the entire predictable variation in ex-post forecast errors. It is therefore infor-

[28] Interestingly, in unreported results we fail to establish a similarly strong relationship for the forecasts of the Fed staff. This is intuitive to the extent that the Fed believes monetary policy can influence the path of macro variables.

[29] For the FFR we report estimates of (24) using the forecast error and forecast revision of the median forecaster to be consistent with the previous results. 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.

mative to see whether forecast updates alone subsume predictive information contained in lagged interest rates. To this end, in columns (2) through (4) of Table XI, we augment regression (24) with variables that we have found to contain information about the FFR forecast errors, $MP_t^{\perp}$, lagged FFR cycle, FFR_{t-1}^c and lagged slope S_{t-1}, respectively, i.e.

$$FE_{t,t+h}^{FFR} = \beta_0 + \beta_1 \left[E_t^s(FFR_{t+h}) - E_{t-1/4}^s(FFR_{t+h}) \right] + \beta_X X_t + \varepsilon_{t+h}, \tag{25}$$

where β_X represents the loading on each of these additional factors. The results of the extended test suggest that lagged yield curve information has explanatory power beyond forecast updates, which is increasing with the forecast horizon. For instance, at the three-month horizon, $MP_t^{\perp}$ raises $\bar{R}^2$ of the regression by 14% relative to the baseline case (24), and is highly statistically significant (t-statistic of 4.1). Similar results pertain to the lagged values of the FFR cycle and also, albeit somewhat weaker, to the lagged term structure slope. The lower significance of the latter is consistent with the fact that the slope partially reflects risk premium variation which should not predict forecast errors.

One way to assess whether frictions that we document reflect a more general feature of the expectations formation is to study their explanatory power for forecast errors about macro variables other than the FFR. To this end, we estimate equations analogous to (25) for the forecasts of unemployment and CPI inflation. In constructing both we use unrevised data and the forecasts from the SPF survey. The evidence in favor of expectations frictions is particulary strong for unemployment, where the amount of predictable variation in ex-post forecast errors reaches $\bar{R}^2$'s up to 30%. We notice that our measures of frictions are statistically and economically significant, contributing a large fraction to the explained variation. Since it is hard to argue that forecast errors about unemployment are confounded by risk premium effects, this evidence provides additional support to the importance of expectations frictions that can be extracted from the yield curve.

VI.F. Evidence from money market flows

In addition to survey forecasts, the relative merit of the expectations frictions interpretation can be further assessed through the lens of investors' actions. Since our results pertain to the way people form expectations about the short rate, we should be able to trace the potential effect of frictions to positions investors take in short-term interest rate instruments, such as money market funds. We obtain monthly values of net assets in the US money market funds from the H.6 statistical release of the Fed Board. We define a proxy of annual money market flows as the year-over-year log change in the funds held in the money market funds, and denote this variable as $\text{Flows}_{t-1,t}$. We distinguish between retail and institutional funds, each representing 24% and 68% of the total money market fund assets, respectively, because these two components feature somewhat different flow patterns that are interesting in our context.[30]

If investors were fully forward looking and able to exploit the predictable variation in the short rate in real time, we would expect their money market allocations to increase in anticipation of a higher short rate (tightening) and decrease otherwise (easing). To the extent that a higher $MP_t^{\perp}$ is a signal that the short rate will increase in the near future (see equation (16)), we should observe its positive correlation with the flows. Figure 7 suggests that the opposite is in fact true in the data: the flows have a highly negative contemporaneous correlation with $MP_t^{\perp}$. One way to explain the sign is that money market flows simply reflect the flight-to-safety episodes that coincide with monetary policy easings. Contrary to this intuition, however, the relationship between flows and $MP_t^{\perp}$ is symmetric rather than one-sided, i.e. it holds both in easing and tightening episodes. Another possibility, consistent with the expectations frictions story, is that to a large degree market participants extrapolate from the recent past and thus do not accommodate the long-range dependence present in the short rate.

In panel A of Table XII we report predictive regressions of the changes in FFR and the FFR forecast errors, respectively, from t to $t+1$ on the money market flows in the year ending at time t. The regression coefficients are negative for both retail and institutional flows, with a stronger statistical significance in the latter case. Specifically, increased institutional flows are associated with a subsequent monetary policy that is easier than initially expected (i.e. the FFR forecast errors observed ex-post are low or negative).

In panel B of Table XII, we provide four sets of regressions. In column (1), we establish that flows are high when the monetary policy is unexpectedly easy during the same year, as measured by $MP_t^{\perp}$. For instance, the standardized coefficient loadings of institutional flows on $MP_t^{\perp}$ is -0.81 (t-stat $= -13.76$, $R^2 = 0.66$), meaning that a one standard deviation decrease in $MP_t^{\perp}$ coincides with an increase in institutional money market assets of nearly

[30]As of 2010 year-end, the total net assets in money market funds in the US reached about 2.8tr USD, making it one of the largest asset classes, according to the 2012 Investment Company Factbook. For these two classes, respectively, the percentage flows have a mean of 5% and 14%, standard deviation of 13% and 16%, a minimum of -32% and -30%, and a maximum of 29% and 49%. While part of these fluctuations are simply due to the changes in money market rates, it is likely to be a small fraction of that due to net flows, given the extent of the overall variation in the net asset values.

13%. A similar relationship, yet slightly weaker, holds true for the retail funds. In column (2), we augment $MP_t^{\perp}$ with a number of contemporaneous controls for safety and liquidity.[31] In the presence of controls, the economic and statistical relationship between the flows and $MP_t^{\perp}$ remains largely unchanged as visible in the reported coefficients. In columns (3) and (4), we predict flows over the subsequent year (from t to $t+1$) with the time-t monetary policy cycle FFR_t^c and the term structure slope S_t, respectively. The sign of the loading on FFR_t^c in column (3) is positive meaning that the flows into money markets are high (low) if the monetary policy has been tight (easy) in the recent past. Similar results are obtained with the slope as a regressor in column (4), noticing that a high slope is associated with an easy monetary policy. One interpretation is that when the FFR has been high in the past agents expect high interest rates to continue to prevail in the future. As such, the direction of money market flows is in line with our evidence about expectations formation in that expectations do not reflect the extent of mean reversion that is present in the physical dynamics of the short rate.

These results are interesting in the context of the findings of Piazzesi and Swanson (2008). Specifically, Piazzesi and Swanson (2008) show that the realized returns in fed fund futures are predictable with the net open interest of speculators in *eurodollar* futures. This suggests that certain market participants are able to exploit the predictability in the short rate at the expense of others. Interestingly, while we are able to replicate this result in our sample, i.e. net open interest of speculators in eurodollar futures predicts ex-post FFR forecast errors, we fail to establish an analogous link with the net open interest of traders in the fed fund futures market itself. Open interest in the fed funds futures appears completely unrelated to the predictable variation in the errors. Taken together with the evidence suggesting the presence of frictions for the cash money market investors, these results might point towards market segmentation, whereby a particular specialized segment of the derivatives market is able to correctly recognize and exploit the expectations frictions. While this topic deserves a deeper investigation, we leave it to our subsequent research.[32]

[31] We include the market-wide liquidity of Pastor and Stambaugh (2003), the value of funding liquidity of Fontaine and Garcia (2012), noise illiquidity measure of Hu, Pan, and Wang (2012), and stock market volatility series VXO. In several other specifications that are unreported in any table we have extended the set of controls with real activity indicators (CFNAI) and have found essentially unchanged results.

[32] We note that while less developed and smaller than the Eurodollar, the fed funds futures market has been expanding rapidly in the last decade reaching 50% of the size of the Eurodollar market in mid-2004 as measured by the nominal open interest. At the same time, after Piazzesi and Swanson (2008) results were made public in 2004, we have not observed a weakening of the link between the realized fed fund futures returns and the open interest in the eurodollar market.

VII. Conclusions

This paper studies how agents form expectations about the short rate and thus about the future path of monetary policy actions. We show that distant lags of the short rate from over a year ago forecast future short rate changes beyond the information embedded in today's cross section on yields. This fact is surprising for two reasons. First, it characterizes the data after the creation of the Fed but much less so before. Second, in a frictionless world, in which agents form expectations in an optimal way, today's yield curve should, in general, contain all information relevant for forecasting. We find that real-time expectations of the private sector deviate from this benchmark logic along several dimensions. While the short rate features complex dynamics characterized by inertia in the short run and mean reversion at the business cycle frequency, the expectations of agents fail to fully accommodate the magnitude of the latter in real time. As such, their ex-post forecast errors about the path of policy rates are predictable with past information. We show that such expectations frictions pertain not only to the private sector's forecasts but also in a similar way to the forecasts of the Federal Reserve staff. This suggests that they may not just reflect the ignorance of forecasters, unavailability of data or irrationality but may be induced more broadly by the dynamics of the economy. In fact, it is not trivial to find a statistical model that would outperform survey forecasts of the short rate in real time.

These findings are potentially important for understanding the information content of the yield curve as a reflection of risk premia and 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 constraints, we show that they induce dynamics of bond returns that are distinct from the variation in statistical and survey-based measures of bond risk premia. More generally, however, our results leave open the issue of the specific channels through which expectations frictions arise. The answer to this question matters for the interpretation of unanticipated monetary policy shocks and thus for the analysis of the real effects of monetary policy. We leave this investigation to our future research.

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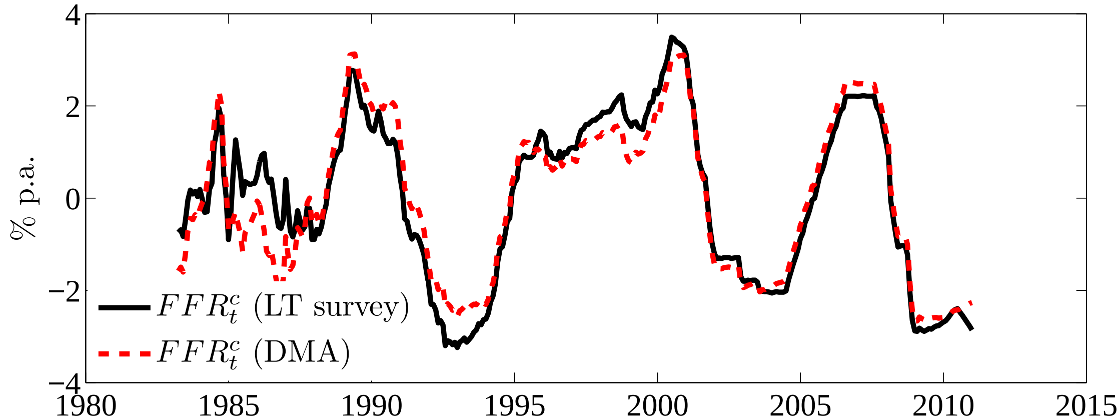
A. Figures

a. Monetary policy cycle, 1983-2010



b. Comparison of $E_t^s(FFR_{t+1}^c)$ and $\hat{S}_t$ (both demeaned), 1983-2010

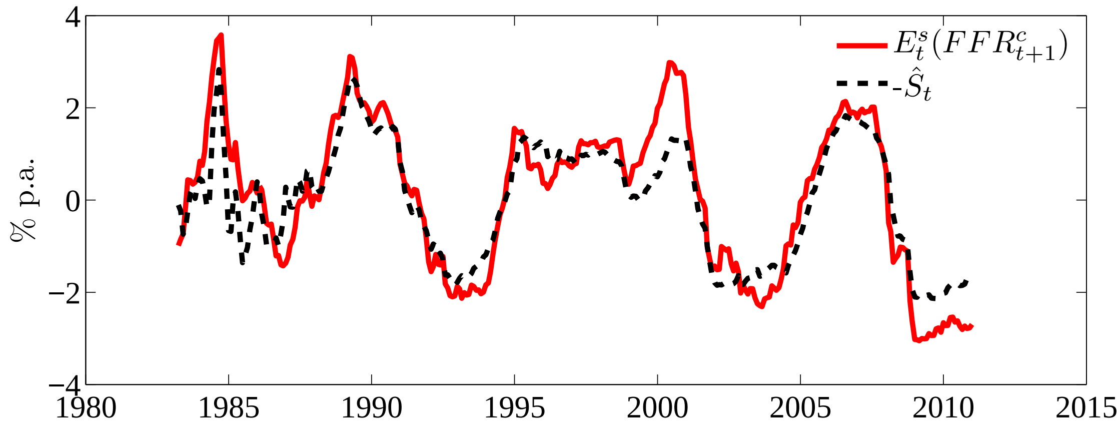


Figure 1: Monetary policy cycle and $\hat{S}_t$

Panel *a* plots the monetary policy cycle defined in equation (9), using long-term inflation surveys (labeled FFR_t^c (LT survey)) and the discounted moving average of past core CPI inflation τ_t^{CPI} (labeled FFR_t^c (DMA)) to measure long-horizon inflation expectations, $E_t(\pi_{t+\infty})$. Panel *b* compares the expected monetary policy cycle (obtained with τ_t^{CPI}) with the fitted value of the slope $\hat{S}_t$ from equation (7). Both series are demeaned. In both panels, the data are monthly and span March 1983 through December 2010.

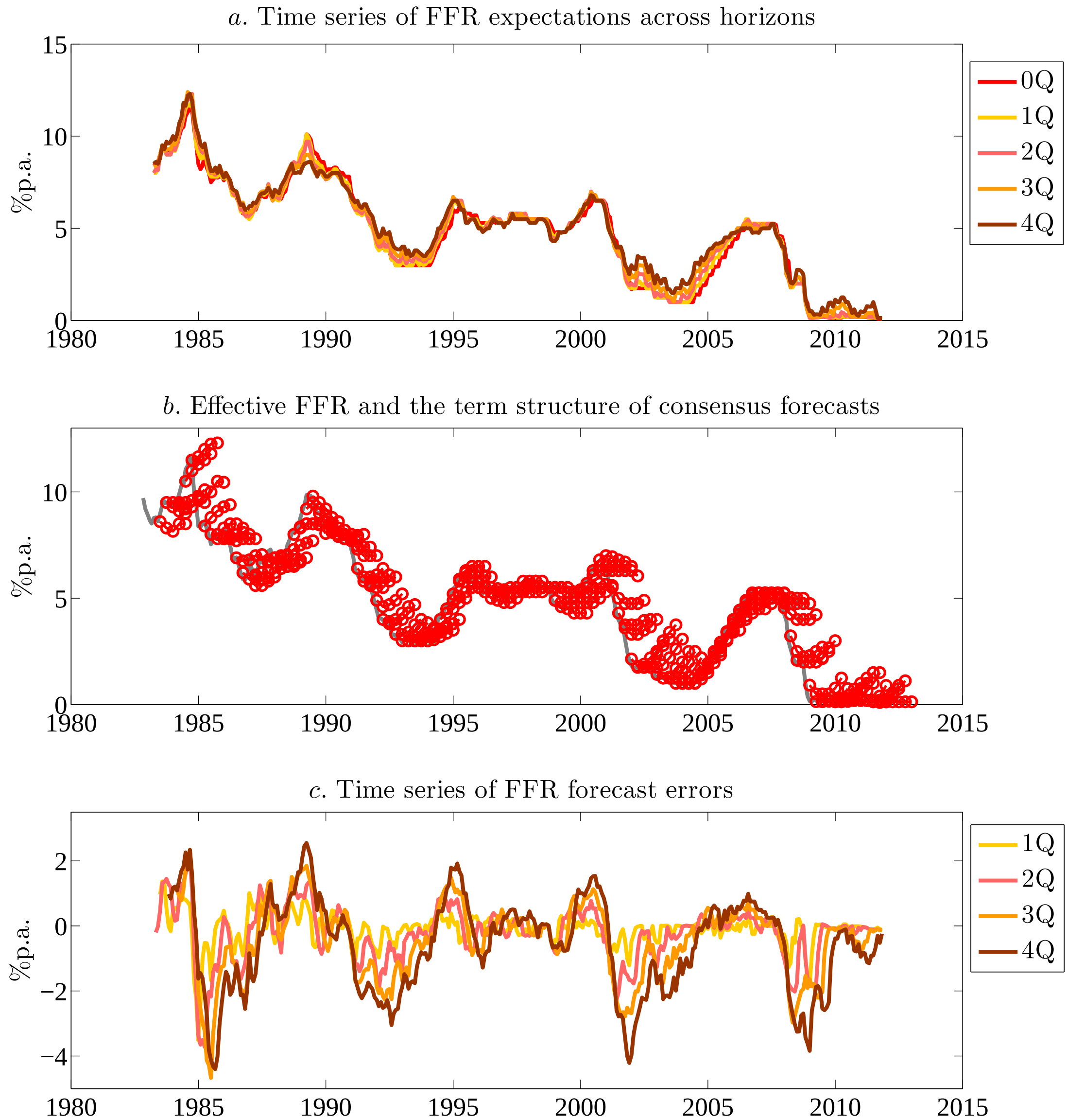


Figure 2: Short rate expectations

Panel *a* plots the time series of FFR forecasts from the BCFF survey at the time that the forecasts are made. 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. Feb, May, Aug and Nov of each year. Panel *c* displays the time series of forecast errors for horizons from one through four quarters ahead.

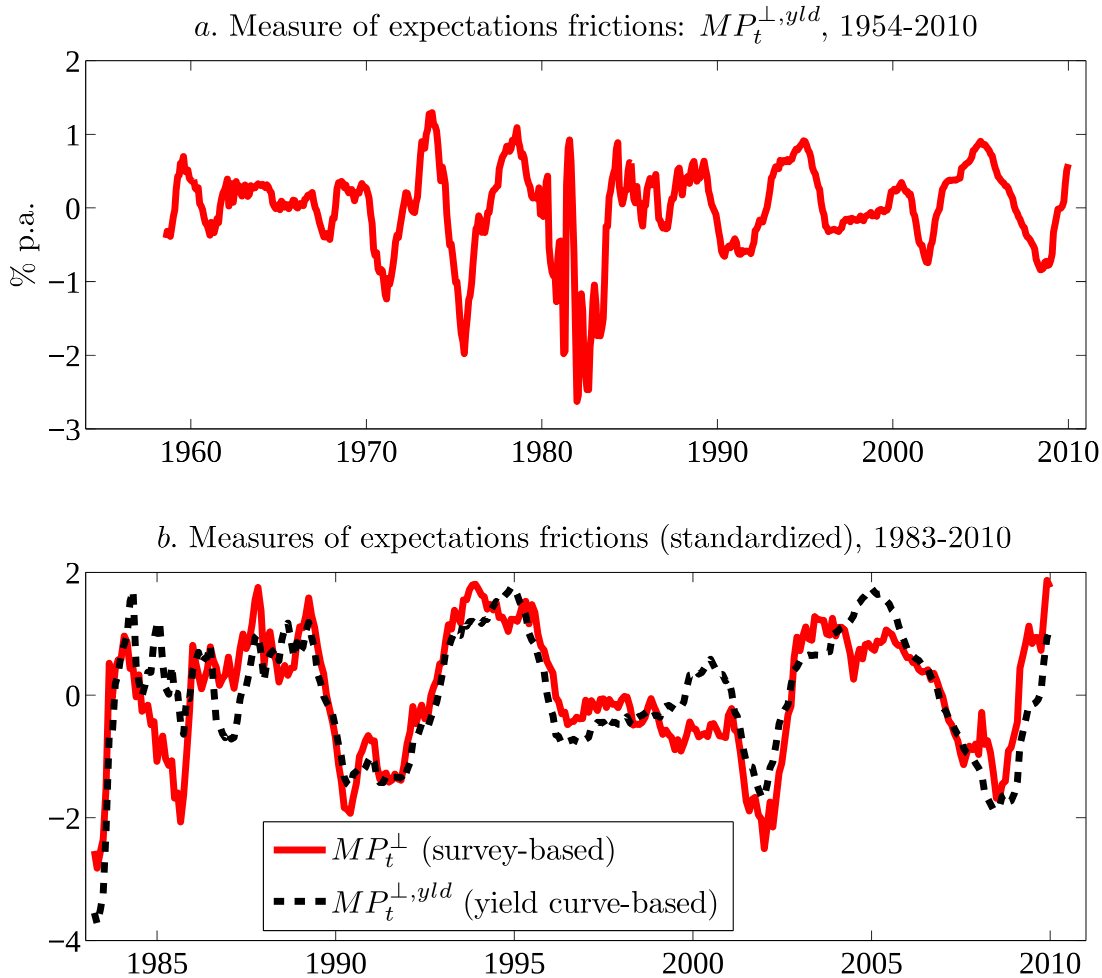


Figure 3: $MP_t^{\perp,yld}$, a measure of expectations frictions, 1954-2010

Panel a plots the yield curve-baed measure of frictions in short rate expectations denoted by $MP_t^{\perp,yld}$. It is a fitted value from regression (7). The data used to construct $MP_t^{\perp,yld}$ are the Treasury yields from the Fama-Bliss dataset, realized Federal funds rate, availability of which determines the start of the sample in July 1954. The data are monthly. Panel b compares the two versions of expectations friction measure denoted by $MP_t^{\perp}$ and $MP_t^{\perp,yld}$, respectively. The first version is survey-based (red line) and the second version uses an empirical model given by equations (17)–(19). These two versions are compared in the sample spanning March 1983 through December 2010. The sample start is determined by the availability of Federal funds rate surveys. $MP_t^{\perp,yld}$ is estimated in sample 1954-2010. Both series are standardized.

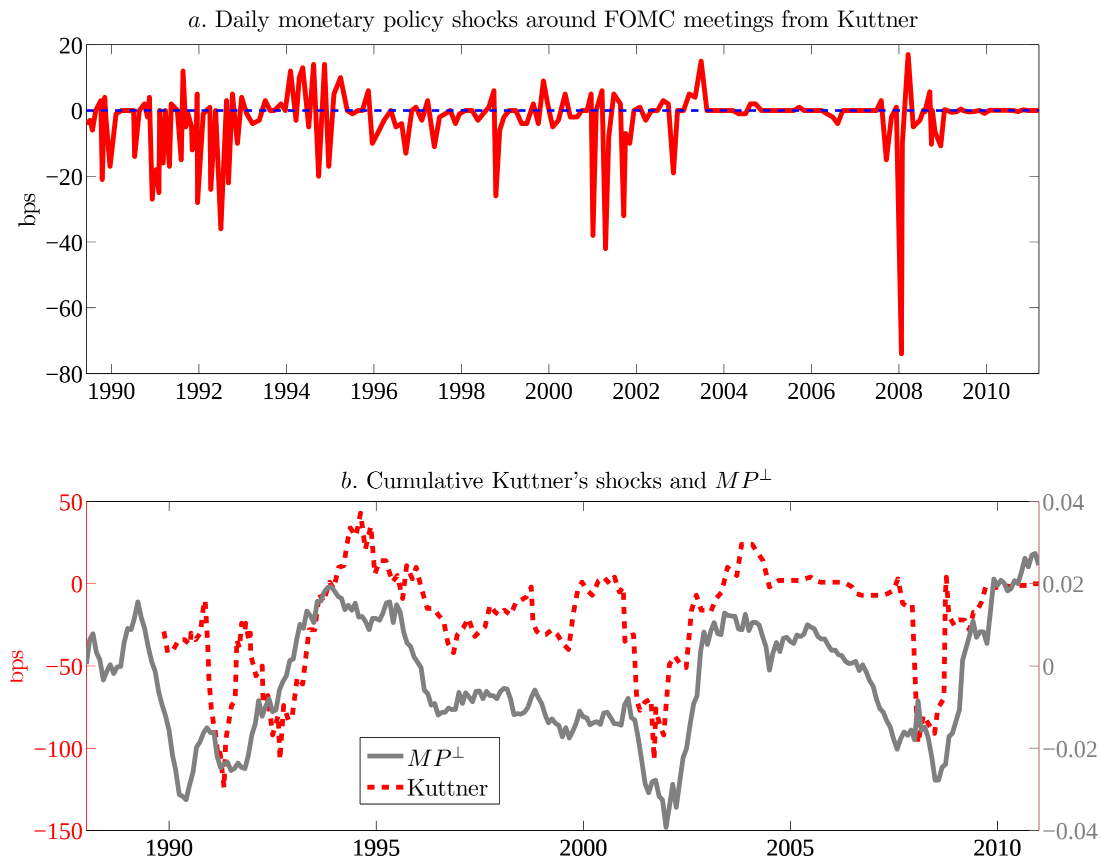


Figure 4: Monetary policy surprises

Panel a plots monetary policy shocks constructed by Kuttner (2001) and available on his webpage for the sample period 1989:06–2008:06, which we extend through 2010:12 using the same methodology. Kuttner obtains his measure of monetary policy surprises from daily changes in the fed fund futures around the days of target changes by the FOMC. Panel b superimposes $MP^{\perp}$ with the monetary policy surprises. Kuttner's surprises are obtained as a moving sum of the daily surprises over eight consecutive FOMC meetings. The left axis is in basis points p.a.; the right axis is in fractions p.a.

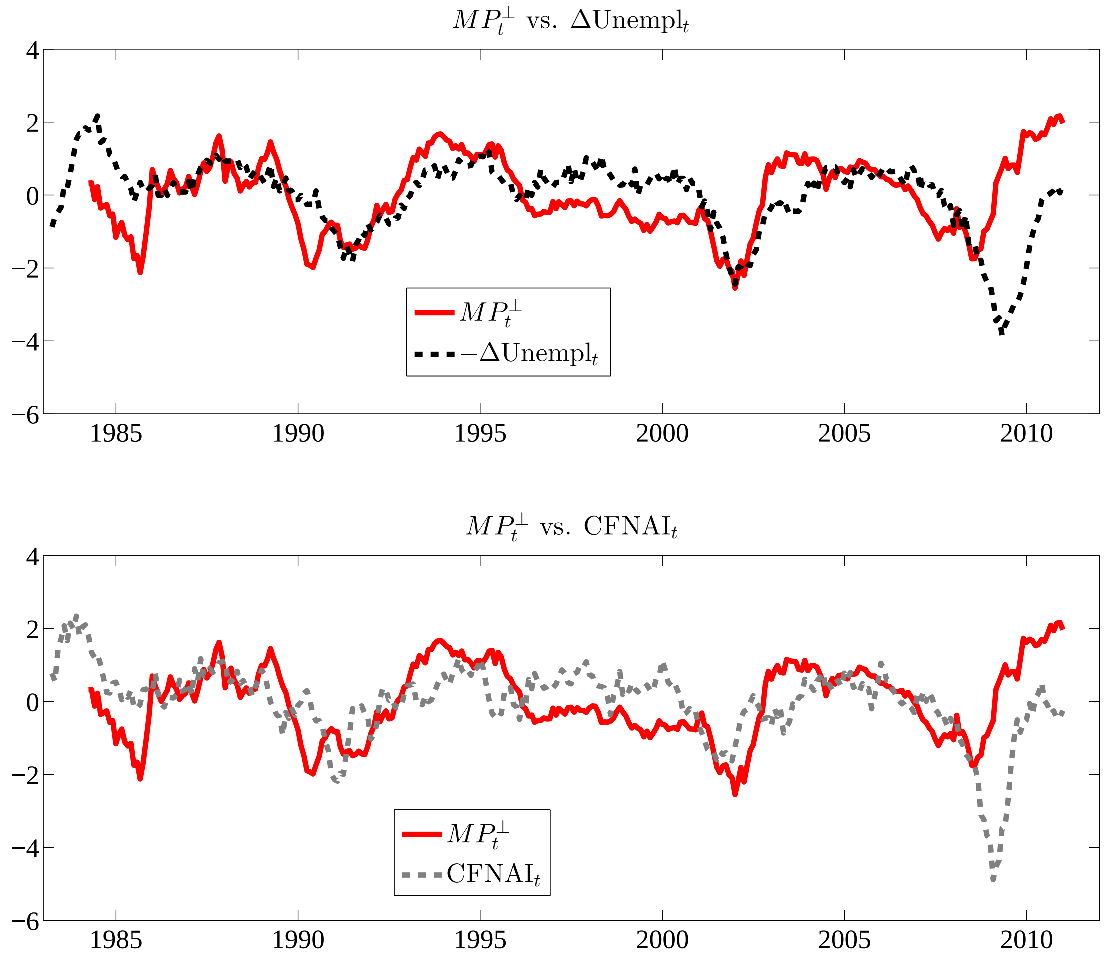


Figure 5: Expectation frictions and real activity

The figure plots the measure of friction in monetary policy expectations $MP_t^\perp = \Delta FFR_{t-1,t} - E_t^s(FFR_{t+1}^c)$ and two real activity variables: the annual unemployment growth (ΔUnempl_t) and the Chicago Fed National Activity Index (CFNAI_t). Unemployment growth is multiplied with -1 so that it has a positive correlation with CFNAI_t and $MP_t^\perp$. For comparability, all variables are standardized.

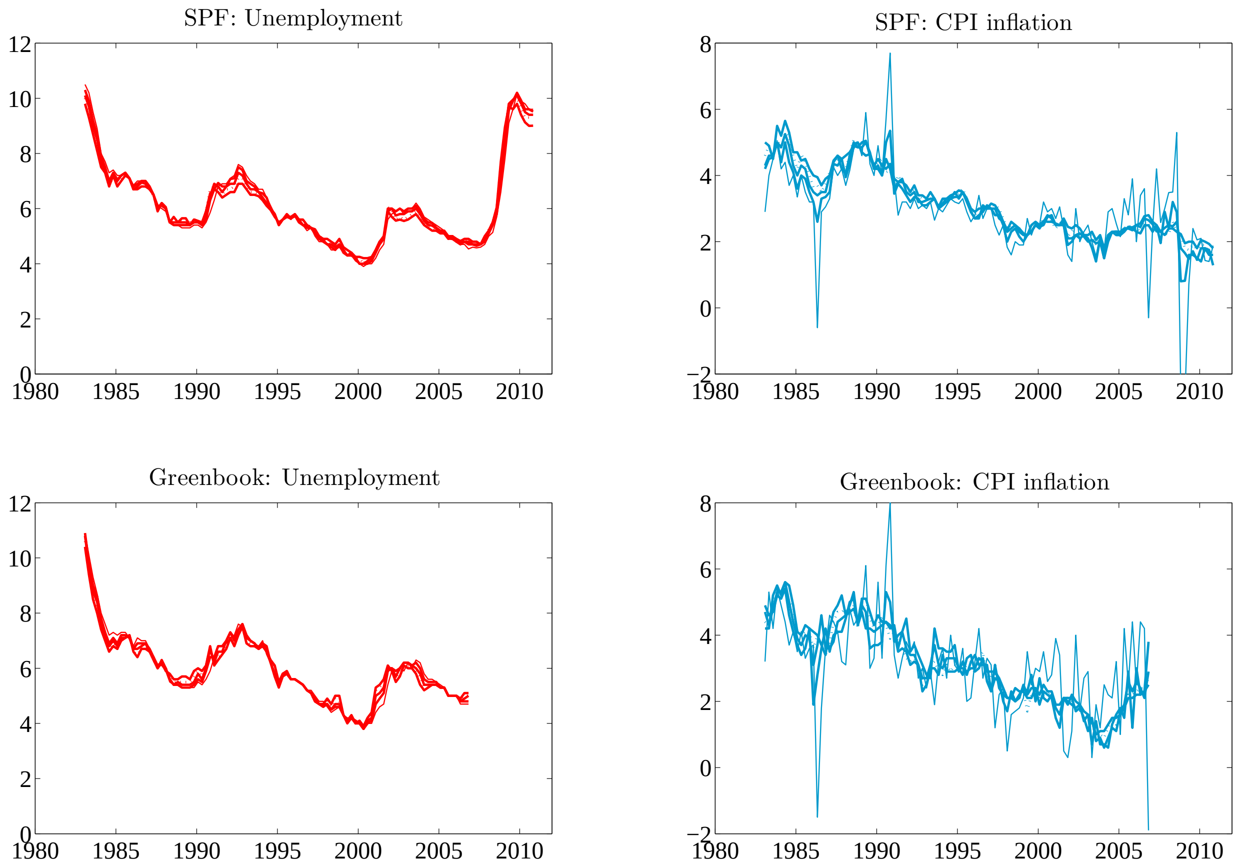


Figure 6: Term structure of macro expectations

The figure plots the term structures of expectations of CPI inflation and unemployment. The term structures span horizons from the current quarter up to four quarters ahead. Upper panels contain expectations of the private sector (SPF); bottom panels—of the Federal Reserve's staff from the Greenbook.

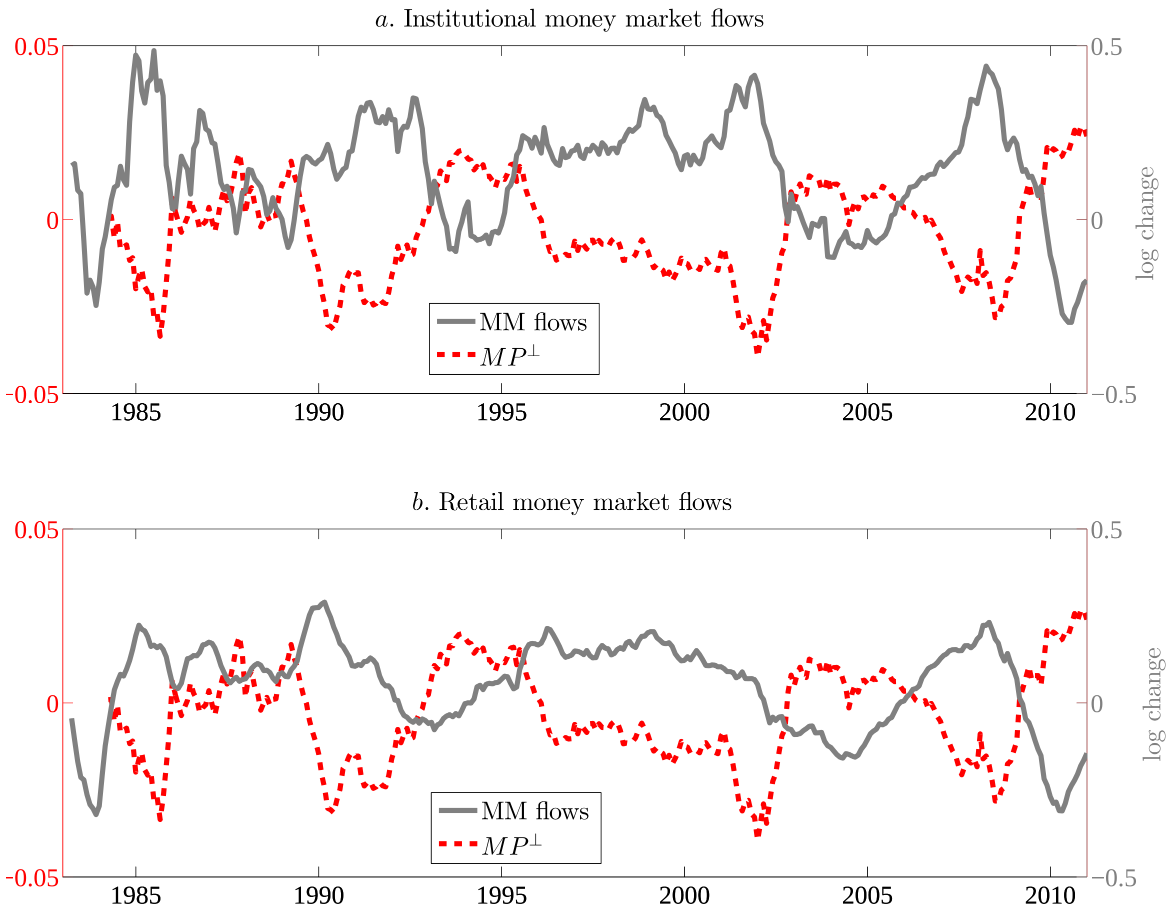


Figure 7: Money market flows

The figure superimposes money market flows with the contemporaneous values of $MP_t^{\perp}$. The flows are defined annual log changes in the assets of the money market funds. Panel a displays institutional flows; panel b retail flows.

B. Tables

Table I: Statistical model of the short rate with lags, 1875-2011

Panel A reports the results from the predictive regression of one-year change in the short rate. Four lags of the short rate are used as predictors. Maximum lag is 16 quarters. Panel B of the table reports the decomposition of the slope given by (7). Panel C reports the estimation results for a predictive regression using the fitted value (short rate expectations) and the residual (risk premia) from (7). Excess return on a ten-year bond is constructed from total return indices on ten-year bond and three-month Tbill, both obtained from the GFD database. Numbers in parentheses in the $\bar{R}^2$ column report the $\bar{R}^2$'s obtained with the Cochrane-Piazzesi factor. Panel D reports the results for predicting the short rate changes using $\hat{S}_t$. Data are quarterly and are from the Global Financial Database. The slope is constructed as a difference between ten-year par coupon yield on Treasuries and the three-month yield. The three-month yield is spliced from the three-month commercial paper (1875-1933) and three-month Treasury bill (1934-2011). Newey-West adjusted (6 lags) t-statistics are reported in parentheses.

	A. $\Delta i_{t,t+1} = \alpha_c + \sum_{j\in 0,1,2,4} \alpha_j i_{t-j} + \varepsilon^i_{t+1}$					
Sample	α_0	α_1	α_2	α_4	$\bar{R}^2$	$\bar{R}^2$ no lags
1875:3-1913:4	-0.81	0.02	0.10	-0.05	0.40	0.40
	(-5.21)	(0.14)	(1.10)	(-1.54)		
1914:1-1951:2	-0.22	0.00	0.15	-0.03	0.07	0.05
	(-1.81)	(0.02)	(1.27)	(-0.20)		
1951:3-1979:2	-0.52	-0.37	0.34	0.51	0.39	0.04
	(-3.47)	(-2.78)	(3.26)	(3.71)		
1984:1-2011:4	0.02	-0.47	-0.01	0.23	0.41	0.11
	(0.27)	(-3.63)	(-0.10)	(3.16)		
1951:3-2011:4	-0.01	-0.27	0.04	0.14	0.13	0.06
	(-0.10)	(-1.88)	(0.38)	(1.59)		
	B. $S_t = \delta_c + \sum_{j\in 0,1,2,4} \delta_j i_{t-j} + RP^S_t$					
Sample	δ_0	δ_1	δ_2	δ_4	$\bar{R}^2$	$\bar{R}^2$ no lags
1875:3-1913:4	-1.02	-0.01	0.04	0.08	0.96	0.94
	(-63.31)	(-0.56)	(2.64)	(4.23)		
1914:1-1951:2	-0.78	0.02	0.10	0.08	0.94	0.91
	(-12.20)	(0.29)	(2.91)	(1.65)		
1951:3-1979:2	-0.56	0.14	0.31	0.19	0.79	0.10
	(-9.96)	(3.16)	(5.71)	(3.05)		
1984:1-2011:4	-0.39	-0.10	0.22	0.23	0.68	0.15
	(-5.71)	(-1.42)	(3.60)	(7.45)		
1951:3-2011:4	-0.44	0.08	0.21	0.20	0.70	0.12
	(-9.79)	(1.46)	(4.33)	(5.15)		
	C. $rx^{(10)}_{t+1} = \beta_0 + \beta^e \hat{S}_t + \beta^{rx}\widehat{RP}^S_t + \varepsilon^{rx}_{t+1}$			D. $\Delta i_{t,t+1} = \beta_0 + \beta^e \hat{S}_t + \varepsilon^e_{t+1}$		
Sample	β^e	β^{rx}	$\bar{R}^2$	β^e	$\bar{R}^2$	$\bar{R}^2$ slope
1875:3-1913:4	0.09	0.22	0.05	1.13	0.39	0.35
	(0.75)	(0.92)		(5.70)		
1914:1-1951:2	0.15	0.40	0.18	0.28	0.07	0.06
	(0.98)	(2.37)		(1.60)		
1951:3-1979:2	-0.03	0.31	0.08 [0.04]	0.56	0.17	0.14
	(-0.25)	(2.59)		(3.61)		
1984:1-2011:4	-0.03	0.56	0.30 [0.21]	0.50	0.12	0.09
	(-0.22)	(5.68)		(2.65)		
1951:3-2011:4	0.16	0.38	0.16 [0.20]	0.26	0.02	0.03
	(1.21)	(3.90)		(1.25)		

Table II: Predicting short rate changes with lags, 1952-2011

The table reports the results from a predictive regression for one-year change in the short term interest rate. We use principal components and lags of the short term interest rate. Panel A reports the results for three principal components and Panel B for six principal components. Each panel displays the results for three different sub-samples; (*i*) pre-Volcker period and (*ii*) post-Volcker period and (*iii*) full sample. Lags of the short rate are optimally selected using BIC selection criteria. The maximum lag is 16 quarters. Selected lags are reported in the last two columns of each panel. First column reports the adj. R^2 obtained with PCs, the second column reports the adj. R^2 using PCs and two optimally selected lags. The data are quarterly and PCs are obtained from the Fama-Bliss yield data augmented by the three-month Tbill to capture the information at the short end.

	$\bar{R}^2$ PCs only	$\bar{R}^2$ PCs & lags	Wald p-val	Opt. lag1 (Qtrs.)	Opt. lag2 (Qtrs.)
	(1)	(2)	(3)	(4)	(5)
A. $i_{t+1} - i_t = \beta_0 + \sum_{j=1}^{3} \beta_j PC_t^j + \delta_1 i_{t-lag1/4} + \delta_2 i_{t-lag2/4} + \varepsilon_{t+1}$					
1952:3–1979:2	0.09	0.39	0.00	9	14
1984:1–2011:4	0.38	0.53	0.00	4	16
1952:3–2011:4	0.14	0.21	0.01	3	16
B. $i_{t+1} - i_t = \beta_0 + \sum_{j=1}^{6} \beta_j PC_t^j + \delta_1 i_{t-lag1/4} + \delta_2 i_{t-lag2/4} + \varepsilon_{t+1}$					
1952:3–1979:2	0.08	0.36	0.00	13	–
1984:1–2011:4	0.37	0.55	0.00	5	16
1952:3–2011:4	0.18	0.25	0.01	3	16

Table III: Private sector forecasts of short rate changes

The table reports regressions of the realized changes in the federal funds rate on the change expected by forecasters in the BCFF survey.

$$FFR_{t+h} - FFR_t = \gamma_2 + \gamma_2 \left[E_t^s(FFR_{t+h}) - FFR_t\right] + \varepsilon_{t+h}^{FE}$$

The data is monthly. T-statistics are Newey-West adjusted with 12 lags.

	$h = 1$Q	$h = 2$Q	$h = 3$Q	$h = 4$Q
γ_2	-0.09	-0.24	-0.44	-0.63
	(-1.53)	(-1.96)	(-2.27)	(-2.34)
γ_3	0.83	0.94	1.05	1.06
	(4.68)	(3.01)	(3.23)	(3.36)
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)
$\bar{R}^2$	0.25	0.19	0.19	0.18

Table IV: Private sector's expectations of monetary policy

Panel A reports the regressions of the FFR changes on the expected change in the short rate and the lagged monetary policy cycle. Panel B reports analogous regressions for the forecast errors. We estimate the following equation:

$$\Delta FFR_{t,t+h} = \gamma_0 + \gamma_1 \left[E_t^s(FFR_{t+h}) - FFR_t\right] + \gamma_2 FFR_{t-1}^c + \varepsilon_{t+h} \tag{26}$$

and analogous for forecast errors ($FE_{t,t+h}^{FFR}$) as the LHS variable in panel B. Time subscripts and horizons are expressed as the fraction of the year, i.e. FFR_{t-1}^c is lagged by one year. The data is monthly in the period 1983–2010. Since relative to Table III the sample is truncated due to lags, the third section of panel A does not exactly match Table III. We report the results for direct comparison.

	$h = 1$Q	$h = 2$Q	$h = 3$Q	$h = 4$Q
A. Short rate changes $\Delta FFR_{t,t+h}$				
const	-0.00	-0.00	-0.00	-0.00
	(-2.23)	(-2.50)	(-2.27)	(-1.94)
$E_t^s(FFR_{t+h}) - FFR_t$	0.74	0.63	0.49	0.37
	(4.48)	(2.19)	(1.89)	(1.92)
FFR_{t-1}^c	-0.09	-0.22	-0.39	-0.59
	(-3.22)	(-3.81)	(-4.87)	(-6.06)
$\bar{R}^2$	0.35	0.34	0.39	0.45
const	-0.00	-0.00	-0.00	-0.00
	(-1.31)	(-1.40)	(-1.40)	(-1.35)
FFR_{t-1}^c	-0.16	-0.31	-0.49	-0.67
	(-4.73)	(-5.01)	(-5.49)	(-6.18)
$\bar{R}^2$	0.20	0.28	0.36	0.44
const	-0.00	-0.00	-0.01	-0.01
	(-2.16)	(-2.55)	(-2.63)	(-2.55)
$E_t^s(FFR_{t+h}) - FFR_t$	0.93	1.04	1.11	1.11
	(5.67)	(3.54)	(3.51)	(3.57)
$\bar{R}^2$	0.31	0.24	0.22	0.20
B. Forecast errors $FE_{t,t+h}^{FFR}$				
const	-0.00	-0.00	-0.00	-0.01
	(-2.24)	(-2.53)	(-2.70)	(-2.78)
FFR_{t-1}^c	-0.06	-0.17	-0.29	-0.46
	(-2.70)	(-3.19)	(-3.65)	(-4.48)
$\bar{R}^2$	0.04	0.10	0.17	0.26

Table V: Forecasting realized excess bond returns

The table present the predictive regressions of realized excess bond returns across maturities. The explanatory variables the cycle factor of Cieslak and Povala (2011) as the measure of bond risk premium RP_t, the proxy for information frictions $MP_t^{\perp} = \Delta FFR_{t-1,t} - E_t^s(FFR_{t+1}^c)$, and separately each component of the difference. For ease of comparison, both left- and right-hand variables are standardized. The data is monthly and covers the period 1983–2010. T-statistics use Newey-West standard errors adjusted with 12 lags.

	$rx^{(2)}$	$rx^{(3)}$	$rx^{(5)}$	$rx^{(7)}$	$rx^{(10)}$	$rx^{(20)}$
A. $rx_{t,t+1}^{(n)} = \delta_0 + \delta_1 RP_t + \varepsilon_{t,t+1}$						
RP_t	0.51	0.55	0.64	0.69	0.73	0.71
	(4.26)	(5.22)	(6.62)	(7.23)	(8.09)	(7.11)
$\bar{R}^2$	0.26	0.31	0.42	0.48	0.54	0.51
B. $rx_{t,t+1}^{(n)} = \delta_0 + \delta_1 RP_t + \delta_2 MP_t^{\perp} + \varepsilon_{t,t+1}$						
RP_t	0.43	0.48	0.58	0.64	0.69	0.68
	(3.83)	(4.88)	(6.45)	(7.35)	(8.31)	(7.95)
$MP_t^{\perp}$	-0.54	-0.51	-0.42	-0.35	-0.28	-0.17
	(-5.38)	(-5.09)	(-4.29)	(-3.52)	(-2.76)	(-1.46)
$\bar{R}^2$	0.52	0.54	0.57	0.59	0.60	0.53
C. $rx_{t,t+1}^{(n)} = \delta_0 + \delta_1 RP_t + \delta_2 \Delta FFR_{t-1,t} + \delta_3 E_t^s(FFR_{t+1}^c) + \varepsilon_{t,t+1}$						
RP_t	0.44	0.49	0.59	0.64	0.69	0.69
	(3.94)	(5.11)	(6.67)	(7.59)	(8.56)	(8.18)
$\Delta FFR_{t-1,t}$	-0.57	-0.54	-0.44	-0.36	-0.28	-0.16
	(-5.23)	(-5.26)	(-4.48)	(-3.59)	(-2.60)	(-1.19)
$E_t^s(FFR_{t+1}^c)$	0.66	0.62	0.51	0.44	0.38	0.23
	(5.23)	(4.56)	(3.73)	(3.37)	(3.17)	(2.19)
$\bar{R}^2$	0.54	0.56	0.58	0.60	0.62	0.54
D. $rx_{t,t+1}^{(n)} = \delta_0 + \delta_1 RP_t + \delta_4 FFR_{t-1}^c + \varepsilon_{t,t+1}$						
RP_t	0.60	0.64	0.71	0.75	0.78	0.75
	(4.66)	(5.96)	(7.45)	(7.95)	(8.60)	(6.90)
FFR_{t-1}^c	0.53	0.51	0.43	0.38	0.32	0.23
	(5.12)	(4.99)	(4.40)	(3.72)	(3.03)	(1.72)
$\bar{R}^2$	0.51	0.53	0.58	0.60	0.62	0.56

Table VI: Expected returns versus expectations frictions

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 dependent variables, we consider the unexpected return $rx^{(2)}_{t,t+1} - E^s_t(rx^{(2)}_{t,t+1}) = -(y^{(1)}_{t+1} - E^s_t(y^{(1)}_{t+1}))$, private sector's forecast error about the federal funds rate four quarters ahead $FE^{FFR}_{t,t+1} = FFR_{t+1} - E^s_t(FFR_{t+1})$, and the expected return component $E_t(rx^{(2)}_{t,t+1}) = f^{(2,1)}_t - E^s_t(y^{(1)}_{t+1})$. We explain the variation in the dependent variables with our measure of information rigidities $MP^{\perp}_t$, and with its components in equation (16). In panel B, we regress the same dependent variables on two macro factors related to the real activity: the year-over-year growth 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 forecasts in the BCFF survey.

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

	Unexpected return, $rx^{(2)}_{t,t+1} - E^s_t(rx^{(2)}_{t,t+1})$						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)
$MP^{\perp}_t$	-0.60						-0.05						0.59					
	(-5.12)						(-0.34)						(5.39)					
$\Delta FFR_{t-1,t}$		-0.70	-0.30					-0.09	-0.11					0.73	0.37			
		(-5.40)	(-2.72)					(-0.49)	(-0.70)					(5.76)	(3.52)			
$E^s_t(FFR^c_{t+1})$		0.66		0.22				-0.02		-0.08				-0.58		-0.13		
		(3.81)		(1.38)				(-0.11)		(-0.53)				(-3.59)		(-0.90)		
FFR^c_{t-1}					0.53						-0.14						-0.57	
					(4.09)						(-0.86)						(-4.74)	
RP_t						0.17						0.48						-0.10
						(1.22)						(4.33)						(-0.78)
$\bar{R}^2$	0.35	0.35	0.09	0.05	0.28	0.02	0.00	0.00	0.01	0.00	0.01	0.23	0.35	0.35	0.14	0.01	0.32	0.01

B. Regressions of components of realized returns on macro variables

	Unexpected return, $rx^{(2)}_{t,t+1} - E^s_t(rx^{(2)}_{t,t+1})$				Expected return, $E^s_t(rx^{(2)}_{t,t+1})$				Forecast error, $FE^{FFR}_{t,t+1}$			
Regressor	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
CFNAI$_t$	-0.39		-0.22		0.17		0.21		0.42		0.26	
	(-2.43)		(-2.08)		(1.49)		(1.92)		(2.08)		(1.73)	
ΔUnempl$_t$		0.42		0.24		-0.05		-0.08		-0.42		-0.24
		(2.63)		(2.37)		(-0.47)		(-0.82)		(-2.27)		(-2.00)
$MP^{\perp}_t$			-0.53	-0.51			-0.12	-0.08			0.51	0.51
			(-4.50)	(-4.17)			(-0.85)	(-0.55)			(4.54)	(4.16)
$\bar{R}^2$	0.15	0.18	0.39	0.40	0.02	0.00	0.03	0.00	0.17	0.18	0.41	0.40

Table VII: Private sector forecasts of short rate changes

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 forecast, (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) Bayesian VAR(2) estimated with the Minnesota prior (reset at each iteration), (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 data become available. T-statistics test for the difference between the respective MSEs; the correlation is between the survey and futures-based forecast errors.

	$h = 1$Q	$h = 2$Q	$h = 3$Q	$h = 4$Q
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) VAR(2) Bayesian	1.14	1.46	1.75	2.02
(7) TVP VAR(2)	0.56	1.02	1.42	1.79
B. RMSE for surveys and fed fund futures, 1988:12-2010:12				
Fed fund futures	0.33	0.70	–	–
FFR survey	0.36	0.72	–	–
t-stat (diff = 0)	2.49	0.86	–	–
correlation	0.89	0.93	–	–

Table VIII: Correlations

The table reports unconditional correlations between forecast errors made by the private sector (professional forecasters) and the Fed staff (Greenbook). Private sector forecasts are from the BCFF survey for the FFR, and from the SPF survey for CPI inflation and unemployment. All forecasts are for four quarters ahead. The data is quarterly in the sample 1983:Q1–2006:Q4.

	$FFR^\star$	$UNE^\star$	$CPI^\star$	$FFR^\dagger$	$UNE^\dagger$	$CPI^\dagger$
$FFR^\star$	1.000					
$UNE^\star$	-0.744	1.000				
$CPI^\star$	0.317	-0.080	1.000			
$FFR^\dagger$	0.883	-0.703	0.286	1.000		
$UNE^\dagger$	-0.736	0.905	-0.121	-0.679	1.000	
$CPI^\dagger$	0.296	-0.066	0.975	0.299	-0.146	1.000

* denotes private sector (professional forecasters) forecasts; $\dagger$ denotes the Greenbook forecasts.

Table IX: Fed's staff monetary policy expectations from Greenbook

Panel A reports the regressions of the FFR changes on lagged expected path of the short rate and lagged monetary policy cycle. Panel B reports analogous regressions for the forecast errors. We estimate the following equation:

$$\Delta FFR_{t,t+h} = \gamma_0 + \gamma_1 \left[E_t^{GB}(FFR_{t+h}) - FFR_t\right] + \gamma_2 FFR_{t-1}^c + \varepsilon_{t+h} \tag{27}$$

and analogous for forecast errors ($FE_{t,t+h}^{FFR}$) as the LHS variable. Time subscripts and horizons are expressed as the fraction of the year, i.e. FFR_{t-1}^c is lagged by one year. The data is at the frequency of the FOMC meetings and spans the period 1983:3–2006:12, having 191 observations in total.

A. Short rate changes $\Delta FFR_{t,t+h}$				
	$h = 1$Q	$h = 2$Q	$h = 3$Q	$h = 4$Q
const	-0.13	-0.28	-0.38	-0.49
	(-2.52)	(-2.34)	(-2.08)	(-2.05)
$E_t^s(FFR_{t+1}) - FFR_t$	0.98	0.82	0.56	0.49
	(7.08)	(4.66)	(2.47)	(1.97)
FFR_{t-1}^c	-0.06	-0.18	-0.32	-0.44
	(-1.76)	(-2.64)	(-3.08)	(-3.07)
$\bar{R}^2$	0.37	0.31	0.28	0.29
const	-0.10	-0.20	-0.29	-0.39
	(-1.45)	(-1.48)	(-1.53)	(-1.62)
FFR_{t-1}^c	-0.12	-0.25	-0.38	-0.50
	(-2.88)	(-3.32)	(-3.44)	(-3.27)
$\bar{R}^2$	0.12	0.18	0.23	0.26
const	-0.11	-0.23	-0.30	-0.39
	(-1.87)	(-1.60)	(-1.37)	(-1.38)
$E_t^s(FFR_{t+1}) - FFR_t$	1.09	1.02	0.86	0.87
	(7.61)	(4.94)	(3.23)	(2.75)
$\bar{R}^2$	0.34	0.22	0.13	0.10
B. Forecast errors $FE_{t,t+h}^{FFR}$				
const	-0.13	-0.29	-0.44	-0.58
	(-2.32)	(-2.46)	(-2.43)	(-2.44)
FFR_{t-1}^c	-0.07	-0.18	-0.29	-0.39
	(-1.95)	(-2.54)	(-2.62)	(-2.57)
$\bar{R}^2$	0.05	0.11	0.14	0.18

Table X: IV regressions with macro expectations

The table 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 outcome of 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.

	Sample: 1983:Q1–2010:Q4				Sample: 1983:Q1–2006:Q4			
Forecast errors, $FE_{t,t+h}^{FFR}$								
	$h = 3Q$		$h = 4Q$		$h = 3Q$		$h = 4Q$	
	LS	IV	LS	IV	LS	IV	LS	IV
$FE_{t,t+h}^{CPI}$	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
$FE_{t,t+h}^{UNE}$	-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								
	$FE_{t,t+h}^{CPI}$		$FE_{t,t+h}^{UNE}$		$FE_{t,t+h}^{CPI}$		$FE_{t,t+h}^{UNE}$	
	$h = 3Q$	$h = 4Q$	$h = 3Q$	$h = 4Q$	$h = 3Q$	$h = 4Q$	$h = 3Q$	$h = 4Q$
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 XI: Tests of information frictions

Panel A, column (1) denoted "Baseline", reports estimates of equation (24). Columns (2)–(4) augments this regression respectively with: $MP_t^{\perp}$ in column (2), FFR_{t-1}^c in column (3) and S_{t-1} in column (4). Panels B and C perform the same test for forecast errors about unemployment and CPI inflation, respectively, i.e. forecast errors for each macro variable are regressed on the corresponding forecast update. 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 1983:Q2–2010: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)	(10)	(11)	(12)
Coeff.	Baseline	$MP_t^{\perp}$	FFR_{t-1}^c	S_{t-1}	Baseline	$MP_t^{\perp}$	FFR_{t-1}^c	S_{t-1}	Baseline	$MP_t^{\perp}$	FFR_{t-1}^c	S_{t-1}
Horizon, $h = 1Q$												
β_0	-0.09	-0.09	-0.09	-0.09	-0.05	-0.05	-0.05	-0.05	-0.07	-0.07	-0.07	-0.07
	(-2.14)	(-2.56)	(-2.52)	(-2.32)	(-1.58)	(-1.67)	(-1.65)	(-1.76)	(-0.88)	(-0.89)	(-0.88)	(-0.89)
β_1	0.15	0.13	0.11	0.14	0.16	0.15	0.14	0.16	0.19	0.19	0.19	0.19
	(6.95)	(5.23)	(3.22)	(5.36)	(3.01)	(2.86)	(2.51)	(3.06)	(2.62)	(2.60)	(2.58)	(2.59)
β_X	–	0.12	-0.12	0.07	–	-0.07	0.09	-0.06	–	0.03	-0.00	0.02
	–	(3.18)	(-2.78)	(1.66)	–	(-2.64)	(3.30)	(-1.75)	–	(0.28)	(-0.01)	(0.21)
$\bar{R}^2$	0.09	0.15	0.15	0.10	0.23	0.27	0.28	0.25	0.03	0.02	0.02	0.02
Horizon, $h = 2Q$												
β_0	-0.24	-0.24	-0.24	-0.24	-0.04	-0.04	-0.04	-0.04	-0.17	-0.17	-0.17	-0.17
	(-2.24)	(-2.73)	(-2.55)	(-2.43)	(-0.63)	(-0.66)	(-0.67)	(-0.68)	(-1.26)	(-1.26)	(-1.26)	(-1.26)
β_1	0.20	0.15	0.12	0.18	0.26	0.24	0.20	0.24	-0.02	-0.03	-0.02	-0.02
	(3.09)	(2.45)	(1.57)	(2.72)	(3.58)	(3.26)	(2.74)	(3.58)	(-0.16)	(-0.22)	(-0.16)	(-0.14)
β_X	–	0.29	-0.29	0.17	–	-0.13	0.17	-0.12	–	0.12	0.01	0.05
	–	(3.92)	(-2.91)	(2.08)	–	(-2.44)	(3.04)	(-2.06)	–	(0.90)	(0.06)	(0.33)
$\bar{R}^2$	0.05	0.15	0.15	0.08	0.25	0.31	0.34	0.29	0.00	0.00	0.00	0.00
Horizon, $h = 3Q$												
β_0	-0.43	-0.43	-0.43	-0.43	-0.00	-0.00	-0.00	-0.00	-0.26	-0.26	-0.26	-0.26
	(-2.52)	(-3.14)	(-2.87)	(-2.78)	(-0.02)	(-0.02)	(-0.02)	(-0.02)	(-1.76)	(-1.78)	(-1.72)	(-1.77)
β_1	0.34	0.26	0.22	0.29	0.30	0.26	0.21	0.26	-0.00	-0.01	-0.00	0.00
	(2.99)	(2.57)	(1.97)	(2.73)	(3.39)	(2.83)	(2.11)	(3.06)	(-0.05)	(-0.12)	(-0.00)	(0.00)
β_X	–	0.46	-0.44	0.29	–	-0.24	0.31	-0.23	–	0.18	-0.08	0.12
	–	(4.08)	(-3.00)	(2.54)	–	(-2.57)	(3.07)	(-2.41)	–	(1.44)	(-0.66)	(1.03)
$\bar{R}^2$	0.08	0.22	0.20	0.13	0.18	0.28	0.34	0.27	0.00	0.00	0.00	0.00

Table XII: Evidence from money market flows

Panel A runs predictive regressions of changes in the FFR and forecast errors on the annual money market flows, for retail and institutional money market funds, respectively. Panel B explains the annual change in the flows with three variables: contemporaneous measure of information rigidities $MP^{\perp}_{t+1}$, and lagged values of the monetary policy cycle FFR^c_t, and slope S_t. In column (2) we report the results using $MP^{\perp}$ and the control variables for the flight to quality and liquidity: Pastor-Stambaugh market-wide liquidity, Hu-Pan-Wang noise illiquidity, Fontaine-Garcia value of funding liquidity, and stock market volatility VXO. Annual flows are log year-over-year changes in the money market funds. All variables are standardized. T-statistics are Newey-West adjusted with 12 lags. The sample is monthly in the period 1983:3-2010:12, except for the regression in panel B marked with * where we use the period 1987:01–2010:12, due to availability of some of the controls.

A. Predicting short rate with flows: $Y_{t,t+1} = \alpha + \beta \text{Flow}_{t-1,t} + \varepsilon_{t,t+1}$

	Retail flows		Institutional flows	
Dependent $Y_{t,t+1}$:	$\Delta FFR_{t,t+1}$	$FE^{FFR}_{t,t+1}$	$\Delta FFR_{t,t+1}$	$FE^{FFR}_{t,t+1}$
	(1)	(2)	(1)	(2)
β	-0.39	-0.19	-0.52	-0.44
	(-3.43)	(-1.65)	(-4.55)	(-4.38)
$\bar{R}^2$	0.15	0.03	0.26	0.19

B. Predicting flows: $\text{Flow}_{t,t+1} = \alpha + \beta X_t + \varepsilon_{t,t+1}$

	Retail flows				Institutional flows			
Regressor X_t:	$MP^{\perp}_{t+1}$	$MP^{\perp}_{t+1}$ w/controls*	FFR^c_t	S_t	$MP^{\perp}_{t+1}$	$MP^{\perp}_{t+1}$ w/controls*	FFR^c_t	S_t
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
β	-0.60	-0.78	0.68	-0.69	-0.81	-0.82	0.79	-0.69
	(-7.93)	(-5.75)	(4.52)	(-5.83)	(-13.76)	(-7.53)	(9.55)	(-5.83)
$\bar{R}^2$	0.35	0.58	0.46	0.48	0.66	0.67	0.62	0.47

Appendix

C. Lag selection for the short rate

Table C-XIII: The predictive power of slope for short rate changes

The table reports the predictive power of the short rate i_t for the future one-year change in the short rate $i_{t+1} - i_t$, considering the short rate at different lags k. We use the BIC to select the lag length for the short rate considering all possible combinations of lags from zero to 16. For the best specification, the table reports the BIC, the $\bar{R}^2$, the specific lags chosen, and the relative probability (Rel.prob. no lags). Rel.prob. no lags measures the probability of a model without lags, i.e. based on i_{t-k} $(k = 0)$, relative to the first best specification with lags. Relative probability is obtained as: $\exp\{(BIC_{\text{best}} - BIC_{k=0})T/2\}$, where $BIC = \ln(\hat{\sigma}^2) + 2n/T$, n is the number of regressors, $\hat{\sigma}^2 = SSE/T$ of the regression, and T is the sample size. Similarly, Rel. prob. fix lags measures the probability of the model with fixed lags relative to the best lag specification. The data is quarterly.

$i_{t+1} - i_t = \gamma_c + \sum_k \gamma_k i_{t-k} + \varepsilon_{t+1}$									
Sample	BIC	$\bar{R}^2$	$\bar{R}^2$ no lags	Rel. prob. no lags	$\bar{R}^2$ fixed lags	Rel. prob. fix lags	Lag 1	Lag 2	Lag 3
1875:3–1913:4	0.53	0.42	0.37	0.05	0.38	0.00	0	8	14
1914:1–1951:2	0.00	0.15	0.06	0.02	0.07	0.00	1	7	11
1951:3–1979:2	0.33	0.31	0.00	0.00	0.30	0.01	2	14	–
1979:3–2011:4	0.27	0.42	0.11	0.00	0.42	0.02	4	16	–
1951:3–2011:4	0.86	0.15	0.06	0.00	0.13	0.00	3	16	–

D. 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 D-XIV summarizes the results. We fail to reject the null at all horizons suggesting the private sector reports unbiased forecasts of the future FFR.

D.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:

$$y_t^{(1)} = \underbrace{\gamma_0}_{-6e^{-4}\ [-0.74]} + \underbrace{\gamma_1}_{0.99\ [62.62]} \frac{1}{5}\sum_{k=0}^{4} E_t^s(FFR_{t+\frac{k}{4}}) + \nu_t, \quad \bar{R}^2 = 0.99, \tag{28}$$

Table D-XIV: Testing for survey bias

Table reports the Mincer-Zarnowitz test for survey bias for four forecasting horizons: one ($h = 1$Q) through four ($h = 4$Q) 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 D-XV: Forecast errors across monetary policy regimes

The table reports the means and standard deviations of the forecast errors across forecast horizons from one to four quarters ahead. 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

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 D-XVI: Forecast errors for unemployment and CPI inflation

Table reports RMSE for unemployment and CPI inflation. The level of variables and the RMSE is in percentages. We report the RMSE for the Greenbook and SPF forecasts. The numbers in parentheses are RMSEs divided by the standard deviation of the realized inflation and unemployment, respectively. The data is quarterly. In Panel I, the sample period is 1983:Q2–2006:Q4, i.e. when the Greenbook sample ends. In Panel II, the sample period is 1974:Q4–1991:Q4 for unemployment and 1981:Q3–1991:Q4 for CPI inflation. The end of the sample used in Panel II is consistent with the end of sample used by Romer and Romer (2000).

	h=Q1	h=Q2	h=Q3	h=Q4
Panel I. 1983:Q1–2006:Q4 sample				
A. Greenbook				
UNEMPL	0.30	0.42	0.56	0.67
	(0.23)	(0.33)	(0.44)	(0.52)
CPI	1.60	1.72	1.76	1.81
	(0.92)	(0.99)	(1.02)	(1.04)
B. SPF				
UNEMPL	0.28	0.42	0.56	0.66
	(0.22)	(0.32)	(0.43)	(0.51)
CPI	1.56	1.64	1.70	1.77
	(0.90)	(0.95)	(0.98)	(1.02)
Panel II. Pre-1992 sample				
A. Greenbook				
UNEMPL	0.43	0.63	0.74	0.87
(1974:Q4–1991:Q4)	(0.43)	(0.64)	(0.75)	(0.88)
CPI	2.10	2.19	2.03	2.15
(1981:Q3–1991:Q4)	(1.21)	(1.26)	(1.17)	(1.24)
B. SPF				
UNEMPL	0.44	0.64	0.79	0.95
(1974:Q4–1991:Q4)	(0.45)	(0.65)	(0.80)	(0.97)
CPI	1.94	2.13	2.18	2.34
(1981:Q3–1991:Q4)	(1.12)	(1.23)	(1.25)	(1.35)