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Monetary Policy Expectation Errors*

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Abstract

How are financial markets pricing the monetary policy outlook? We use survey expectations to decompose excess returns on money market instruments into expectation errors and term premia. We find excess returns to be driven primarily by expectation errors, whereas term premia are negligible. Our findings point to challenges faced by investors when learning about the Federal Reserve's response to large, but infrequent, negative shocks in real-time. Rather than reflecting risk compensation, excess returns stem from investors underestimating by how much the central bank would ease policy in response to such rare shocks. We document similar results in an international sample.

JEL Classification: E43, E44, G12, G15
Keywords: Expectation Formation, Monetary Policy, Federal Funds Futures, Overnight Index Swaps, Uncertainty

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1. Introduction

Overnight money market rates are at the heart of the financial system and commonly serve as the policy target of central banks around the globe. Forward information from the term structure of money market rates is a common ingredient in central banks' market monitoring, especially ahead of policy decisions, and serves as an important tool to assess market expectations of future short-term interest rates. A key question in this context is whether this term structure can be trusted to accurately reflect market participants' short rate expectations, or whether signals are distorted due to the presence of term premia.

We study the information about future monetary policy embedded in money market derivatives such as fed funds (FF) futures and overnight index swaps (OIS). In doing so, we provide novel insights into how expectations about future monetary policy are formed, a better understanding of when and how market expectations and central bank actions diverge, as well as shed light on the nature of the central bank's reaction function more generally. A crucial part of our analysis is to combine data on the pricing of money market derivatives with survey expectations about future short-term interest rates.

As a starting point, we document that implied future short rates extracted from money market derivatives systematically exceed the actual short rates realized at the maturity of the contracts. In other words, FF futures and OIS are biased predictors of future short rates – a well-known finding, not only in money markets but across many asset classes.[1] As such, investors have earned positive excess returns by entering into contracts that lock in fixed rates today while paying the realized short rate in the future. This rejection of the unbiasedness hypothesis has commonly been attributed to the presence of countercyclical risk premia (e.g., Piazzesi and Swanson, 2008; Ludvigson and Ng, 2009; Cochrane, 2011; Hamilton and Okimoto, 2011, and Krishnamurthy and Vissing-Jorgensen, 2011).

Drawing on survey expectations about future monetary policy from Blue Chip Financial

[1]See, e.g., Krueger and Kuttner (1996) and Söderström (2001). More recently, Gürkaynak et al. (2007) test the predictive power of various money market rates and find that FF futures provide the most accurate predictions of future short rates (the most likely reason being that the rates on other money market instruments contain significant funding and liquidity premia, see e.g., Duffee, 1996; Longstaff, 2000; Nagel, 2016). They also, however, conclude that FF futures rates systematically exceed future realized short rates.

Forecasts, we subsequently decompose these excess returns into: (i) a term premium component, and (ii) a component due to expectation errors. While expectation errors should not play a systematic role under the classical full-information, rational expectations (FIRE) assumption, our findings reveal that they are in fact crucial for understanding excess returns on money market derivatives: essentially *all* excess returns stem from expectation errors, while the contribution of term premia is economically small and even slightly negative.[2]

These findings are in sharp contrast to the prevailing view that the rates on money market derivatives primarily reflect risk premia and not expected short-term interest rates. In this view, business cycle downturns coincide with periods of high expected returns on these contracts, but our finding that term premia are negative on average suggests that this interpretation is incomplete. FF futures and OIS are purely financial derivatives as opposed to investment assets or funding instruments. As such, any term premium variation in these contracts should not be viewed as compensation for holding risky assets in periods of economic downturn, but instead reflects the price that institutions active in the money market are willing to pay to hedge against future short rate changes.[3]

Having established these new stylized facts, we proceed with a deeper analysis of *why* market participants have been prone to "monetary policy expectation errors" that did not average out over time. The expectation errors we document could be driven by different economic mechanisms, such as a tendency by market participants to have systematically overestimated future inflation and/or underestimated future growth (cf. Bauer and Rudebusch, 2020). However, diagnosing the patterns of how these errors occur supports an interpretation of "conservatism" in forecasts: when market participants correctly predict the direction of future interest rate changes, they tend to underestimate the magnitude of the subsequent changes. Importantly, this underestimation of the magnitude of short rate changes is highly asymmetric and significantly more pronounced for interest rate cuts than for hikes. In essence, our findings show that market participants have, over the past 30 years, underestimated how aggressively the Federal Reserve (Fed) was going to cut interest rates in times of economic downturn.

[2] Also see Crump et al. (2018) and Crump et al. (2021), who show via variance decompositions that expected short rates dominate term premia.

[3] Negative term premia in money market derivatives also make sense from a standard asset pricing perspective: a long position in FF futures or OIS has a high payoff when central banks cut policy rates, which normally happens during periods of economic downturn. Hence, a long position in these contracts serves as a hedge against adverse shocks to the economy.

Crucially, our results reveal a tight link between expectation errors and monetary policy itself—particularly market participants' uncertainty about the central bank's reaction function in specific time periods. First, we show that expectation errors are significantly correlated with policy rate deviations from what the conventional Taylor rule prescribes: when the Fed takes a loose monetary policy stance and cuts the short rate below the rate implied by the Taylor rule, market expectations of future interest rates are "too high" relative to subsequent realized interest rates. Second, we find that excess returns tend to be elevated in periods of deteriorating financial conditions, notably when stock prices fall. A drop in equity prices significantly predicts *higher* excess returns on FF futures and OIS, both in-sample and out-of-sample.[4] Moreover, we observe a strong asymmetry in this relation: lower stock returns predict higher excess returns on money market derivatives whereas rising stock returns do not contain any predictive power. Third, we find uncertainty about future short rates - as measured by the dispersion of expectations across forecasters - to be a strong predictor of expectation errors. Such uncertainty appears to relate to the macroeconomic outlook itself as well as the anticipated response of the central bank (the reaction function). At times when such uncertainty is elevated, the Fed has subsequently cut interest rates more than what was expected by market participants, thereby giving rise to the positive excess returns on money market derivatives observed over the last three decades.

In sum, we find that money market excess returns are predictable and that expectation errors, rather than term premia, are key for this predictability.[5] On the face of it, these findings are well in line with a story where market participants face uncertainty about the inputs and/or parameters of the Fed's reaction function and have to learn about them in real time, as emphasized for instance by Bauer and Swanson (2020). However, we also show that the lion's share of this predictability is concentrated in periods with large and negative macroeconomic shocks, when uncertainty of both investors and policymakers is at its highest. Arguably the most plausible explanation for our findings is therefore that it is especially difficult for market participants to learn about a central bank's response to large, but infrequent, negative shocks.

[4]This finding is robust to controlling for the macroeconomic variables intended to capture countercyclical term premium variation suggested in, e.g., Piazzesi and Swanson (2008).

[5]This interpretation implies that market participants' short rate expectations deviated from the FIRE assumption over our sample period. However, we would caution against interpreting this deviation as being due to investor irrationality. Instead, it appears to reflect that market participants have incomplete information about the central bank reaction function, but are learning about it in real time. This learning process then manifests itself as a systematic and predictable deviation from the expectations hypothesis benchmark. For earlier work emphasizing such aspects, see, e.g. Mankiw and Miron (1986) and Rudebusch (1995).

Expectation errors thus primarily stem from market participants underestimating the extent to which the Fed would be easing monetary policy in response to such "rare events". This gives rise to the pattern we observe in the data that falling stock prices and rising forecaster uncertainty, both of which tend to occur in periods of deteriorating economic fundamentals, are followed by aggressive cuts in policy rates to levels lower than previously anticipated.[6]

We run several additional tests and robustness exercises to scrutinize the validity of our findings and interpretations. In particular, we show that results are not driven by measurement issues or the specific type of Taylor rule that we employ. We also find expectation errors to be predictable by broader measures of financial conditions rather than just stock market returns. Most importantly, we go beyond the US and analyze a panel of six major currency areas: Australia, Canada, the euro area, the United Kingdom, Japan, and Switzerland. We find that our main results apply here as well: in the three currency areas with available survey data (the euro area, the United Kingdom, and Switzerland) expectation errors account for the bulk of excess returns on OIS contracts. Moreover, in all six currency areas, the local stock market predicts excess returns with a negative and significant coefficient. Overall, these findings are very similar to the US results, suggesting that the fundamental mechanisms unveiled in this paper are part of a broader phenomenon and not confined to Fed policy.

Related Literature Our paper adds to the nascent literature that challenges the predominant view on the role of term premia in fixed-income markets and instead stresses errors in investor expectations. An important contribution is Cieslak (2018), who argues that the Fed easing more aggressively than expected has led to expectation errors and large marked-to-market profits in the Treasury bond market.[7] While our findings and interpretations are closely related, we contribute by documenting the dominant role of expectation errors in the pricing of *money market derivatives*. Specifically, we carefully examine the signals that these contracts (commonly used to gauge market participants' short rate expectations) provide about future monetary policy. Second, we link expectation errors directly to the time-varying nature of the central

[6]A related view is that the Fed lowered rates to cushion the effect of severe stock market declines (see, e.g., Cieslak and Vissing-Jorgensen, 2021, on the so-called "Fed put"), i.e., that stock price declines cause Fed policy.

[7]Specifically, Cieslak (2018) find that errors in expectations about the real rate, rather than inflation, drives expectation errors over the business cycle. Furthermore, she shows that unexpected declines in the real rate trend are of minor importance to expectation errors, which could otherwise pose an important explanation for the phenomenon given recent evidence by Bauer and Rudebusch (2020).

bank's reaction function, and show how deteriorating financial conditions are key to understand the Fed's aggressive policy rate cuts over the sample. Finally, we reveal the important role of expectation errors internationally. By studying an international sample, we find that the same results apply to the money markets of several major currency areas around the globe as well.

The results of this paper also speak to the broader literature that uses survey data to decompose asset returns into a risk premium and an expectation error component. Studies such as Froot (1989), Froot and Frankel (1989), Gourinchas and Tornell (2004), and Bacchetta et al. (2009) show that expectation errors play a key role for excess returns on stocks, bonds, and in FX markets. Survey data may, however, come with caveats such as measurement noise and difficulties of interpretation (e.g., Cochrane, 2011). That said, several papers have shown how survey expectations tend to align closely with actual, real-world behavior. For example, Greenwood and Shleifer (2014) show that survey expectations of future stock returns are strongly correlated with inflows into mutual funds; Gennaioli et al. (2016) show that corporate investments are well explained by survey data on CFOs' expectations of earnings growth; Bork et al. (2020) show that survey responses regarding housing buying conditions strongly outperform several macroeconomic variables typically used to forecast house prices; Egan et al. (2020) show that the time-varying distribution of expected returns estimated from a model of realized choices for ETFs correlates strongly with the survey expectations used by Greenwood and Shleifer; finally, Giglio et al. (2020) show that the beliefs of wealthy investors as measured by surveys are reflected in their portfolio allocations. For our purpose, the Blue Chip Financial Forecasts survey is an optimal source of expectations, as the survey respondents encompass around 45 experts from leading institutions that are actively participating in financial markets.

Our findings also contribute to the literature on the expectations hypothesis (EH) of the term structure of interest rates. While the EH is typically rejected for long-term interest rates, evidence at the short end of the term structure is mixed.[8] Importantly, Longstaff (2000) shows that short-term repo rates with maturities up to three months are nearly unbiased predictors of the short rate, and that term premia in these instruments are small in economic terms and statistically insignificant. Della Corte et al. (2008) expand this analysis and find statistical evidence against the EH for an updated dataset of repo rates. However, when performing an

[8] See e.g., Shiller et al. (1983), Fama and Bliss (1987), Campbell and Shiller (1991), Bekaert et al. (1997), and Cochrane and Piazzesi (2005) for evidence on long-term interest rates.

economic assessment of this finding, they conclude that there are no tangible economic gains to an investor who seeks to exploit departures from the EH in these contracts. While these studies have focused on the interest rate expectations implied by short-term funding rates, this paper analyzes the expectations implied by money market derivatives. We arrive at a similar conclusion nonetheless: the information at the short end of the term structure should not be discounted due to term premium distortions, but should be taken as an important signal of market participants' expectations of future short-term interest rates as suggested by the EH.

2. Return Decomposition and New Stylized Facts

2.1. Fed Funds Futures and Overnight Index Swaps

FF futures have been trading on the Chicago Board of Trade since 1988 and are highly standardized contracts designed to hedge fluctuations in the US overnight rate, the effective federal funds rate (EFFR), over a specific future month. Let $f_t^{(n)}$ denote the fixed rate on FF futures as observed on the last business day of month t, where $n = 1$ indicates that the contract settles over the following month, $n = 2$ for a contract settling in two months' time and so forth. An investor who has taken a long position in FF futures receives fixed payments known at t and pays a floating rate at $t + n$ depending on the realization of the EFFR. Upon expiry of the contract she earns the following payoff:

$$rx_{t+n}^{(n)} = f_t^{(n)} - i_{t+n}, \tag{1}$$

where $rx_{t+n}^{(n)}$ denotes the excess return and i_{t+n} is the short rate over month $t + n$.[9] FF futures are forward-looking and embed financial market participants' expectations about future excess returns and short rates. To see this, we can isolate the futures rate in Eq. (1) and take conditional expectations,

$$f_t^{(n)} = \underbrace{E_t[rx_{t+n}^{(n)}]}_{\text{term premium}} + \underbrace{E_t[i_{t+n}]}_{\text{EH term}}, \tag{2}$$

[9]Going forward, we let "short rate" refer to the average realized EFFR over a given horizon n.

by which it becomes evident that the rate on FF futures consists of a maturity-specific term premium, as well as market participants' expectations of the future short rate, the EH term. As such, an upward-sloping (downward-sloping) term structure of FF futures rates signals that market participants expect either high (low) excess returns, high (low) future short rates, or a combination of the two (see e.g., Sack, 2004, Piazzesi and Swanson, 2008, and Hamilton and Okimoto, 2011).

We also analyze OIS, which have emerged as a popular alternative instrument to FF futures in the US and other major currency areas.[10] OIS have been traded in the US since 2001, and while the market for FF futures is deep and highly liquid for maturities up to six months, OIS trade with liquidity for much longer horizons (Tuckman and Serrat, 2011). OIS are traded over the counter and have various advantages over futures as they, for example, allow for more granular hedging of risk exposures.[11] Similar to FF futures (but with slightly different market conventions), an investor who has taken a long position in OIS will receive payments based on a fixed swap rate known at t and make payments based on the short rate that is realized over the contract's maturity.

The fixed OIS rate, like that of FF futures, contains market participants' expectations about future excess returns and short rates. But OIS differ in two important respects. First, while FF futures settle against the short rate in a specific future month, OIS settle against the *path* of the short rate from contract inception time t until maturity $t+n$. Second, OIS contracts more granularly hedge the risk of rolling loans at the short rate because the accumulation of floating leg payments includes compounding. For simplicity, we use the same notation for FF futures and OIS throughout the paper, but emphasize that the contracts differ in the key respects listed here. Internet Appendix IA.1 provides detailed information on the exact excess return computations for both contract types.

[10]For example, an OIS denominated in EUR uses the EONIA as the floating rate. An OIS denominated in GBP uses SONIA as the floating rate and so forth.

[11]While OIS are traded over the counter, they are generally regarded as free of counterparty credit risk because of collateral requirements and netting, see Duffie and Huang (1996) and Sundaresan et al. (2016). In the interdealer market, variation margin is standardized (regulated by the CSA). This implies that pricing is homogeneous across banks such that the OIS rate paid by, say, JP Morgan will be the same as that paid by, say, Deutsche Bank.

2.2. Decomposing Excess Returns

It is well known that the rates on money market derivatives exceed realized future short rates, and this wedge is commonly ascribed to the presence of term premia. To see how term premia contribute to realized excess returns, substitute the FF futures or OIS rate in Eq. (2) into the expression for excess returns in Eq. (1) and re-arrange,

$$rx_{t+n}^{(n)} = \underbrace{\Big(E_t[rx_{t+n}^{(n)}] + E_t[i_{t+n}]\Big)}_{f_t^{(n)}} - i_{t+n} = \underbrace{E_t[rx_{t+n}^{(n)}]}_{\text{term premium}} + \underbrace{(E_t[i_{t+n}] - i_{t+n})}_{\text{expectation error}}. \tag{3}$$

Here, $E_t[rx_{t+n}^{(n)}]$ is the term premium and $E_t[i_{t+n}] - i_{t+n}$ is the difference between the expected and realized short rate over horizon n, the short rate expectation error.

Under the FIRE assumption, market participants do not make systematic errors in their forecast of the short rate. In this case, Eq. (3) shows that future realized excess returns therefore reflect market participants' required compensation for the risk of entering into the contract, $rx_{t+n}^{(n)} = E_t[rx_{t+n}^{(n)}]$, the term premium. The underlying assumption about short rate forecasts, however, is neither innocuous nor in line with evidence on investors' short rate expectations (e.g., Piazzesi et al., 2015; Guidolin and Thornton, 2018; Cieslak, 2018; Brooks et al., 2018). To the extent that errors in short rate expectations play a role, they contribute to excess returns by an amount which is *unexpected* at the time when the contract is signed. To see this, move the term premium to the left-hand side of Eq. (3):

$$\underbrace{rx_{t+n}^{(n)} - E_t[rx_{t+n}^{(n)}]}_{\text{unexpected return}} = \underbrace{E_t[i_{t+n}] - i_{t+n}}_{\text{expectation error}}. \tag{4}$$

Eq. (4) shows that if ex-post realized excess returns differ from what was required ex-ante, this must be driven by short rates being different from what market participants had expected them to be. More specifically, those with a long position will earn *unexpectedly high* returns when short rates turn out to be unexpectedly low. As documented in the following sections, this relation proves highly important for understanding why excess returns on money market derivatives have been positive over our sample.

2.3. Survey-Based Decomposition

We use survey data to quantify the importance of expectation errors and term premia for money market excess returns. To measure short rate expectations, we use interest rate forecasts from the Blue Chip Financial Forecasts survey. From the survey, we obtain fixed-horizon short rate expectations for $n = 3, 6, 9$, and 12 months, denoted $S_t^{(n)}$.[12] For FF futures and OIS of horizon n, we decompose excess returns by simply adding and subtracting survey expectations with the same horizon from the right-hand side of Eq. (1),

$$rx_{t+n}^{(n)} = \underbrace{f_t^{(n)} - S_t^{(n)}}_{\mathrm{TP}_t^{(n)}} + \underbrace{S_t^{(n)} - i_{t+n}}_{\mathrm{EE}_{t+n}^{(n)}}, \tag{5}$$

which is the survey-based analogue to the decomposition in Eq. (3). Here, $\mathrm{TP}_t^{(n)} = f_t^{(n)} - S_t^{(n)}$ measures the survey-implied term premium and is equal to the amount by which FF futures or OIS rates deviate from expected short rates over the maturity of the contract. Furthermore, $\mathrm{EE}_{t+n}^{(n)} = S_t^{(n)} - i_{t+n}$ is the expectation error, defined as the difference between expected and realized short rates over the same horizon. Importantly, because it is based on future short rate realizations, the expectation error component is not fully known until time $t + n$. On the other hand, the term premium is priced in at contract inception and therefore observable at time t.

Table 1 presents estimates of the size and significance of excess returns, term premia, and expectation errors for FF futures and OIS. We obtain historical FF futures prices and OIS quotes from Bloomberg. For FF futures, the data go back to 1990, while OIS rates are available for the US since December 2001.[13] For both series, the sample ends September 2021. For FF futures, we compute average excess returns on contracts with maturities $n = 3$ and 6 months. For OIS, we focus on contracts with maturities $n = 3, 6, 9$, and 12 months to match the available survey forecast horizons. See Internet Appendix IA.3 for more details on the matching of FF futures and OIS with survey data.

[12] Additional details on the Blue Chip survey is found in Internet Appendix IA.2. We use the mean of individual forecasts, but the results of the following decomposition are robust to using the median instead.

[13] Data on the US short-term interest rate, the EFFR, are from the Federal Reserve Bank of New York. FF futures have been traded since October 1988, but we exclude the first two years due to infrequent trading, as is common in the literature. For both FF futures and OIS, we construct time series of constant-maturity rates by sampling the data end of month. As such, we focus on data with a monthly frequency throughout the paper.

>>> TABLE 1 ABOUT HERE <<<

Panel A of Table 1 shows that mean excess returns are economically sizable and in the range of 4 to 18 basis points for both instruments. This demonstrates that for both FF futures and OIS, the forward-looking term rates systematically *exceed* subsequent short rate realizations. Next, we surprisingly see that survey-implied term premia are slightly *negative*. Meanwhile, average expectation errors are similar in magnitudes to realized excess returns and statistically significant across all maturities. Expectation errors thus appear to be a more important driver of excess returns than term premia. Moreover, Panel B quantifies how much of excess return variation is explained by expectation errors and term premia, respectively, using a simple variance decomposition. This exercise further cements the prominent role of expectation errors: while term premia are uncorrelated with excess returns over time, expectation errors account for essentially all of the excess return variation.[14]

>>> FIGURE 1 ABOUT HERE <<<

To see how excess returns and expectation errors correlate over time, Figure 1 plots excess returns on FF futures together with expectation errors.[15] As can be gleaned from the figure, the two components are tightly linked and covary significantly. It can also be observed that a steady decrease in the size and variability of excess returns and expectation errors took place during the 1990s, which is solidly documented in the literature (e.g., Poole et al., 2002; Lange et al., 2003; Swanson, 2006) and attributed to the Fed taking deliberate steps towards becoming more transparent in its communication and therefore easier to predict. Second, excess returns and expectation errors spike at the beginning of 2001, during 2008, as well as around the COVID-19 crisis in 2020, i.e., in periods of recession. As such, following the Fed's move towards greater transparency, excess returns and expectation errors appear to emerge primarily during economic downturns.

[14] Table IA.3 in the Internet Appendix shows that expectation errors and term premium estimates are robust to being computed based on survey expectations from Reuters Central Bank Polls instead of Blue Chip.

[15] Equivalent plots of expectation errors for OIS are found in Internet Appendix IA.1. Plots of survey-implied term premia are found in Internet Appendix IA.2 and IA.3.

3. Diagnosing Monetary Policy Expectation Errors

To provide a better understanding of these expectation errors, this section provides a detailed look into how they arise and what their implications are for excess returns. To this end, we start with regression-based tests of the EH and then turn to an analysis of asymmetries in the ability of market participants to predict future short rates.

3.1. Expectations Hypothesis Tests

Recall from Eq. (2) that the slope of the term structure of FF futures and OIS rates must reflect expectations of term premia and/or future short rates. To quantify the importance of each of these two components, we regress future realized short rates and excess returns on FF futures and OIS rates. Consider the regression equations,

$$\Delta i_{t+n} = \alpha^{(n)} + \beta^{(n)} \varphi_t^{(n)} + \varepsilon_{t+n}^{(n)}, \tag{6}$$

$$rx_{t+n}^{(n)} = \theta^{(n)} + \delta^{(n)} \varphi_t^{(n)} + \eta_{t+n}^{(n)}, \tag{7}$$

where $\Delta i_{t+n} = i_{t+n} - i_t$ is the future change in short rates from t to $t+n$, and $\varphi_t^{(n)} = f_t^{(n)} - i_t$ is the "term spread" based on the FF futures or the OIS curve. Eq. (6) is the money market equivalent to the classical regression by Campbell and Shiller (1991) to test the validity of the EH in the bond market. In our context, evidence that the slope coefficient is significant, $\beta^{(n)} \neq 0$, shows that the money market term spread contains important information about future short rates. Moreover, evidence that $\alpha^{(n)}, \beta^{(n)} = 0, 1$ shows that the EH holds, i.e., that the term spread only reflects expectations about future short rates and contains no term premium.

If, on the other hand, the term spread contains a time-varying term premium, this component will deteriorate its forecasting performance and lead to estimates of $\beta^{(n)}$ that are significantly different from unity. Specifically, the term spread will predict future excess returns with a coefficient that is directly proportional in size to the deviation from the EH in the short rate regression, $1-\beta^{(n)}=\delta^{(n)}$, see, e.g., Fama and Bliss (1987) and Gürkaynak et al. (2007).[16] To further test if term premia are an important component of FF futures and OIS, we therefore regress future excess returns on the term spread in Eq. (7). Here, a significant slope coefficient, $\delta^{(n)}\neq 0$, is evidence that the term spread predicts future excess returns, and thus that a significant part of FF futures and OIS rates consists of term premia.

>>> TABLE 2 ABOUT HERE <<<

Table 2 presents the results for Eqs. (6) and (7). Turning first to Panel A, we see that all FF futures and OIS spreads significantly predict future short rates.[17] All of the estimated slope coefficients are positive and statistically different from zero and R^2s are as high as 71%. However, while these results show that term spreads are highly informative about future short rates, they also reveal that the spreads do not forecast in accordance with the EH. Specifically, we find all slope coefficients to be significantly *larger* than one. To give an example, for the 12-months-ahead OIS, the estimated slope coefficient is $\beta^{(n)}=1.44$. As such, a predicted 1% change in short rates is, on average, followed by a 1.44% realization. The fact that the slope coefficients exceed unity shows that market participants tend to underestimate future short rate changes. Moreover, the size of the deviation increases with the forecast horizon, showing that forecasting short rates becomes increasingly difficult as the forecast horizon lengthens.

The results in Panel B of Table 2 show that term spreads are also significant predictors of future excess returns. Across all horizons, the estimated slope coefficients are significantly different from zero and of magnitudes consistent with the relation $1-\beta^{(n)}=\delta^{(n)}$. However, this implies that the term spread predicts excess returns with a *negative* coefficient. This finding is surprising, since we know from Eq. (3) that the spread should be positively related to future excess returns if these are driven by term premia.

On the other hand, a negative relation between returns and the term spread may indeed arise

[16]From the relation $1-\beta^{(n)}=\delta^{(n)}$, it is straightforward to see that when term spreads predict short rates in accordance with the EH, $\beta^{(n)}=1$, the slope coefficient in the regression of future excess returns must be zero, i.e. no excess return predictability. In this case, term spread variation is driven entirely by changes in expected future short rates and contains no information about future excess returns.

[17]For consistency with the previous section, the remaining part of the paper focuses on average FF futures rates targeting the short rate from t to $t+n$ rather than individual futures rates targeting the short rate in a specific future month. See Internet Appendix IA.3 for more details. In unreported results, we find that all the results and conclusions presented in this paper are robust to analyzing the individual futures rates as well.

in the data if realized excess returns are driven by expectation errors. To see this, decompose the independent and dependent variables in Eq. (7) into their constituent parts. Following Eq. (3), excess returns consist of a term premium and the expectation error. Following Eq. (2), the term spread also consists of a term premium as well as the expected change in the short rate. Assuming that term premia are negligible, the dependent variable in the regression becomes the expectation error, $E_t[i_{t+n}] - i_{t+n}$, while the independent variable becomes the expected short rate change, $E_t[i_{t+n}] - i_t$. If market participants systematically *underestimate* short rate changes (as our previous evidence suggests), a negative relation between these two components arises mechanically.

For example, when the term spread is positive (i.e. market participants expect rate hikes), the subsequent expectation error is negative because the realized short rate *exceeds* what was expected ex-ante. Similarly, when the spread is negative (i.e. market participants expect rate cuts), the expectation error becomes positive since the realized short rate is below its expected value. As such, the systematic underestimation of changes in short rates induces a negative relation between the term spread and future excess returns. Such evidence that the term spread predicts excess returns with a negative coefficient lends further support to the view that excess returns are driven by expectation errors and not term premia.

3.2. Asymmetric Short Rate Predictability

To further diagnose the predictability pattern, we graphically illustrate the relation between the predicted and realized short rates in Figure 2.

$>>>$ FIGURE 2 ABOUT HERE $<<<$

Predicting the Direction of Short Rate Changes Figure 2 plots the predicted (x-axis) and realized (y-axis) short rate changes for FF futures.[18] Each subplot is divided into four quadrants; the two upper quadrants show when the short rate increased, i.e., where $\Delta i_{t+n} = i_{t+n} - i_t$ was positive, while the two below show when the short rate decreased. Meanwhile, the two quadrants on the right show when market participants anticipated short rate increases, i.e.,

[18] Figure IA.4 in the Internet Appendix gives the equivalent plots for OIS.

where $\varphi_t^{(n)} = f_t^{(n)} - i_t$ was positive, while the two on the left show when they expected declines.

First, consider the two quadrants on the diagonal. The observations here denote when market participants correctly anticipated the direction of the short rate: observations in the upper-right quadrant capture when they correctly predicted short rate increases, while observations in the lower-left capture when they correctly predicted declines. Across all the contract horizons, we see that most of the observations are found in these two quadrants. Taking the 6-months-ahead FF futures as an example, 47% of the observations (upper-right) comprise correctly predicted short rate increases, while 30% of the observations (lower-left) reflect correctly predicted short rate declines.[19]

Next, consider the two off-diagonal quadrants. The observations here represent times when market participants failed to anticipated the direction of the short rate. When it comes to short rate increases, we only observe a handful of cases when market participants were surprised by short rate hikes (upper-left quadrant). Taking again the 6-months-ahead FF futures as example, we see only 4% of the observations are located here. On the other hand, a strikingly large proportion of the observations are found in the lower left quadrant, 18%, and denote short rate cuts that were unanticipated six months before they occurred. This pattern applies to both derivatives instruments, with the number of unexpected rate cuts increasing with the forecast horizon. In fact, for the 12-months-ahead OIS, the amount of unanticipated short rate cuts even exceeds the number of anticipated ones, highlighting a strong asymmetry in market participants' ability to predict the short rate depending on whether it increased or decreased.

Predicting the Magnitude of Short Rate Changes It is also instructive to assess *by how much* the predictions implied by money market term spreads deviate from the actual realizations. To this end, consider the deviations from the 45-degree line in the previous figure.[20] Many large deviations from the line are seen in the lower-left quadrant, i.e. when market participants correctly predicted that the short rate would decrease, but miscalculated the magnitude of the subsequent decrease. Therefore, to investigate if there is also asymmetry in the ability to predict the magnitude of short rate changes, in Table IA.5 in the Internet Appendix we

[19]Table IA.4 in the Internet Appendix provides a summary of these figures.

[20]The line shows to what extent, when market participants correctly predict the direction of the short rate, they are also able to forecast the magnitude of the change correctly. Observations exactly on the line are when market participants predicted the short rate with no error.

analyze how many times market participants correctly predicted an increase or a decrease, but underestimated the size of the change by either 25 or 100 basis points.[21]

This analysis reveals that market participants were often surprised by *how large* short rate cuts turned out to be during our sample period. For the 6-months-ahead FF futures, when the short rate was correctly predicted to go up, market participants underestimated the magnitude of the increase by at least 25 basis points in only 4% of the cases. However, when market participants correctly predicted a decreasing short rate, they subsequently underestimated the magnitude of the decrease by at least 25 basis points in 36% of the cases. As such, the tendency to underestimate short rate changes was much more pronounced when rates declined.[22]

Asymmetry in Expectations Hypothesis Tests In the Internet Appendix IA.4, we provide regression-based evidence that further cement this strong asymmetry. By interacting the term spreads in Eqs. (6) and (7) by their own sign, we find that when market participants expect short rate hikes, i.e., that the term spread is positive, we fail to reject the EH across all forecast horizons. However, and in line with the above narrative, when market participants expect rate cuts and the term structure is inverted, the EH is systematically rejected.

Because underestimating short rate cuts leads to positive excess returns, this should entail that a negative term spread is a strong predictor of future positive excess returns. We also find that to be the case empirically: while a positive term spread contains no information about future returns, an inverted term spread predicts excess returns with a negative coefficient across many horizons. As such, these results further highlight that excess returns appear to be driven by market participants underestimating short rate cuts in periods of economic downturn, while term premia are of minor importance.[23]

[21]Note that these thresholds refer to the overall rate change over horizon n, and not necessarily a single hike or cut.

[22]In Table IA.5 in the Internet Appendix, we count how many times market participants underestimate the change by 100 basis points or more. While market participants never underestimated short rate hikes by 100 basis points or more, they did so for short rate cuts a significant number of times.

[23]Internet Appendix IA.5 shows what these results imply for investor's expectations formation. Running augmented regressions in the spirit of Coibion and Gorodnichenko (2012), we find that investors form expectations of future rate hikes in accordance with the FIRE assumption, but face significant information rigidities ahead of interest rate cuts. Rather than taking this as evidence of irrational expectations, in the remaining part of the paper we trace this result to incomplete knowledge about the central bank reaction function in real time—an issue which is particularly relevant in the case of aggressive rate cuts amid economic downturns.

Taken together, these results reveal a striking asymmetry in predictability: while short rate hikes seem to have been fairly easy to predict, market participants have often been surprised by the Fed's rate cuts. This surprise is both in terms of the *timing* as well as the *size* of rate cuts, and manifests itself as a positive mean excess returns over the sample period.

4. Expectation Errors and the Fed's Reaction Function

What economic mechanisms give rise to these unexpected monetary policy rate cuts? In this section, we dig deeper into the link between the observed patterns and the Fed's reaction function. More specifically, we: (i) investigate the relation between expectation errors and short rate deviations from the Taylor rule, (ii) consider how expectation errors relate to financial conditions (that may play a role either as a separate ingredient in the central bank's reaction function or in providing early signals about the inputs of the policy rule), and (iii) explore the connection between uncertainty (as captured by the dispersion of forecaster beliefs), large shocks, and expectation errors.

4.1. Expectation Errors and the Taylor Rule

While historical transcripts from FOMC meetings suggest that by the late 1980s, the committee had begun using the federal funds rate as a policy instrument in the sense of a Taylor-type rule (Thornton, 2006), studies show that the Fed has paid attention to several different economic variables over time (e.g., Christiano et al., 1994; Cochrane and Piazzesi, 2002; Rigobon and Sack, 2003; Ravn, 2012; Cieslak et al., 2019; Cieslak and Vissing-Jorgensen, 2021). This indicates that the actual policymaker reaction function is unlikely to be time-invariant, but may at times include variables other than those featured in common monetary policy rules. Further, while the variables considered by the policymakers may change, the weights assigned to them in the reaction function may also vary over time, see Ang et al., 2011; Bauer and Swanson, 2020; Andreasen et al., 2021.

In this subsection, we find that periods when the Fed has deviated from the conventional Taylor rule coincide with times of high excess returns and survey-based expectation errors. To show this, we first estimate a benchmark Taylor rule and compute the deviation of the actual short rate from this model-implied level ("Taylor rule deviation"). We then test if this Taylor rule deviation is significantly correlated with excess returns and expectation errors.

As shown by Orphanides (2001), failing to account for publication lag and data revisions in macroeconomic time series can significantly impact the outcome when estimating the Taylor model. We therefore use vintage data and estimate the Taylor-implied short rate as the fitted values from the regression:

$$i_{t+n} = \alpha_{t+n} + \beta_{t+n} u_{t+n} + \gamma_{t+n} \pi_{t+n} + \varepsilon_{t+n}, \tag{8}$$

where u_{t+n} is the unemployment rate, π_{t+n} is the rate of inflation, and the parameters are estimated recursively. This approach improves upon the classical Taylor rule (where a set of fixed parameters is assumed to capture the relation between the short rate and its fundamental determinants), by estimating the short rate as a function of the macroeconomic data that were available to policymakers and market participants in real time.[24] Then, to quantify if monetary policy is easy or tight, we subtract the actual short rate from its model-implied level,

$$\psi_{t+n}^{\text{Taylor}} = \widehat{i}_{t+n} - i_{t+n}, \tag{9}$$

such that the deviation, $\psi_{t+n}^{\text{Taylor}}$, is high when the short rate falls below the level implied by the Taylor rule and vice versa.

>>> TABLE 3 ABOUT HERE <<<

Table 3 shows that there is a close relationship between Taylor rule deviations and both excess returns and expectation errors. The first row in the table reports their contemporaneous correlations with excess returns on FF futures and OIS. These correlations are positive and statistically significant, and reach up to 24% for the contracts with the longest maturities. The

[24] We follow Evans et al. (1998) and use unemployment instead of GDP growth because of its higher data frequency. We estimate Eq. (8) recursively, using an expanding window of observations, with the first estimation window containing 10 years of historical data. In our implementation, we use seasonally adjusted vintage data for unemployment and inflation (computed as the year-on-year growth in the CPI index excluding food and energy), both from the ALFRED database.

second row in the table shows that the Taylor rule deviations and expectation errors are also significantly positively correlated, reaching up to 35%.[25] Taken together, these results reveal that excess returns and expectation errors arise in periods where the Fed deviated from the Taylor rule. Furthermore, the positive correlations show that they are particularly high in periods where the short rate falls below the Taylor-rule-implied level.

4.2. Financial Conditions and Uncertainty About the Fed's Reaction Function

What drove the Fed to aggressively cut interest rates to market participants' surprise? In a recent paper, Cieslak and Vissing-Jorgensen (2021) use FOMC minutes and transcripts to show that the Fed monitors not only macroeconomic variables, but also pays attention to the stock market when setting the policy rate.[26] A plausible explanation in our context could be that Fed reacted preemptively to deteriorating financial conditions that were signaling stress to come, even as hard data on macroeconomic activity were not yet pointing to a slowdown.

This interpretation is consistent with former New York Fed president Bill Dudley's own characterization of the Fed's actions in response to the collapse of Lehman Brothers: *"Given the rapid deterioration in financial conditions, instead of following the prescription from these [different variants of Taylor] rules, the FOMC cut the federal funds rate rapidly over the next three months, pushing the federal funds rate down to a range of 0 to a quarter of 1 percent by year-end"* (Dudley, 2017).[27] As such, if policymakers indeed paid close attention to financial conditions when setting monetary policy, but market participants had incomplete knowledge about its relevance for the central bank reaction function, indicators of financial conditions should have ex-post predictive power for expectation errors and excess returns. To shed light

[25]Figures IA.5 and IA.6 in the Internet Appendix show the time series of Taylor rule deviations together with excess returns and confirm their close link over time. For robustness, Table IA.6 in the Internet Appendix shows that excess returns and expectation errors remain strongly correlated with Taylor rule deviations, when the Taylor-implied short rate is computed based on economically motivated parameters.

[26]See also Rigobon and Sack (2003) who use identification through heteroscedasticity and find a statistically significant monetary policy response to the stock market, and Ravn (2012) who uses similar methods to document that the response is asymmetric. In a similar vein, Peek et al. (2016) find that financial conditions are increasingly referred to in monetary policy announcements and Adrian et al. (2019) document significant welfare gains from including financial conditions along with Taylor rule variables in a policy setting framework.

[27]In his speech, Dudley further notes that *"Because the interactions can shift between financial conditions and the economic outlook - as well as between financial conditions and the federal funds rate - the absence of financial conditions in [the Taylor rule] can cause it to perform poorly as a guide for monetary policy"* (Dudley, 2017).

on this conjecture, we run predictive return regressions of the form,

$$rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)} x_t + \gamma^{(n)} z_t + \varepsilon_{t+n}^{(n)}, \tag{10}$$

where $rx_{t+n}^{(n)}$ is the excess returns on either FF futures or OIS, x_t is an indicator of financial conditions and z_t contains control variables from the literature. In Table 4 we analyze if excess returns on FF futures and OIS can be predicted by one crucial component of financial conditions, namely the return on the stock market. We initially set $\gamma = 0$ and regress future excess returns on FF futures and OIS on current excess returns on the S&P500 index. Subsequently, we regress stock returns together with a range of variables suggested to capture possible term premium variation in money market derivatives: the year-on-year growth in employment, the corporate credit spread and the Treasury yield spread (Piazzesi and Swanson, 2008).[28]

>>> TABLE 4 ABOUT HERE <<<

Panel A of Table 4 shows the estimated slope coefficients and R^2s from Eq. (10) and reveals that the stock market is in fact a strong predictor of excess returns. The magnitude of the estimated coefficients shows that a monthly ten-percent drop in stock returns predicts excess returns on FF futures and OIS of up to 19 basis points with a strongly significant signal across all contract horizons.

We also investigate if the stock market remains a robust predictor when controlling for variables capturing business cycle risk (Panels B-D). In Panel B, we run a horse race between the stock market and growth in nonfarm employment. These regressions reveal that the stock market completely subsumes the information in this business cycle variable, while the magnitude of the estimated coefficient on the stock market remains almost unchanged. The same is true in Panels C and D where we include the credit and Treasury yield spread, showing that the stock

[28]To mimic the information available to financial market participants in real time, we compute the year-on-year growth in nonfarm payroll employment using vintage data from the Philadelphia Fed. Two issues arise in this respect. First, nonfarm payroll numbers for a given month are not released until the first week of the next month, and we therefore have to lag the data by one month in order to avoid look-ahead bias. Second, since the data undergo revisions following their initial release, we compute year-on-year growth rates using the first release of nonfarm employment for month $t-1$ and the revised value for month $t-13$, as is common in the literature. The credit spread is the difference between Moody's seasoned Baa corporate bond yield relative to the yield on 10-year Treasuries, and the Treasury yield spread is the difference between the yield on 10-year and 2-year Treasury bonds. All financial series are from the FRED database.

market provides a powerful signal about future excess returns over and above the information contained in these predictors.

>>> TABLE 5 ABOUT HERE <<<

There is reason to suspect that the effect of the stock market is asymmetric. Such a pattern could arise if the Fed forcefully reacted only to negative, but not positive, stock returns—in line with a so-called central bank put. Alternatively, it could stem from the Fed reacting to large, negative shocks, that are associated with a sharp deterioration in financial conditions (see also the discussion in Section 4.3 below). To test this, we introduce a modified version of the predictive return regression in Eq. (10),

$$\begin{aligned} rx_{t+n}^{(n)} = \alpha_{POS}^{(n)} 1_{\{rx_t^{\text{S\&P500}}>0\}} + \beta_{POS}^{(n)} rx_t^{\text{S\&P500}} 1_{\{rx_t^{\text{S\&P500}}>0\}} \\ + \alpha_{NEG}^{(n)} 1_{\{rx_t^{\text{S\&P500}}\leq 0\}} + \beta_{NEG}^{(n)} rx_t^{\text{S\&P500}} 1_{\{rx_t^{\text{S\&P500}}\leq 0\}} + \varepsilon_{t+n}, \end{aligned} \tag{11}$$

where we interact the independent variable with indicator variables that measure its sign. Specifically, the dummy variable $1_{\{rx_t^{\text{S\&P500}}>0\}}$ takes the value one when stock returns are positive, while the dummy variable $1_{\{rx_t^{\text{S\&P500}}\leq 0\}}$ takes the value one whenever stock returns are zero or negative. Table 5 presents the results from Eq. (11) and confirms the conjecture that the link between stock market returns and subsequent excess returns is highly asymmetric. While positive stock market movements have no relation with future excess returns, negative stock returns contain strong and significant predictive information. The estimated slope coefficients for negative stock returns are also negative as expected: as the stock market drops, the Fed cuts interest rates more than expected by market participants, which in turn leads to positive returns on FF futures and OIS.

4.3. Uncertainty, Rare Negative Shocks, and Expectation Errors

Our results so far show that market participants, over the course of our three-decades long sample, systematically underestimated the extent to which the Fed would cut rates in the wake of low stock returns. A natural interpretation of these findings is that market participants had to learn about the Fed's reaction to large, negative shocks typically accompanied by deteriorating financial conditions, and that they were surprised by the magnitude by the central bank's monetary policy easing in these periods. While market participants' knowledge about the central bank's reaction function is incomplete also in normal periods (see, e.g., Bauer and Swanson, 2020), it is especially the response to "rare disaster"-type events, which occur infrequently by definition, that market participants have the least information about.

To examine this interpretation, the results in Table IA.7 in the Internet Appendix show that mean excess returns on all FF futures and OIS contracts are strongly statistically significant in recessions and of magnitudes many times greater than in economic expansions.[29] As such, the lion's share of excess returns stems from a handful of large negative shocks such as the Great Financial Crisis in 2008 and the COVID-19 shock in March 2020, i.e., episodes that saw a sharp deterioration in financial conditions. This unambiguously shows that expectation errors arise because market participants underestimated the Fed's rate cuts in response to large, negative shocks. Next, we turn to the link between expectation errors and uncertainty, which we proxy for by computing the dispersion in short rate forecasts across respondents in the Blue Chip survey. If market participants have incomplete knowledge about the Fed's reaction function and had to learn over time how the Fed would respond to these negative shocks, we would expect (i) disagreement/uncertainty about the outlook for monetary policy to be highest during times of large shocks and (ii) that survey expectations overestimate future short rates the most during these episodes. To test this, we run the following predictive regression:

$$rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)}\text{Disagreement}_t^{(n)} + \epsilon_{t+n}^{(n)}, \tag{12}$$

where disagreement at each time t is computed as the difference between the 90th and the 10th percentile of individual short rate forecasts for horizon n.[30] Table 6 provides results from this test.

>>> TABLE 6 ABOUT HERE <<<

Interestingly, the results in Table 6 show that high forecaster uncertainty is associated with

[29]In fact, excess returns are not statistically significant outside recessions, except for FF futures were the sample is longer and contains data from the early period where the Fed was making changes to its policy implementation and communication, as discussed in Section 2.3.

[30]We note that the results from the subsequent regressions are robust to using the standard deviation as measure of disagreement instead.

higher expectation errors going forward, i.e., forecasters *underestimate* the extent of future rate cuts exactly at those in times when they are most uncertain about the future course of monetary policy. Conversely, in times of low forecast uncertainty, expectation errors are muted and the Fed does not tend cut rates more than expected. A striking feature of the results in Table 6 is that forecast dispersion is a strong predictor of excess returns on FF futures and OIS, on par with stock returns (see Table 4 above). For example, at a 12-month forecast horizon, the R^2 in a regression of excess returns on forecast dispersion is 19%. Importantly, this result does not simply imply that high forecast uncertainty comes along with high subsequent forecast errors but rather that high forecast uncertainty is followed by short rates systematically dropping below what had been previously anticipated.

>>> FIGURE 3 ABOUT HERE <<<

To see how excess returns and expectation errors correlate over time, Figure 3 plots excess returns on FF futures together with forecaster disagreement. As can be seen from the figure, disagreement and future excess returns move together closely.[31] Overall, these results lend credence to the view that significantly positive excess returns observed in money markets stem from difficulties faced by market participants when learning about the Fed's reaction to large, but infrequent, negative shocks in real-time.

5. International Evidence, Additional Tests, and Robustness

Next, we analyze whether the main findings of our paper are exclusive to the US or whether excess returns can be attributed to monetary policy expectation errors internationally as well. Moreover, we also analyze our main results from various additional angles and document the results of robustness checks.

International Evidence Our international analysis focuses on advanced economies with sufficiently deep OIS markets. We relegate information on data sources and sample sizes to Appendix IA.6.

[31]Equivalent plots for excess returns on OIS and forecaster disagreement are found in Internet Appendix IA.7.

>>> TABLE 7 ABOUT HERE <<<

Table 7 reports the average excess returns on international OIS (with maturities $n = 3, 6, 9$, and 12 months) for a panel of major currency areas. In line with the previous results, the estimates of mean excess returns are almost all positive and of similar sizes to those in the US, and either statistically significant or marginally significant.

>>> TABLE 8 ABOUT HERE <<<

Having established the existence of positive OIS excess returns outside the US, we test whether these returns are also predominantly driven by short rate expectation errors. To this end, we use Reuters Central Bank Polls for the currency areas where the survey is available for sufficiently long samples (the euro area, the United Kingdom and Switzerland). If excess returns are related to unexpected easing decisions by the respective central banks, we should see a significant correlation with expectation errors. For plots of excess returns with expectation errors, see IA.8, IA.9 and IA.10 in the Internet Appendix. Table 8 shows that excess returns and expectation errors are indeed strongly correlated in this international sample.[32] Correlations at all maturities and across all currency areas are highly statistically significant, and especially high for longer-horizon expectations (up to 97%).

>>> TABLE 9 ABOUT HERE <<<

In Table 9 we test the predictability of excess returns on international OIS, using the local stock market as an indicator of financial conditions. The results show a remarkable degree of homogeneity: In all currency areas, the stock market is a strong predictor of future excess returns, with estimated coefficients almost identical in size to those found in the equivalent regressions for the US.

[32]The correlation is relatively low for the EU three-month horizon. This is because respondents in the Reuters survey are asked to predict the European Central Bank Main Refinancing Rate (MRO) and not the EONIA which OIS settle against in the euro area. While the EONIA is a market rate determined by interbank unsecured transactions, the MRO is a policy rate that was floored at zero for large parts of the sample period. Due to excess liquidity created by the ECB's asset purchases and lending programs, EONIA fluctuated more closely in line with the rate of the ECB's deposit facility rate (DFR). This creates different circumstances under which survey respondents and market participants forecast, and the discrepancy is strongest at the three-month horizon. Despite this fact, the correlation at this maturity remains relatively high and statistically significant.

To summarize, we find broadly similar results when considering a sample of international OIS. We find that mean excess returns are primarily positive in other major currency areas, and that these positive excess returns can be attributed to short rate expectation errors. We further show that local stock markets all constitute strong predictors of future excess returns. This suggests that the fundamental mechanisms unveiled in this paper are part of a broader phenomenon and not confined to Fed policy.

Out-of-Sample Evidence As documented by Goyal and Welch (2008), variables that are found to forecast returns accurately in-sample do not necessarily do so in real time. Table IA.8 in the Internet Appendix therefore tests the out-of-sample predictive power of the stock market and the alternative predictor variables from the literature. The results here strongly support that the stock market has been a powerful predictor of excess returns over the past three decades: while none of the alternative predictor variables consistently outperform the EH benchmark, R^2_{OOS} statistics for the stock market are positive and statistically significant for excess returns across all horizons.

Other Measures of Financial Conditions Since there is reason to believe that the Fed not only monitors equity prices, but also considers a broad range of financial indicators when setting policy, Table IA.9 in the Internet Appendix tests if the predictive results obtained in the previous sections are robust to using an alternative measure of financial conditions: the Chicago Fed's National Financial Conditions Index (NFCI). The NFCI is constructed from 101 financial indicators, including the TED spread, the VIX index, Treasury and stock market options, and various repo spreads (Brave and Butters, 2011). The results in this table show that return predictability remains high when using this alternative measure of financial conditions. Furthermore, the estimated coefficients take the expected sign: deteriorating financial conditions (high index values) predict excess returns with a positive and strongly significant coefficient, consistent with the idea that periods of deteriorating financial conditions precede unexpected rate cuts and therefore high excess returns on FF futures and OIS.

Tests With Survey-Based Expectation Errors Tables IA.10 and IA.11 in the Internet Appendix report the results from estimating Eqs. (10) and (11) using survey-based expectation errors as the dependent variable instead of excess returns. These results are remarkably similar to the previous results, with coefficient estimates of the same sign and almost identical in size and significance, providing further support for the idea that excess returns are driven by expectation errors.

6. Conclusion

How market participants form expectations about future monetary policy is crucial to macroeconomics and finance. In this paper, we use survey data on monetary policy expectations to understand why key money market derivatives – fed funds futures and overnight index swaps – are biased predictors of the future short rate. This bias means that long positions in these instruments have on average delivered positive excess returns over the last three decades.

We document that the biased expectations and positive excess returns stem from market participants underestimating the size of the Fed's interest rate cuts in response to large, but infrequent, negative shocks. These episodes go hand in hand with deteriorating financial conditions, declining stock prices, and high uncertainty about the future course of monetary policy. Consequently, we show that a fall in stock returns predicts high excess returns, because market participants underestimate the extent to which the Fed would cut rates in response to these shocks. Importantly, there is a strong asymmetry in this relationship: whereas lower stock prices strongly predict higher excess returns (both in-sample and out-of-sample), higher stock prices do not predict unexpected rate hikes and subsequently low excess returns. Similarly, high disagreement about future short rates, which is related to the extent of forecasters' uncertainty about the monetary policy outlook, is systematically followed by higher excess returns and expectation errors. Taken together, this suggests that market participants have historically underestimated the aggressiveness of monetary policy during periods of large and negative shocks when uncertainty was at its highest, giving rise to the positive excess returns observed over our sample.

The results in our paper have implications for several areas in macroeconomics and finance. First, from an asset pricing perspective, our finding that FF futures and OIS, at least in normal environments, emerge as more reliable gauges of monetary policy expectations than previously appreciated in the literature, rehabilitates the expectations hypothesis for short-term interest rates. According to our new interpretation, most of the excess returns observed in the data can be traced to a handful of large, negative shocks from the late 1990s to 2021 and the extraordinary easing response by central banks, rather than being due to irrational behavior or risk premia. Second, our results have implications for the broader literature on monetary policy and macroeconomics in that they provide support for models featuring strong asymmetries, for instance due to occasionally binding financial constraints or rare disasters that come along with spikes in uncertainty. Third, they have implications for communication strategies by central banks (see, e.g., Cecchetti and Schoenholtz, 2019). In particular, they indicate the possible virtues of central banks giving more explicit information about the conduct of monetary policy, not only under central scenarios, but also of clarifying the likely response to shocks that are deeper in the tails.

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Tables and Figures

Table 1: Decomposing Excess Returns on FF Futures and OIS

Panel A shows the mean excess returns on FF futures and OIS, as well as expectation errors and survey-implied term premia. We regress each series on a constant and report coefficient estimates in basis points. t-statistics use standard errors computed using a block bootstrap, with the block length determined according to Politis and White (2004) and Patton et al. (2009). In Panel B, we perform a simple variance decomposition to test how much excess return variation is attributed to expectation errors and term premia, respectively. We compute the contribution of expectation errors as $cov(rx_{t+n}^{(n)}, \mathrm{EE}_{t+n}^{(n)})/var(rx_{t+n}^{(n)})$, where $rx_{t+n}^{(n)}$ are excess returns and $\mathrm{EE}_{t+n}^{(n)}$ are the expectation errors over the same horizon. We compute the contribution of term premia as $cov(rx_{t+n}^{(n)}, \mathrm{TP}_{t}^{(n)})/var(rx_{t+n}^{(n)})$. The sample for FF futures is 1990:11 to 2021:09 and the sample for OIS is 2001:12 to 2021:09.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
			Panel A: Mean Estimates			
Excess Returns	5.91	12.19	3.54	7.55	12.37	18.25
	(3.82)	(2.98)	(2.15)	(1.74)	(1.73)	(1.75)
Expectation Errors	7.37	13.05	6.23	10.55	16.61	24.13
	(3.17)	(2.82)	(2.88)	(2.19)	(2.22)	(2.31)
Term Premia	-1.45	-0.86	-2.69	-3.00	-4.24	-5.88
	(-1.41)	(-0.54)	(-3.56)	(-2.12)	(-2.08)	(-2.20)
			Panel B: Variance Decomposition			
Expectation Errors	1.08	1.02	1.16	1.04	1.00	0.98
Term Premia	-0.08	-0.02	-0.16	-0.04	0.00	0.02

Table 2: Expectations Hypothesis Tests

Panel A reports the results for Eq. (6), where future short rate changes are regressed on current FF futures and OIS term spreads. Panel B reports the results for Eq. (7), where we replace short rates with the excess returns earned over the same horizon. We report intercept and slope coefficients, and $t-$statistics where standard errors are computed using a block bootstrap, with the block length determined according to Politis and White (2004) and Patton et al. (2009). For the short rate regressions in Panel A, we test both whether the term spread has predictive power for future short rates ($\beta^{(n)} = 0$) and whether the term spread is an efficient predictor ($\beta^{(n)} = 1$). For the excess return regressions in Panel B, we test only whether the term spread has predictive power for future excess returns ($\delta^{(n)} = 0$). The sample for FF futures is 1990:11 to 2021:09 and the sample for OIS is 2001:12 to 2021:09.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
Panel A: $\Delta i_{t+n} = \alpha^{(n)} + \beta^{(n)} \varphi_t^{(n)} + \varepsilon_{t+n}^{(n)}$						
$\alpha^{(n)}$	-6.31	-13.69	-3.96	-9.11	-16.16	-25.01
$t_{\alpha^{(n)}=0}$	(-5.00)	(-3.98)	(-2.57)	(-3.10)	(-2.80)	(-2.87)
$\beta^{(n)}$	1.21	1.27	1.17	1.26	1.37	1.44
$t_{\beta^{(n)}=0}$	(21.16)	(13.11)	(14.92)	(11.83)	(9.44)	(7.99)
$t_{\beta^{(n)}=1}$	(3.65)	(2.81)	(2.18)	(2.47)	(2.57)	(2.44)
R^2	0.71	0.65	0.66	0.64	0.63	0.60
Panel B: $rx_{t+n}^{(n)} = \theta^{(n)} + \delta^{(n)} \varphi_t^{(n)} + \eta_{t+n}^{(n)}$						
$\theta^{(n)}$	6.31	13.69	3.96	9.11	16.16	25.01
$t_{\theta^{(n)}=0}$	(5.00)	(3.96)	(2.63)	(3.13)	(2.72)	(2.84)
$\delta^{(n)}$	-0.21	-0.27	-0.17	-0.26	-0.37	-0.44
$t_{\delta^{(n)}=0}$	(-3.69)	(-2.81)	(-2.20)	(-2.48)	(-2.58)	(-2.42)
R^2	0.07	0.08	0.04	0.07	0.11	0.12

Table 3: Taylor Rule Deviations and Unexpected Returns

The table reports the correlations between Taylor rule deviations, excess returns and expectation errors, as well as p-values for correlations being larger than zero. The first row shows the correlations between Taylor rule deviations from Eq. (9), and excess returns on FF futures and OIS. The second row reports correlations between Taylor rule deviations and expectation errors. The sample for FF futures is 1990:11 to 2021:09 and the sample for OIS is 2001:12 to 2021:09.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
$\rho\left(\psi_{t+n}^{\text{Taylor}}, rx_{t+n}^{(n)}\right)$	0.18	0.24	0.08	0.06	0.18	0.22
	[0.00]	[0.00]	[0.21]	[0.35]	[0.01]	[0.00]
$\rho\left(\psi_{t+n}^{\text{Taylor}}, \text{EE}_{t+n}^{(n)}\right)$	0.25	0.35	0.15	0.17	0.29	0.31
	[0.00]	[0.00]	[0.02]	[0.01]	[0.00]	[0.00]

Table 4: Predicting Excess Returns using Stock Market Returns

The table shows the results from the predictive regression Eq. (10). In Panel A, we regress future excess returns on FF futures and OIS on monthly excess returns on the S&P500. The coefficient estimates denote the basis point change in excess returns following a 1% (100 bps) return on the stock market. In Panel B, we run a horse race between the stock market and nonfarm employment growth. The coefficient $\gamma^{(n)}$ shows the basis point change in excess returns following a 1% change in nonfarm employment. In Panels C and D, we use the corporate bond spread and the Treasury yield spread as control variables instead of nonfarm employment, respectively. Here, $\gamma^{(n)}$ measures the basis point change in excess returns following a 1% change in either of these two variables. We report t-statistics with standard errors computed using a block bootstrap, where the block length is determined according to Politis and White (2004) and Patton et al. (2009). The sample for FF futures is 1990:11 to 2021:09 and the sample for OIS is 2001:12 to 2021:09.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
Panel A: $rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)} rx_t^{\text{S\&P500}} + \epsilon_{t+n}^{(n)}$						
$\beta^{(n)}$	-0.89	-1.44	-0.91	-1.21	-1.49	-1.92
	(-4.58)	(-4.22)	(-3.95)	(-3.10)	(-2.28)	(-2.71)
R^2	0.05	0.05	0.07	0.04	0.04	0.03
Panel B: $rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)} rx_t^{\text{S\&P500}} + \gamma^{(n)}\text{Employment Growth}_t + \epsilon_{t+n}^{(n)}$						
$\beta^{(n)}$	-0.90	-1.48	-0.92	-1.24	-1.55	-2.01
	(-4.64)	(-4.23)	(-4.01)	(-3.14)	(-2.76)	(-2.34)
$\gamma^{(n)}$	-0.32	-0.89	-0.18	-0.32	-0.97	-2.07
	(-0.55)	(-0.58)	(-0.35)	(-0.21)	(-0.39)	(-0.60)
R^2	0.06	0.05	0.07	0.05	0.04	0.04
Panel C: $rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)} rx_t^{\text{S\&P500}} + \gamma^{(n)}\text{Corporate Bond Spread}_t + \epsilon_{t+n}^{(n)}$						
$\beta^{(n)}$	-0.88	-1.43	-0.87	-1.16	-1.40	-1.80
	(-4.54)	(-4.35)	(-3.86)	(-2.98)	(-2.26)	(-2.17)
$\gamma^{(n)}$	0.83	0.65	1.88	3.05	5.32	7.48
	(0.43)	(0.11)	(1.03)	(0.73)	(0.75)	(0.75)
R^2	0.06	0.05	0.07	0.05	0.05	0.05
Panel D: $rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)} rx_t^{\text{S\&P500}} + \gamma^{(n)}\text{Treasury Yield Spread}_t + \epsilon_{t+n}^{(n)}$						
$\beta^{(n)}$	-0.89	-1.44	-0.91	-1.21	-1.48	-1.91
	(-4.58)	(-4.25)	(-3.94)	(-3.05)	(-2.28)	(-2.73)
$\gamma^{(n)}$	-0.97	-2.30	-0.98	-1.87	-2.33	-2.87
	(-0.59)	(-0.53)	(-0.54)	(-0.43)	(-0.31)	(-0.27)
R^2	0.06	0.05	0.07	0.05	0.04	0.04

Table 5: Predicting Excess Returns: Asymmetric Effects

The table reports the results from Eq. (11), where we regress future excess returns on FF futures and OIS on positive and negative stock market returns. Here, the variable $rx_t^{\text{S\&P500}} 1_{(rx_t^{\text{S\&P500}} > 0)}$ contains all positive stock returns and takes the value zero whenever stock returns are negative, while the variable $rx_t^{\text{S\&P500}} 1_{(rx_t^{\text{S\&P500}} \leq 0)}$ contains all negative stock returns and takes the value zero whenever stock returns are positive. We report slope coefficients (the basis point change in excess returns following a 1% monthly increase or decrease in the stock market) and $t-$statistics based on standard errors computed using a block bootstrap, where the block length is determined according to Politis and White (2004) and Patton et al. (2009). The sample for FF futures is 1990:11 to 2021:09 and the sample for OIS is 2001:12 to 2021:09.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
$\beta_{\text{POS}}^{(n)}$	-0.04	-0.35	-0.17	-0.25	-0.12	0.38
	(-0.11)	(-0.38)	(-0.33)	(-0.28)	(-0.09)	(0.19)
$\beta_{\text{NEG}}^{(n)}$	-1.77	-2.57	-1.52	-2.08	-2.60	-3.45
	(-3.75)	(-2.75)	(-2.81)	(-2.18)	(-1.68)	(-1.66)
R^2	0.07	0.06	0.08	0.06	0.05	0.05

Table 6: Predicting Excess Returns using Forecaster Disagreement

In Panel A, we regress future excess returns on FF futures and OIS on disagreement among professional forecasters about the short rate. Disagreement at each time point is computed as the difference between the 90th and the 10th percentile of individual short rate forecasts for horizon n from Blue Chip Financial Forecasts. In Panel B, we regress future survey expectation errors on disagreement. For both panels, the coefficient estimates denote the basis point change in excess returns or expectation errors following a 1 bps move in disagreement. We report t-statistics with standard errors computed using a block bootstrap, where the block length is determined according to Politis and White (2004) and Patton et al. (2009). The sample for FF futures is 1990:11 to 2021:09 and the sample for OIS is 2001:12 to 2021:09.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
Panel A: $rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)}\text{Disagreement}_t^{(n)} + \epsilon_{t+n}^{(n)}$						
$\beta^{(n)}$	0.37	0.64	0.21	0.45	0.81	1.03
	(3.77)	(3.12)	(1.47)	(1.77)	(2.39)	(2.65)
R^2	0.07	0.11	0.02	0.05	0.13	0.19
Panel B: $\text{EE}_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)}\text{Disagreement}_t^{(n)} + \epsilon_{t+n}^{(n)}$						
$\beta^{(n)}$	0.45	0.59	0.51	0.61	0.87	1.03
	(3.08)	(2.41)	(2.85)	(2.11)	(2.26)	(2.42)
R^2	0.07	0.08	0.07	0.07	0.13	0.17

Table 7: Mean Excess Returns on International OIS

The table shows the mean excess returns on international OIS. We regress each series on a constant and report coefficient estimates in basis points. t-statistics use standard errors computed using a block bootstrap, with the block length determined according to Politis and White (2004) and Patton et al. (2009). See appendix IA.6 for details on sample sizes and data sources.

	Overnight Index Swaps			
$n =$	3	6	9	12
Australia	-1.61	-1.47	0.68	4.59
	(-1.22)	(-0.65)	(0.18)	(0.79)
Canada	1.41	4.82	9.09	9.22
	(1.37)	(2.00)	(2.13)	(1.05)
Euro area	2.49	5.48	10.67	13.94
	(2.27)	(2.04)	(1.94)	(2.06)
United Kingdom	3.04	6.55	11.35	17.21
	(1.48)	(1.58)	(1.71)	(1.82)
Japan	0.23	0.57	1.22	2.02
	(0.58)	(0.81)	(0.91)	(1.12)
Switzerland	2.10	5.75	10.39	15.44
	(1.01)	(1.38)	(1.68)	(1.84)

Table 8: Expectation Errors and Excess Returns on International OIS

The table shows the correlations between excess returns on OIS and expectation errors internationally. Survey expectations are from Reuters Central Bank Polls. We consider excess returns on contracts with horizons $3, 6, 9$, and 12 months and report $p-$values for the correlations being larger than zero.

	Overnight Index Swaps			
$n =$	3	6	9	12
Euro area	0.17	0.68	0.83	0.87
	[0.00]	[0.00]	[0.00]	[0.00]
United Kingdom	0.91	0.96	0.97	0.96
	[0.00]	[0.00]	[0.00]	[0.00]
Switzerland	0.75	0.84	0.86	0.87
	[0.00]	[0.00]	[0.00]	[0.00]

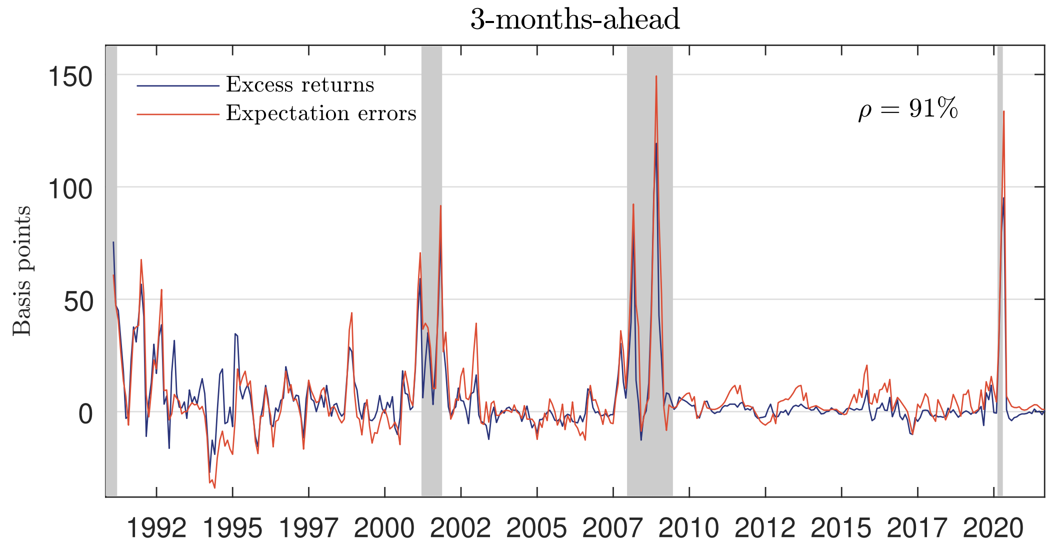
Table 9: Predicting Excess Returns using the Local Stock Market

The table reports the results from Eq. (10), where we regress excess returns on international OIS on the local stock market. Here, $rx_t^{\text{stock market}}$ is the monthly excess return on the stock market in a given currency area. Because short-term Treasury bills are not available in all currencies as a measure of the risk-free rate of interest, we subtract the one-month-ahead OIS rate observed on the last day of month $t-1$ from the following month's stock return. In unreported results, we find that the results are robust to excluding this transformation. We report slope coefficients (the basis point change in excess returns following a 1% increase or decrease in the stock market) and t-statistics based on standard errors computed using a block bootstrap, where the block length is determined according to Politis and White (2004) and Patton et al. (2009).

		Overnight Index Swaps			
$n =$		3	6	9	12
		$rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)} rx_t^{\text{stock market}} + \epsilon_{t+n}^{(n)}$			
Australia	$\beta^{(n)}$	-0.35	-0.96	-1.69	-2.59
		(-1.52)	(-1.97)	(-2.27)	(-2.65)
	R^2	0.01	0.02	0.03	0.04
Canada	$\beta^{(n)}$	-0.70	-1.25	-1.63	-2.17
		(-3.42)	(-3.30)	(-3.11)	(-2.77)
	R^2	0.06	0.06	0.05	0.04
Euro area	$\beta^{(n)}$	-0.22	-0.96	-1.74	-2.25
		(-1.34)	(-3.01)	(-3.02)	(-3.36)
	R^2	0.01	0.04	0.06	0.06
United Kingdom	$\beta^{(n)}$	-1.49	-2.29	-2.85	-3.49
		(-5.56)	(-4.77)	(-4.31)	(-4.04)
	R^2	0.11	0.09	0.07	0.07
Japan	$\beta^{(n)}$	-0.09	-0.15	-0.19	-0.23
		(-2.26)	(-2.32)	(-1.90)	(-2.05)
	R^2	0.03	0.03	0.02	0.02
Switzerland	$\beta^{(n)}$	-0.95	-1.47	-1.97	-2.79
		(-4.29)	(-3.82)	(-3.44)	(-3.34)
	R^2	0.10	0.09	0.08	0.10

Figure 1: Excess Returns on FF Futures and Expectation Errors

The figure shows excess returns on FF futures, $rx_{t+n}^{(n)} = f_t^{(n)} - i_{t+n}$, with contemporaneous expectation errors, $\mathrm{EE}_{t+n}^{(n)} = S_t^{(n)} - i_{t+n}$, from the decomposition in Eq. (5). Survey data are from Blue Chip Financial Forecasts. The series are plotted with National Bureau of Economic Research (NBER) recession periods in gray shading. All values are denoted in basis points and the sample is 1990:11 to 2021:09.



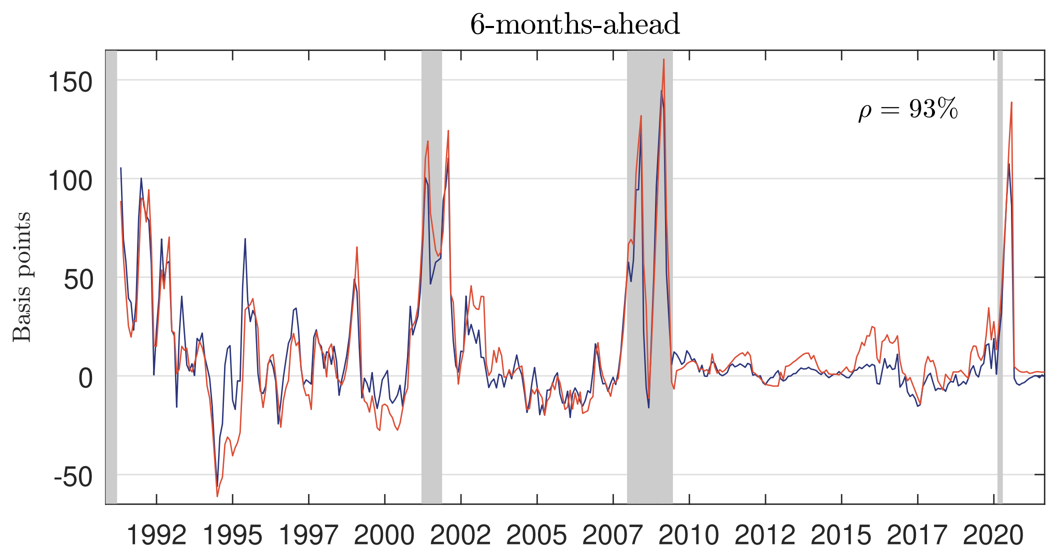


Figure 2: Prediction-Realization Diagrams: FF Futures

The figure shows the time $t+n$ realized short rate change together with its time t predicted value from FF futures. The realized change, $\Delta i_{t+n} = i_{t+n} - i_t$, is the change in the short rate from t to $t+n$. The predicted value is $\varphi_t^{(n)} = f_t^{(n)} - i_t$, where $f_t^{(n)}$ is the rate on FF futures. The dotted line is the regression line from Eq. (6). All values are denoted in basis points and the sample is 1990:11 to 2021:09.

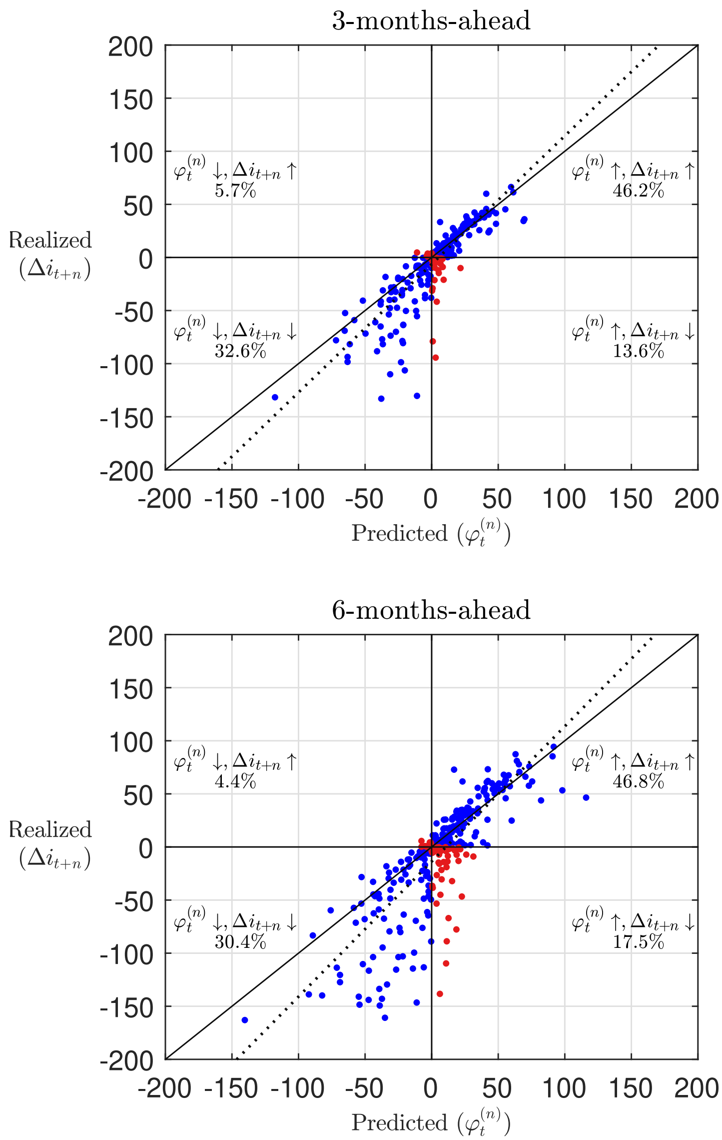
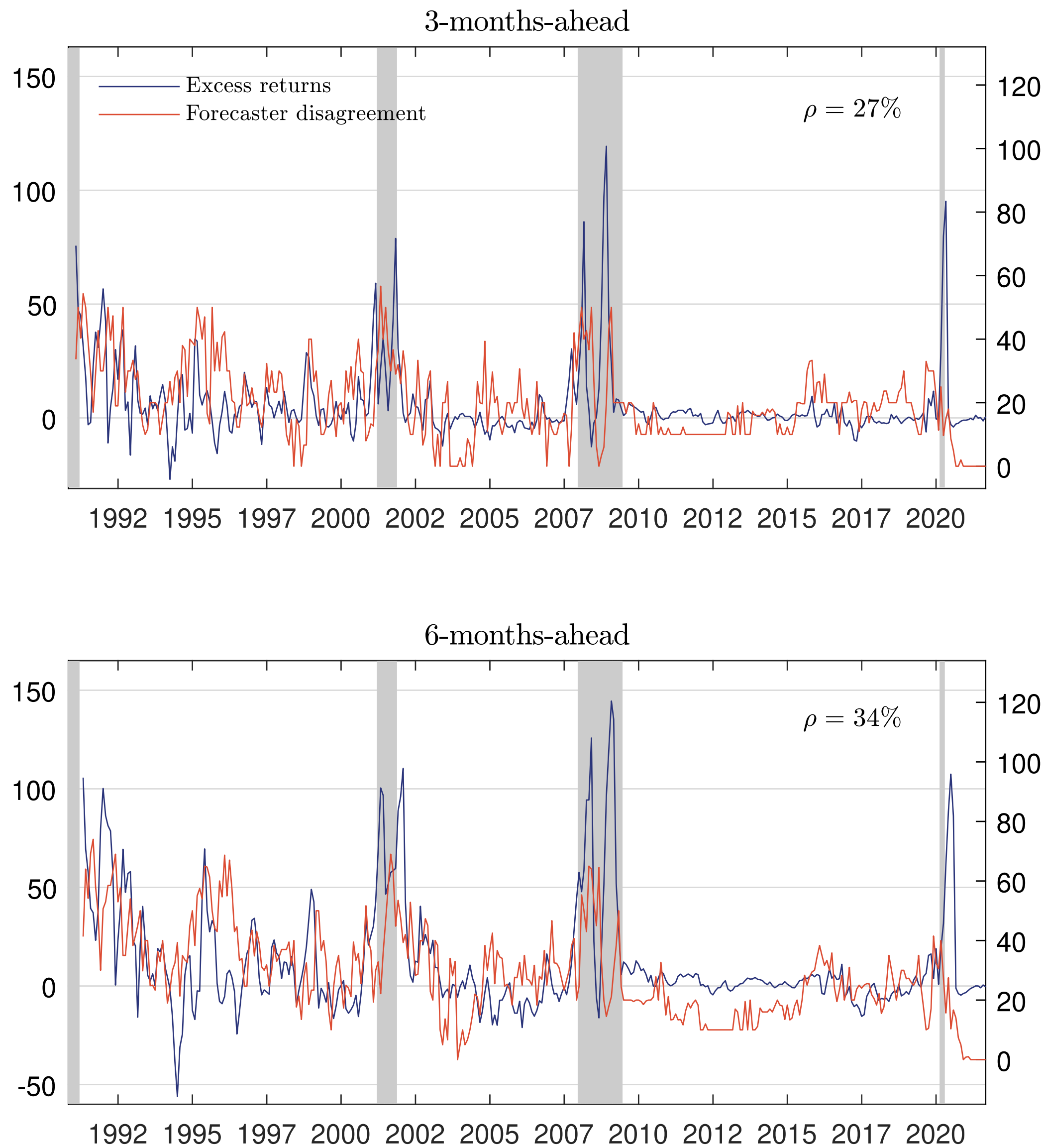


Figure 3: Excess Returns on FF Futures and Forecaster Disagreement

The figure shows excess returns on FF futures, $rx_{t+n}^{(n)} = f_t^{(n)} - i_{t+n}$, with time t disagreement among forecasters about the short rate over horizon n. Disagreement at each time point is computed as the difference between the 90th and the 10th percentile of the cross-section of individual forecasts from Blue Chip Financial Forecasts. Units of excess returns are plotted on the left axis, units of disagreement are on the right, and both are in basis points. The series are plotted with National Bureau of Economic Research (NBER) recession periods in gray shading. The sample is 1990:11 to 2021:09.



Internet Appendix for

Monetary Policy Expectation Errors

(not for publication)

Internet Appendix: Additional Details

IA.1. Excess Return Details

FF Futures An investor who has taken a long position in FF futures receives fixed payments and pays floating. In practice, the fixed and floating payments are calculated based on a $5 million deposit and the 30-day month and the 360-day year convention. This deposit is used to compute the dollar amount of the daily payments and is never actually exchanged between the two parties in the contract.

The floating rate consists of the average overnight (O/N) rate over target month n, which we refer to as the "short rate". As such, FF futures settle against the short rate in a future time interval, and not the path of the short rate from contract inception t until maturity $t+n$. Recall the definition of excess returns on a long position in FF futures:

$$rx_{t+n}^{(n)} = f_t^{(n)} - i_{t+n}.$$

Here, $i_{t+n} = 1/30 \sum_{j=1}^{30} r_j$ denotes the short rate in target month n. Specifically, r_j is the EFFR observed on day j, denoted as an annual percentage rate. $j = 1$ is the first day of the month, and 30 is the total number of days in the month following the market convention.

At maturity, the long investor receives the deposit times the difference between the fixed rate and the short rate. Importantly, the differential between these two annual rates is converted into a monthly rate by multiplying by the factor 30/360. The realized payoff is thus $5 million $\times$ $(f_t^{(n)} - i_{t+n}) \times 30/360$. In this paper, we focus on the differential between the two annual rates, rather than the specific dollar amount, and label this component the "excess return" as is common in the literature.

Overnight Index Swaps Similarly to FF futures, an investor who has taken a long position in OIS receives a fixed swap rate and pays floating based on variations in the O/N rate, consistent with the notation $rx_{t+n}^{(n)} = f_t^{(n)} - i_{t+n}$. However, OIS differ in two important respects. First, while FF futures settle against the short rate over target month n, OIS settle against the compounded path of the short rate from the first day following contract inception time t until its maturity $t+n$. Second, the interest over this interval is compounded daily.

Let k denote the number of days in the interval t to $t+n$. At maturity, fixed and floating leg payments are exchanged. For a notional of \$5 million, the long investor earns the payoff \$5 million $\times$ $(k/360 \times f_t^{(n)} - [\prod_{j=1}^{k}(1+r_j/360)-1])$, where $f_t^{(n)}$ is the OIS fixed rate, r_j is the O/N rate observed on day j and denoted as an annual percentage rate. Note that the fixed leg pays simple interest, while the variable leg rate is compounded daily.

For comparability with excess returns on FF futures, we move the conversion term $k/360$ outside the parenthesis by multiplying both the fixed and variable leg components by the factor 360/k, which annualizes both rates. As such, we define excess returns on OIS as the difference between the annual percentage rate of the fixed and floating legs, where the latter is compounded over the number of days in the contract k and subsequently annualized. The excess return is thus,

$$rx_{t+n}^{(n)} = f_t^{(n)} - i_{t+n},$$

where $i_{t+n} = [\prod_{j=1}^{k}(1+r_j/360)-1] \times 360/k$.

IA.2. Blue Chip Survey Data

The Blue Chip Financial Forecasts survey contains forecasts from around 45 professional forecasters from leading financial institutions. The survey is conducted each month and the survey participants are asked to predict the average (as opposed to end-of-period) EFFR over each quarter of the year, with horizons up to 5 quarters ahead. Survey responses are collected during the last week of the month and published on the first business day of the following month. For this reason, we treat surveys published on the first business day of a given month as the end-of-month expectation of the previous month.

Because forecast horizons vary (for example, survey participants are asked to predict the EFFR over Q1 when they are in December, January, and February, i.e., the forecast horizon is shrinking as each month goes by) we linearly interpolate survey forecasts to get time series of fixed-horizon forecasts. As an example, the 3-months-ahead forecast as observed on the last day of February consists of 1/3 times the forecast of Q1 (which targets the average EFFR for January, February, and March), and 2/3 times the forecast of Q2 (which targets the average EFFR for April, May, and June). The same interpolation approach is applied to longer forecast horizons.[33] However, the subsequent fixed-horizon forecasts target future time intervals (for example, the 6-months-ahead fixed-horizon forecast targets the average EFFR from $t + 4$ to $t+6$). For this reason, we average the 3 and 6 months fixed-horizon forecasts to get an expected path of the short rate over the next six months. The same method is applied to get the expected path of the short rate for the nine and twelve months horizons.

[33] See e.g., De la O and Myers (2020) and Sutherland (2020) for recent papers applying the same interpolation to obtain fixed-horizon survey forecasts. To test the impact of interpolating Blue Chip surveys, Table IA.12 in the Internet Appendix shows that the results from the return decomposition are the same when we sample the data at a quarterly frequency and therefore do not have to interpolate to get fixed-horizon forecasts.

IA.3. Matching Surveys with FF Futures and OIS

FF Futures We want to compare excess returns, survey-implied term premia and expectation errors across FF futures and OIS. However, because FF futures target the short rate in a future interval, while OIS target the path of the short rate from contract inception until maturity, we average FF futures contracts of various maturities so as to get "term rates", i.e., the expected short rate from time t to $t+n$. More specifically, we compute average returns over 3 and 6 months as,

$$rx_{t+n}^{(n)} = \frac{1}{n}\sum_{i=1}^{n} f_t^{(i)} - \frac{1}{n}\sum_{i=1}^{n} i_{t+i},$$

where $\frac{1}{n}\sum_{i=1}^{n} f_t^{(i)}$ is the average rate on FF futures contracts observed at time t, with maturities $n = 1, ..., 3$ or $n = 1, ..., 6$ months, respectively. $\frac{1}{n}\sum_{i=1}^{n} i_{t+i}$ is the simple average short rate that is subsequently realized over these horizons. We then add and subtract survey expectations to the above expression, as the forecast horizons match.

Overnight Index Swaps There is no need to average OIS rates as the forecast horizons of these contracts match those in the Blue Chip survey. Nonetheless, there is a small discrepancy between the variable being forecast by the survey and OIS. Blue Chip survey participants are asked to predict the simple average EFFR, while OIS target the compounded EFFR. Unfortunately, we cannot simply compound the rate implied by survey expectations, since the expectation of a compounded variable is not the same as the compounded expectation (Jensen's inequality). As such, we proceed by matching survey forecasts of the arithmetic average EFFR with OIS forecasts of the compounded average. This difference does not, however, constitute a major challenge to our analysis. For example, for a 3-months-ahead OIS, a 2% interest rate translates into 2.005% when compounded daily over the contract's horizon. As such, the difference in size between the simple and the compounded average EFFR is negligible, and the term premium and expectation error estimates for OIS do not differ much from the estimates for FF futures of equal horizons, where there is no such issue with compounding.

IA.4. Asymmetry in Expectations Hypothesis Tests

Our findings in Section 3.2 of the main text indicate a substantial degree of asymmetry in the predictive content of the money market term spread. In this subsection we formalize these findings with regression-based tests. To this end, we estimate augmented versions of Eqs. (6) and (7) that allow the coefficients to take different values depending on whether the money market curve is upwards sloping or inverted. To do so, we construct dummy variables, $1_{\{\varphi_t^{(n)}>0\}}$, that take the value one when term spreads are positive and zero otherwise, as well as dummies, $1_{\{\varphi_t^{(n)}\leq 0\}}$, that take the value one when term spreads are flat or negative and zero otherwise. The augmented regression equations are,

$$\Delta i_{t+n} = \alpha_{POS}^{(n)} 1_{\{\varphi_t^{(n)}>0\}} + \beta_{POS}^{(n)} \varphi_t^{(n)} 1_{\{\varphi_t^{(n)}>0\}} + \alpha_{NEG}^{(n)} 1_{\{\varphi_t^{(n)}\leq 0\}} + \beta_{NEG}^{(n)} \varphi_t^{(n)} 1_{\{\varphi_t^{(n)}\leq 0\}} + \tilde{\varepsilon}_{t+n}^{(n)}, \tag{IA..1}$$

$$rx_{t+n}^{(n)} = \theta_{POS}^{(n)} 1_{\{\varphi_t^{(n)}>0\}} + \delta_{POS}^{(n)} \varphi_t^{(n)} 1_{\{\varphi_t^{(n)}>0\}} + \theta_{NEG}^{(n)} 1_{\{\varphi_t^{(n)}\leq 0\}} + \delta_{NEG}^{(n)} \varphi_t^{(n)} 1_{\{\varphi_t^{(n)}\leq 0\}} + \tilde{\eta}_{t+n}^{(n)}, \tag{IA..2}$$

where, through the interaction terms, we estimate separate coefficients for when the slope of the term structure is positive (anticipating short rate hikes) or negative (anticipating rate cuts).

Panel A of Table IA.1 reports the results for Eq. (IA..1) and confirms the striking asymmetry documented in the previous section. For the positive term spread, we fail to reject that $\alpha_{POS}^{(n)}, \beta_{POS}^{(n)} = 0, 1$ across all horizons of FF futures and OIS, implying that market participants' short rate forecasts are entirely consistent with the EH when they expect rate hikes. In contrast, when the term spread is negative, i.e., the pricing of derivatives indicates that short rates are expected to decrease, there is clear evidence that the EH fails. For almost all horizons, intercepts and slope coefficients deviate significantly from zero and one, respectively. What is more, the slope coefficients on the negative term spread, $\beta_{NEG}^{(n)}$, are all significantly above one, corroborating the previous finding that market participants systematically underestimate the magnitude of *short rate cuts*. For example, for the 6-months-ahead FF futures, when market participants expect a 1% decline, the subsequent short rate decline is on average 1.35%. For the 12-months-ahead OIS, the underestimation is even larger. Here, the estimated slope coefficient is $\beta_{NEG}^{(n)} = 1.75$, thus entailing that one-year-ahead short rate cuts are, on average, almost twice as large as expected.

Table IA.1: Asymmetry in Expectations Hypothesis Tests

Panel A presents the results for Eq. (IA..1), where we regress future short rate changes on the upwards-sloping and inverted term spread, respectively. $\alpha_{POS}^{(n)}$ and $\beta_{POS}^{(n)}$ are the estimated intercept and slope coefficients for the upwards-sloping term spread, while $\alpha_{NEG}^{(n)}$ and $\beta_{NEG}^{(n)}$ are the estimated intercept and slope coefficients for the inverted term spread. We provide $t-$statistics for the intercepts being equal to zero and for slope coefficients being equal to one. Panel B presents the results from Eq. (IA..2), where we regress excess returns on the upwards-sloping and inverted term spread, respectively. $\theta_{POS}^{(n)}$ and $\delta_{POS}^{(n)}$ are the estimated intercept and slope coefficients for the upwards-sloping term spread, while $\theta_{NEG}^{(n)}$ and $\delta_{NEG}^{(n)}$ are the estimated intercept and slope coefficients for the inverted term spread. In this panel, we provide $t-$statistics for the intercept and slope coefficients being equal to zero, respectively. All t-statistics use standard errors that are computed using a block bootstrap, with the block length determined according to Politis and White (2004) and Patton et al. (2009). The sample for FF futures is 1990:11 to 2021:09 and the sample for OIS is 2001:12 to 2021:09.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
Panel A: $\Delta i_{t+n} = \alpha_{POS}^{(n)} 1_{\{\varphi_t^{(n)}>0\}} + \beta_{POS}^{(n)} \varphi_t^{(n)} 1_{\{\varphi_t^{(n)}>0\}} + \alpha_{NEG}^{(n)} 1_{\{\varphi_t^{(n)}\leq 0\}} + \beta_{NEG}^{(n)} \varphi_t^{(n)} 1_{\{\varphi_t^{(n)}\leq 0\}} + \tilde{\varepsilon}_{t+n}^{(n)}$						
$\alpha_{POS}^{(n)}$	-3.49	-7.04	-3.95	-7.42	-10.82	-15.86
$t_{\alpha_{POS}^{(n)}=0}$	(-1.82)	(-1.61)	(-1.85)	(-1.73)	(-1.59)	(-1.37)
$\beta_{POS}^{(n)}$	1.02	1.03	1.16	1.20	1.20	1.17
$t_{\beta_{POS}^{(n)}=1}$	(0.23)	(0.24)	(1.07)	(1.06)	(0.92)	(0.62)
$\alpha_{NEG}^{(n)}$	-5.77	-15.81	-3.47	-10.50	-17.97	-21.67
$t_{\alpha_{NEG}^{(n)}=0}$	(-2.69)	(-3.07)	(-1.25)	(-1.96)	(-2.10)	(-1.56)
$\beta_{NEG}^{(n)}$	1.30	1.35	1.19	1.27	1.46	1.75
$t_{\beta_{NEG}^{(n)}=1}$	(3.40)	(2.32)	(1.69)	(1.60)	(1.96)	(2.75)
R^2	0.72	0.66	0.66	0.64	0.64	0.62
Panel B: $rx_{t+n}^{(n)} = \theta_{POS}^{(n)} 1_{\{\varphi_t^{(n)}>0\}} + \delta_{POS}^{(n)} \varphi_t^{(n)} 1_{\{\varphi_t^{(n)}>0\}} + \theta_{NEG}^{(n)} 1_{\{\varphi_t^{(n)}\leq 0\}} + \delta_{NEG}^{(n)} \varphi_t^{(n)} 1_{\{\varphi_t^{(n)}\leq 0\}} + \tilde{\eta}_{t+n}^{(n)}$						
$\theta_{POS}^{(n)}$	3.49	7.04	3.95	7.42	10.82	15.86
$t_{\theta_{POS}^{(n)}=0}$	(1.84)	(1.62)	(1.85)	(1.73)	(1.62)	(1.36)
$\delta_{POS}^{(n)}$	-0.02	-0.03	-0.16	-0.20	-0.20	-0.17
$t_{\delta_{POS}^{(n)}=0}$	(-0.24)	(-0.23)	(-1.08)	(-1.09)	(-0.92)	(-0.60)
$\theta_{NEG}^{(n)}$	5.77	15.81	3.47	10.50	17.97	21.67
$t_{\theta_{NEG}^{(n)}=0}$	(2.65)	(3.06)	(1.25)	(1.96)	(2.13)	(1.55)
$\delta_{NEG}^{(n)}$	-0.30	-0.35	-0.19	-0.27	-0.46	-0.75
$t_{\delta_{NEG}^{(n)}=0}$	(-3.45)	(-2.27)	(-1.68)	(-1.61)	(-1.99)	(-2.75)
R^2	0.09	0.11	0.04	0.07	0.13	0.16

Panel B of Table IA.1 reports the results for Eq. (IA..2). The results here are consistent with the previous interpretations: when market participants expect the short rate to go up, their forecasts are in accordance with the EH and the term spread provides no information about future excess returns. However, when market participants expect the short rate to decrease, the term spread predicts future excess returns with a negative coefficient, equal in size to the deviation from the EH in the short rate regression. As such, an inverted term spread predicts future *positive* excess returns because market participants underestimate by how much the Fed cuts interest rates in economics downturns.

IA.5. Investor Expectation Formation

In this section, we test if investors' expectation formation deviates from the FIRE assumption, which presupposes that expectation errors should be unconditionally zero. While the FIRE assumption underlies most contemporary economic models, an increasing body of literature finds that market participants do in fact face frictions and limitations when processing information.[34] To study the role of such information rigidities when forecasting the short rate, we run the regression put forth by Coibion and Gorodnichenko (2015),

$$i_{t+n} - S_t^{(n)} = \omega^{(n)} + \kappa^{(n)} RV_t^{(n)} + \xi_{t+n}^{(n)},$$

where $i_{t+n} - S_t^{(n)}$ is the difference between the expected and realized short rate (the expectation error), and $RV_t^{(n)} = S_t^{(n)} - S_{t-1}^{(n)}$ is the change in expectations of the future short rate that takes place between time t and $t-1$ (the forecast revision).[35]

If market participants have rational expectations and full information about the central bank's reaction function, new information is immediately incorporated into their forecast and the revision term should, as a consequence, be uninformative about future expectation errors. If, however, market participants face information rigidities and never actually observe the reaction function, a gradual adjustment in expectations and ex-post predictability of forecast errors can arise.[36] As such, evidence that forecast revisions have predictive power for future expectation errors ($\kappa^{(n)} \neq 0$), is a strong sign that market participants face information rigidities and are

[34] See e.g., Mankiw and Reis, 2002; Sims, 2003; Woodford, 2001; Coibion and Gorodnichenko, 2012, and Coibion and Gorodnichenko, 2015. For short rate expectations, Brunner and Meltzer (1997) note that: *"Under [the rational expectations hypothesis], people are assumed to know the policy rule used by the monetary (and fiscal) authorities and to have detailed knowledge about the structure of the economy including the size and timing of responses to shocks of various kinds. These assumptions make the models analytically tractable but, taken literally (as they often are), they distort the economist's view of the policy problem by ignoring uncertainty, incomplete knowledge about the structure of the economy and the costs of acquiring information and reducing uncertainty."*

[35] Note that we switch the order between the expected and realized value in the "expectation error" term relative to the notation introduced in section 2.2. We do so here in order to be consistent with the methodology of Coibion and Gorodnichenko (2015) and to ease the interpretation of the results in this section.

[36] More specifically, because market participants do not know whether new information reflects noise or innovations to the variable being predicted, they adjust their beliefs only gradually in response to news. As an example, see Erceg and Levin (2003) who interpret large and persistent inflation expectation errors as being due to market participants using this form of signal extraction to infer the central bank's inflation target during the 1970s. They conclude that persistent expectation errors is consistent with rational expectations subject to limited information about the underlying data-generating process.

learning about the Fed's reaction function.

Table IA.2: Tests of the Short Rate Expectation Formation Process

Panel A reports the results from regressing future expectation errors on past forecast revisions. Panel B provides the results for the augmented version of the regression, in which intercepts and slope coefficients differ depending on whether market participants revise their short rate expectations upwards or downwards. We report coefficient estimates and $t-$statistics based on standard errors computed using a block bootstrap, with the block length determined according to Politis and White (2004) and Patton et al. (2009). The data are sampled on a quarterly frequency and the sample goes from 1988:Q1 to 2021:Q3. Forecasts with horizon $n = 15$ months are needed to compute revisions to the one-year-ahead expectations, but these forecasts were not introduced into the Blue Chip survey until 1996:Q4. Consequently, the sample for one-year-ahead forecast revisions begins at this later time period.

$n =$	3	6	9	12
Panel A: $i_{t+n} - S_t^{(n)} = \omega^{(n)} + \kappa^{(n)} RV_t^{(n)} + \xi_{t+n}^{(n)}$				
$\kappa^{(n)}$	0.11	0.21	0.36	0.45
	(2.67)	(3.30)	(3.92)	(3.07)
R^2	0.05	0.08	0.13	0.13
$1/(1+\kappa^{(n)})$	0.90	0.82	0.74	0.69
Panel B: $i_{t+n} - S_t^{(n)} = \omega_{POS}^{(n)} 1_{\{RV_t^{(n)}>0\}} + \kappa_{POS}^{(n)} RV_t^{(n)} 1_{\{RV_t^{(n)}>0\}} + \omega_{NEG}^{(n)} 1_{\{RV_t^{(n)}\leq 0\}} + \kappa_{NEG}^{(n)} RV_t^{(n)} 1_{\{RV_t^{(n)}\leq 0\}} + \tilde{\xi}_{t+n}^{(n)}$				
$\kappa_{POS}^{(n)}$	0.14	0.20	0.33	0.54
	(0.97)	(0.96)	(1.06)	(0.71)
$\kappa_{NEG}^{(n)}$	0.04	0.13	0.28	0.42
	(0.74)	(1.50)	(2.24)	(2.40)
R^2	0.08	0.10	0.14	0.13

Panel A of the Table runs the above regression with Blue Chip short rate expectations for horizons $n = 3, 6, 9,$ and 12 months, and shows that information rigidities are indeed present when market participants forecast the short rate.[37] Across all horizons, the estimated slope coefficients on the forecast revision term are positive and statistically significant, implying that market participants' short rate expectation formation process deviates from FIRE.

[37] We sample survey expectations quarterly to match the data frequency with the increments of survey forecast horizons. For the survey expectation of a given quarter, we use the last available observation.

Moreover, we can infer the degree of information rigidity by computing the Kalman gain, $G = 1/(1+\kappa^{(n)})$, which reveals how much weight is put on new information relative to previous forecasts. We see that all estimates of the Kalman gain are well above 0.5, implying that market participants put more emphasis on new information than on their previous forecasts. As such, while they face significant information rigidities when forecasting the short rate, market participants are relatively quick to update their expectations when new information becomes available. Furthermore, the Kalman gain is largest for the shortest horizons, showing that expectations over more near term horizons are updated faster than expectations for the far future. As such, these results are consistent with the previous results, which showed that the size of forecast errors is increasing in the forecast horizon. Here, they point to a relatively slow updating of expectations as the key reason for the subsequent underestimation of short rate cuts at these horizons.

As the previous section shows, market participants are especially error-prone when it comes to anticipating the *magnitude* of short rate cuts. In the context of information rigidities, this is equivalent to them revising their expectations downwards too slowly. To test for asymmetries in the expectation formation process, we therefore augment the previous regression by interacting with dummy variables that measure when market participants revise their expectations upwards, $1_{\{RV_t^{(n)}>0\}}$, or when they are unchanged or revised downwards, $1_{\{RV_t^{(n)}\leq 0\}}$. This leads to the regression,

$$
\begin{aligned}
i_{t+n} - S_t^{(n)} = {} & \omega_{POS}^{(n)} 1_{\{RV_t^{(n)}>0\}} + \kappa_{POS}^{(n)} RV_t^{(n)} 1_{\{RV_t^{(n)}>0\}} \\
& + \omega_{NEG}^{(n)} 1_{\{RV_t^{(n)}\leq 0\}} + \kappa_{NEG}^{(n)} RV_t^{(n)} 1_{\{RV_t^{(n)}\leq 0\}} + \tilde{\xi}_{t+n}^{(n)},
\end{aligned}
$$

which allows the slope coefficients to take different values depending on the sign of the forecast revision ($\kappa_{POS}^{(n)}, \kappa_{NEG}^{(n)}$). The results are reported in Panel B of the above table and provide evidence of asymmetry in the expectation formation process. While the slope coefficients for upwards revisions have no predictive power for future forecast errors, slope coefficients for downwards revisions are large and strongly significant for the longest forecast horizons.

These findings actively demonstrate that investors update their expectations upwards in accordance with FIRE, but face significant information rigidities when revising their expectations of the short rate downwards. These results corroborate recent work on short rate expectation formation, e.g. Bordalo et al. (2020) who argue that market participants "underreact to news" when forecasting the short rate. We contribute to this body of literature by showing that this underreaction is highly asymmetric: when faced with positive news, market participants do in fact adjust their expectations in accordance with FIRE. When faced with negative news, however, market participants are not pessimistic enough and underestimate by how much the Fed will cut interest rates.

IA.6. Overview of International Data

The table summarizes the sources of international data. OIS in all currency areas target overnight interest rates, while survey participants in Reuters Central Bank Polls report their expectations of the future monetary policy target (Australia, Canada, and Japan were introduced late into the survey, hence their exclusion). Data on OIS, overnight rates, and stock returns are from Bloomberg (in 2018:01, SARON replaced TOIS as the official overnight rate in Switzerland), while survey responses are retrieved from the Thomson Reuters database. Policy rates are from the Bank for International Settlements. While the series have different starting dates as denoted below, they all end 2021:09.

	Overnight Index Swaps		**Reuters Central Bank Polls**		**Stock Market**
Currency Area	Overnight Rate	Sample Start	Policy Rate	Sample Start	Index
Australia	RBA IBOC	2001:11			S&P/ASX 200
Canada	CORRA	2003:05			S&P/TSX Index
Euro area	EONIA	1999:03	ECB MRO	2004:10	STOXX Europe 600
United Kingdom	SONIA	2001:01	BOE Bank rate	2004:12	FTSE 100
Japan	TONAR	2002:04			Nikkei 225
Switzerland	TOIS/SARON	2002:01	SNB 3M Target LIBOR Rate	2006:03	SMI Index

Internet Appendix: Tables

Table IA.3: Robustness of Expectation Errors and Term Premia

Panel A of the table reports the root-mean-square error in basis points from predicting the short rate using Blue Chip Financial Forecasts and Reuters Central Bank Polls, as well as Diebold and Mariano (2002) tests of equal predictive accuracy between forecasts from the two surveys. Panel B shows mean estimates of expectation errors and term premia computed based on the two surveys. We regress each series on a constant and report coefficient estimates in basis points. t-statistics use standard errors computed using a block bootstrap, with the block length determined according to Politis and White (2004) and Patton et al. (2009). For comparability, all series span the same time period, namely 2005:10 until 2021:09, which is when Reuters Central Bank Polls data are available for the US.

$n =$		3	6	9	12
Panel A: Forecast Accuracy					
RMSE	Blue Chip	22.05	32.13	42.62	54.90
	Reuters	23.19	33.78	44.81	57.49
	H_0(BC=Reuters)	[0.98]	[0.98]	[0.98]	[0.98]
Panel B: Mean Estimates					
Expectation Errors	Blue Chip	7.39	12.45	19.28	27.71
		(2.91)	(2.62)	(2.41)	(2.57)
	Reuters	9.65	14.94	21.62	29.82
		(3.91)	(3.11)	(2.69)	(2.72)
Term Premia	Blue Chip	-2.94	-3.35	-4.51	-6.16
		(-3.46)	(-2.77)	(-2.31)	(-2.09)
	Reuters	-5.20	-5.84	-6.86	-8.26
		(-4.09)	(-3.29)	(-2.83)	(-2.48)

Table IA.4: Predicting the Direction of Short Rate Changes

In the table, we count the number of times market participants correctly predicted short rate changes and how many times they were surprised by them. Columns two and three summarize the number of correctly predicted and surprise short rate *increases*, computed as a fraction of the total number of realized changes. Columns four and five show the correctly predicted and surprise short rate *decreases*, computed as a fraction of the total number of realized changes. Panel A shows these results for FF futures of horizons $n = 3$ and 6 months, while Panel B shows the equivalent results for OIS across horizons $n = 3, 6, 9$, and 12 months. The sample for FF futures is 1990:11 to 2021:09 and the sample for OIS is 2001:12 to 2021:09.

	Short Rate Hike		**Short Rate Cut**	
$n =$	Anticipated	Surprise	Anticipated	Surprise
Panel A: FF Futures				
3	46.2%	5.7%	32.6%	13.6%
6	46.8%	4.4%	30.4%	17.5%
Panel B: Overnight Index Swaps				
3	50.6%	6.4%	25.5%	17.4%
6	51.7%	3.9%	25.9%	18.5%
9	50.7%	3.9%	24.5%	21.0%
12	53.5%	3.1%	20.4%	23.0%

Table IA.5: Predicting the Magnitude of Short Rate Changes

In the table, we count the number of times market participants correctly predicted a short rate increase or decrease, but underestimated the magnitude of the change by either 25 or 100 basis points. Panels A and B show the results for FF futures and OIS when the threshold is 25 basis points, while Panels C and D show the results for when the threshold is 100 basis points. Columns two and three show the number of times market participants overestimated and underestimated the short rate *increase* by the given threshold, computed as a fraction of the total number of correctly predicted increases. Columns four and five show the number of times they overestimated and underestimated the size of the short rate *decline* by the given threshold, computed as a fraction of the total number of correctly predicted declines. We show results for FF futures of horizons $n = 3$ and 6 months and for OIS across horizons $n = 3, 6, 9$, and 12 months. The sample for FF futures is 1990:11 to 2021:09 and the sample for OIS is 2001:12 to 2021:09.

	Short Rate Hike		**Short Rate Cut**	
$n =$	Overestimate	Underestimate	Overestimate	Underestimate
Threshold: 25 basis points				
Panel A: FF Futures				
3	0.6%	1.2%	0.0%	20.0%
6	1.8%	4.1%	0.0%	36.0%
Panel B: Overnight Index Swaps				
3	0.0%	0.0%	0.0%	10.0%
6	0.8%	0.0%	0.0%	20.0%
9	0.9%	6.9%	0.0%	39.3%
12	5.0%	16.5%	0.0%	54.3%
Threshold: 100 basis points				
Panel C: FF Futures				
3	0.0%	0.0%	0.0%	0.8%
6	0.0%	0.0%	0.0%	5.4%
Panel D: Overnight Index Swaps				
3	0.0%	0.0%	0.0%	1.7%
6	0.0%	0.0%	0.0%	5.0%
9	0.0%	0.0%	0.0%	14.3%
12	0.0%	0.0%	0.0%	19.6%

Table IA.6: Taylor Rule Deviations: Structural Approach

The table reports correlations between Taylor rule deviations, excess returns and expectation errors, as well as p-values for correlations being larger than zero. The first row shows correlations between Taylor rule deviations and excess returns. The second row shows correlations between Taylor rule deviations and expectation errors from Eq. (5). The Taylor rule implied short rate is here found following Evans et al. (1998) as,

$$\widehat{i}_{t+n} = r + \pi_{t+n} + \frac{1}{2} \times \text{okun} \times (u^* - u_{t+n}) + \frac{1}{2} \times (\pi_{t+n} - \pi^*),$$

where r is the level of the real interest rate, π_{t+n} is the inflation rate, *okun* is the parameter relating output to unemployment gaps (Okun, 1963), u^* is the natural rate of unemployment, u_{t+n} is the unemployment rate, and π^* is the target inflation rate. For parameter values, we follow Evans et al. (1998) and set $r = 2\%$, okun $= 3$, $u^* = 6\%$, and $\pi^* = 2\%$. Notably, the assumption that the real interest rate is 2% is criticizable given the low interest rate environment experienced over the past decade. However, as our data go back three decades, it is not unreasonable to assume that the average real interest rate has been 2% over this period. The sample for FF futures is 1990:11 to 2021:09 and the sample for OIS is 2001:12 to 2021:09.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
$\rho\left(\psi^{\text{Taylor}}_{t+n}, rx^{(n)}_{t+n}\right)$	0.20	0.28	0.14	0.21	0.31	0.36
	[0.00]	[0.00]	[0.04]	[0.00]	[0.00]	[0.00]
$\rho\left(\psi^{\text{Taylor}}_{t+n}, \text{EE}^{(n)}_{t+n}\right)$	0.23	0.32	0.19	0.26	0.35	0.40
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]

Table IA.7: Excess Returns in Recessions

The table reports the coefficient estimates from regressions of excess returns on a constant and a recession dummy, $rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)}\text{NBER}_t + \varepsilon_{t+n}^{(n)}$, where NBER_t is the National Bureau of Economic Research (NBER) recession indicator which takes the value one whenever the economy is in recession and zero otherwise. We report t-statistics based on standard errors computed using a block bootstrap, where the block length is determined according to Politis and White (2004) and Patton et al. (2009). The sample for FF futures is 1990:11 to 2021:09 and the sample for OIS is 2001:12 to 2021:09.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
$\alpha^{(n)}$	4.08	8.90	2.17	4.99	8.43	13.07
	(3.43)	(2.94)	(1.56)	(1.80)	(1.65)	(1.57)
$\beta^{(n)}$	20.49	36.34	16.13	29.75	45.18	58.49
	(5.33)	(4.01)	(3.59)	(3.28)	(2.86)	(2.40)
R^2	0.12	0.13	0.09	0.11	0.13	0.13

Table IA.8: Excess Return Predictability: Out-of-Sample

The table reports the Campbell and Thompson (2008) R^2_{OoS} statistic for predicting excess returns out-of-sample using either the stock market, nonfarm employment growth, the credit spread, or the Treasury yield spread as the predictor variable. The forecasts are formed as $\widehat{rx}^{(n)}_{t+n} = \widehat{\alpha}^{(n)}_t + \widehat{\beta}^{(n)}_t x_t$, where x_t contains the given predictor variable and the coefficients are estimated recursively based on an expanding window of observations, where the initial estimation window contains five years of data. Square brackets present Clark and West (2007) $p-$values for tests of equal predictive accuracy between these forecasts and the EH benchmark.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
S&P500	0.06	0.05	0.03	0.03	0.03	0.04
	[0.00]	[0.00]	[0.01]	[0.01]	[0.02]	[0.01]
Employment Growth	-0.07	-0.19	-0.04	-0.13	-0.26	-0.36
	[0.42]	[0.36]	[0.95]	[0.91]	[0.77]	[0.45]
Corporate Bond Spread	-0.07	-0.12	-0.07	-0.08	-0.05	0.02
	[0.34]	[0.75]	[0.64]	[0.52]	[0.25]	[0.15]
Treasury Yield Spread	-0.01	-0.02	-0.01	-0.03	-0.04	-0.03
	[0.71]	[0.74]	[0.93]	[0.98]	[0.95]	[0.97]

Table IA.9: Predicting Excess Returns using the NFCI

The table reports the results from Eq. (10) where x_t contains another measure of financial conditions: the Chicago Fed's National Financial Conditions Index (NFCI). In Panel A, we run the univariate regressions of ΔNFCI (we take the first difference of the index due to its high persistence). The estimated coefficients denote the basis point change in excess returns following a 1% (100 bps) increase or decrease in ΔNFCI. In Panel B, we run a horse race between ΔNFCI and nonfarm employment growth. The coefficient $\gamma^{(n)}$ shows the basis point change in excess returns following a 1% change in employment growth. Panels C and D use the corporate bond spread and the Treasury yield spread as controls, respectively, where $\gamma^{(n)}$ measures the basis point change in excess returns following a 1% change in either of these two variables. We report t-statistics based on standard errors computed using a block bootstrap, where the block length is determined according to Politis and White (2004) and Patton et al. (2009). The sample for FF futures is 1990:11 to 2021:09 and the sample for OIS is 2001:12 to 2021:09.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
Panel A: $rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)}\Delta\text{NFCI}_t + \epsilon_{t+n}^{(n)}$						
$\beta^{(n)}$	0.36	0.38	0.43	0.52	0.61	0.69
	(4.56)	(2.53)	(5.76)	(3.73)	(4.00)	(3.54)
R^2	0.08	0.03	0.18	0.10	0.07	0.05
Panel B: $rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)}\Delta\text{NFCI}_t + \gamma^{(n)}\text{Employment Growth}_t + \epsilon_{t+n}^{(n)}$						
$\beta^{(n)}$	0.39	0.43	0.46	0.56	0.68	0.81
	(5.00)	(2.97)	(5.98)	(3.71)	(3.51)	(3.14)
$\gamma^{(n)}$	-0.71	-1.30	-0.64	-0.95	-1.83	-3.27
	(-1.10)	(-0.81)	(-1.29)	(-0.68)	(-0.76)	(-0.95)
R^2	0.09	0.04	0.19	0.10	0.08	0.07
Panel C: $rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)}\Delta\text{NFCI}_t + \gamma^{(n)}\text{Corporate Bond Spread}_t + \epsilon_{t+n}^{(n)}$						
$\beta^{(n)}$	0.38	0.39	0.45	0.55	0.66	0.75
	(4.93)	(2.60)	(6.56)	(4.00)	(3.28)	(2.82)
$\gamma^{(n)}$	1.91	2.03	3.45	5.02	7.67	10.25
	(1.00)	(0.41)	(2.19)	(1.21)	(1.10)	(1.03)
R^2	0.09	0.03	0.20	0.12	0.10	0.08
Panel D: $rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)}\Delta\text{NFCI}_t + \gamma^{(n)}\text{Treasury Yield Spread}_t + \epsilon_{t+n}^{(n)}$						
$\beta^{(n)}$	0.36	0.37	0.43	0.51	0.60	0.68
	(4.59)	(2.54)	(5.84)	(3.80)	(3.96)	(3.64)
$\gamma^{(n)}$	-0.57	-1.89	-0.42	-1.21	-1.55	-2.05
	(-0.30)	(-0.42)	(-0.26)	(-0.28)	(-0.20)	(-0.19)
R^2	0.08	0.03	0.18	0.10	0.07	0.05

Table IA.10: Predicting Expectation Errors using the Stock Market

The table reports the results from replacing excess returns with survey expectation errors in Eq. (10). In Panel A, we run univariate regressions using the excess returns on the S&P500 as the predictor variable. The estimated coefficients denote the basis point change in expectation errors following a 1% (100 bps) increase or decrease in the stock market. In Panel B, we run a horse race between the stock market and nonfarm employment growth. The coefficient $\gamma^{(n)}$ shows the basis point change in expectation errors following a 1% change in employment growth. Panels C and D use the corporate bond spread and the Treasury yield spread as controls, respectively, where $\gamma^{(n)}$ measures the basis point change in expectation errors following a 1% change in either of these two variables. We report t-statistics based on standard errors computed using a block bootstrap, where the block length is determined according to Politis and White (2004) and Patton et al. (2009). The sample for FF futures is 1990:11 to 2021:09 and the sample for OIS is 2001:12 to 2021:09.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
Panel A: $\text{EE}^{(n)}_{t+n} = \alpha^{(n)} + \beta^{(n)} rx^{\text{S\&P500}}_t + \epsilon^{(n)}_{t+n}$						
$\beta^{(n)}$	-1.11	-1.76	-1.33	-1.70	-2.04	-2.52
	(-4.42)	(-4.60)	(-4.67)	(-4.15)	(-3.71)	(-3.42)
R^2	0.06	0.06	0.09	0.07	0.06	0.05
Panel B: $\text{EE}^{(n)}_{t+n} = \alpha^{(n)} + \beta^{(n)} rx^{\text{S\&P500}}_t + \gamma^{(n)}\text{Employment Growth}_t + \epsilon^{(n)}_{t+n}$						
$\beta^{(n)}$	-1.15	-1.82	-1.36	-1.71	-2.07	-2.57
	(-4.98)	(-4.87)	(-4.86)	(-3.99)	(-3.65)	(-3.49)
$\gamma^{(n)}$	-0.78	-1.43	-0.33	-0.23	-0.47	-1.15
	(-1.06)	(-0.86)	(-0.51)	(-0.14)	(-0.18)	(-0.32)
R^2	0.07	0.07	0.09	0.07	0.06	0.06
Panel C: $\text{EE}^{(n)}_{t+n} = \alpha^{(n)} + \beta^{(n)} rx^{\text{S\&P500}}_t + \gamma^{(n)}\text{Corporate Bond Spread}_t + \epsilon^{(n)}_{t+n}$						
$\beta^{(n)}$	-1.05	-1.69	-1.26	-1.61	-1.94	-2.39
	(-4.51)	(-4.80)	(-4.61)	(-3.89)	(-3.63)	(-3.52)
$\gamma^{(n)}$	4.28	5.29	4.13	5.10	6.62	8.42
	(1.84)	(1.00)	(1.78)	(1.10)	(0.84)	(0.75)
R^2	0.08	0.07	0.12	0.09	0.08	0.07
Panel D: $\text{EE}^{(n)}_{t+n} = \alpha^{(n)} + \beta^{(n)} rx^{\text{S\&P500}}_t + \gamma^{(n)}\text{Treasury Yield Spread}_t + \epsilon^{(n)}_{t+n}$						
$\beta^{(n)}$	-1.11	-1.76	-1.33	-1.69	-2.04	-2.52
	(-4.37)	(-4.63)	(-4.73)	(-4.13)	(-3.71)	(-3.39)
$\gamma^{(n)}$	-0.20	-1.32	-0.05	-0.98	-1.60	-1.93
	(-0.08)	(-0.28)	(-0.02)	(-0.19)	(-0.21)	(-0.19)
R^2	0.06	0.06	0.09	0.07	0.06	0.05

Table IA.11: Predicting Expectation Errors: Asymmetric Effects

The table reports estimates from the predictive regression Eq. (11) where excess returns are replaced with expectation errors, $\text{EE}_{t+n}^{(n)}$. The variable $rx_t^{\text{S\&P500}} 1_{(rx_t^{\text{S\&P500}}>0)}$ contains all positive stock returns and takes the value zero whenever stock returns are negative, while the variable $rx_t^{\text{S\&P500}} 1_{(rx_t^{\text{S\&P500}}\leq 0)}$ contains all negative stock returns and takes the value zero whenever stock returns are positive. We report slope coefficients (the basis point change in expectation errors following a 1% monthly increase or decrease in the stock market) and t-statistics based on standard errors computed using a block bootstrap, where the block length is determined according to Politis and White (2004) and Patton et al. (2009). The sample for FF futures is 1990:11 to 2021:09 and the sample for OIS is 2001:12 to 2021:09.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
$\beta_{\text{POS}}^{(n)}$	0.28	-0.10	0.08	0.00	0.09	0.61
	(0.53)	(-0.10)	(0.13)	(0.02)	(0.07)	(0.32)
$\beta_{\text{NEG}}^{(n)}$	-2.88	-3.80	-2.79	-3.22	-3.64	-4.38
	(-5.13)	(-3.78)	(-4.27)	(-3.12)	(-2.31)	(-2.01)
R^2	0.11	0.08	0.14	0.10	0.08	0.08

Table IA.12: Decomposing Excess Returns with Quarterly Data

Panel A shows the mean excess returns on FF futures and OIS, as well as expectation errors and survey-implied term premia, all based on quarterly data. We regress each series on a constant and report the results in basis points. t-statistics use standard errors computed using a block bootstrap, with the block length determined according to Politis and White (2004) and Patton et al. (2009). In Panel B, we perform a simple variance decomposition to test how much excess return variation is attributed to expectation errors and term premia, respectively. We compute the contribution of expectation errors as $cov(rx_{t+n}^{(n)}, \mathrm{EE}_{t+n}^{(n)})/var(rx_{t+n}^{(n)})$, where $rx_{t+n}^{(n)}$ are excess returns and $\mathrm{EE}_{t+n}^{(n)}$ are the expectation errors over the same horizon. We compute the contribution of term premia as $cov(rx_{t+n}^{(n)}, \mathrm{TP}_t^{(n)})/var(rx_{t+n}^{(n)})$. The sample for FF futures is 1990:11 to 2021:09 and the sample for OIS is 2001:12 to 2021:09.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
Panel A: Mean Estimates						
Excess Returns	6.00	12.50	3.74	7.90	12.74	18.42
	(3.12)	(2.93)	(1.55)	(1.64)	(1.68)	(1.72)
Expectation Errors	6.86	12.21	5.34	9.49	15.59	22.92
	(3.34)	(2.89)	(2.11)	(2.07)	(2.14)	(2.21)
Term Premia	-0.86	0.28	-1.60	-1.59	-2.85	-4.50
	(-1.20)	(0.21)	(-2.40)	(-0.80)	(-1.02)	(-1.27)
Panel B: Variance Decomposition						
Expectation Errors	1.08	0.98	1.13	1.00	0.96	0.95
Term Premia	-0.08	0.02	-0.13	0.00	0.04	0.05

Internet Appendix: Figures

Figure IA.1: Excess Returns on OIS and Expectation Errors

The figure shows excess returns on OIS, $rx_{t+n}^{(n)} = f_t^{(n)} - i_{t+n}$, with contemporaneous expectation errors, $\mathrm{EE}_{t+n}^{(n)} = S_t^{(n)} - i_{t+n}$, from the decomposition in Eq. (5). Survey data are from Blue Chip Financial Forecasts. The series are plotted with National Bureau of Economic Research (NBER) recession periods in gray shading. All values are denoted in basis points and the sample is 2001:12 to 2021:09.

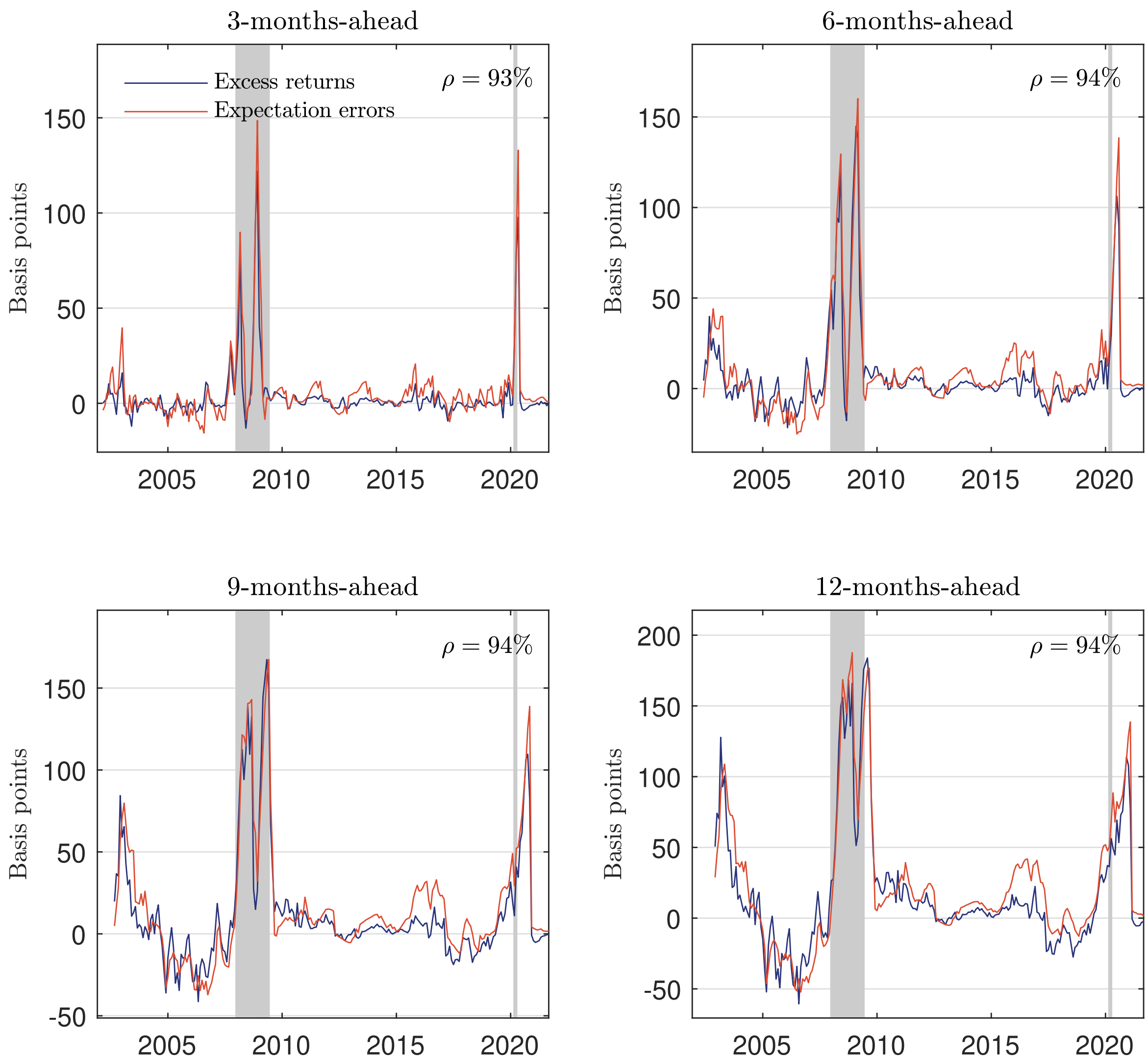


Figure IA.2: Excess Returns on FF Futures and Term Premia

The figure shows excess returns on FF futures, $rx_{t+n}^{(n)} = f_t^{(n)} - i_{t+n}$, with survey-implied term premia, $\mathrm{TP}_t^{(n)} = f_t^{(n)} - S_t^{(n)}$, from the decomposition in Eq. (5). The series are plotted with National Bureau of Economic Research (NBER) recession periods in gray shading. All values are denoted in basis points and the sample is 1990:11 to 2021:09.

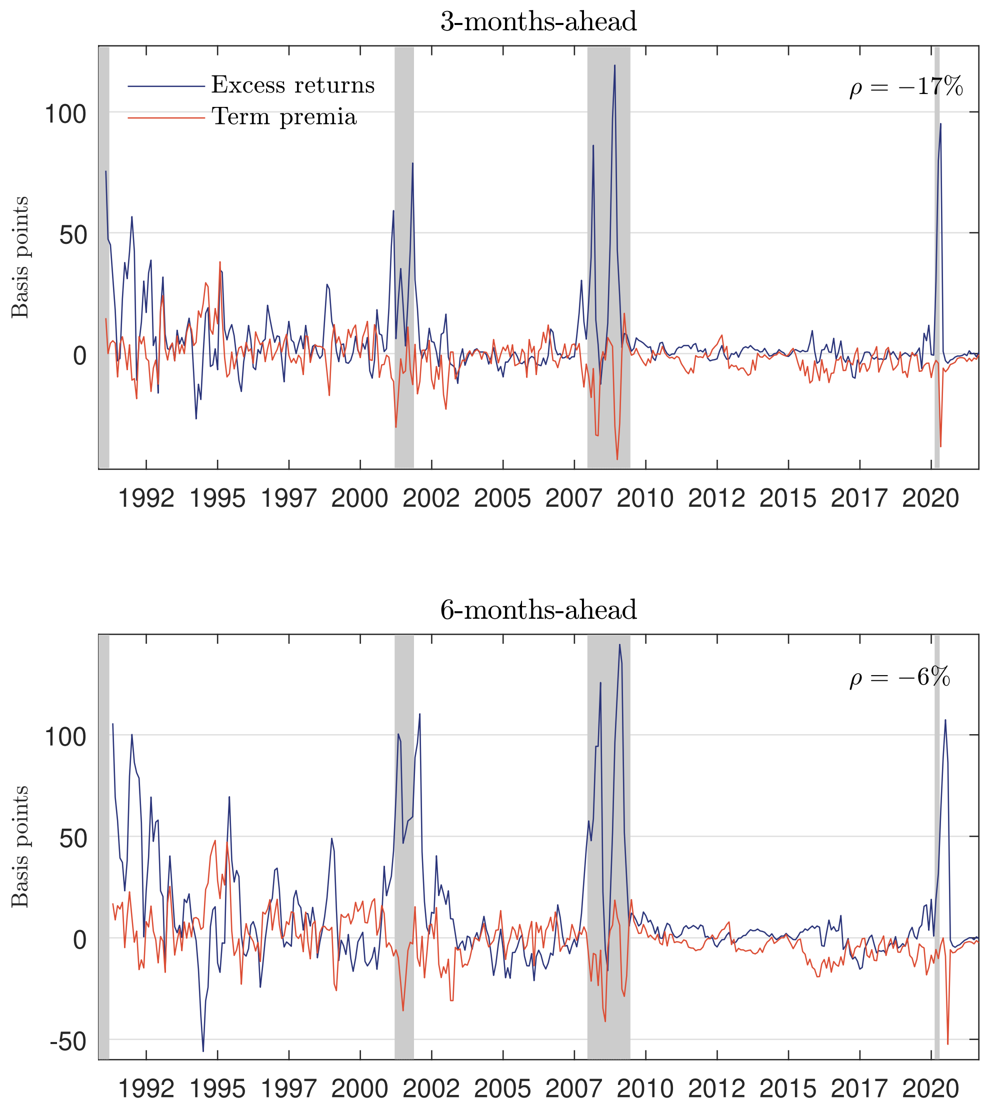


Figure IA.3: Excess Returns on OIS and Term Premia

The figure shows excess returns on OIS, $rx_{t+n}^{(n)} = f_t^{(n)} - i_{t+n}$, with survey-implied term premia, $\mathrm{TP}_t^{(n)} = f_t^{(n)} - S_t^{(n)}$, from the decomposition in Eq. (5). The series are plotted with National Bureau of Economic Research (NBER) recession periods in gray shading. All values are denoted in basis points and the sample is 2001:12 to 2021:09.

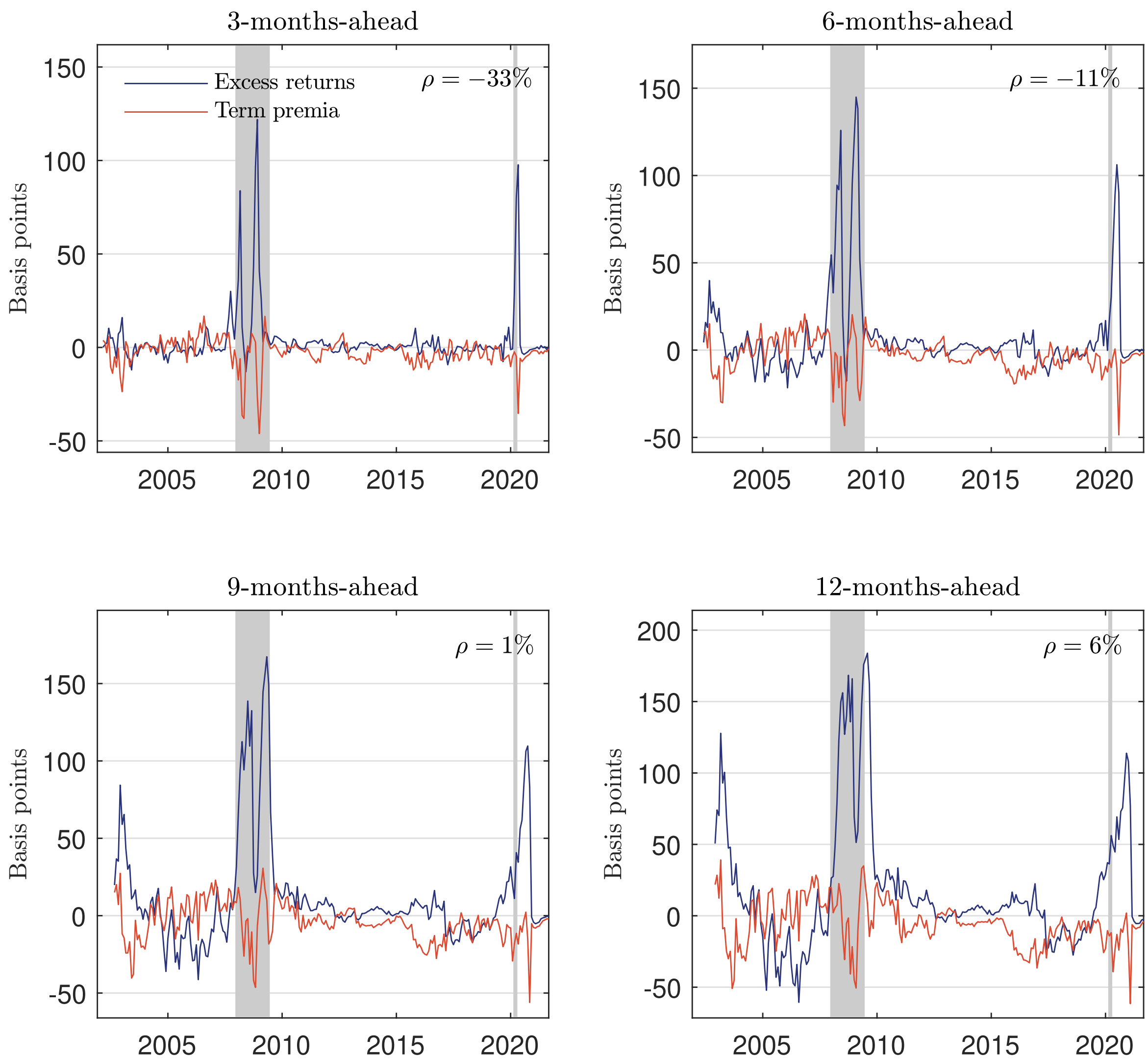


Figure IA.4: Prediction-Realization Diagrams: OIS

The figure shows the time $t+n$ realized short rate change together with its time t predicted value from OIS. The realized change, $\Delta i_{t+n} = i_{t+n} - i_t$, is the change in the short rate from t to $t+n$. The predicted value is $\varphi_t^{(n)} = f_t^{(n)} - i_t$, where $f_t^{(n)}$ is the rate on OIS. The dotted line is the regression line from Eq. (6). All values are denoted in basis points and the sample is 2001:12 to 2021:09.

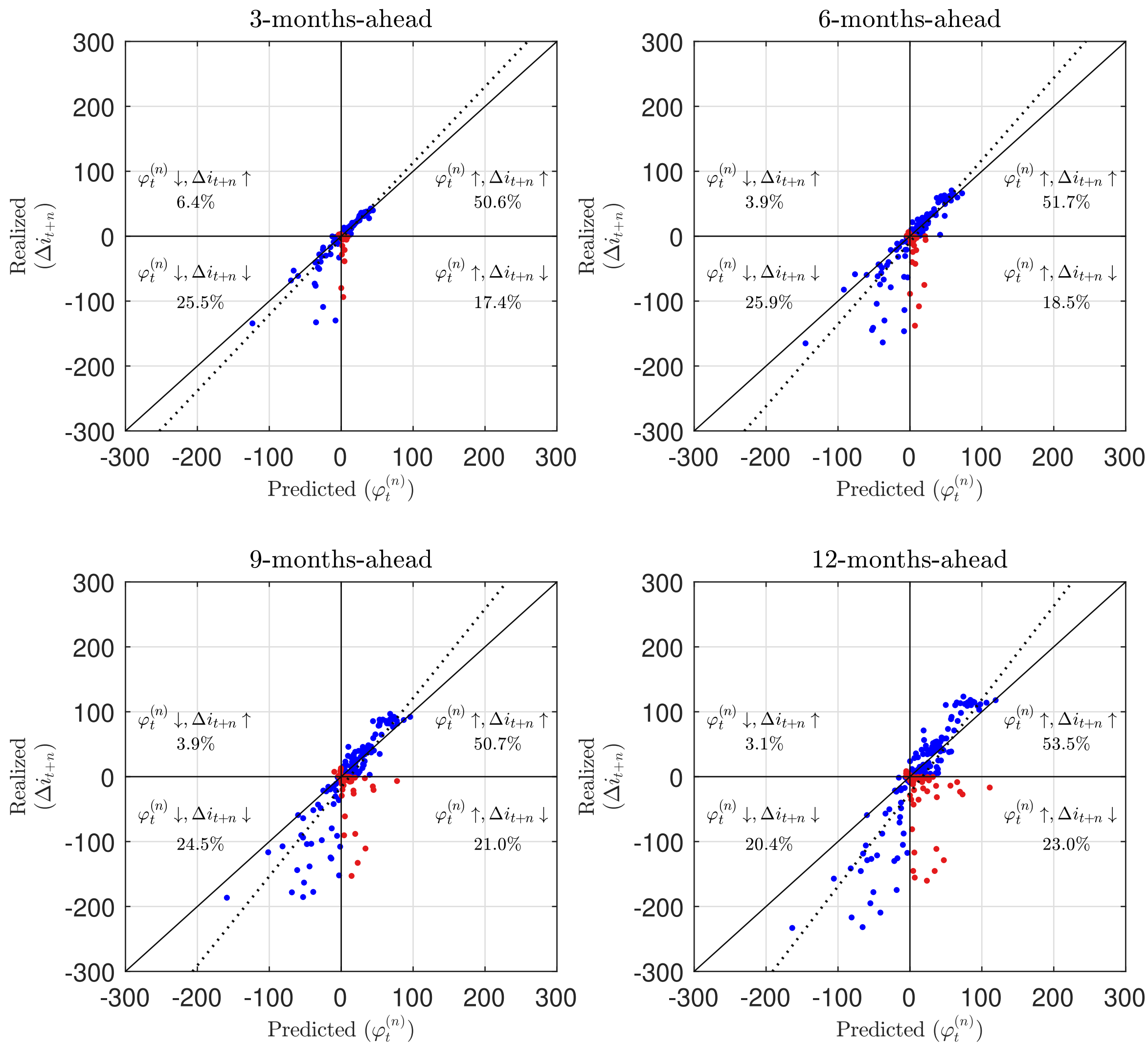


Figure IA.5: Excess Returns on FF Futures and Taylor Rule Deviations

The figure shows excess returns on FF futures with contemporaneous Taylor rule deviations from Eq. (9). When Taylor rule deviations are positive, short rates are below the level implied by the Taylor rule and vice versa. The series are plotted with National Bureau of Economic Research (NBER) recession periods in gray shading. Both series are standardized to have mean zero and unit variance and the sample is 1990:11 to 2021:09.

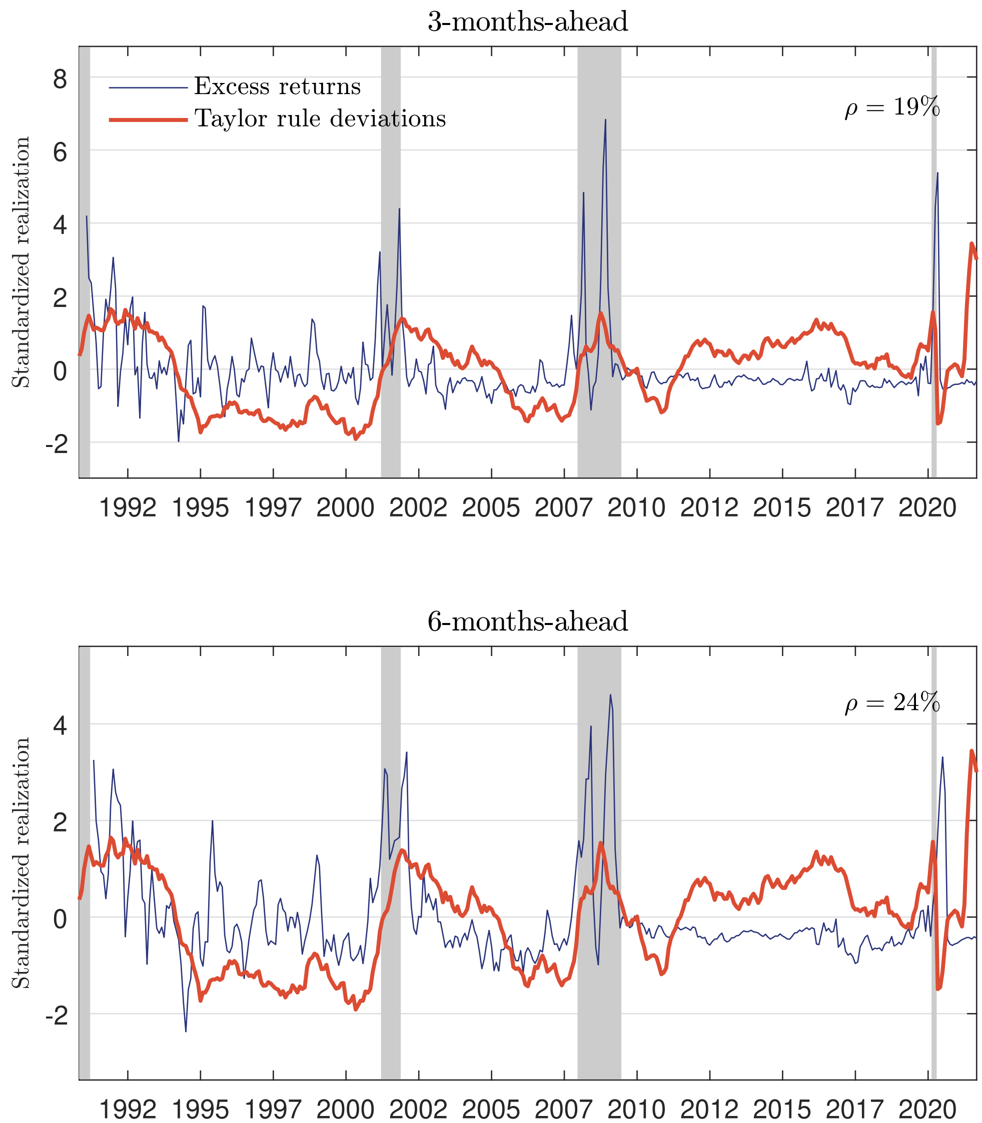


Figure IA.6: Excess Returns on OIS and Taylor Rule Deviations

The figure shows excess returns on OIS with contemporaneous Taylor rule deviations from Eq. (9). When Taylor rule deviations are positive, short rates are below the level implied by the Taylor rule and vice versa. The series are plotted with National Bureau of Economic Research (NBER) recession periods in gray shading. Both series are standardized to have mean zero and unit variance and the sample is 2001:12 to 2021:09.

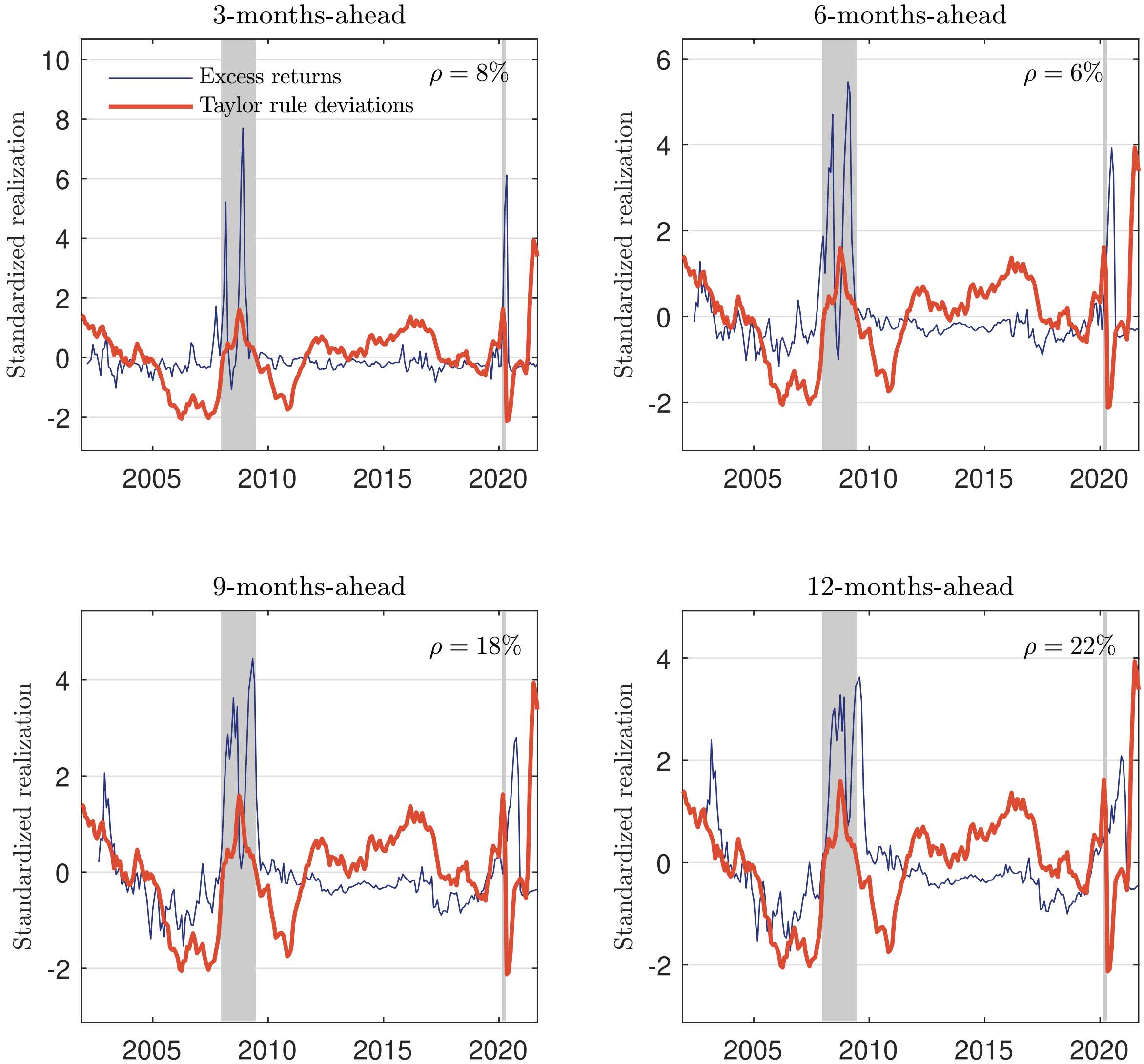


Figure IA.7: Excess Returns on OIS and Forecaster Disagreement

The figure shows excess returns on OIS, $rx_{t+n}^{(n)} = f_t^{(n)} - i_{t+n}$, with time t disagreement among forecasters about the short rate over horizon n. Disagreement at each time point is computed as the difference between the 90th and the 10th percentile of the cross-section of individual forecasts from Blue Chip Financial Forecasts. Units of excess returns are plotted on the left axis, units of disagreement are on the right, and both are in basis points. The series are plotted with National Bureau of Economic Research (NBER) recession periods in gray shading. The sample is 2001:12 to 2021:09.

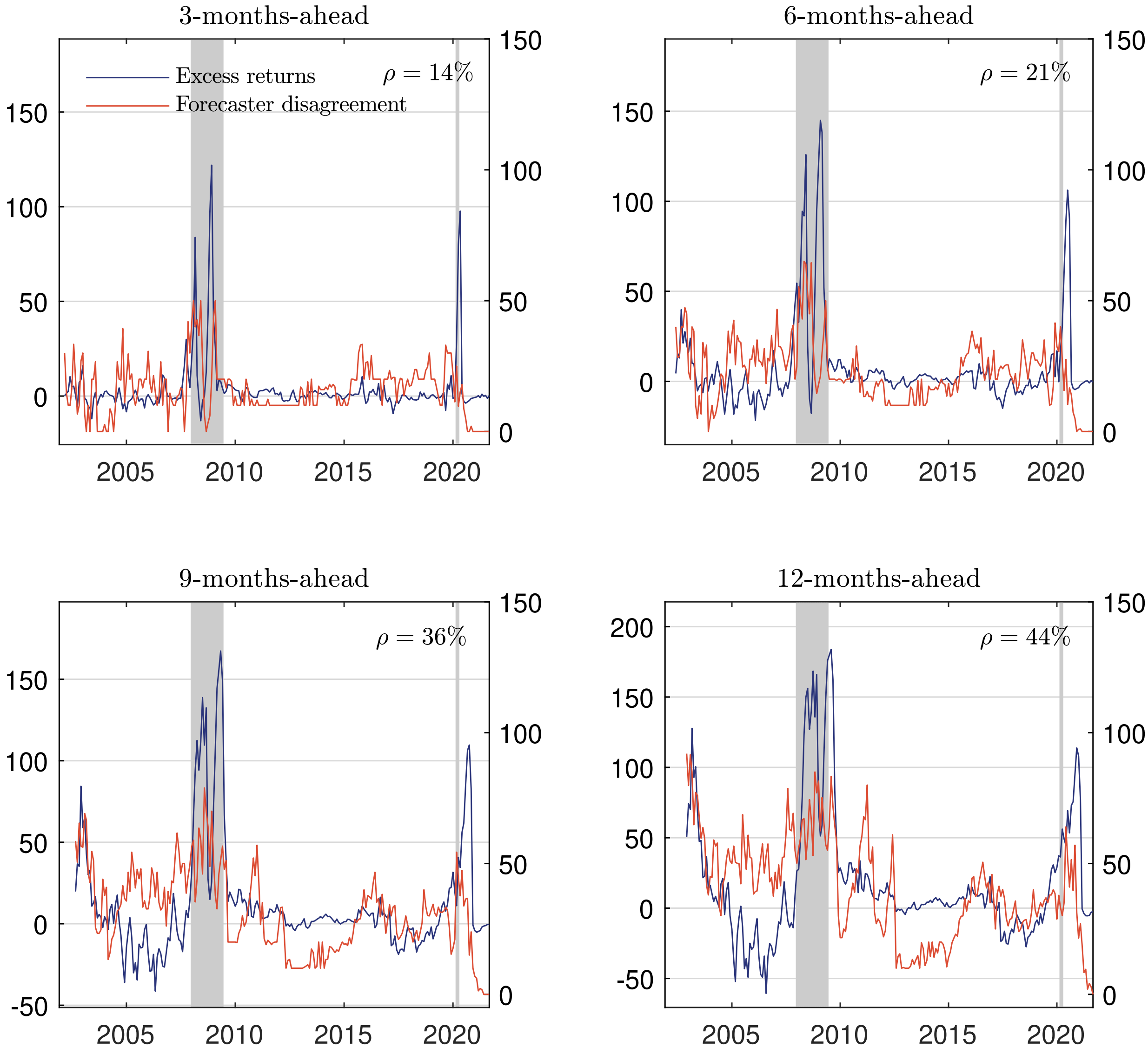


Figure IA.8: Excess Returns and Expectation Errors: Euro area

The figure shows excess returns on OIS with contemporaneous expectation errors from the decomposition in Eq. (5). For the international evidence, survey data are from Reuters Central Bank Polls. The sample is 2004:10 to 2021:09, the frequency of observations is monthly, and all values are denoted in basis points.

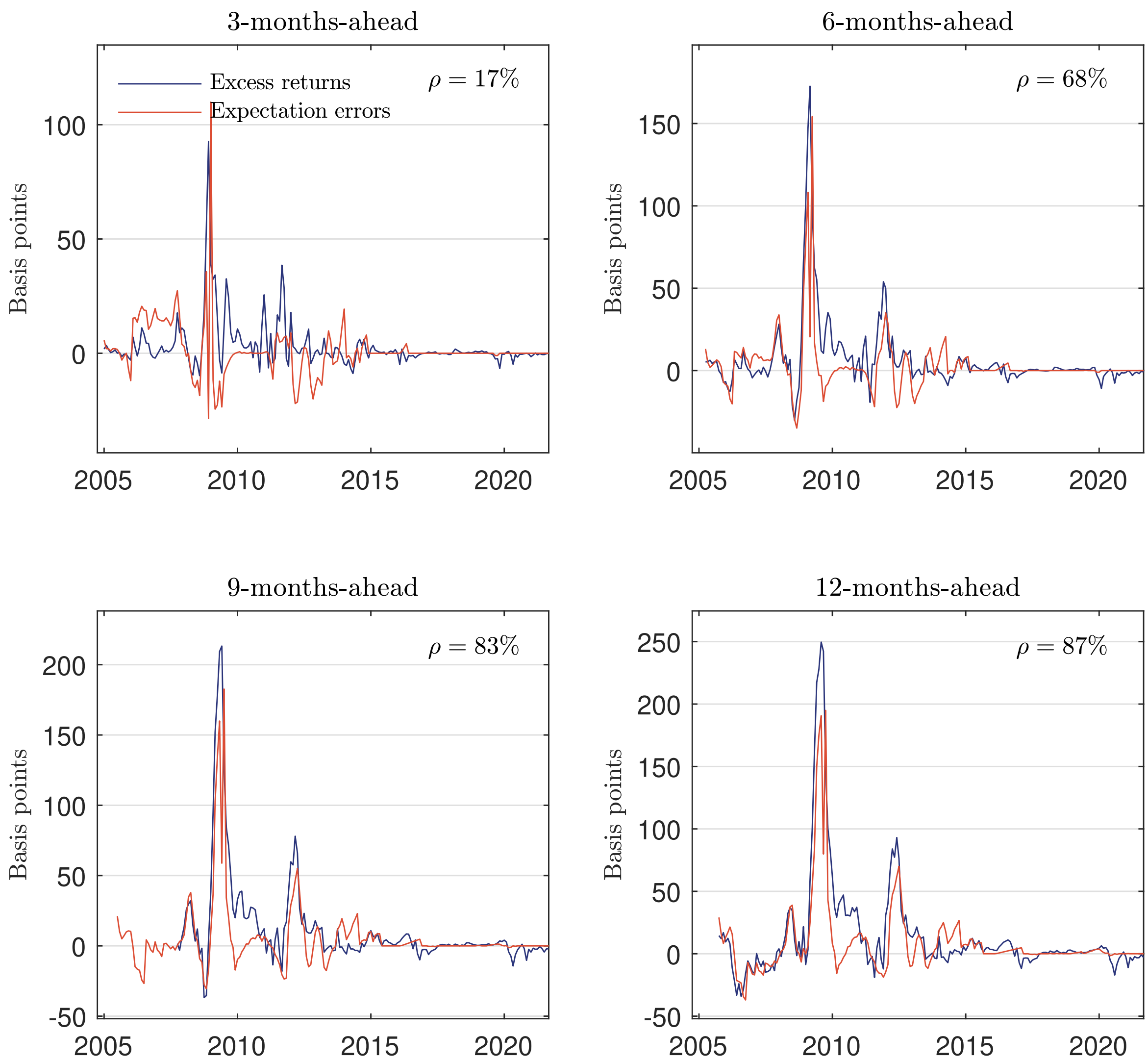


Figure IA.9: Excess Returns and Expectation Errors: United Kingdom

The figure shows excess returns on OIS with contemporaneous expectation errors from the decomposition in Eq. (5). For the international evidence, survey data are from Reuters Central Bank Polls. The sample is 2004:12 to 2021:09, the frequency of observations is monthly, and all values are denoted in basis points.

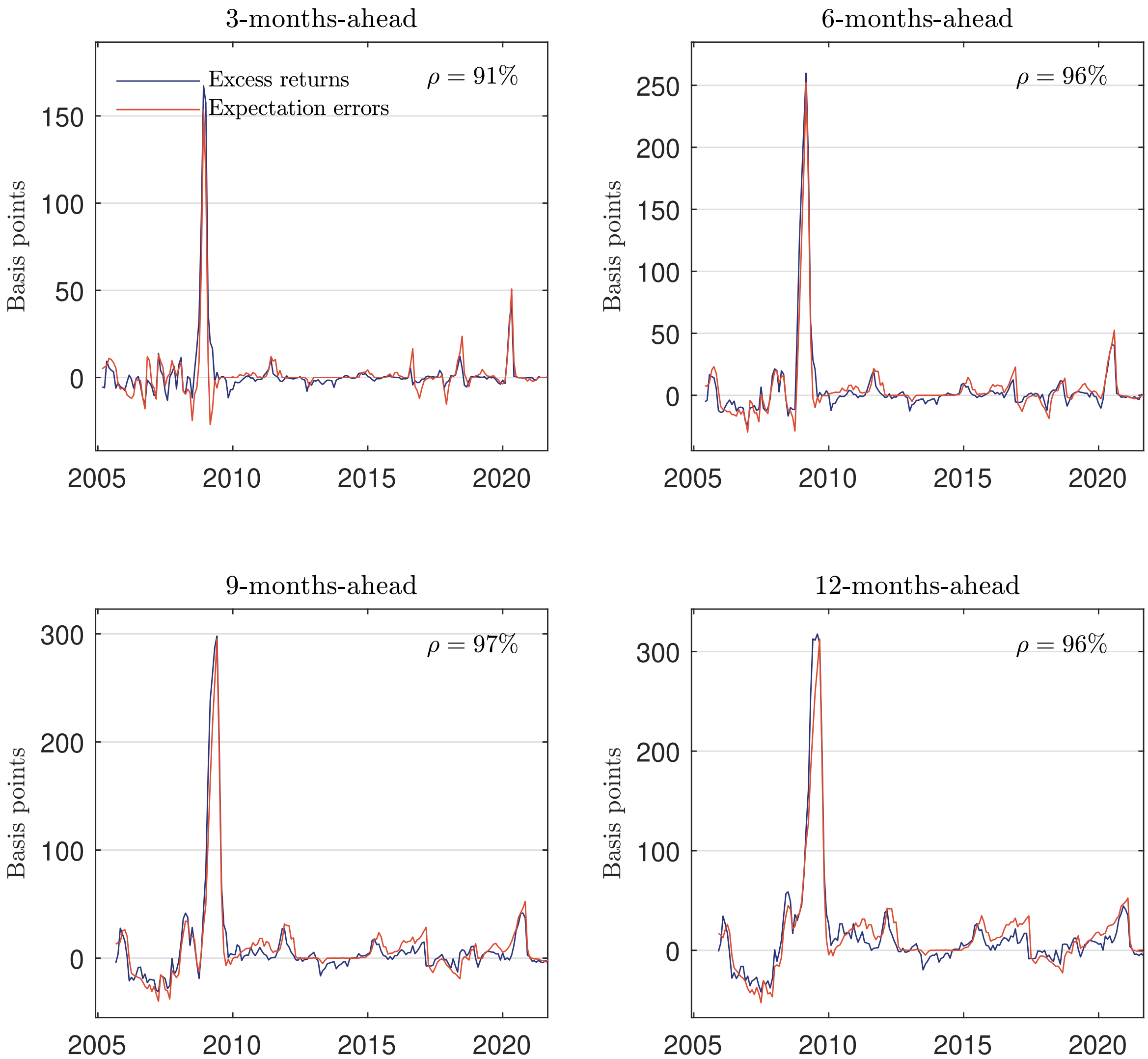
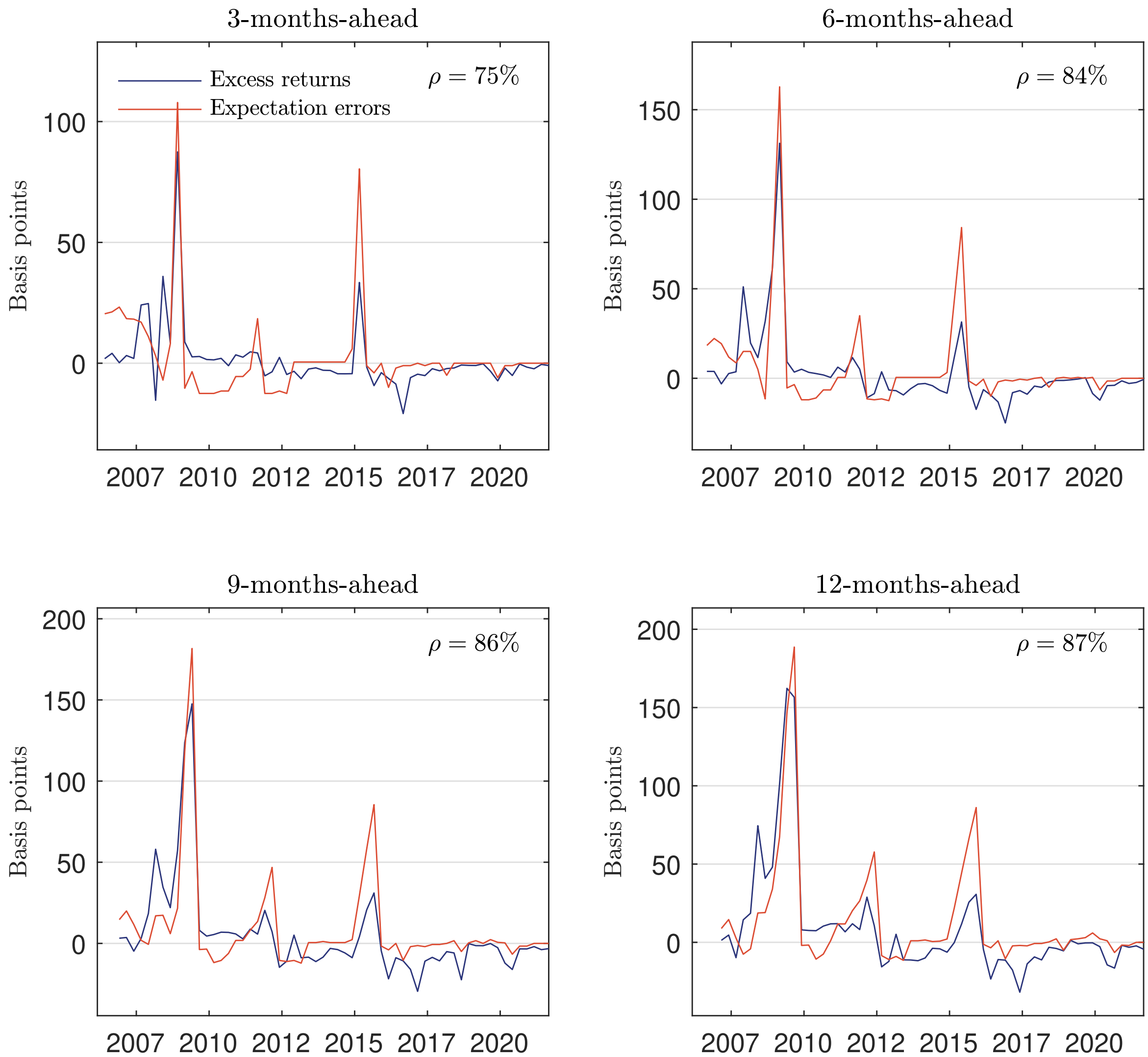


Figure IA.10: Excess Returns and Expectation Errors: Switzerland

The figure shows excess returns on OIS with contemporaneous expectation errors from the decomposition in Eq. (5). For the international evidence, survey data are from Reuters Central Bank Polls. The sample is 2006:3 to 2021:09, the frequency of observations is quarterly, and all values are denoted in basis points.



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