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Monetary Policy Expectation Errors

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Abstract
We use survey expectations about future monetary policy to decompose excess returns on fed funds futures and overnight index swaps into a term premium and an expectation error component. We find that excess returns are primarily driven by expectation errors, while term premia are economically small and negative on average. Most expectation errors stem from market participants underestimating how aggressively the Federal Reserve has eased policy during the last three decades. Our findings reveal that market participants are continuously learning about the central bank's reaction function and have been slow to recognize the rising importance attributed to deteriorating financial conditions and falling stock prices. We document similar results in an international sample of six major currency areas.

Resume
Vi bruger data om forventningerne til den fremtidige pengepolitik til at opdele merafkastet på fed funds futures og overnight index swaps i henholdsvis en risikopræmie og en forventningsfejl. Vi finder, at merafkastet primært drives af forventningsfejl, mens risikopræmierne er økonomisk små og i gennemsnit negative. De fleste forventningsfejl opstår, fordi markedsdeltagerne i stor udstrækning har undervurderet Federal Reserves' kraftige pengepolitiske lempelser over de seneste tre årtier. Vores resultater viser, at markedsdeltagerne løbende lærer om reaktionsfunktionen og kun langsomt er blevet opmærksomme på centralbankens øgede fokus på forværrede finansielle forhold og faldende aktiekurser. Vi finder lignende resultater i en international stikprøve bestående af seks store valutaområder.

Key words
Interest-rate swaps, monetary policy, the money and currency markets

JEL classification
E43; E44; G12; G15

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The authors alone are responsible for any remaining errors.

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Keywords: Fed funds futures, overnight index swaps, forecast evaluation, expectation formation, monetary policy

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1. Introduction

Money markets are at the heart of the international monetary and financial system and a crucial source of funding for key market participants such as banks, dealers, hedge funds, and shadow banking entities. Overnight (O/N) money market rates commonly serve as the policy target of central banks around the globe and form an integral part of monetary policy implementation frameworks. In fact, the term structure of market-implied future O/N rates is a common ingredient in central banks' market monitoring, especially ahead of policy decisions, and serves as a tool to assess the market's expectations of future short-term interest rates. A key question in this context is whether the term structure of money market derivatives can be trusted to accurately reflect market participants' short rate expectations, or whether it is distorted due to the presence of term premia or certain biases.[1]

The main goal of this paper is to provide a better understanding of how market participants form expectations about the future course of monetary policy and to link this to the pricing of money market derivatives. More specifically, we study the information about future monetary policy that is embedded in instruments such as fed funds (FF) futures and overnight index swaps (OIS). A crucial part of our analysis is to complement data on the pricing of these derivatives with survey expectations about future short-term interest rates.

Our analysis generates new insights in three broad areas. First, from an asset pricing perspective, it provides new facts on how and when the expectations hypothesis (EH) holds in the term structure of money market rates. Second, it allows for a better understanding of how market participants form expectations about future short-term interest rates. Third, by studying when and how prior market expectations and subsequent actions by the central bank deviate from each other, we shed new light on an important area of monetary economics: the nature of the central bank's reaction function.

As a starting point, we document that the implied future short rates extracted from money

[1] Current reform efforts to transition away from LIBOR towards a set of new, risk-free O/N benchmark rates add further relevance to this question. In the context of benchmark rate reform, derivatives linked to the O/N risk-free rates (e.g., SOFR in the US, ESTR in the Eurozone, SONIA in the UK, and TONAR in Japan) are seen as highly important in accomplishing the transition. The main idea is to rely on transactions in these derivatives to construct so-called forward-looking term rates that can replace term rates such as the 3-month LIBOR in financial contracts (see, e.g., Schrimpf and Sushko, 2019).

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.[2] As such, investors can earn 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 is commonly 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 Forecasts, we decompose excess returns on long FF futures and OIS positions 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 expectation errors 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*.

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, we argue that any term premium variation in these contracts should not be interpreted as compensation for holding risky assets in periods of economic downturn, but instead reflects the price that hedging institutions active in the money markets are willing to pay to insure themselves against future short rate changes.[3]

[2]See 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.

[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.

Having established these new stylized facts, the remainder of the paper aims to provide a better understanding 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. Most noticeable, these effects are highly asymmetric and significantly more pronounced for interest rate cuts than for interest rate hikes. In essence, our findings imply that there are several instances where market participants have, over the past 30 years, underestimated how aggressively the Federal Reserve (Fed) would cut interest rates in times of economic downturn.

Crucially, our results reveal a tight link between expectation errors and monetary policy itself, in particular the nature of the central bank's reaction function. First, we show that expectation errors are significantly correlated with deviations of policy rates from what the conventional Taylor rule prescribes: when the central bank sets the short rate below the rate implied by the Taylor rule ("loose monetary policy stance"), market expectations of future interest rates are "too high" relative to realized interest rates. Second, we find that past revisions to short rate expectations contain predictive power for future expectation errors, indicating that market participants face information rigidities and are learning about the central bank's reaction in real time (see, e.g., Coibion and Gorodnichenko, 2015). Third, we find that money market excess returns are significantly related to past stock market returns. Empirically, a drop in the stock market predicts *higher* excess returns on FF futures and OIS both in-sample and out-of-sample.[4] A natural interpretation is that poor stock market returns precede periods when the Fed eased more aggressively than what market participants had expected and thus what was embedded in their forecasts. Finally, we go beyond the US and analyze a panel of six major currency areas: Australia, Canada, the Eurozone, the United Kingdom, Japan, and Switzerland. We find that our main results apply here as well: in the three currency areas with available

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

survey data (the Eurozone, 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 in line with the US results.

The most plausible explanation for these findings seems to be that monetary policy expectation errors stem from the difficulties faced by market participants when assessing the central bank's reaction function in an environment of uncertainty. Indeed, we find the connection between stock market returns and subsequent expectation errors to be highly asymmetric and entirely driven by negative stock market returns. This lends credence to the idea that the Fed lowered rates to cushion the effect of severe stock market declines (see, e.g., Cieslak and Vissing-Jorgensen, 2020, on the so-called "Fed put") over our sample period. Such aggressive and asymmetric easing on the back of declining equity prices and deteriorating financial conditions, however, took market participants by surprise. Put differently, market participants appear to have underestimated the role of financial conditions as an important ingredient in the Fed's reaction function, thereby giving rise to the positive excess returns on money market derivatives that are observed ex post.[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 do not have full, ex-ante information about the time-varying reaction function, but are in fact learning about it in real time. This learning process then manifests itself as a systematic and predictable deviation from the EH benchmark.[6]

Related Literature. Our paper adds to the 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 lead to predictable expectation errors and large excess returns

[5]This interpretation is closely related to recent work by Bauer and Swanson (2020), who call into question the information effect interpretation of monetary policy shocks (see e.g., Campbell et al., 2012; Nakamura and Steinsson, 2018), and instead emphasize the unpredictable nature of the central bank's reaction function.

[6]This view corroborates earlier work by Rudebusch (1995) and Mankiw and Miron (1986), who show that deviations from the EH can be explained by the unpredictable manner in which the Fed controls the policy rate, rather than as a result of irrational expectations or time-varying term premia.

on Treasury bonds. 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 perform an in-depth examination of 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 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.

The results of this paper also relate 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 foreign exchange 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 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 financial institutions that are actively participating in money markets.

Our findings also relate to the literature on the 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.[7] 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 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. As such, they conclude that the EH provides a reasonable approximation to the term structure of short-term interest rates, consistent with Longstaff's conclusion. 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 the same 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.

Roadmap. The remainder of the paper is structured as follows. The following section presents our return decomposition using survey data. Section 3 investigates the drivers of expectation errors and their link to monetary policy. Section 4 explores how a time-varying central bank reaction function can lead to predictable expectation errors. Section 5 reports international evidence that expands our analysis to other major currency areas and confirms the robustness of our results. Finally, section 6 concludes.

2. Return Decomposition and New Stylized Facts

2.1. Fed Funds Futures and Overnight Index Swaps

FF futures have been traded on the Chicago Board of Trade (CBOT) since 1988 and are highly standardized contracts designed to hedge fluctuations in the US overnight rate, the effective

[7] 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.

federal funds rate (EFFR), over a specific future month.[8] 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 O/N rate. 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,

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

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 upwards-sloping (downwards-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). Like conventional LIBOR swaps, OIS are traded over the counter and have various advantages over futures as

[8] As an example, a bank with surplus cash that lends it out overnight in the federal funds market can buy FF futures to hedge against the risk that a falling short rate reduces the interest payments it earns.

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

[10] For example, an OIS denominated in EUR uses the Euro Overnight Index Average (EONIA) as the floating rate. An OIS denominated in GBP uses the Sterling Overnight Index Average (SONIA) as the floating rate and so forth.

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 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.

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,

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

[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.

Here, $E_t[rx^{(n)}_{t+n}]$ 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, $rx^{(n)}_{t+n} = E_t[rx^{(n)}_{t+n}]$, 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):

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

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, market participants earn *unexpectedly high* returns when short rates turn out to be unexpectedly low.[12] As we will see, this particular 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 $S^{(n)}_t$. Additional details on the Blue Chip survey can be found in Internet Appendix IA.2. For FF futures and OIS of horizon n, we decompose excess returns by simply adding and subtracting survey expectations with the same

[12]The same dynamics apply to investments in Treasury bonds: when long-term yields decline more than expected, investors earn unexpectedly high mark-to-market returns on their positions and vice versa, see Cieslak (2018).

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 known 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 going back to 1990 from the Chicago Mercantile Exchange (CME). OIS rates are from Bloomberg and are available for the US since December 2001.[13] 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.

>>> TABLE 1 ABOUT HERE <<<

Panel A of Table 1 shows that mean excess returns are economically sizable and in the range of 3 to 16 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* across all maturities. Meanwhile, average expectation errors are similar in magnitudes to realized excess returns

[13]Data on the US short-term interest rate, the Effective Federal Funds Rate (EFFR), are from the Federal Reserve Bank of New York. FF futures originally started trading on the CBOT, which was merged with the CME in 2007. The contracts 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.

and either statistically significant or marginally statistically significant. As such, expectation errors 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 explained in the table text. 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.

Taken together, these initial findings do not support the idea that FF futures and OIS are biased predictors of future short rates because of positive term premia. In contrast, we find term premia to be small and slightly negative, while expectation errors are large and strongly correlated with realized excess returns.

>>> 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.[14] 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 as well as during 2008, 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.[15]

[14]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.

[15]To further examine this observation, the results in Table IA.1 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.

3. Diagnosing Monetary Policy Expectation Errors

To provide a better understanding of expectation errors in the money market term structure, 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 78%. 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 $\beta^{(n)} = 1.42$. As such, a predicted 1% change in short rates is, on average, followed by a 1.42% 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 spreads predict excess returns with a *negative* coefficient. This finding is surprising, since we know from Eq. (3) that the spreads should be positively related to future excess returns if these are driven by term premia.

On the other hand, a negative relation can arise if realized excess returns are driven by

[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.

expectation errors instead. To see this, we can decompose the independent and dependent variables in Eq. (7) into their constituent parts. Following Eq. (3), excess returns consist of a required return component, the 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 irrelevant, 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 term 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. Consequently, the evidence that the term spread predicts excess returns with a negative coefficient further supports that excess returns are driven by expectation errors and not term premia.

3.2. Asymmetric Short Rate Predictability

To further diagnose the pattern of predictability documented in the previous section, we graphically illustrate the relation between the predicted and realized short rates using prediction-realization diagrams.[18]

>>> 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.[19] 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

[18]Introduced by Theil (1961), the diagrams provide a visual impression of how well market participants have predicted the *direction* of a short rate change (increase or decrease), as well as the *magnitude* of the change (how large an increase or decrease).

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

quadrants on the right show when market participants expected short rate increases, i.e., where $\varphi_t^{(n)} = f_t^{(n)} - i_t$ was positive, while the two quadrants on the left show when they expected declines.

First, consider the two quadrants on the diagonal. The observations here denote when market participants correctly predicted 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 quadrant 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, 49.2% of the observations (upper-right quadrant) are correctly predicted short rate increases.[20] Meanwhile, 28.4% of the observations (lower-left quadrant) are correctly predicted short rate declines. As such, only 3.3% of the observations (upper-left quadrant) are short rate increases that market participants were surprised by. Quite strikingly, this entails that a large proportion, 19%, of all observations (lower-right quadrant) are 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 number of unanticipated short rate declines 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.[21] For the upper-right quadrant, more observations are found above the line than below. This means that when market participants correctly predicted short rate hikes, they often underestimated how large the hikes would be. In a similar vein, more observations are found below the line than above in the lower-left quadrant. Here, this entails that market participants also often underestimated the magnitude of short rate cuts.

Many large deviations from the line are seen in the lower-left quadrant. To test if there is

[20] Table IA.2 in the Internet Appendix provides a summary of these numbers.

[21] 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.

also asymmetry in the ability to predict the magnitude of short rate changes, Table IA.3 in the Internet Appendix reports 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.[22] This analysis reveals that market participants were systematically surprised by how large *short rate cuts* turned out to be. For the 6-months-ahead FF futures, when market participants correctly predicted that short rates would go up, they underestimated the magnitude of the increase by at least 25 basis points in only 4.3% of the cases. Meanwhile, when they correctly predicted decreasing short rates, they underestimated the magnitude of the decrease by at least 25 basis points in 37.2% of the cases. As such, the tendency to underestimate short rate changes was much more pronounced when the rate declined.[23]

Taken together, these results reveal a striking asymmetry: while short rate hikes 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* of rate cuts, as well as *how aggressive* the Fed has cut rates over our sample.

3.2. Asymmetry in Expectations Hypothesis Tests

To formalize these findings, we estimate augmented versions of Eqs. (6) and (7) that allow the estimated coefficients to take different values depending on whether the money market curve is upwards sloping or inverted. To this end, 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,

[22] Note that these thresholds refer to the sum of rate changes over horizon n, and not necessarily a single hike or cut.

[23] In Table IA.3 in the Internet Appendix, we count how many times market participants underestimate the change by 100 basis points or more. These results further cement the strong asymmetry; 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.

$$\Delta i_{t+n} = \alpha_{POS}^{(n)} 1_{\{\varphi_t^{(n)}>0\}} + \beta_{POS}^{(n)} \varphi_t^{(n)} 1_{\{\varphi_t^{(n)}>0\}} + \alpha_{NEG}^{(n)} 1_{\{\varphi_t^{(n)}\leq 0\}} + \beta_{NEG}^{(n)} \varphi_t^{(n)} 1_{\{\varphi_t^{(n)}\leq 0\}} + \tilde{\varepsilon}_{t+n}^{(n)}, \quad (8)$$

$$rx_{t+n}^{(n)} = \theta_{POS}^{(n)} 1_{\{\varphi_t^{(n)}>0\}} + \delta_{POS}^{(n)} \varphi_t^{(n)} 1_{\{\varphi_t^{(n)}>0\}} + \theta_{NEG}^{(n)} 1_{\{\varphi_t^{(n)}\leq 0\}} + \delta_{NEG}^{(n)} \varphi_t^{(n)} 1_{\{\varphi_t^{(n)}\leq 0\}} + \tilde{\eta}_{t+n}^{(n)}, \quad (9)$$

where, through the interaction terms, we estimate separate coefficients for the positive and negative slope of the money market curve for predicting future short rates and excess returns.

>>> TABLE 3 ABOUT HERE <<<

Panel A of Table 3 reports the results for Eq. (8) 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. Further, 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 1.37%. For the 12-months-ahead OIS, the underestimation is even larger. Here, the estimated slope coefficient is $\beta_{\text{NEG}}^{(n)} = 1.81$, thus entailing that one-year-ahead short rate cuts are, on average, almost twice as large as expected.[24]

Panel B of Table 3 reports the results for Eq. (9). 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,

[24]These findings corroborate Cieslak (2018), who finds large short rate expectation errors in survey data, and argues that these arise because the Fed eases policy more aggressively than the public expects. In this section, we show that the same unexpected rate cutting also leads to large errors in the short rate expectations extracted from money market derivatives, suggesting that the expectation formation processes underlying the two sources of forecasts are closely related.

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 systematically underestimate by how much the Fed cuts interest rates over the sample.

4. Expectation Errors and the Central Bank's Reaction Function

So, what underlying economic mechanisms give rise to these monetary policy expectation errors? In the following sections, we explore if the documented patterns stem from the Fed setting interest rates in a way that was not consistent with the reaction function perceived by market participants. To tackle this question, we: (i) investigate the link between expectation errors and short rate deviations from the Taylor rule, (ii) assess whether market participants face information rigidities and learn about the reaction function in real time, and (iii) consider the role of financial conditions as an important ingredient in the central bank's reaction function that market participants had overlooked.

4.1. Unexpected Returns 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 and Vissing-Jorgensen, 2020). This indicates that the actual policymaker reaction function is not time-invariant, but may at times include variables other than those featured in common monetary policy rules. In this section, 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 results when estimating the Taylor model. To avoid potential look-ahead bias, we therefore use vintage data and estimate the Taylor-implied short rate as the fitted values from the regression,

$$i_{t+n} = \alpha_{t+n} + \beta_{t+n} u_{t+n} + \gamma_{t+n} \pi_{t+n} + \varepsilon_{t+n}, \tag{10}$$

where u_{t+n} is the unemployment rate and π_{t+n} is the rate of inflation and the parameters are estimated recursively. This approach improves upon the classic 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.[25] Then, to quantify if monetary policy is easy or tight relative to the Taylor rule, we subtract the actual short rate from its model-implied level,

$$\psi_{t+n}^{\text{Taylor}} = \widehat{i}_{t+n} - i_{t+n}, \tag{11}$$

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 5 ABOUT HERE <<<

Table 5 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 30% for the contracts with the longest maturities. The second row in the table shows that the Taylor rule deviations and expectation errors are also

[25] We follow Evans et al. (1998) and use unemployment instead of GDP growth because of its higher data frequency. We estimate Eq. (10) 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.

significantly positively correlated, reaching up to 41%.[26] 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. Information Rigidities as Market Participants Learn About the Reaction Function

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 (see e.g., Mankiw and Reis, 2002; Sims, 2003; Woodford, 2001; Coibion and Gorodnichenko, 2012, and Coibion and Gorodnichenko, 2015).[27] To study the role of such information rigidities when forecasting the short rate, we run the regression put forth by Coibion and Gorodnichenko (2015),

$$i_{t+n} - S_t^{(n)} = \omega^{(n)} + \kappa^{(n)} RV_t^{(n)} + \xi_{t+n}^{(n)}, \tag{12}$$

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).[28]

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

[26]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.4 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.

[27]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."*

[28]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.

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.[29] 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 continuously learning about the Fed's reaction function.

>>> TABLE 4 ABOUT HERE <<<

Panel A of Table 4 runs regression Eq. (12) 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.[30] 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.

Moreover, we can infer the degree of information rigidity by computing the Kalman gain, $G = 1/(1 + \kappa^{(n)})$, which reveals how much weight market participants place on new information relative to their 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 results in the previous sections, 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

[29] 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.

[30] 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.

equivalent to them revising their expectations downwards too slowly. To test for asymmetries in the expectation formation process, we therefore augment Eq. (12) 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,

$$
\begin{aligned}
i_{t+n} - S_t^{(n)} = {} & \omega_{POS}^{(n)} 1_{\{RV_t^{(n)}>0\}} + \kappa_{POS}^{(n)} RV_t^{(n)} 1_{\{RV_t^{(n)}>0\}} \\
& + \omega_{NEG}^{(n)} 1_{\{RV_t^{(n)}\leq 0\}} + \kappa_{NEG}^{(n)} RV_t^{(n)} 1_{\{RV_t^{(n)}\leq 0\}} + \tilde{\xi}_{t+n}^{(n)},
\end{aligned}
\tag{13}
$$

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 Table 4 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 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. We trace this result to difficulties for market participants in assessing the Fed's reaction function in real time, and in the following section, explore the potential drivers of the reaction function that may have been overlooked by market participants.[31]

4.3. Financial Conditions as a Missing Ingredient in the Reaction Function?

What drove the Fed to aggressively cut interest rates to market participants' surprise? In a recent paper, Cieslak and Vissing-Jorgensen (2020) use FOMC minutes and transcripts to show that the Fed not only responds to macroeconomic variables, but also to the stock market when setting the policy rate. In a similar vein, Peek et al. (2016) find that financial conditions are

[31] 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. In the following section, we identify deteriorating financial conditions as the key source of bad news to which market participants did not react strongly enough to over the sample.

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. A possible explanation in our context may therefore be, that the Fed reacted preemptively to deteriorating financial conditions even as hard data on macroeconomic activity were not yet pointing to a slowdown.[32]

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). As such, if financial conditions were indeed an important component of the central bank's reaction function, but one whose relevance for the Fed's policymaking investors underestimated at the time, indicators of financial conditions should predict expectation errors and excess returns. To shed light on this conjecture, we run predictive return regressions of the form,

$$rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)} x_t + \gamma^{(n)} z_t + \varepsilon_{t+n}^{(n)}, \tag{14}$$

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 6 we analyze if excess returns on FF futures and OIS can be predicted by a key 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 from CRSP. Subsequently, we regress stock returns together with a range of variables suggested to capture term premium variation in money market derivatives: the year-on-year growth in employment, the corporate

[32] Cieslak (2018) studies the quantitative importance of different types of shocks in accounting for the variation of expectation errors based on a variance decomposition. She finds that most expectation errors are not accounted for by shocks to inflation or unemployment, which lends credence to the idea that variables outside the Taylor rule impact Fed policy. Furthermore, she shows that unexpected declines in the real rate trend are also of minor importance to expectation errors, which could otherwise pose an important explanation for the phenomenon given recent evidence by Bauer and Rudebusch (2020).

credit spread and the Treasury yield spread.[33] While these variables are intended to capture term premium variation with the business cycle, our use of the return on the stock market stems from its close link with financial conditions, and therefore potentially, the Fed's reaction function.

>>> TABLE 6 ABOUT HERE <<<

Panel A of Table 6 shows the estimated slope coefficients and R^2s from Eq. (14) and reveals that the stock market is 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 24 basis points with a strongly significant signal across all contract horizons.

We also run checks to see 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 size of the slope 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 market provides a powerful signal about future excess returns above and beyond the information contained in these predictors. Finally, Panel E includes an NBER recession dummy in the regressions to capture whether stock returns contain predictive information outside of recession periods.[34] These regressions show that the stock market remains a strong predictor even when controlling for recessions across most FF futures and OIS horizons.

>>> TABLE 7 ABOUT HERE <<<

[33] 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.

[34] It is important to note that the NBER dummy should not be seen as a real-time predictor variable, as it is published with a significant time delay.

There is reason to suspect that the effect of the stock market is asymmetric; while the Fed potentially reacts to negative stock returns, it might not react to positive stock returns at all. To test this, we introduce a modified version of the predictive return regression in Eq. (14),

$$
\begin{aligned}
rx_{t+n}^{(n)} = \alpha_{POS}^{(n)} 1_{\{rx_t^{\text{S\&P500}}>0\}} + \beta_{POS}^{(n)} rx_t^{\text{S\&P500}} 1_{\{rx_t^{\text{S\&P500}}>0\}} \\
+ \alpha_{NEG}^{(n)} 1_{\{rx_t^{\text{S\&P500}}\leq 0\}} + \beta_{NEG}^{(n)} rx_t^{\text{S\&P500}} 1_{\{rx_t^{\text{S\&P500}}\leq 0\}} + \varepsilon_{t+n},
\end{aligned} \tag{15}
$$

where, again, 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 7 presents the results from Eq. (15) and confirms the conjecture that the predictive information of the stock market is asymmetric. While positive stock market movements contain no relevant information, negative stock returns contain a strong and significant signal about future excess returns. 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 following Eq. (4).

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.5 in the Internet Appendix tests if the predictive results obtained in this section 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, and again, that the information in the alternative predictor variables is subsumed when including 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.

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.6 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.

Tests With Survey-Based Expectation Errors. Tables IA.7 and IA.8 in the Internet Appendix report the results from estimating Eqs. (14) and (15) 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.

Taken together, while market participants are able to predict an increasing short rate with ease, our results show that they have historically been surprised by large short rate cuts. Our analysis suggests that the underlying reason has been aggressive rate cuts by the Fed in response to deteriorating financial conditions. These actions were taken preemptively in an environment of substantial uncertainty, where hard economic data had yet to show signs of an economic slowdown. In this interpretation, market participants faced information rigidities when assessing the central bank's reaction function. As a consequence, they were conservative in their expectations about future short rates and underestimated the prominent role of financial conditions in the Fed's reaction function.

5. International Evidence

Finally, we analyze whether the above narrative is exclusive to the US or whether excess returns can be attributed to monetary policy expectation errors in a sample of international currencies. We relegate information on data sources and sample sizes to Appendix IA.4.

>>> TABLE 8 ABOUT HERE <<<

Table 8 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 here all positive and of similar sizes to those in the US (with the exception of Japan, where the policy rate is very persistent and never exceeded 50 basis points over the sample), and either statistically significant or marginally significant.

>>> TABLE 9 ABOUT HERE <<<

Having established the existence of positive OIS excess returns outside the US, we test if these returns are also correlated with 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 Eurozone, 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.7, IA.8 and IA.9 in the Internet Appendix. Table 9 shows that excess returns and expectation errors are indeed strongly correlated in this international sample.[35] Correlations at all maturities and across all currency areas are highly statistically significant, and especially high for longer-horizon expectations (up to 96%).

[35] 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 Eurozone. 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.

>>> TABLE 10 ABOUT HERE <<<

In Table 10 we test the predictability of excess returns on international OIS, using the local stock market as an indicator of financial conditions. The table's results show a remarkable degree of homogeneity in the predictive content of local stock markets for future OIS excess returns. In all currency areas (except Japan), 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.

To summarize, we find broadly similar results when considering a sample of international OIS. We find that excess returns on these money market derivatives are, on average, positive in all other major currency areas around the world, and that the positive excess returns can be attributed to short rate expectation errors. Furthermore, we show that local stock markets all constitute strong predictors of future excess returns. This suggests that financial market conditions were an overlooked ingredient in the central bank's reaction function more broadly and not only in case of the Fed.

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 our sample.

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 deteriorating financial conditions. We underpin this interpretation with evidence that the stock market is a powerful predictor of future excess returns on FF futures and OIS. In other words, declining stock prices predict a more aggressive drop in interest rates compared to market expectations, leading to large unexpected returns on long positions in these money market derivatives. 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 rate hikes and subsequently low excess returns.

We caution against interpreting the observed persistent and systematic expectation errors as evidence of investor irrationality. Instead, our results favor an explanation based on market participants learning about the central bank's reaction function over time – especially in periods of heightened uncertainty. Such a learning process then manifests itself as a systematic and predictable deviation from the expectations hypothesis benchmark.

These results have implications for the understanding of money market derivatives and their reliability as gauges of expectations about future monetary policy. As our results indicate, the observed positive excess returns reflect monetary policy actions that were unanticipated due to incomplete knowledge about the central bank's reaction function. As such, the information at the short end of the term structure of interest rates should not be discounted due to term premium distortions, but rather be taken as an important signal of market participants' expectations of future short rates as suggested by the expectations hypothesis.

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Appendix

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 2018:11 and the sample for OIS is 2001:12 to 2019:07.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
Panel A: Mean Estimates						
Excess Returns	5.92	12.17	3.00	6.43	10.57	15.63
	(3.56)	(2.75)	(1.76)	(1.36)	(1.32)	(1.39)
Expectation Errors	7.00	12.31	5.36	8.87	13.92	20.43
	(2.81)	(2.52)	(2.44)	(1.73)	(1.73)	(1.82)
Term Premia	-1.09	-0.15	-2.36	-2.44	-3.36	-4.81
	(-1.01)	(-0.09)	(-2.91)	(-1.63)	(-1.56)	(-1.67)
Panel B: Variance Decomposition						
Expectation Errors	1.07	1.02	1.13	1.00	0.96	0.95
Term Premia	-0.07	-0.02	-0.13	0.00	0.04	0.05

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 2018:11 and the sample for OIS is 2001:12 to 2019:07.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
Panel A: $\Delta i_{t+n} = \alpha^{(n)} + \beta^{(n)}\varphi_t^{(n)} + \varepsilon_{t+n}^{(n)}$						
$\alpha^{(n)}$	-6.45	-14.00	-3.58	-8.53	-15.31	-23.58
$t_{\alpha^{(n)}=0}$	(-4.88)	(-3.71)	(-2.30)	(-2.13)	(-2.25)	(-2.29)
$\beta^{(n)}$	1.20	1.27	1.15	1.25	1.35	1.42
$t_{\beta^{(n)}=0}$	(20.69)	(12.17)	(14.22)	(9.66)	(8.05)	(6.92)
$t_{\beta^{(n)}=1}$	(3.46)	(2.59)	(1.85)	(1.95)	(2.10)	(2.05)
R^2	0.73	0.66	0.70	0.65	0.61	0.57
Panel B: $rx_{t+n}^{(n)} = \theta^{(n)} + \delta^{(n)}\varphi_t^{(n)} + \eta_{t+n}^{(n)}$						
$\theta^{(n)}$	6.45	14.00	3.58	8.53	15.31	23.58
$t_{\theta^{(n)}=0}$	(4.97)	(3.73)	(2.32)	(2.11)	(2.27)	(2.30)
$\delta^{(n)}$	-0.20	-0.27	-0.15	-0.25	-0.35	-0.42
$t_{\delta^{(n)}=0}$	(-3.44)	(-2.64)	(-1.85)	(-1.93)	(-2.12)	(-2.05)
R^2	0.07	0.08	0.04	0.07	0.10	0.10

Table 3: Asymmetry in Expectations Hypothesis Tests

Panel A presents the results for Eq. (8), 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. (9), 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 2018:11 and the sample for OIS is 2001:12 to 2019:07.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
Panel A: $\Delta i_{t+n} = \alpha_{POS}^{(n)} 1_{\{\varphi_t^{(n)}>0\}} + \beta_{POS}^{(n)} \varphi_t^{(n)} 1_{\{\varphi_t^{(n)}>0\}} + \alpha_{NEG}^{(n)} 1_{\{\varphi_t^{(n)}\leq 0\}} + \beta_{NEG}^{(n)} \varphi_t^{(n)} 1_{\{\varphi_t^{(n)}\leq 0\}} + \tilde{\varepsilon}_{t+n}^{(n)}$						
$\alpha_{POS}^{(n)}$	-2.83	-7.62	-3.12	-6.73	-10.66	-15.14
$t_{\alpha_{POS}^{(n)}=0}$	(-1.51)	(-1.53)	(-1.43)	(-1.33)	(-1.29)	(-1.26)
$\beta_{POS}^{(n)}$	1.00	1.04	1.12	1.18	1.19	1.17
$t_{\beta_{POS}^{(n)}=1}$	(-0.04)	(0.26)	(0.87)	(0.90)	(0.79)	(0.56)
$\alpha_{NEG}^{(n)}$	-7.54	-15.62	-4.29	-10.55	-17.06	-19.68
$t_{\alpha_{NEG}^{(n)}=0}$	(-3.27)	(-2.62)	(-1.55)	(-1.56)	(-1.65)	(-1.13)
$\beta_{NEG}^{(n)}$	1.26	1.37	1.14	1.26	1.47	1.81
$t_{\beta_{NEG}^{(n)}=1}$	(2.79)	(2.36)	(1.18)	(1.32)	(1.71)	(2.17)
R^2	0.74	0.67	0.70	0.65	0.62	0.58
Panel B: $rx_{t+n}^{(n)} = \theta_{POS}^{(n)} 1_{\{\varphi_t^{(n)}>0\}} + \delta_{POS}^{(n)} \varphi_t^{(n)} 1_{\{\varphi_t^{(n)}>0\}} + \theta_{NEG}^{(n)} 1_{\{\varphi_t^{(n)}\leq 0\}} + \delta_{NEG}^{(n)} \varphi_t^{(n)} 1_{\{\varphi_t^{(n)}\leq 0\}} + \tilde{\eta}_{t+n}^{(n)}$						
$\theta_{POS}^{(n)}$	2.83	7.62	3.12	6.73	10.66	15.14
$t_{\theta_{POS}^{(n)}=0}$	(1.49)	(1.54)	(1.45)	(1.32)	(1.28)	(1.25)
$\delta_{POS}^{(n)}$	0.00	-0.04	-0.12	-0.18	-0.19	-0.17
$t_{\delta_{POS}^{(n)}=0}$	(0.05)	(-0.26)	(-0.85)	(-0.88)	(-0.79)	(-0.56)
$\theta_{NEG}^{(n)}$	7.54	15.62	4.29	10.55	17.06	19.68
$t_{\theta_{NEG}^{(n)}=0}$	3.27	2.64	1.55	1.56	1.66	1.12
$\delta_{NEG}^{(n)}$	-0.26	-0.37	-0.14	-0.26	-0.47	-0.81
$t_{\delta_{NEG}^{(n)}=0}$	(-2.78)	(-2.37)	(-1.18)	(-1.31)	(-1.69)	(-2.13)
R^2	0.10	0.11	0.04	0.07	0.11	0.14

Table 4: Tests of the Short Rate Expectation Formation Process

Panel A reports the results from Eq. (12), where we regress future expectation errors on past forecast revisions. Panel B provides the results for the augmented version Eq. (13), 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 2019: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: $i_{t+n} - S_t^{(n)} = \omega^{(n)} + \kappa^{(n)} RV_t^{(n)} + \xi_{t+n}^{(n)}$				
$\kappa^{(n)}$	0.12	0.23	0.38	0.50
	(2.68)	(3.56)	(4.04)	(3.18)
R^2	0.05	0.09	0.15	0.15
$1/(1+\kappa^{(n)})$	0.89	0.81	0.72	0.67
Panel B: $i_{t+n} - S_t^{(n)} = \omega_{POS}^{(n)} 1_{\{RV_t^{(n)}>0\}} + \kappa_{POS}^{(n)} RV_t^{(n)} 1_{\{RV_t^{(n)}>0\}} + \omega_{NEG}^{(n)} 1_{\{RV_t^{(n)}\leq 0\}} + \kappa_{NEG}^{(n)} RV_t^{(n)} 1_{\{RV_t^{(n)}\leq 0\}} + \tilde{\xi}_{t+n}^{(n)}$				
$\kappa_{POS}^{(n)}$	0.13	0.20	0.34	0.54
	(0.86)	(0.85)	(1.11)	(0.72)
$\kappa_{NEG}^{(n)}$	0.05	0.16	0.33	0.51
	(0.79)	(1.64)	(2.52)	(2.67)
R^2	0.08	0.11	0.15	0.15

Table 5: 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. (11), 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 2018:11 and the sample for OIS is 2001:12 to 2019:07.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
$\rho\left(\psi_{t+n}^{\text{Taylor}}, rx_{t+n}^{(n)}\right)$	0.19	0.30	0.06	0.13	0.21	0.25
	[0.00]	[0.00]	[0.38]	[0.07]	[0.00]	[0.00]
$\rho\left(\psi_{t+n}^{\text{Taylor}}, \text{EE}_{t+n}^{(n)}\right)$	0.28	0.41	0.19	0.28	0.37	0.40
	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]

Table 6: Predicting Excess Returns using Stock Market Returns

The table shows the results from the predictive regression Eq. (14). 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. Finally, Panel D shows the marginal predictive power of the stock market when controlling for NBER recessions. 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 2018:11 and the sample for OIS is 2001:12 to 2019:07.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
Panel A: $rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)} rx_t^{\text{S\&P500}} + \epsilon_{t+n}^{(n)}$						
$\beta^{(n)}$	-0.87	-1.58	-0.82	-1.29	-1.77	-2.35
	(-3.68)	(-4.12)	(-3.47)	(-2.78)	(-2.40)	(-2.25)
R^2	0.05	0.05	0.06	0.05	0.04	0.04
Panel B: $rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)} rx_t^{\text{S\&P500}} + \gamma^{(n)}\text{Employment Growth}_t + \epsilon_{t+n}^{(n)}$						
$\beta^{(n)}$	-0.86	-1.57	-0.82	-1.31	-1.80	-2.37
	(-4.10)	(-4.06)	(-3.56)	(-3.32)	(-3.03)	(-2.97)
$\gamma^{(n)}$	-1.41	-3.54	-1.16	-2.66	-4.93	-7.77
	(-1.40)	(-1.30)	(-1.22)	(-0.99)	(-1.09)	(-1.24)
R^2	0.07	0.08	0.08	0.08	0.09	0.11
Panel C: $rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)} rx_t^{\text{S\&P500}} + \gamma^{(n)}\text{Corporate Bond Spread}_t + \epsilon_{t+n}^{(n)}$						
$\beta^{(n)}$	-0.84	-1.55	-0.76	-1.20	-1.60	-2.10
	(-4.03)	(-4.23)	(-3.15)	(-2.81)	(-2.44)	(-2.28)
$\gamma^{(n)}$	1.21	1.15	2.89	4.81	7.78	10.62
	(0.64)	(0.23)	(1.66)	(1.15)	(1.10)	(1.08)
R^2	0.05	0.05	0.09	0.08	0.08	0.08
Panel D: $rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)} rx_t^{\text{S\&P500}} + \gamma^{(n)}\text{Treasury Yield Spread}_t + \epsilon_{t+n}^{(n)}$						
$\beta^{(n)}$	-0.87	-1.57	-0.82	-1.30	-1.78	-2.36
	(-3.72)	(-4.13)	(-3.47)	(-2.81)	(-2.45)	(-2.27)
$\gamma^{(n)}$	-0.78	-2.04	0.14	0.34	1.17	1.83
	(-0.39)	(-0.43)	(0.06)	(0.08)	(0.15)	(0.17)
R^2	0.05	0.06	0.06	0.05	0.05	0.04
Panel E: $rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)} rx_t^{\text{S\&P500}} + \gamma^{(n)}\text{NBER}_t + \epsilon_{t+n}^{(n)}$						
$\beta^{(n)}$	-0.72	-1.32	-0.58	-0.84	-1.04	-1.36
	(-3.84)	(-3.51)	(-2.53)	(-2.24)	(-1.89)	(-1.94)
$\gamma^{(n)}$	21.47	37.96	17.33	33.03	50.99	66.37
	(5.75)	(4.33)	(4.59)	(3.83)	(2.83)	(2.45)
R^2	0.20	0.20	0.18	0.20	0.21	0.21

Table 7: Predicting Excess Returns: Asymmetric Effects

The table reports the results from Eq. (15), where we regress 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 2018:11 and the sample for OIS is 2001:12 to 2019:07.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
$\beta_{\text{POS}}^{(n)}$	0.14	-0.13	-0.02	0.00	0.48	1.04
	(0.29)	(-0.13)	(-0.04)	(-0.01)	(0.32)	(0.50)
$\beta_{\text{NEG}}^{(n)}$	-2.11	-3.25	-1.68	-2.54	-3.63	-4.81
	(-4.31)	(-3.04)	(-3.07)	(-2.46)	(-2.09)	(-1.93)
R^2	0.08	0.07	0.09	0.07	0.07	0.07

Table 8: 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.4 for details on sample sizes and data sources.

	Overnight Index Swaps			
$n =$	3	6	9	12
Australia	0.00	2.06	6.28	12.13
	(0.00)	(0.67)	(1.24)	(1.59)
Canada	1.14	4.66	8.96	8.11
	(1.55)	(2.00)	(1.89)	(0.88)
Eurozone	3.57	8.24	13.76	19.94
	(2.64)	(2.41)	(2.38)	(2.43)
United Kingdom	3.45	7.79	13.18	19.62
	(1.44)	(1.58)	(1.70)	(1.79)
Japan	0.52	1.10	2.00	2.93
	(1.34)	(1.58)	(1.86)	(1.55)
Switzerland	2.93	6.30	11.03	15.29
	(1.53)	(1.60)	(1.85)	(2.01)

Table 9: Expectation Errors and Excess Returns on International OIS

The table shows the correlations between excess returns on OIS and expectation errors from Eq. (5). Survey expectations are from Reuters Central Bank Polls. We consider 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
Eurozone	0.35	0.75	0.85	0.88
	[0.00]	[0.00]	[0.00]	[0.00]
United Kingdom	0.93	0.96	0.96	0.96
	[0.00]	[0.00]	[0.00]	[0.00]
Switzerland	0.69	0.82	0.85	0.86
	[0.00]	[0.00]	[0.00]	[0.00]

Table 10: Predicting Excess Returns using the Local Stock Market

The table reports the results from Eq. (14), 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	$\beta^{(n)}$	-0.48	-1.37	-2.34	-3.40
		(-1.42)	(-2.00)	(-2.27)	(-2.57)
	R^2	0.01	0.03	0.04	0.05
Canada	$\beta^{(n)}$	-0.66	-1.43	-2.00	-2.55
		(-3.84)	(-3.45)	(-2.91)	(-2.42)
	R^2	0.08	0.08	0.06	0.04
Eurozone	$\beta^{(n)}$	-0.36	-1.26	-2.01	-2.79
		(-1.81)	(-3.05)	(-3.18)	(-3.35)
	R^2	0.02	0.06	0.06	0.07
United Kingdom	$\beta^{(n)}$	-1.55	-2.57	-3.23	-3.93
		(-4.70)	(-4.37)	(-3.89)	(-3.85)
	R^2	0.09	0.08	0.07	0.07
Japan	$\beta^{(n)}$	-0.08	-0.13	-0.17	-0.22
		(-1.91)	(-1.87)	(-1.70)	(-1.83)
	R^2	0.02	0.02	0.02	0.02
Switzerland	$\beta^{(n)}$	-0.77	-1.05	-1.31	-1.89
		(-3.07)	(-2.41)	(-2.03)	(-2.35)
	R^2	0.05	0.04	0.03	0.04

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 2018:11.

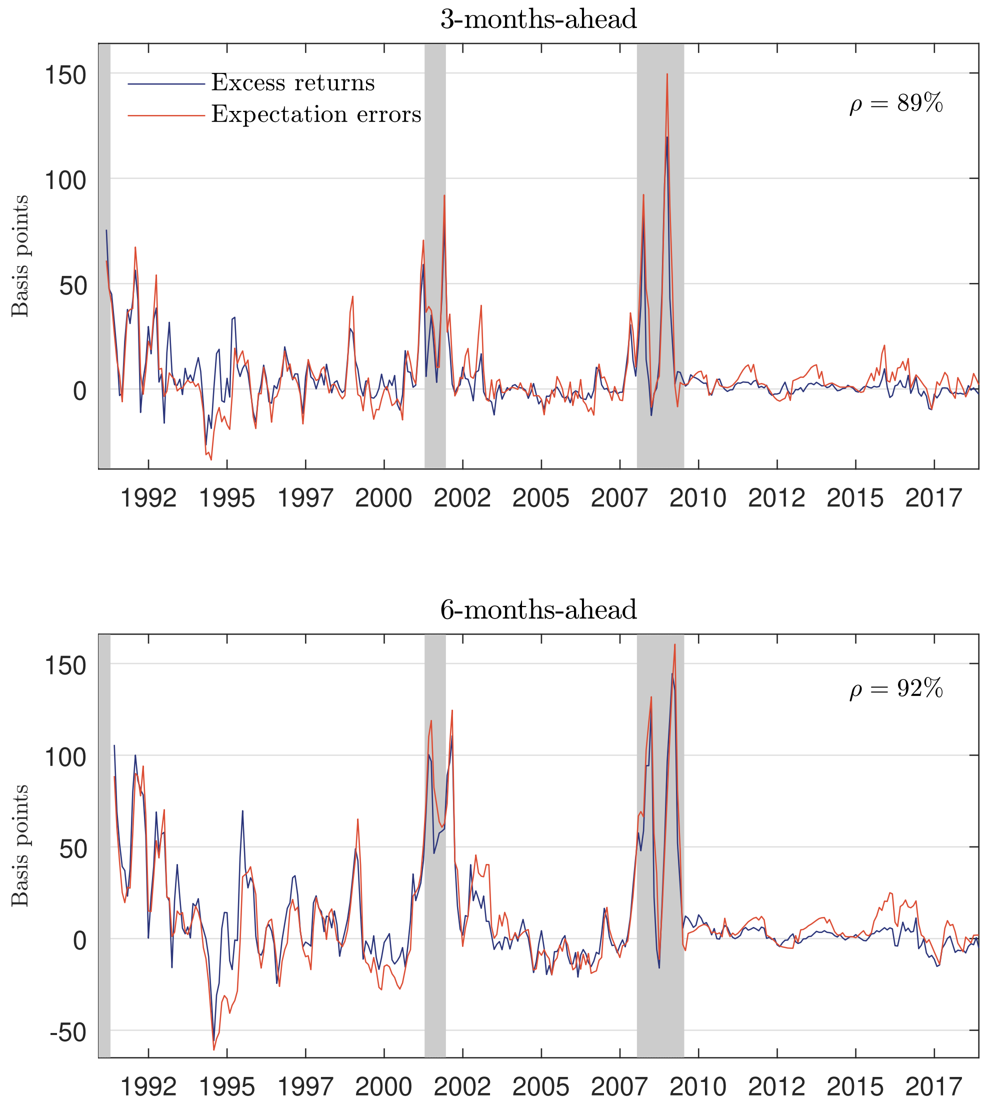
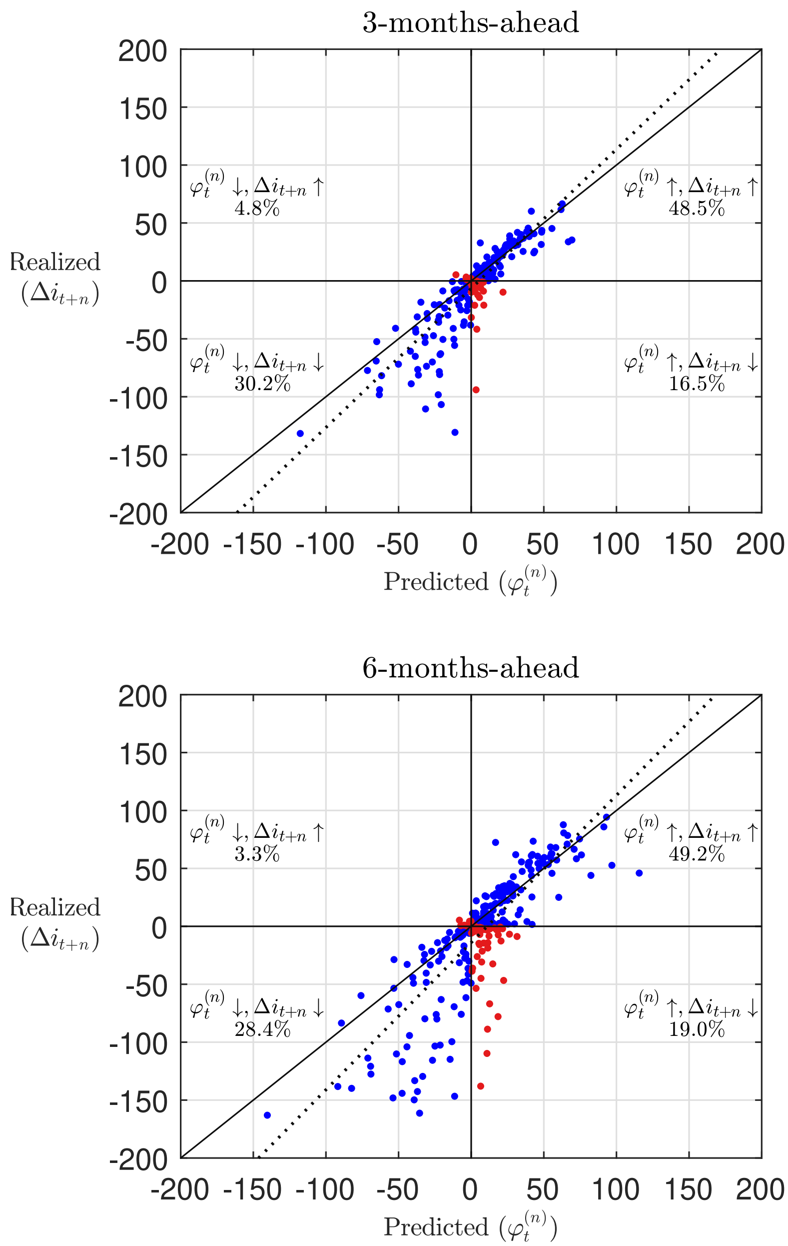


Figure 2: Prediction-Realization Diagrams: FF Futures

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 2018:11.



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 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.[36] 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.

[36] 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.9 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 rates 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. 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.

	Overnight Index Swaps		**Reuters Central Bank Polls**		**Stock Market**
Currency Area	Overnight Rate	Sample Start	Policy Rate	Sample Start	Index
Australia	RBA IBOC	2001:10			S&P/ASX 200
Canada	CORRA	2003:04			S&P/TSX Index
Eurozone	EONIA	1999:02	ECB MRO	2004:10	STOXX Europe 600
United Kingdom	SONIA	2000:12	BOE Bank rate	2004:12	FTSE 100
Japan	TONAR	2002:03			Nikkei 225
Switzerland	TOIS/SARON	2001:04	SNB 3M Target LIBOR Rate	2006:03	SMI Index

Internet Appendix: Tables

Table IA.1: 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 2018:11 and the sample for OIS is 2001:12 to 2019:07.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
$\alpha^{(n)}$	3.83	8.44	1.36	3.32	5.77	9.29
	(3.15)	(2.67)	(1.17)	(1.24)	(1.14)	(1.10)
$\beta^{(n)}$	22.46	39.77	19.06	35.52	54.08	70.47
	(5.78)	(4.34)	(4.90)	(4.05)	(3.52)	(2.61)
R^2	0.17	0.16	0.15	0.18	0.20	0.19

Table IA.2: 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 2018:11 and the sample for OIS is 2001:12 to 2019:07.

	Short Rate Hike		**Short Rate Cut**	
$n =$	Anticipated	Surprise	Anticipated	Surprise
Panel A: FF Futures				
3	48.5%	4.8%	30.2%	16.5%
6	49.2%	3.3%	28.4%	19.0%
Panel B: Overnight Index Swaps				
3	54.5%	6.2%	21.1%	18.2%
6	57.3%	2.9%	19.9%	19.9%
9	56.2%	3.0%	18.2%	22.7%
12	58.5%	2.0%	15.0%	24.5%

Table IA.3: 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 2018:11 and the sample for OIS is 2001:12 to 2019:07.

	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%	22.8%
6	1.8%	4.3%	0.0%	37.2%
Panel B: Overnight Index Swaps				
3	0.0%	0.0%	0.0%	11.4%
6	0.8%	0.0%	0.0%	19.5%
9	0.9%	7.0%	0.0%	35.1%
12	3.4%	17.1%	0.0%	43.3%
Threshold: 100 basis points				
Panel C: FF Futures				
3	0.0%	0.0%	0.0%	1.0%
6	0.0%	0.0%	0.0%	5.3%
Panel D: Overnight Index Swaps				
3	0.0%	0.0%	0.0%	2.3%
6	0.0%	0.0%	0.0%	4.9%
9	0.0%	0.0%	0.0%	16.2%
12	0.0%	0.0%	0.0%	23.3%

Table IA.4: 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). Rather than estimating the Taylor rule implied short rate recursively, it is here found following Evans et al. (1998) as,

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

where r is the level of the real interest rate, π_t is the inflation rate, *okun* is the parameter relating output to unemployment gaps (Okun, 1963), u^* is the natural rate of unemployment, u_t 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 2018:11 and the sample for OIS is 2001:12 to 2019:07.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
$\rho\left(\psi^{\text{Taylor}}_{t+n}, rx^{(n)}_{t+n}\right)$	0.19	0.31	0.07	0.19	0.33	0.44
	[0.00]	[0.00]	[0.29]	[0.01]	[0.00]	[0.00]
$\rho\left(\psi^{\text{Taylor}}_{t+n}, \text{EE}^{(n)}_{t+n}\right)$	0.22	0.35	0.17	0.27	0.38	0.48
	[0.00]	[0.00]	[0.02]	[0.00]	[0.00]	[0.00]

Table IA.5: Predicting Excess Returns using the NFCI

The table reports the results from Eq. (14) 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. Finally, Panel D shows the marginal predictive power of ΔNFCI when controlling for recessions. 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 2018:11 and the sample for OIS is 2001:12 to 2019:07.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
Panel A: $rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)}\Delta\text{NFCI}_t + \epsilon_{t+n}^{(n)}$						
$\beta^{(n)}$	0.37	0.40	0.45	0.57	0.69	0.78
	(4.74)	(2.46)	(6.16)	(4.91)	(4.05)	(3.48)
R^2	0.08	0.03	0.22	0.12	0.09	0.06
Panel B: $rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)}\Delta\text{NFCI}_t + \gamma^{(n)}\text{Employment Growth}_t + \epsilon_{t+n}^{(n)}$						
$\beta^{(n)}$	0.43	0.52	0.50	0.67	0.85	1.02
	(5.70)	(3.78)	(7.41)	(5.70)	(3.80)	(3.25)
$\gamma^{(n)}$	-2.29	-4.62	-2.29	-4.17	-6.84	-10.11
	(-1.97)	(-1.70)	(-2.80)	(-1.65)	(-1.61)	(-1.64)
R^2	0.12	0.08	0.28	0.18	0.17	0.16
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	0.42	0.48	0.63	0.77	0.90
	(5.01)	(2.53)	(7.67)	(4.42)	(3.71)	(3.08)
$\gamma^{(n)}$	2.40	2.82	4.63	7.20	10.79	14.37
	(1.00)	(0.59)	(3.38)	(1.80)	(1.56)	(1.42)
R^2	0.10	0.04	0.29	0.18	0.15	0.12
Panel D: $rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)}\Delta\text{NFCI}_t + \gamma^{(n)}\text{Treasury Yield Spread}_t + \epsilon_{t+n}^{(n)}$						
$\beta^{(n)}$	0.37	0.39	0.45	0.58	0.70	0.80
	(4.79)	(2.40)	(6.15)	(4.85)	(4.32)	(3.78)
$\gamma^{(n)}$	-0.36	-1.62	0.71	1.05	1.99	2.89
	(-0.17)	(-0.34)	(0.34)	(0.21)	(0.24)	(0.24)
R^2	0.08	0.03	0.22	0.12	0.09	0.07
Panel E: $rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)}\Delta\text{NFCI}_t + \gamma^{(n)}\text{NBER}_t + \epsilon_{t+n}^{(n)}$						
$\beta^{(n)}$	0.39	0.44	0.44	0.56	0.67	0.76
	(5.55)	(3.20)	(7.83)	(4.79)	(4.03)	(3.51)
$\gamma^{(n)}$	23.10	40.49	18.62	34.99	53.41	69.72
	(6.47)	(4.16)	(6.09)	(4.87)	(3.18)	(2.72)
R^2	0.26	0.20	0.37	0.29	0.28	0.25

Table IA.6: 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. Square brackets present Clark and West (2007) $p-$values for tests of equal predictive accuracy between these forecasts and the EH benchmark. We use an initial estimation window of five years, such that the out-of-sample evaluation period for FF futures is 1995:11 to 2018:11 and 2007:04 to 2019:07 for OIS.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
S&P500	0.05	0.06	0.01	0.03	0.04	0.06
	[0.01]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
Employment Growth	-0.05	-0.12	-0.02	-0.09	-0.18	-0.22
	[0.29]	[0.20]	[0.43]	[0.65]	[0.51]	[0.20]
Corporate Bond Spread	-0.08	-0.13	-0.08	-0.08	-0.03	0.07
	[0.32]	[0.75]	[0.91]	[0.83]	[0.31]	[0.14]
Treasury Yield Spread	-0.01	-0.03	-0.01	-0.03	-0.05	-0.02
	[0.72]	[0.75]	[0.59]	[0.83]	[0.90]	[0.77]

Table IA.7: Predicting Expectation Errors using the Stock Market

The table reports the results from replacing excess returns with survey expectation errors in Eq. (14). 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. Finally, Panel D shows the marginal predictive power of the stock market when controlling for recessions. 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 2018:11 and the sample for OIS is 2001:12 to 2019:07.

	FF Futures		**Overnight Index Swaps**			
$n=$	3	6	3	6	9	12
Panel A: $\text{EE}_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)} rx_t^{\text{S\&P500}} + \epsilon_{t+n}^{(n)}$						
$\beta^{(n)}$	-1.07	-1.87	-1.28	-1.78	-2.32	-2.91
	(-3.83)	(-4.35)	(-4.35)	(-4.17)	(-3.71)	(-3.52)
R^2	0.05	0.06	0.09	0.08	0.07	0.06
Panel B: $\text{EE}_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)} rx_t^{\text{S\&P500}} + \gamma^{(n)}\text{Employment Growth}_t + \epsilon_{t+n}^{(n)}$						
$\beta^{(n)}$	-1.06	-1.86	-1.28	-1.79	-2.34	-2.93
	(-4.32)	(-4.47)	(-4.49)	(-3.90)	(-3.44)	(-3.25)
$\gamma^{(n)}$	-2.30	-4.38	-1.26	-2.06	-3.51	-5.67
	(-1.65)	(-1.52)	(-0.99)	(-0.72)	(-0.79)	(-0.91)
R^2	0.08	0.10	0.10	0.09	0.09	0.10
Panel C: $\text{EE}_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)} rx_t^{\text{S\&P500}} + \gamma^{(n)}\text{Corporate Bond Spread}_t + \epsilon_{t+n}^{(n)}$						
$\beta^{(n)}$	-0.97	-1.75	-1.17	-1.64	-2.11	-2.63
	(-4.02)	(-4.48)	(-4.21)	(-3.85)	(-3.44)	(-3.24)
$\gamma^{(n)}$	4.79	6.09	5.36	7.22	9.64	12.27
	(2.09)	(1.13)	(2.60)	(1.54)	(1.25)	(1.12)
R^2	0.09	0.08	0.15	0.13	0.12	0.11
Panel D: $\text{EE}_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)} rx_t^{\text{S\&P500}} + \gamma^{(n)}\text{Treasury Yield Spread}_t + \epsilon_{t+n}^{(n)}$						
$\beta^{(n)}$	-1.07	-1.87	-1.29	-1.80	-2.35	-2.94
	(-3.90)	(-4.42)	(-4.46)	(-4.26)	(-3.78)	(-3.54)
$\gamma^{(n)}$	0.51	-0.08	1.84	2.45	3.76	5.14
	(0.22)	(-0.02)	(0.84)	(0.50)	(0.46)	(0.45)
R^2	0.05	0.06	0.10	0.09	0.08	0.07
Panel E: $\text{EE}_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)} rx_t^{\text{S\&P500}} + \gamma^{(n)}\text{NBER}_t + \epsilon_{t+n}^{(n)}$						
$\beta^{(n)}$	-0.89	-1.61	-0.98	-1.34	-1.69	-2.10
	(-4.08)	(-4.29)	(-3.64)	(-3.33)	(-2.72)	(-2.70)
$\gamma^{(n)}$	25.54	38.45	21.98	32.07	43.91	54.07
	(5.27)	(3.50)	(4.21)	(3.10)	(2.39)	(1.93)
R^2	0.20	0.19	0.21	0.20	0.19	0.17

Table IA.8: Predicting Expectation Errors: Asymmetric Effects

The table reports estimates from the predictive regression Eq. (15) where excess returns are replaced with expectation errors, $\mathrm{EE}_{t+n}^{(n)}$. The variable $rx_t^{\mathrm{S\&P500}} 1_{(rx_t^{\mathrm{S\&P500}}>0)}$ contains all positive stock returns and takes the value zero whenever stock returns are negative, while the variable $rx_t^{\mathrm{S\&P500}} 1_{(rx_t^{\mathrm{S\&P500}}\leq 0)}$ 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 2018:11 and the sample for OIS is 2001:12 to 2019:07.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
$\beta_{\mathrm{POS}}^{(n)}$	0.46	0.05	0.19	0.17	0.52	1.03
	(0.77)	(0.06)	(0.29)	(0.16)	(0.34)	(0.48)
$\beta_{\mathrm{NEG}}^{(n)}$	-3.17	-4.38	-2.99	-3.61	-4.47	-5.50
	(-4.96)	(-3.87)	(-4.44)	(-3.01)	(-2.44)	(-2.13)
R^2	0.12	0.10	0.15	0.12	0.10	0.10

Table IA.9: 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 2018:11 and the sample for OIS is 2001:12 to 2019:07.

	FF Futures		**Overnight Index Swaps**			
$n =$	3	6	3	6	9	12
Panel A: Mean Estimates						
Excess Returns	6.41	12.97	3.81	7.96	12.68	18.10
	(3.00)	(2.80)	(1.38)	(1.44)	(1.43)	(1.47)
Expectation Errors	6.96	12.00	5.15	9.17	14.89	21.77
	(3.52)	(2.51)	(1.78)	(1.69)	(1.82)	(1.89)
Term Premia	-0.55	0.97	-1.34	-1.21	-2.21	-3.67
	(-0.67)	(0.60)	(-1.80)	(-0.58)	(-0.74)	(-1.00)
Panel B: Variance Decomposition						
Expectation Errors	1.09	0.99	1.14	1.00	0.95	0.93
Term Premia	-0.09	0.01	-0.14	0.00	0.05	0.07

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 2019:07.

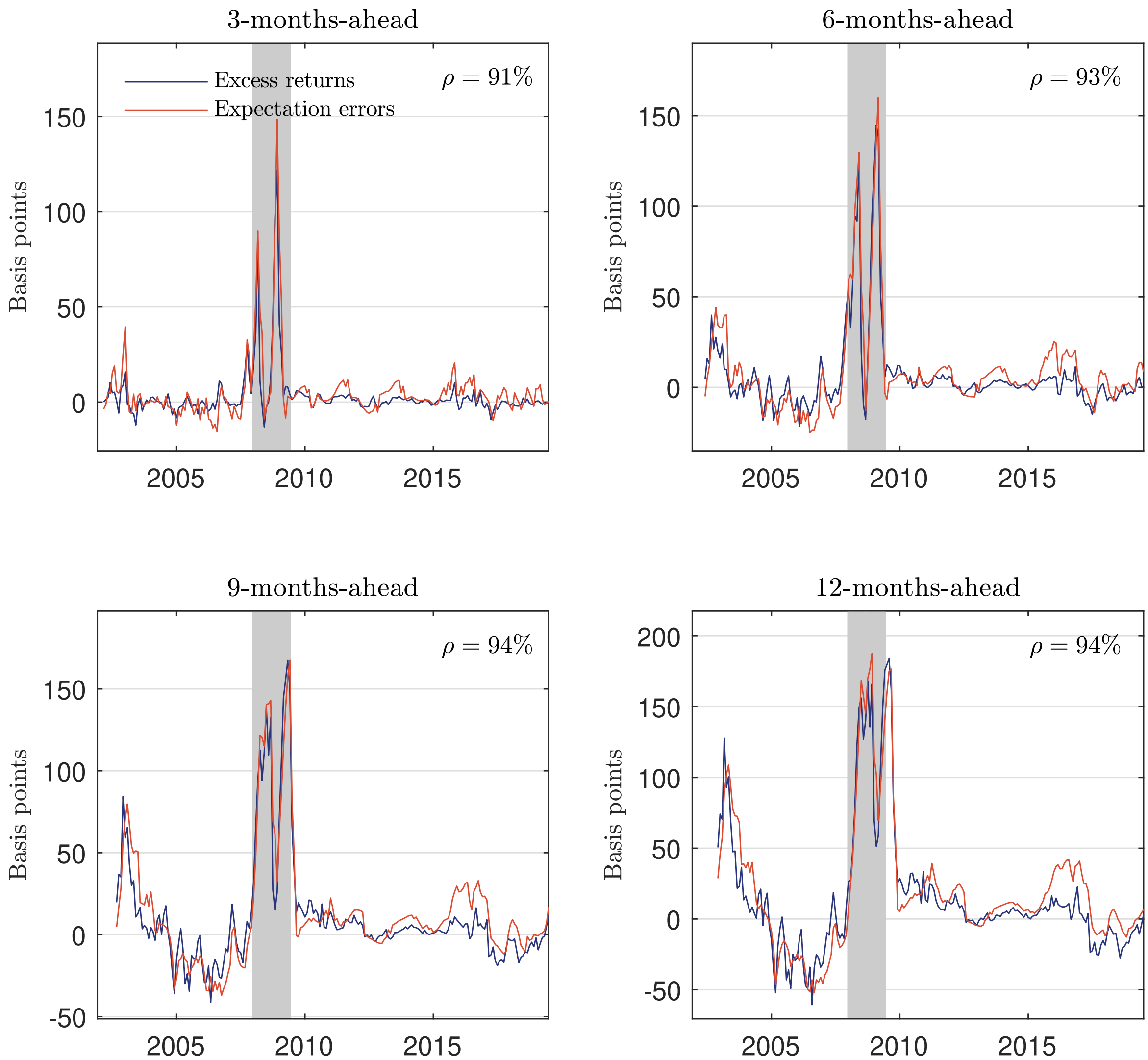
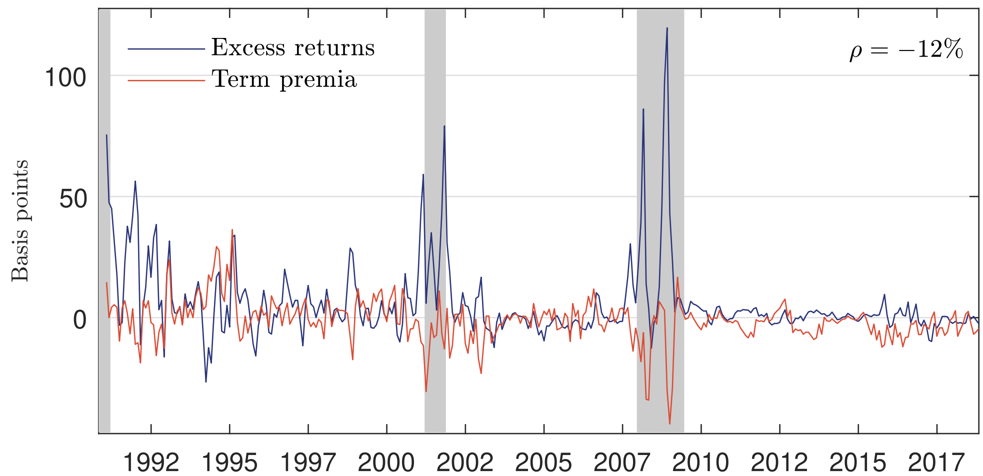


Figure IA.2: Excess Returns on FF Futures and Term Premia

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 2018:11.

3-months-ahead



6-months-ahead

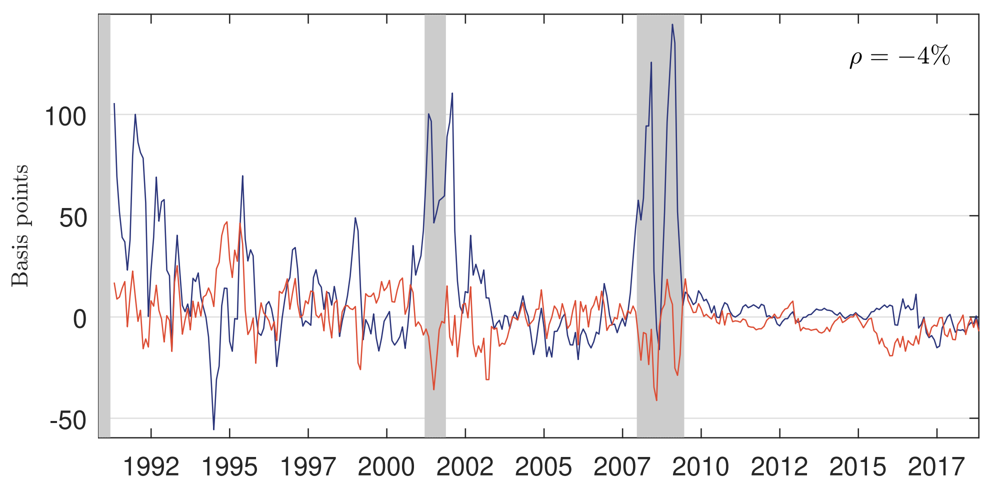


Figure IA.3: Excess Returns on OIS and Term Premia

The figure shows excess returns on OIS, $rx_{t+n}^{(n)} = f_t^{(n)} - i_{t+n}$, with survey-implied term premia, $\text{TP}_t^{(n)} = f_t^{(n)} - S_t^{(n)}$, 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 2019:07.

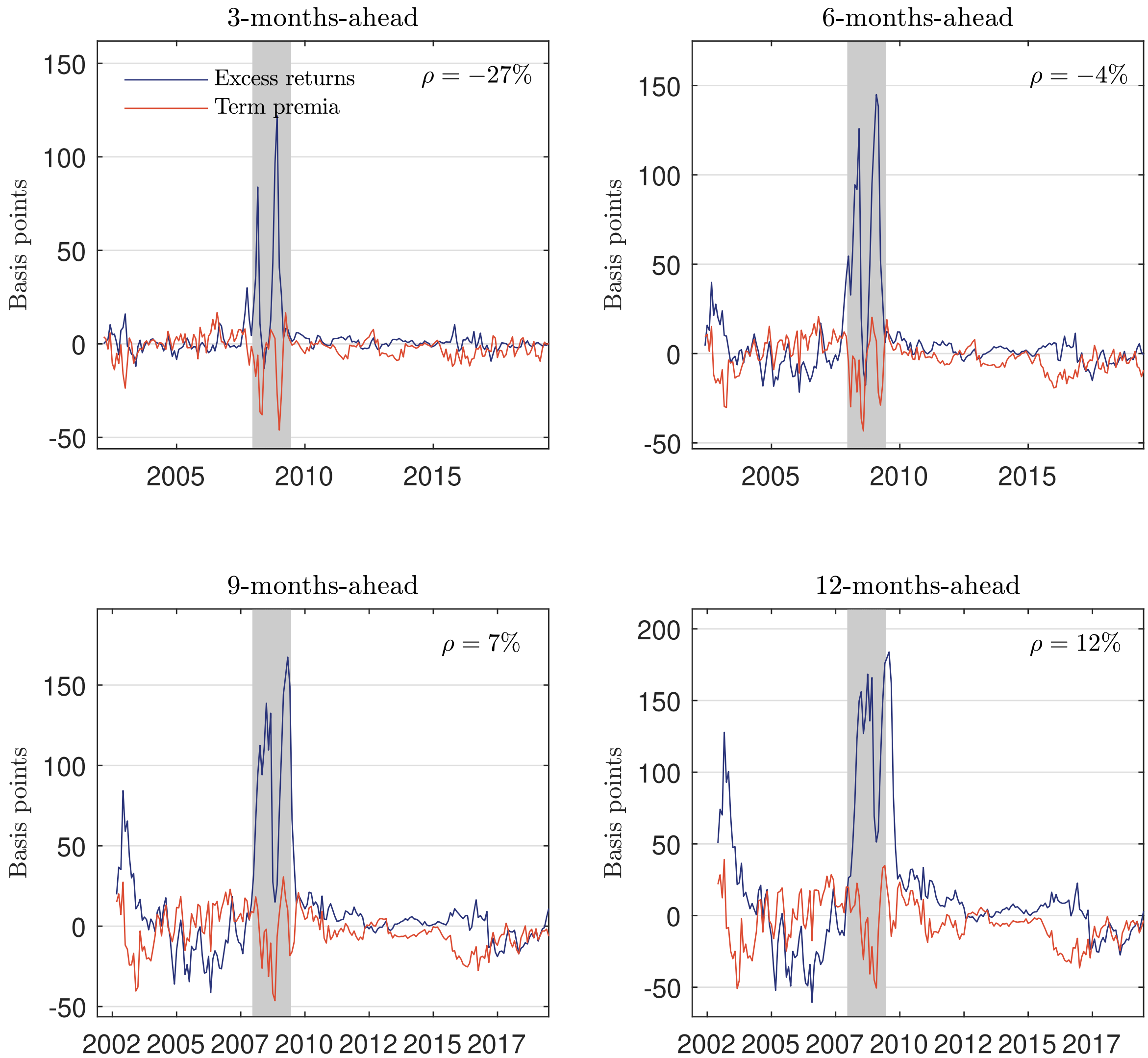


Figure IA.4: Prediction-Realization Diagrams: OIS

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 2019:07.

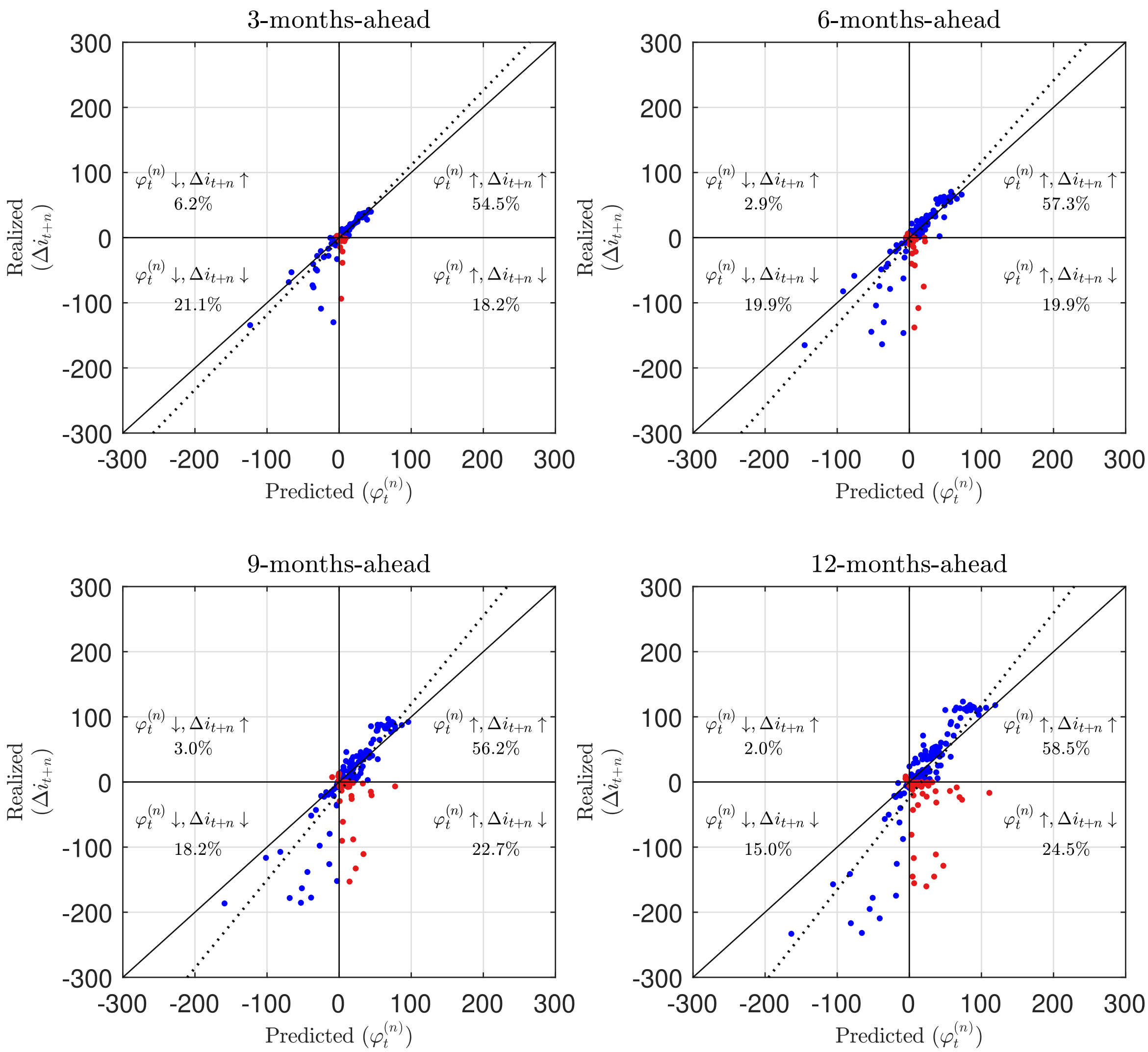


Figure IA.5: Excess Returns on FF Futures and Taylor Rule Deviations

The figure shows excess returns on FF futures with contemporaneous Taylor rule deviations from Eq. (11). When Taylor rule deviations are positive, short rates are below the level implied by the Taylor rule and vice versa. Both series are standardized to have mean zero and unit variance and the sample is 1990:11 to 2018:11.

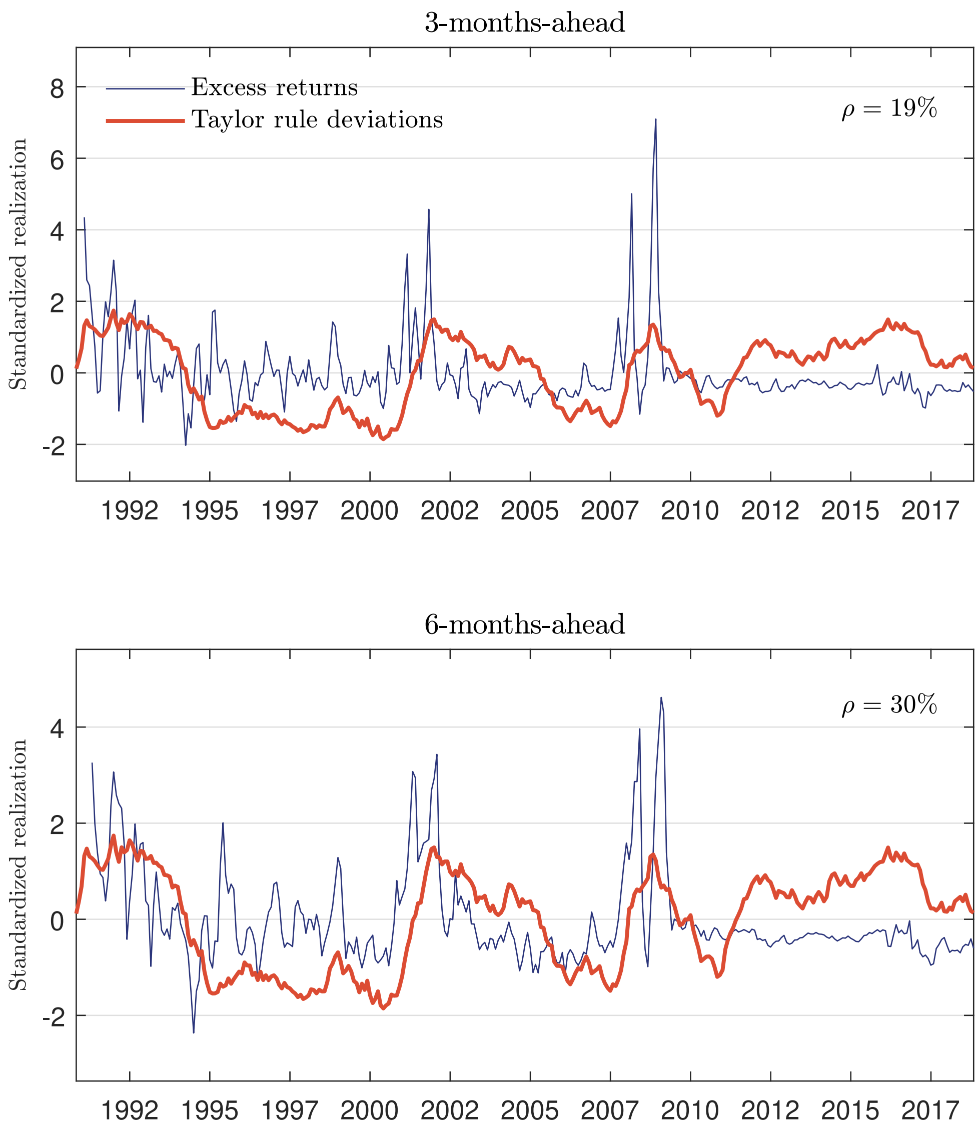


Figure IA.6: Excess Returns on OIS and Taylor Rule Deviations

The figure shows excess returns on OIS with contemporaneous Taylor rule deviations from Eq. (11). When Taylor rule deviations are positive, short rates are below the level implied by the Taylor rule and vice versa. Both series are standardized to have mean zero and unit variance and the sample is 2001:12 to 2019:07.

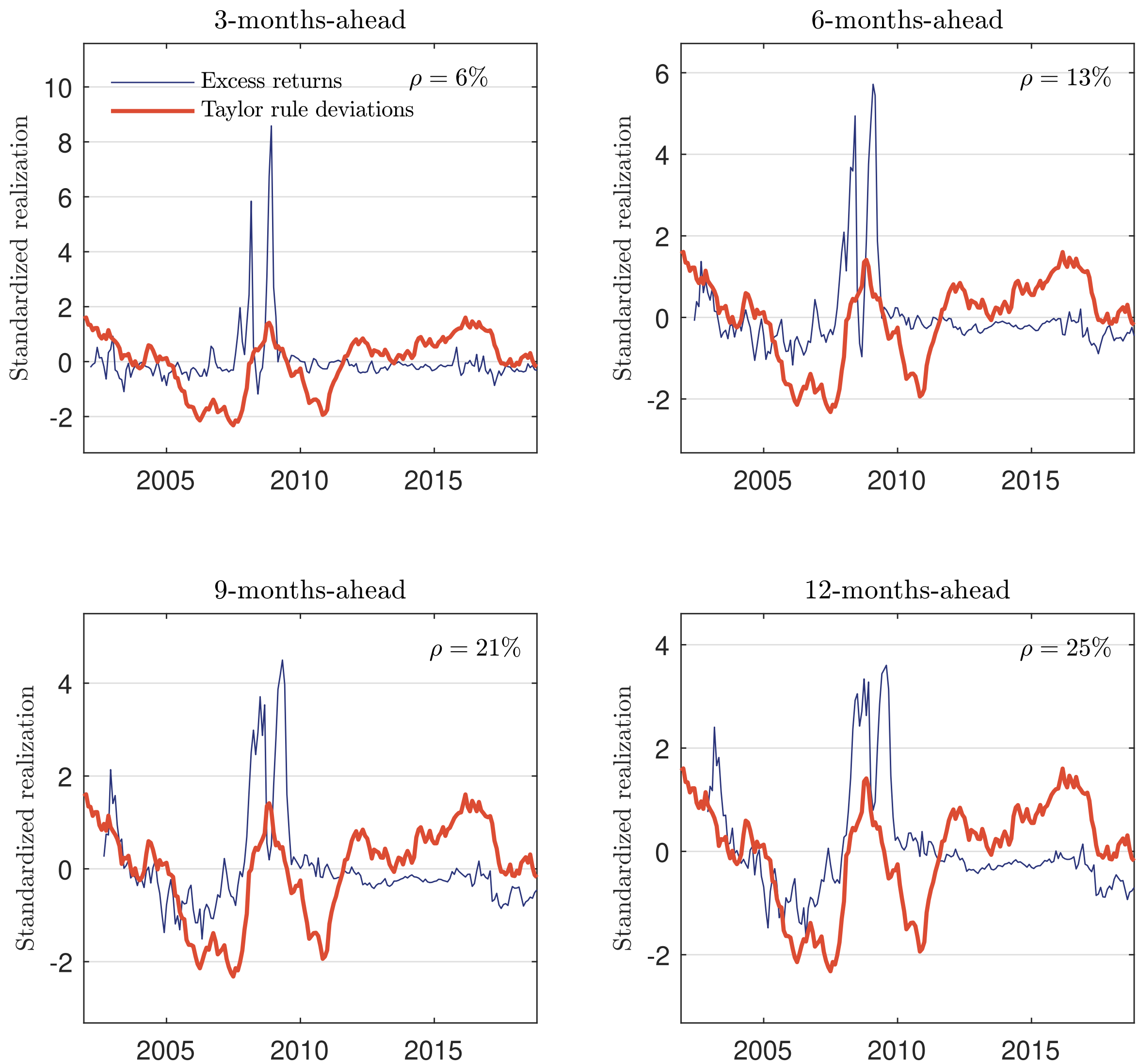


Figure IA.7: Excess Returns and Expectation Errors: Eurozone

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 2019:07, the frequency of observations is monthly, and all values are denoted in basis points.

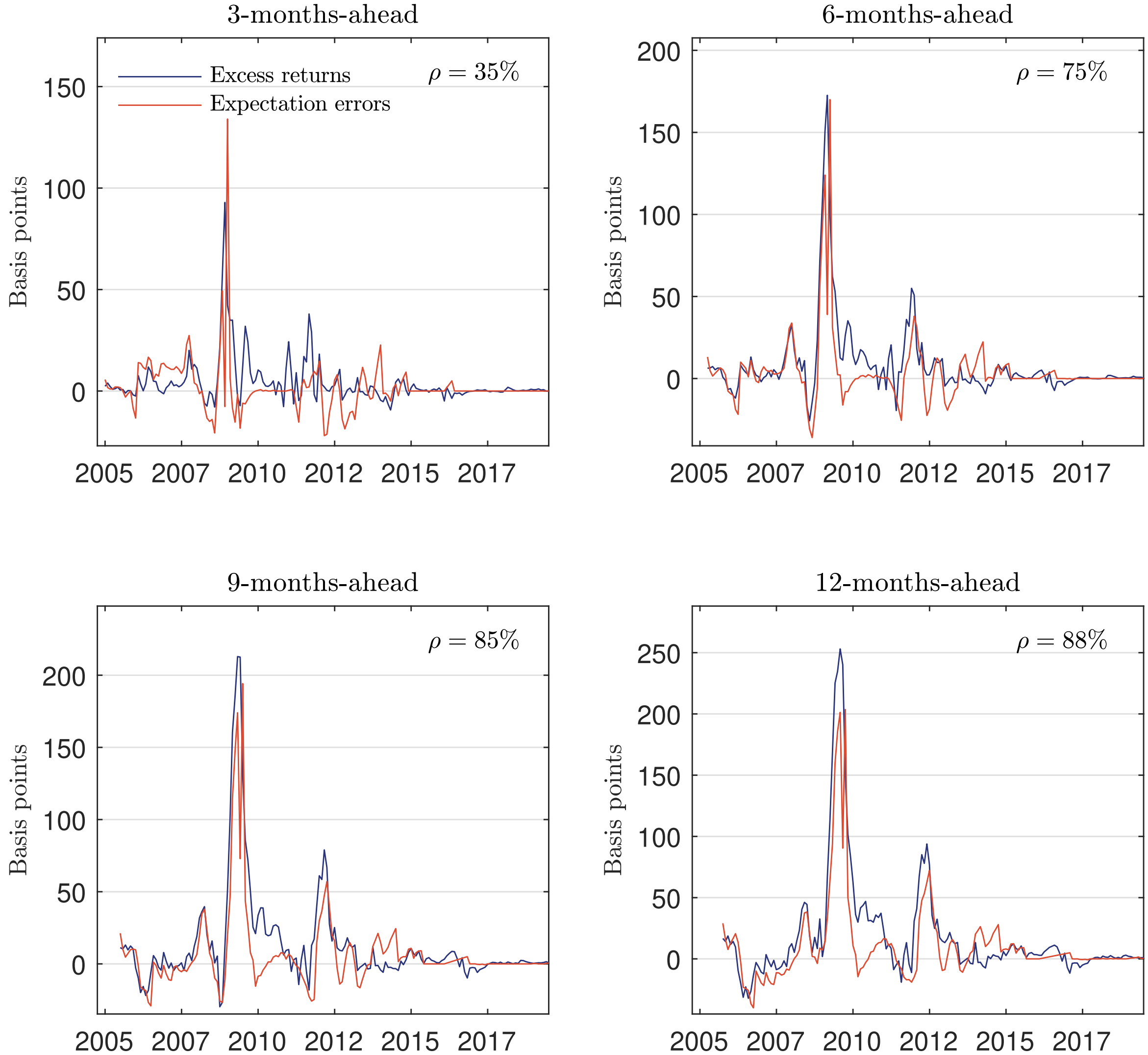


Figure IA.8: Excess Returns and Expectation Errors: United Kingdom

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 2019:07, the frequency of observations is monthly, and all values are denoted in basis points.

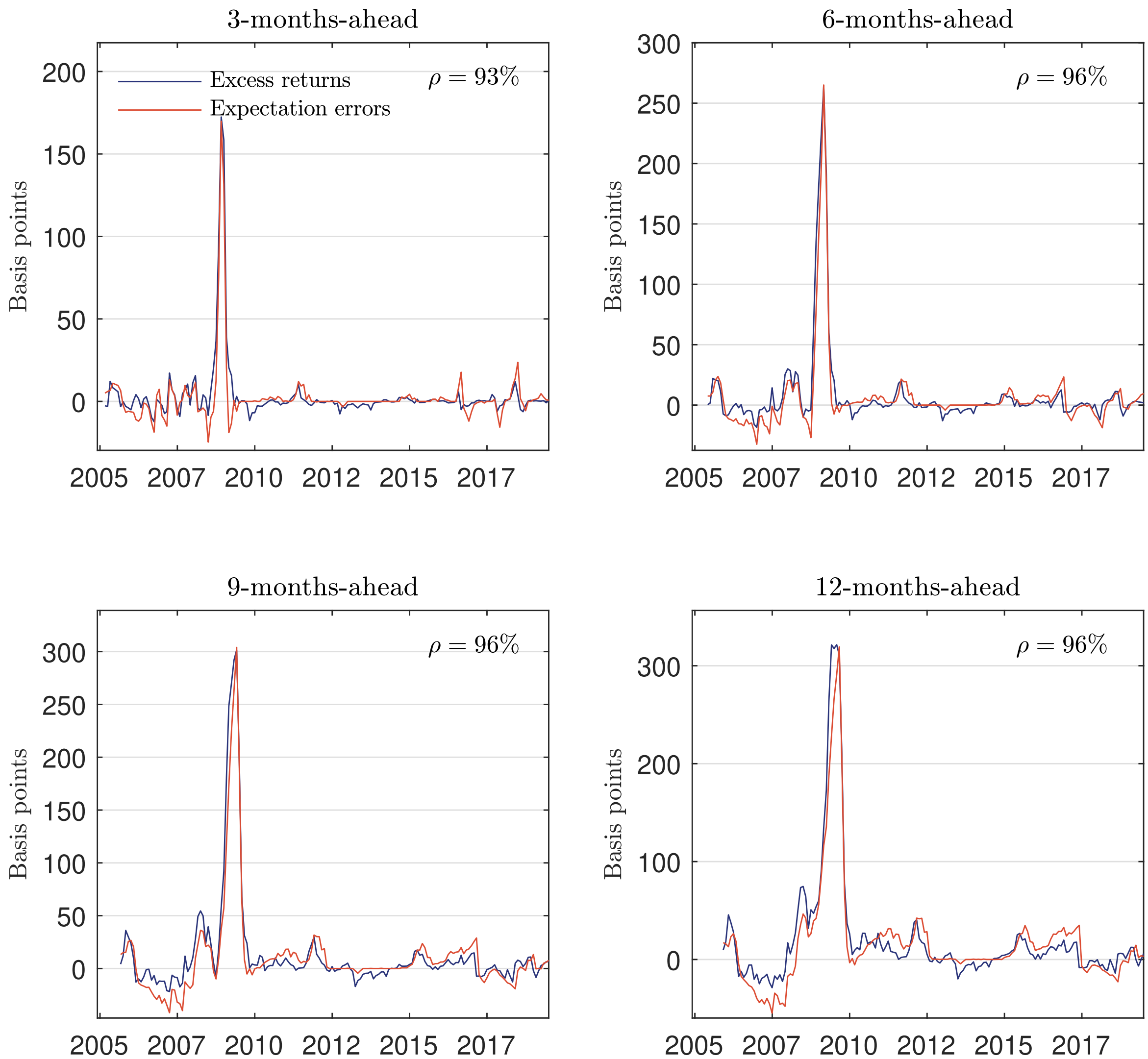
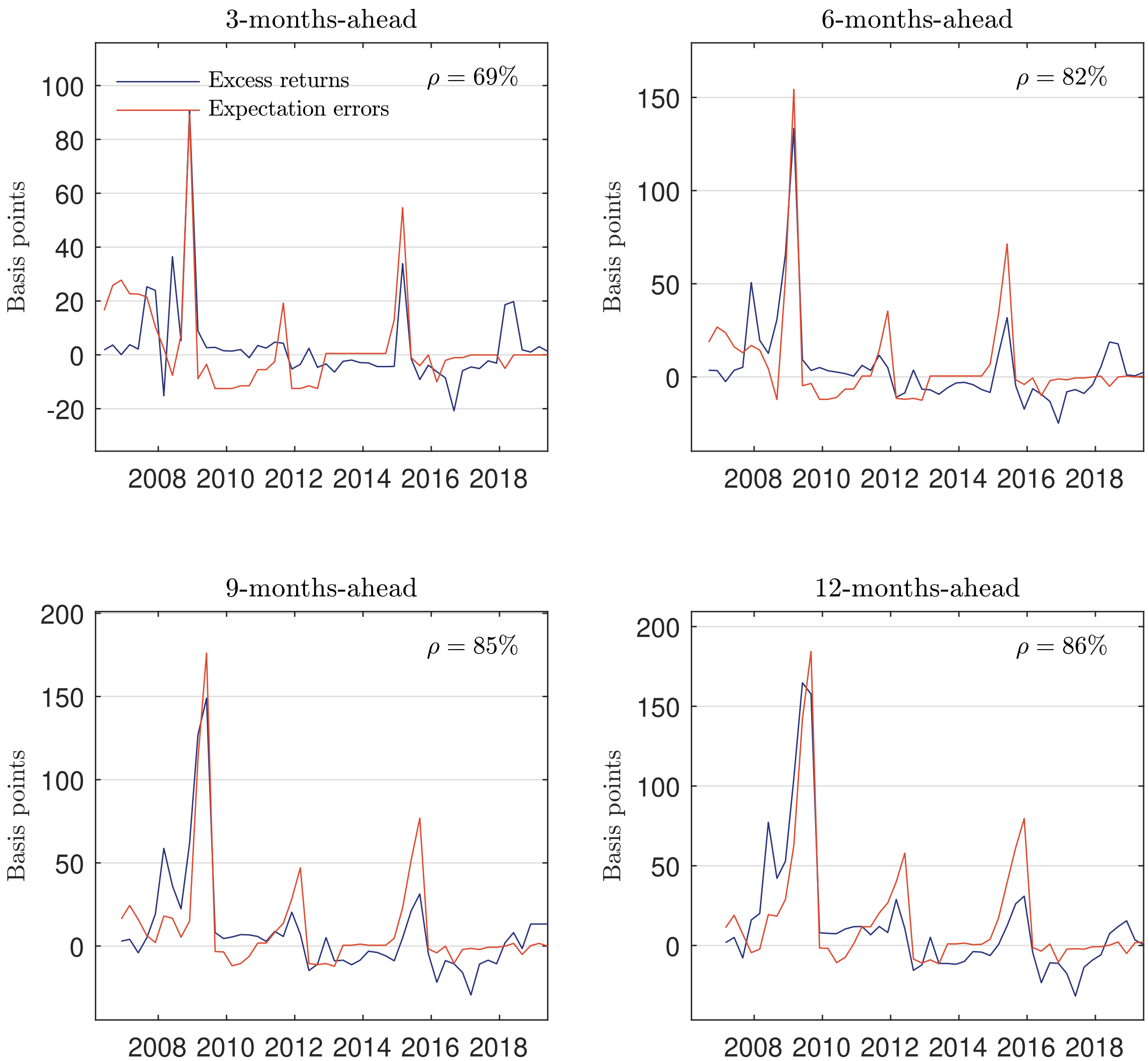


Figure IA.9: Excess Returns and Expectation Errors: Switzerland

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 2019:06, the frequency of observations is quarterly, and all values are denoted in basis points.



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