Watching the FedWatch

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Abstract

The popularity of the CME FedWatch as a tool for forecasting monetary policy has increased rapidly. We investigate its statistical and economic value for market participants. Our analysis shows that this simple binary model can predict the Federal Open Market Committee (FOMC) rate decisions with an 88% accuracy 30 days before FOMC meetings. On the other hand, conventional predictions based on Fed fund futures result in a 75% accuracy. A simple backtesting procedure demonstrates that this 13% accuracy improvement translates into significant economic gains. Further empirical evidence indicates that the tool effectively reduces uncertainty ahead of FOMC meetings, mitigating the well-documented pre-FOMC drift. Despite its strong predictive power, the FedWatch has remained largely overlooked until recently, according to traffic data. We explore several mechanisms to explain why market participants have not fully exploited such tools. One key reason lies in the fact that bond yields on FOMC days are predominantly driven by unexpected rate surprises, which remain unpredictable even for sophisticated investors.

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1 Introduction

Existing research has largely focused on risk premia in equity markets, resulting in a well-documented "factor zoo" (Bryzgalova et al., 2023), while the fixed-income (henceforth FI) market remains comparatively underexplored. Although recent studies, such as those on corporate bond factors (Dickerson et al., 2023), have begun to address this gap, the opaque nature of fixed-income markets has made such progress more challenging (Bessembinder et al., 2020). This opaqueness is characterized by limited liquidity, especially in the OTC market (Schestag et al., 2016), despite advances in electronic and algorithmic trading. Among the various elements driving fixed-income asset pricing, interest rate forecasts/expectations remain the most critical factors in fixed-income pricing (Kuttner, 2001; Swanson, 2021; Bianchi et al., 2021).

Central bank policy interventions are among the most influential mechanisms for regulating price and economic stability, shaping variables such as consumption, investment, asset valuation, and financial system resilience (Padoa-Schioppa, 2003). This influence was recently exemplified by the collapse of Silicon Valley Bank (SVB). Shifts in policy actions create ripple effects across financial markets and the broader economy, highlighting the importance of understanding how these changes are anticipated and reflected in market behavior. This raises a fundamental question: how do market participants interpret and prepare for adjustments in monetary policy frameworks?

Earlier work by Kwapil and Scharler (2013) investigates the impact of expected monetary policy on the dynamics of bank lending, whereas more recent research by Boguth et al. (2019) explores the role of investor attention toward FOMC meetings, comparing those with and without press conferences (PCs), and the dissemination of price-relevant information. However, significantly less attention has been paid to understanding how the broader investing public perceives and prepares for upcoming monetary policies, who may lack access to sophisticated tools yet are still significantly affected by these policy shifts. This is highly relevant given the recent inflationary and turbulent times that characterized both equity and FI markets in 2022.

Motivated by these observations, our research examines a recently popular tool, the FedWatch by the Chicago Mercantile Exchange (CME). The tool provides market participants with forward-looking implied probabilities of monetary policy decisions over the next 12 months' meetings. In 2022, the Federal Reserve implemented multiple rate increases to counter post-pandemic inflation. This hawkish policy coincided with a significant surge in the popularity of CME FedWatch, according to Google Trends and SemRush, which had previously attracted much less interest (see Figure 6). Other probability trackers are available to market participants, offering insights into future FOMC target rate expectations. Among these, we select the CME FedWatch Tool as our primary focus, given its widespread popularity and accessibility to both institutional investors and the broader investing public alike.[1]

Dating back to the 1990s, the literature extensively documents the pivotal role of Fed funds futures in the price discovery process. These instruments effectively capture market expectations of future Federal Reserve rate decisions and demonstrate significant predictive accuracy in forecasting policy changes (Krueger et al., 1996; Kuttner, 2001; Gürkaynak, 2005; Hamilton, 2009). Additionally, recent advancements in data science, along with natural language processing (NLP) and computer vision, have led to the development of tools that analyze Federal Reserve communications to predict monetary policy decisions. For instance, academic research has extensively investigated the use of such tools to analyze Federal Reserve communications, offering interpretable analyses of FOMC statements and minutes to forecast interest rate movements (Huang and Kuan, 2021; Tadle, 2022; Curti and Kazinnik, 2023).[2]

Given that Fed funds futures are widely recognized for their role in price discovery, the recent surge of interest in FOMC communications and probability trackers among academics and practitioners begs several important questions. First, how accurate is the CME FedWatch Tool in predicting future FOMC target rate decisions? Interestingly, our study reveals that though being criticized as overly simple (Liu et al., 2022), the binary model of the CME FedWatch achieves an accuracy of up to 88% in forecasting the next FOMC meeting's target rate 30 days before. Despite the price discovery inherent in Fed funds futures, a direct method that extracts market expectations from these futures achieves a 75% accuracy rate for predicting the outcome of the next FOMC meeting within a 30-day horizon.

To get a better understanding of our first finding, we recall that the payoffs of Fed funds futures are determined by the actual average effective Federal funds rate (EFFR) over the contract month. Hence, for a month with an FOMC meeting, the futures price can be assumed to incorporate information about the new target rate r_1 set after the meeting. However, estimating the expected EFFR for the days leading up to an FOMC meeting (r_0) is challenging, as the Fed transitioned to the corridor system in December 2008, establishing

[1] In particular, Bloomberg offers the World Interest Rate Probabilities (WIRP), and the Federal Reserve Bank of Atlanta provides the Market Probability Tracker (MPT). However, access to WIRP data is inaccessible to retail investors without a Bloomberg Terminal subscription. Additionally, the MPT tool by the Atlanta Fed has attracted little attention since its launch, as indicated by SemRush traffic data (e.g., see Figure 6).

[2] In recent developments, Morgan Stanley has introduced the MNLPFEDS Sentiment Index, an AI-powered tool that utilizes NLP to evaluate the sentiment of FOMC communications. This index offers market participants a straightforward assessment of potential policy shifts by categorizing the sentiment as either dovish, hawkish, or neutral.

a target rate range instead of a fixed target rate. For example, estimates can be based on the midpoint of the target range, the upper or lower bound, or the 7-day moving average of the past EFFR values. To address this challenge, the CME FedWatch methodology begins with a month without an FOMC meeting, calculating the implied monthly EFFR from the Fed funds futures price and using this rate as the estimate for r_0. The details of this approach are discussed further in Section 2.

To better understand the 13% accuracy improvement of the CME FedWatch tool compared to the outright approach, we also examine its economic implications by implementing two trading strategies: one using Fed Funds Futures and the other using the iShares Core U.S. Aggregate Bond ETF (AGG). Specifically, if a rate cut or no change is predicted, a long position is taken in the bond ETF or Fed Funds Futures. Otherwise, a short position is initiated. Both analyses demonstrate that the use of the CME FedWatch tool enhances trading performance. In particular, for the strategy directly involving Fed Funds Futures, the Sharpe ratio doubles compared to the baseline model.

However, we note that the accuracy of the CME FedWatch decreases significantly over longer horizons, dropping to 68%, 54%, and 45% for the second, third, and fourth meetings, respectively. As new economic data releases and FOMC statements/minutes along the way reshape market expectations, the uncertainty of longer-term predictions is amplified. Given the lower accuracy of extracting market expectations directly from Fed funds futures prices, we do not pursue further calculations of their predictive accuracy for the target rate decisions of the second and subsequent FOMC meetings. The prediction errors for future target rates will only be amplified if an accurate estimate of the next target rate r_1 is unavailable.

Second, given that the simple CME FedWatch Tool predicts FOMC target rate decisions in the near term with high accuracy and offers the investing public an accessible visualization interface, our research next examines whether investors fully utilize the tool and base their trading decisions on its predictions. To do so, we examine the relationship between CME FedWatch's organic traffic and the well-documented pre-FOMC announcement drift (Lucca and Moench, 2015), a well-documented phenomenon the literature mostly attributes to heightened uncertainty and its subsequent resolution (Kurov et al., 2021; Hu et al., 2022). In particular, we investigate whether investors effectively utilize the FedWatch Tool, resulting in lower uncertainty regarding future target rate decisions around FOMC dates and, therefore, mitigating the announcement drift.

Consistent with previous studies, our research demonstrates that pre-announcement drifts are mainly driven by uncertainty and have become less pronounced in recent years due to reduced uncertainties beforehand (Kurov et al., 2021). Nonetheless, we do not find a relationship between the pre-announcement drift and the popularity of CME FedWatch. We attribute this to two potential explanations: (i) the limited data availability post-2020, when CME FedWatch began gaining significant attention, and (ii) institutional investors, who are key drivers of the drift, likely rely on proprietary, sophisticated models. Nonetheless, our findings support the notion that the FedWatch mitigates uncertainty, as measured by VIX, prior to FOMC meetings.

Other key drivers of the post-announcement drift relate to the economic outlook as well as other forward guidance information revealed during the meetings. For instance, Gu et al. (2018) documents a post-announcement drift for meetings accompanied by the Summary of Economic Projections (SEP), attributing this phenomenon to greater uncertainty resolution, as measured by the change in the VIX index before and after the meetings. Our empirical analysis supports this view, finding no direct relationship between the popularity of CME FedWatch and the resolution of uncertainty following FOMC meetings, as the resolution is likely influenced by the new economic information disclosed rather than solely by the target rate decision.

Third, we study the interdependence between the Fed funds futures, the bond market, and the stock market. By design, the CME FedWatch Tool directly extracts probabilities of future FOMC target rate decisions from Fed funds futures, offering market participants a clear framework for understanding short-term rate expectations in capital markets. In this regard, we are interested in two aspects: (i) how do changes in market expectations regarding future Fed target rates influence the bond and stock markets? and (ii) does the FedWatch Tool provide the potential for predicting bond yields and stock returns?

We begin by decomposing realized FOMC rate decisions into expected and unexpected components, analyzing their distinct impacts on bond yield changes during FOMC announcement days. This approach allows us to understand how market expectations and unexpected rate movements influence bond yields differently, providing a closer look at the interaction between Federal Reserve policy signals and market responses. We demonstrate that the bond yields are mainly driven by the Federal Reserve's unexpected part of the rate decisions rather than the anticipated ones, evidence consistent with earlier literature (Kuttner, 2001). Additionally, we document the time-varying effects of unexpected rate changes on bond yields by controlling for high-yield periods. Specifically, while there is a positive relationship between rate surprises and Treasury bond yields during normal periods, this impact diminishes significantly during high-yield periods. For long-term bonds, the relationship may even reverse, possibly due to increased demand for long-term bonds in response to positive rate surprises.

Next, we analyze the relationship between daily changes in market expectations for future FOMC rate decisions and bond yields while assessing whether expected rate changes exhibit predictive power for bond yield movements. The probability-weighted market expectations for the future Fed target rate are calculated using the CME FedWatch Tool, which provides potential target rates and their associated probabilities. For the same-day analysis, we identify a positive yet inverse U-shaped relationship between daily expected rate changes and bond yield changes across maturities, ranging from short to long. This pattern becomes more pronounced during high-yield periods. A potential explanation is that during high short-term yield periods, an increase in market expectations of a rate hike makes medium-term bonds less desirable, as risk-averse investors prefer to lock in long-term interest rates. From a risk management perspective, the potential for a rate hike in the near future tends to shorten the duration of liabilities. Consequently, asset managers sell medium to long-term bonds and purchase short-term bonds to align the duration of their assets and liabilities.

Finally, we leverage a vector autoregressive (VAR) model to understand the Granger causality between the change in expected rates, the change in the 3-month Treasury Bill rate, and SPY returns. Overall, we find a causal relationship between changes in the expected rate and bond yield changes; the predictive power of expected rate changes for next-day bond yield changes is minimal due to its nearly negligible magnitude. Furthermore, we do not find a causal relationship between expected rate changes and SPY returns.

Our paper contributes to different streams of literature. First, we add to the body of work on extracting market expectations of future Federal funds target rates (Carlson et al., 2005; Gürkaynak, 2005; Emmons et al., 2006; Bauer et al., 2012; Jung, 2016; Husted et al., 2020; Bauer et al., 2022) and the broader literature on predicting the future trajectory of monetary policy (Hamilton and Jorda, 2002; Hu and Phillips, 2004; Kim et al., 2009; van den Hauwe et al., 2013; Hayo and Neuenkirch, 2010; Gerlach-Kristen, 2004). For instance, Carlson et al. (2005) utilize American-style options on Federal funds futures to derive implied probability distributions of the Federal Reserve's target rate decisions made by the Federal Open Market Committee (FOMC). Additionally, Emmons et al. (2006) utilizes the method of Carlson et al. (2005) and asserts that option-based predictions prove most useful when there are more than two possible outcomes for the Federal fund's target rate at an upcoming FOMC meeting. However, among the various methods, Fed funds futures are widely documented as the most reliable tool for extracting market expectations and predicting future Fed funds target rates (Robertson et al., 1997; Kuttner, 2001; Gürkaynak, 2005; Hamilton, 2009). Krueger et al. (1996) first documents the usefulness of the Fed funds futures rate as a predictor of Fed target rate changes because of its unique structure and payoff. Later, Kuttner (2001) utilized Fed funds futures to decompose changes in the Fed funds rate into anticipated and unexpected components, showing that only the unexpected changes are associated with bond yield movements. Unlike previous studies, our research converts Federal funds futures prices into rate movement probabilities using the methodology outlined by the CME Group for their

FedWatch Tool and evaluates its accuracy. Our findings reveal that this straightforward binary tool achieves an accuracy of 88% in predicting the target rate for future FOMC meetings in 30 days.

Second, our paper contributes to the literature on the impact of FOMC meetings on the stock market (Bernanke and Kuttner, 2005; Gómez-Cram and Grotteria, 2022), specifically the well-documented phenomenon of the "pre-FOMC announcement drift" (Lucca and Moench, 2015; Ai and Bansal, 2018; Cieslak et al., 2019; Kurov et al., 2021; Ai et al., 2021; Hu et al., 2022). The paper by Lucca and Moench (2015) is the first to document such drift, highlighting significant average excess returns on U.S. equities in the days preceding scheduled FOMC meetings over the past few decades. Building on this, Cieslak et al. (2019) find that the equity premium is predominantly earned during even weeks of the FOMC cycle and attribute Lucca and Moench's (2015) drift to this cyclical pattern (Ai and Bansal, 2018; Ai et al., 2021; Hu et al., 2022). Ai and Bansal (2018) and Ai et al. (2021) attribute the drift to potential information leaks from the Fed and investors' endogenous information acquisition while Hu et al. (2022) empirically link the return drifts to the buildup of heightened uncertainty and its subsequent resolution before the announcement. In addition to the VIX index, we construct an uncertainty measure directly from Fed funds futures prices and validate previous findings that the pre-FOMC announcement drift is driven by the level of uncertainty before FOMC meetings. However, our measure, based on financial instrument prices, shows weaker explanatory power for the drift compared to other metrics. Furthermore, using web traffic data as a proxy for popularity, we show that the CME FedWatch Tool plays a significant role in reducing uncertainty prior to FOMC meetings by informing investors about potential target rates, thereby helping to mitigate the pre-announcement drift.

Finally, our paper contributes to the literature on predicting bond excess returns (Cochrane and Piazzesi, 2005; Bianchi et al., 2021; Huang et al., 2023; Campbell and Thompson, 2008) by examining the impact of expected rate changes on bond yields. Our study demonstrates a strong connection between the Fed funds futures market and the Treasury bond market, revealing a statistically significant causal relationship between changes in the expected target rate and Treasury bond yield changes. However, this relationship is economically insignificant due to its negligible magnitude. Additionally, the standard deviation of daily expected rate changes is approximately four basis points. A one-standard-deviation increase in the expected rate would result in only a 0.36-basis-point increase in the next day's 30-day T-Bill rate.

Overall, the FedWatch Tool serves as a valuable proxy for market expectations, providing accessible insights to the broader investing public. To the best of our knowledge, our study is the first to systematically investigate the implications of such publicly available information on key market phenomena. In an era where advanced, proprietary models leveraging alternative and big data are often exclusive to institutional investors, our research underscores the critical role that accessible tools like the FedWatch play in mitigating asymmetric information between broader investors and sophisticated investors (Lei, 2019), *leveling the informational playing field*.

The rest of the paper is organized as follows. We devote Section 2 to the descriptions of the CME FedWatch and the reverse engineering idea behind it. Section 3 describes the sample construction and data source. In Section 4, we discuss our main findings, which we split into three parts: accuracy, popularity, and predictive power of CME FedWatch. Finally, Section 6 concludes.

2 Methodology Behind the CME FedWatch Tool

In this section, we present the methodology employed by the CME FedWatch Tool to calculate the unconditional probabilities of various possible target rate ranges from daily Fed funds futures data[3]. Based on the methodology introduced by CME Group, we follow the same approach as the CME FedWatch Tool to calculate the probabilities of possible future target rates. Readers who are familiar with the methodology may skip this section and proceed to Section 3. Nonetheless, the purpose of this discussion is to differentiate the tool's tool projection compared to the one extracted from conventional Fed fund futures.

The FedWatch Tool calculates unconditional probabilities for FOMC meeting outcomes using a binary probability tree, drawing on 30-day Fed funds futures (ZQ) listed by CME Group. These futures prices reflect market expectations for the average daily EFFR during their contract months, which is a transaction-volume weighted average of the previous day's overnight unsecured loan rates between depository institutions, published daily by the Federal Reserve Bank of New York.

We first begin with stating six important assumptions used by the CME FedWatch Tool:

1. The calculation of the probability for a rate hike/cut is based on adding the probabilities of all potential target rates that are either above (for hikes) or below (for cuts) the current target range.

2. FOMC's decision on rate hikes/cuts are uniformly sized in increments of 25 bps (0.25%), and the EFFR will react proportionally to the size of the hike/cut. The probabilities of possible Federal funds target rates are then calculated based on the daily Fed funds futures

[3]We refer readers to the methodology webpage of CME FedWatch Tool for more details

data, derived from the average daily EFFR for a particular month, which is bounded below zero.

3. The FOMC adheres to a pre-determined schedule for its meetings, evenly distributed throughout the year, with eight meetings annually. Consequently, one month in each quarter is designated without a meeting.

4. In months with a FOMC meeting, the price of the corresponding monthly Fed funds futures is used to calculate the probabilities of interest rate hikes/cuts, which reflects the market expectations.

5. The starting rate of the EFFR in a given month is set to be equal to the projected end-of-month EFFR from the preceding month.

6. If a FOMC meeting month follows a month without a meeting, the previous month's futures price remains unaffected by the rate decision of the current month. Similarly, in a FOMC meeting month preceding a month without a scheduled meeting, the futures price for the following month solely reflects outcomes from the current month's meeting.

Given the above-stylized facts, the implied monthly average EFFR rate for month m is computed as:

$$\text{EFFR}_m^{\text{Avg}} = 100 - \text{FF Contract Price}_m. \tag{1}$$

To calculate the projected month-end and month-start EFFRs, we first start with the nearest month m without an FOMC meeting. Then, the projected month-end and month-start EFFR rates are set to the rate from Equation (1), i.e., the implied average EFFR rate computed from the Federal fund's futures for month m, such that

$$\text{EFFR}_m^{\text{Avg}} = \text{EFFR}_{m-1}^{\text{end}} = \text{EFFR}_{m+1}^{\text{start}}. \tag{2}$$

For the months with an FOMC meeting that precede months with no meetings, the projected month-end EFFR is set as the next month's implied average EFFR. In this case, the month-start projected EFFR rate is calculated as

$$\text{EFFR(Start)}_m = \left\{\text{EFFR(Avg)}_m - \left[\left(\frac{M}{M+N}\right) \cdot \text{EFFR(End)}_m\right]\right\} / \left(\frac{N}{M+N}\right), \tag{3}$$

where

$$N = \text{days in the month before the FOMC meeting,}$$
$$M = \text{days in the month after the FOMC meeting (including meeting day).}$$

Similarly, for the months with an FOMC meeting but no meeting in the preceding month, the projected month-start EFFR is determined by the previous month's average implied EFFR, such that the month-end projected EFFR rate is computed as

$$\text{EFFR(End)}_m = \left\{\text{EFFR(Avg)}_m - \left[\left(\frac{N}{M+N}\right) \cdot \text{EFFR(Start)}_m\right]\right\} / \left(\frac{M}{M+N}\right). \tag{4}$$

Lastly, for those months that have FOMC meetings scheduled in the preceding, current, and following months, the projected month-start (month-end) EFFR rate would be set to the calculated month-end (month-start) EFFR rate of the previous (following) month. Figure 1 presents a timeline illustrating the calculation of the projected start, end, and average EFFR for various months.

With the projected month-start and month-end EFFR rates calculated, we can derive the equivalent number of 25bp hikes or cuts as the expected EFFR change in month m divided by 25 bps. The integer obtained above sets the minimum threshold for a possible rate hike or cut with a possibility of one minus fractional part. For example, if the expected EFFR change in a given month is 0.5276% (53 bps), then the expected number of 25 bps hikes is $0.5276/0.2500 = 2.1103$. Namely, the probability of a 50 bps hike is $1 - 0.1103 = 89.97\%$, and a 75 bps hike with a probability of 11.03%. For the next upcoming FOMC meeting, there will be a binary probability for a rate hike/cut and unchanged based on the calculation introduced above. Starting from the second nearest FOMC meeting, one can get cumulative results by simply multiplying the probabilities of each outcome with those of the previous meetings.

3 Empirical Design

In this section, we discuss the empirical design used to conduct our major analysis. In particular, we discuss the different data sources and the sample construction.

3.1 Fed Funds and Probabilities

Given the methodology behind the CME FedWatch, we begin constructing our data sample of unconditional probabilities for different potential target rate ranges for future FOMC meetings using daily Fed funds futures data from Bloomberg. The reason we rely on Bloomberg is because the CME FedWatch provides historical data to a limited extent. For instance, in June 2024, users can only trace back the data for the Jan 2024 meeting. As a result, we leverage futures data from Bloomberg to obtain a longer sample period than the one publicly available by CME. In unreported results, we confirm the replication of the tool using the Bloomberg data with one smaller subset provided by CME.

We begin our data sample in February 1994, when the FOMC began to announce its target Federal funds rate on the meeting day. However, due to missing data on Fed funds futures in the early days, the first FOMC meeting included in our dataset is from May 1994. The dataset extends to March 2024, covering a total of 232 scheduled FOMC meetings. In December 2008, the Federal Reserve made a significant adjustment to its monetary policy framework, shifting from targeting a specific Federal funds rate to targeting a range for the rate (Fed, 2008). For consistency in our study, we focus on the lower bound of the target rate range post-December 2008 to align it with the previous regime.

3.2 Yields and Rates

We obtain daily yields of Treasury bills/bonds from the U.S. Department of the Treasury website. We select the 3 and 6-month Treasury bills and the 1, 2, 5, 10, and 20-year Treasury bond yields to represent the yield curve. These maturities have been consistently available throughout the entire data sample period without any missing values. Furthermore, the Federal funds target rate/range and daily EFFR are downloaded from the Federal Reserve Economic Data (FRED) database. In Figure 2, we display several key interest rates from 1994 to 2024 to provide a detailed financial overview. This includes the Federal Reserve's target rate, the EFFR, 3 and 6-month Treasury bills, and the 1, 2, 5, 10, and 20-year Treasury bond yields. The gray shaded areas represented those dates when the 3-month T-bill yields exceeded the top 20th percentile of our data sample, which is 5.07%.

3.3 Implementation and Additional Data

In terms of implementation, we primarily use the Python package *yfinance* to retrieve daily SPY and VIX data from Yahoo Finance and other libraries to conduct our main empirical analysis. To investigate the pre-FOMC announcement drift, intraday high-frequency data is employed, with S&P 500 futures price data obtained from Refinitiv Thomson Reuters Tick History (TRTH), covering a period starting in January 1996. The analysis uses S&P 500 E-mini futures prices from 1998 onward, as these contracts, introduced in 1997, have quickly become popular due to their flexibility. For the earlier period, from 1996 to 1998, standard S&P 500 futures prices are utilized.

3.4 Summary Statistics

Table 1 presents a summary of the statistics for all variables used in the analysis. Panel A highlights the main variables, including the date range (1994-2024) and key variables such as the Federal fund's target rate, expected rate, and Treasury bill/bond yields across various maturities. Notably, the mean Federal funds target rate is 2.25%, with a maximum of 6.50%. Treasury bond yields range from an average of 2.13% (3-month) to 4.19% (20-year), reflecting an upward-sloping yield curve over the sample period. Panel B focuses on daily changes in SPY returns, expected rate changes, and 3-month Treasury yield changes, with SPY returns exhibiting a mean of 0.03% with daily volatility of 1.18% (corresponding to annual volatility of approximately 19%). Panel C summarizes FOMC-event-related variables with 226 observations covering the whole meetings in our sample. These variables include market return pre-FOMC drift, uncertainty measured using the VIX index, pre-FOMC drift in basis points (with an average mean of 0.37 bps), and normalized VIX (mean: 0.07). Additionally, the panel covers the monthly visits (using traffic data from SemRush) to the CME FedWatch webpage, which increased substantially over time as Figure 6.

4 Main Findings

The following section summarizes the main analysis and findings of our paper. The discussion is split into two major parts. First, we focus on the predictive power of the CME FedWatch and compare its performance against conventional Fed funds futures. Second, we explore its popularity and proxy the attention the investment public gives to this tool while reconciling its increased popularity with mitigating uncertainty surrounding FOMC events.

4.1 Accuracy of CME FedWatch Tool

4.1.1 Implementation

Using the CME FedWatch probabilities, we predict the target federal funds rate by selecting the rate with the highest probability as the predicted rate. Prediction accuracy is then calculated by comparing this predicted rate with the actual realized target rate set by the Federal Reserve. In particular, there are two forward-looking methods for predicting the target federal funds rate: "days before" and "meetings before." The former uses calendar days as the reference point, calculating probabilities for a set number of days leading up to the event. Alternatively, the latter approach generates predictions based on probabilities derived immediately after the prior FOMC meeting, using the number of meetings as the time horizon.

To enhance the rigor of our predictions, we impose a constraint requiring that the ideal prediction date and the actual date differ by no more than 5 days. For instance, under the "meetings before" method, the prediction for the target rate on December 13, 2023, should be made on November 2, following the conclusion of the previous FOMC meeting on November 1. We ensure that the prediction date falls within the 5-day window from November 2 to November 7. This guarantees that the analysis focuses on observations with close temporal proximity, minimizing the inclusion of data points that might be less relevant or timely for accurate predictions. This constraint does not affect rate predictions for recent FOMC meetings but has a significant impact on earlier meetings, particularly those from the 1990s. Consequently, although our data sample starts in April 1995, 14 meetings are missing due to the unavailability of Fed funds futures prices in Bloomberg. This reflects the illiquid trading of Fed funds futures until 2000, as documented in Cieslak et al. (2019).

Furthermore, we do not assume interest rates to turn negative, as the Federal Reserve has never adopted negative rates historically. However, due to the configuration of the CME FedWatch, during the Zero-Lower Bound (ZLB) period, there may be days when positive probabilities are assigned to potential negative interest rates. For example, consider the case of August 20, 2020, preceding two FOMC meetings scheduled for September 16, 2020, and November 5, 2020. The Fed funds futures prices for September (ZQU20), October (ZQV20), and November (ZQX20) were 99.9250, 99.9350, and 99.9450, respectively. From futures prices, it is evident that the expectation for the EFFR is decreasing.[4] However, this decline is driven not by an increased market expectation of a rate cut (assuming the market also does not anticipate negative rates) but by a reduction in the *cost of carry*. In contrast, the CME FedWatch model attributes this negative monthly change in the implied EFFR to an increased probability of a rate cut, thereby assigning positive probabilities to negative rates. To overcome this limitation, we aggregate all probabilities of negative interest rates and incorporate them into the zero rates.

4.1.2 Prediction Results

After the above adjustments, we utilize the extracted target rates from the FedWatch compare with the actual values. As a performance summary, we report the tool's accuracy in Table 2. A number of important observations follow from the prediction investigation. First, we observe that the FedWatch performs relatively well with 84% (88%) accuracy when considering a time window of one meeting (30 days) prior to the FOMC meeting. Nonetheless,

[4] Recall that Fed fund futures prices are quoted as 100 minus $EFFR_m^{Avg}$, where $EFFR_m^{Avg}$ is the arithmetic average of daily effective federal funds rates during the contract month.

the prediction accuracy for future FOMC meetings declines sharply over time. For the fourth FOMC meeting in the future, the accuracy drops to approximately 48.57%, compared to a high of 83.72% for the next immediate meeting. Similarly, using calendar day-based measures, the accuracy for predicting an FOMC meeting decreases to 58.85% for a meeting that is 120 days ahead of the actual prediction. This trend reflects the greater uncertainty that market participants face in making accurate predictions over the longer horizon.

Second, in Figure 3a, we plot the accuracy of predictions for FOMC meetings occurring within the next 30 days. The Fed funds target rate is represented using a dashed line in the background, while incorrect predictions are marked with red dots, and correctly realized rates are highlighted using blue dots. The magnitude of the error is visually represented by the length of the red bar. The majority of incorrect predictions occurred during the 1990s, with notable improvements in accuracy observed in more recent years. Additionally, market participants are particularly prone to misjudging unexpected Fed rate cuts during periods of heightened uncertainty (Bernanke and Kuttner, 2005), such as the 2008 financial crisis and the onset of the COVID-19 pandemic in 2020. These episodes are marked by increased volatility and widespread economic distress, often amplifying the market's reliance on the Fed's actions to stabilize financial conditions. Our empirical evidence aligns with the theory of the "Fed put" (Cieslak and Vissing-Jorgensen, 2021), which suggests that the Fed tends to intervene aggressively during market downturns by easing monetary policy, effectively acting as a safety net for investors.

Third, we calculate the expected rate for future FOMC meetings as the probability-weighted average of the possible rates provided by the CME FedWatch Tool and define expectation errors as the absolute difference between the realized rate and the expected rate. The expectation error trend, beginning two meetings before the current one, is presented in Figure 5. To ensure consistency in each cycle, we define the date of the previous FOMC meeting as *Day 0* and include a 25-weekday window before and after the event. Following the Federal Reserve's formal announcement of its long-term inflation goal of 2% (known as the Fed Anchoring Effect), we plot the error trend separately for periods before and after 2012 to examine its impact.[5] The blue dotted line represents the pre-2012 period, while the orange line represents the post-2012 period, with the shaded area indicating the 95% confidence interval. The expectation error is statistically higher in the pre-2012 period compared to the post-2012 period. In the pre-2012 period, we observe a significant drop in expectation errors on the last FOMC day before the current meeting, while this phenomenon is minimal in the post-2012 period. Our findings support the notion that monetary policy actions became

[5]The year 2012 also marks the year in which the Summary of Economic Projections (SEP) publication became available within two hours after the FOMC statement Gu et al. (2018). In this regard, the period of post-2012 represents the era in which the Fed became more transparent.

more predictable, aiding market participants in forming more accurate market expectations about future monetary policy (Gu et al., 2018).

4.1.3 Predictions Based on Fed funds futures

Since the CME FedWatch is built on Fed fund futures, a natural question arises regarding what value the tool brings to the table. To address this, we form outright predictions using the futures prices and compare their performance to one extracted from the FedWatch. To do so, we need to derive FOMC target rate predictions for the next immediate FOMC meeting directly from Fed funds futures prices, which can be achieved as follows. Given the payoff setting of the Fed fund futures, at date t, the price for a given month m with a scheduled FOMC meeting can be calculated as:

$$f_t = \frac{N}{M+N} \times r_0 + \frac{M}{M+N} \times \mathbb{E}_t[r_1] + \mu_t, \tag{5}$$

where r_0 represents the average EFFR rate prior to the scheduled meeting and $\mathbb{E}_t[r_1]$ denotes the expected average EFFR rate following the meeting. Consistent with the definition in the CME FedWatch Methodology from Section 2, N denotes the number of days before the meeting, and M represents the days afterward. We assume that the change in the FOMC target rate announced during the scheduled meeting is the sole factor driving the variation in the average EFFR rate before and after the meeting. The quantity μ_t represents a term premium for the spot month contract, which is approximately 1-3 basis points (Gürkaynak et al., 2007). In our investigation, we set the value to the midpoint, i.e., 1.5 bps.

According to Equation (5), the final component involves approximating the expected EFFR after the next FOMC meeting, $\mathbb{E}_t[r_1]$, as the average EFFR rate, r_0, for the days leading up to the meeting announcement. If the next FOMC meeting is scheduled for the following month or the current date t falls within the first 7 weekdays of the FOMC meeting month, r_0 is approximated as the rolling average of the EFFR over the past 7 days. Otherwise, r_0 is approximated as the average EFFR up to the current date within month m. For the final rate prediction, before the December 2008 FOMC meeting, when the Fed first transitioned from a target rate to a target range, we predict to the nearest 25bps point. After this meeting, predictions are made to the corresponding range.

We summarize the prediction results in Panel (b) from Figure 3. As a benchmark for prediction accuracy 30 days before an FOMC meeting, outright Fed funds futures prices achieve an accuracy of approximately 75%, which is 13% lower than the CME FedWatch. One potential explanation for the underperformance of the outright approach is as follows. For a month with an FOMC meeting, note that the futures price can be assumed to incorporate information about the new target rate r_1 set after the meeting. However, estimating the expected EFFR for the days leading up to an FOMC meeting (r_0) is challenging. This is mainly due to the fact that the Fed transitioned to the corridor system in December 2008, establishing a target rate range instead of a fixed target rate.

4.1.4 Economic Value of CME FedWatch Predictions

A natural follow-up question is: how significant is the 13% accuracy improvement of the outright Fed Funds futures approach compared to the CME FedWatch tool? To answer this, we examine the economic value of this accuracy improvement by implementing two trading strategies: one using Fed Funds futures and the other using the iShares Core U.S. Aggregate Bond ETF (AGG). Specifically, 30 days before an FOMC meeting, a rate prediction is made using either the baseline model or the CME FedWatch tool. If a rate cut or no change is anticipated, bond or Fed Funds futures prices are expected to rise, prompting a long position. Conversely, if a rate hike is predicted, a short position is taken. For our first trading strategy, trades are executed based on the rate prediction using the Fed Funds futures contract set to expire in the month of the next FOMC meeting, with payoffs realized upon the contract's expiration. For simplicity, the returns are calculated based on the quoted price of \$100. For example, if the futures price today is 98.5 and the actual settlement price is 99.5, the return is calculated as 0.1%. Since there are eight FOMC meetings per year, the annualized return and volatility are calculated and reported accordingly. We report the strategy performance in Panel A of Table 3. The sample period of the test ranges from 1994 to 2023. Notably, the Sharpe ratio achieved with the CME FedWatch approach is twice that of the baseline model, and all other metrics of the FedWatch approach outperform those of the naive model.

Our second test trading asset is AGG, theiShare Core U.S. Aggregate Bond ETF. Similarly, when a rate cut or no change is predicted, a long position is taken. Conversely, when a rate hike is anticipated, a short position is initiated for the next FOMC meeting. After the actual rate decision is announced, if the prediction is incorrect, the position is closed until the next FOMC cycle. We report the trading performances of both strategies as well as the overall performance of AGG in Panel B of Table 3. Since AGG began trading on the NYSE in 2003 and gradually gained popularity following the Global Financial Crisis, we define our sample period from 2009 to 2023. Similar to trading Fed Funds futures, utilizing the CME FedWatch tool enhances trading performance across all metrics, though the improvements are less pronounced.

As an illustration, we plot the cumulative return for both strategies and the AGG ETF in Figure 4. There are two important points to consider. First, in our strategy, if the rate prediction is a rate cut or no change, we hold a long position in the AGG ETF. This explains why, up until 2016, the AGG cumulative returns align with the FedWatch's. During the ZLB period, the FedWatch tool consistently predicts that rates would remain unchanged, leading the strategy to continuously hold the AGG ETF. Second, the strategy based on the CME FedWatch performs exceptionally well during the post-COVID period, when the Federal Reserve raises rates at an unprecedented pace, which leads to the plummet of the AGG price. By accurately anticipating future rate hikes, investors can strategically short bond ETFs, such as AGG, to generate profits. Nonetheless, in Section 5, we explore several mechanisms behind our baseline results and highlight some limits to utilizing such profits, providing some explanation as to why market participants have not exploited the CME FedWatch.

4.2 Attention, Uncertainty, and Market Reaction

4.2.1 Public Attention

Given the high predictive accuracy of the CME FedWatch, a follow-up question is: does the investing public utilize this straightforward yet effective resource? To explore this, we proxy attention to the tool from the investing public by studying web traffic data sourced from SemRush. Additionally, we compare the web traffic volume of the CME FedWatch with that of the Atlanta Fed's Market Probability Tracker. Due to the unavailability of web traffic data for Bloomberg's WIRP, it is excluded from our analysis. In addition to actual web traffic data, Google Trends is a valuable tool for tracking popularity over time, which helps us to extract insights into how often specific terms are searched on Google across different regions and time frames.

We present the attention results in Figure 6. On the left axis, we display the web traffic volume data (in units of 1,000) for both the CME FedWatch and the Atlanta Fed's MPT. Notably, there is a sharp rise in attention to the CME FedWatch in 2022, coinciding with the Federal Reserve's series of rate hikes executed to address post-pandemic inflation. In contrast, the Atlanta Fed's MPT has received significantly less attention and is therefore excluded from our further analysis.

Over the sample period, both the MPT and the CME FedWatch underwent URL changes, marked by the orange and blue dashed lines. However, Figure 6 illustrates minimal differences in web traffic patterns before and after these changes. On the right axis, we plot the Google Trends data for the search term "CME FedWatch," showing a popularity trend that closely aligns with the website traffic volume data obtained from SemRush. However, Google Trends indicates that the term "CME FedWatch" has been searched on Google since late 2015, whereas SemRush only began recording its web traffic data in late 2018, likely due to the limited traffic volume before that period.

Despite its rapid growth in popularity, the CME FedWatch Tool has yet to gain substantial attention. While the website reached over 100,000 in web traffic volume in 2024, this remains modest compared to Yahoo Finance, which attracts over 90 million visits, though primarily for stock market information rather than fixed income. Compared to a more direct counterpart FI, such as TreasuryDirect, which exceeds 1.8 million visits, CME FedWatch's traffic is considerably much lower.

Although the tool has not received much popularity compared to more mainstream websites, the traffic results provide a proxy of the investing public attention. In this regard, we are interested in understanding the role that this tool could potentially play in reducing uncertainty regarding future FOMC meeting rate decisions. In particular, we hypothesize that the CME FedWatch Tool enables investors to obtain relatively accurate target rate predictions, reducing their uncertainty about future rates and allowing them to invest accordingly, even ahead of FOMC meetings. In the next discussion, we reconcile the CME FedWatch Tool with the well-documented phenomenon known as the "Pre-FOMC Announcement Drift."

4.2.2 Pre-FOMC Announcement Drift

The "Pre-FOMC Announcement Drift," documented by Lucca and Moench (2015), refers to a consistent pattern in equity markets where stock prices rise steadily in the days leading up to scheduled FOMC meetings, regardless of the meeting outcome. However, Kurov et al. (2021) reports the disappearance of this drift following the conclusion of the first ZLB period in 2015. While the underlying cause remains uncertain, most studies attribute the phenomenon to a reduction in uncertainty (Ai and Bansal, 2018; Ai et al., 2021; Hu et al., 2022; Kurov et al., 2021). In the following analysis, we start by replicating the empirical evidence from Lucca and Moench (2015) and Kurov et al. (2021) in order to study the pre-announcement drift across various periods.

We summarize these results in Figure 7 and confirm the findings reported in the original studies. In particular, FOMC announcement days are defined as *Day 0*, with the three-day window spanning from 9:30 am on the preceding day *Day -1* to 9:30 am two days after *Day 2*. Within this period, we compute the average cumulative returns of S&P 500 futures for FOMC announcement days and compare them to those of non-announcement days. Following Kurov et al. (2021), we standardize the announcement time as 2:15 pm on FOMC announcement days, despite the actual times varying between 12:30 pm and 2:30 pm. This variation is expected to have a minimal impact on the final results. Furthermore, FOMC press conferences were introduced in April 2011, initially held quarterly to coincide with meetings featuring the release of economic projections (a total of 32 press conferences), and were expanded in 2019 to occur after every scheduled meeting, enhancing transparency and communication. Additionally, Kurov et al. (2021) documents that between 2011 and 2019, no significant drifts are observed for FOMC meetings without a press conference.

In the upper panel of Figure 7, we compare the return drifts on announcement days before 2011 with those on non-FOMC announcement days, observing a significant drift consistent with Lucca and Moench (2015). Similarly, the middle panel of Figure 7 displays the drifts for FOMC meeting days from 2011 to 2019, distinguishing between those with and without press conferences. The green dashed line represents days with press conferences, while the red dashed line represents days without. FOMC days with a press conference exhibit both economically and statistically significant pre-announcement drifts, whereas the evidence of the drift is weak for the announcements without a press conference. In the bottom panel, we plot all FOMC days after 2019. Due to the limited number of observations, the drift is not statistically significant, even though the mean drift is still evident.

Next, we examine if the uncertainty about FOMC policy can be used to explain the pre-announcement drift, as documented in both Kurov et al. (2021) and Hu et al. (2022). To do so, we measure such uncertainty using variation in the FedWatch tracker and run the following regression:

$$Ret_t = \alpha + \beta_1 \text{Fed Anchoring}_t + \beta_2 \text{VIX}_t + \beta_3 \text{Uncertainty}_t + \beta_4 \text{3 Mo Rate} + \varepsilon_t. \tag{6}$$

The dependent variable is the pre-announcement drift on FOMC days, whereas Fed Anchoring is a binary indicator variable set to 1 for periods after 2012 when the Federal Reserve formally announced its long-term inflation target of 2%. *VIX* represents the z-score normalized VIX index value on the day $t-2$, and *Uncertainty* corresponds to the standard deviation of target rate expectations over the last 20 days preceding the actual meetings. The final control variable, *3 Mo Rate*, represents the 3-month Treasury bill rate.

We report the regression results in Table 4, where the upper panel presents the results for the full sample period from 1996 to 2024, the middle panel covers the period from 1996 to 2008, and the bottom panel focuses on 2008 to 2024. Among all variables, VIX is the only one that is statistically significant at the 1% level, with positive coefficients indicating a positive relationship between the index and the pre-announcement drift. Nonetheless, uncertainty, derived from daily price changes of Fed funds futures, explains the pre-announcement drift in the early sample period but fails to do so in the latter period. Similarly, for the sample period from 2008 to 2024, the univariate regression of *Fed Anchoring* indicator variable yields a negative coefficient that is statistically significant at the 5% level.

To get better insight, we visualize the relationship between uncertainty and pre-announcement drift by categorizing the variable *uncertainty* and *VIX* into three groups (low, medium, and high). For each group, we compute the average cumulative return from the day before the FOMC meeting to the day after and plot the results. The outcome is presented in Figure 8. The upper panel displays the results grouped by the standard deviation of the expected rate throughout the FOMC cycle, while the lower panel shows the results grouped by the z-score normalized VIX index two days prior to the FOMC meetings. The red dashed line represents FOMC cycles with high uncertainty, the blue line corresponds to medium uncertainty, and the green line indicates low uncertainty. The shaded areas indicate the 95% confidence interval for each group.

Overall, Figure 8 reveals that the pre-announcement drift is more pronounced on days with higher uncertainty, whereas on days with medium/low uncertainty, the drift is neither statistically nor economically significant. The observed disappearance of the pre-FOMC announcement drift (Kurov et al., 2021) may be attributed to the reduced uncertainty regarding future Fed target rate decisions, as illustrated in Figure 5, which highlights the recent decline in expectation errors for the Fed target rate. Specifically, as investors today can derive more accurate expectations from Fed funds futures prices, there is significantly less uncertainty, resulting in a less pronounced pre-announcement drift. In a nutshell, we find empirical evidence to support the hypothesis that uncertainty drives the pre-announcement drift, with the VIX as a direct measure of stock market uncertainty, demonstrating the strongest explanatory power from the regression analysis.

4.2.3 Resolution of Uncertainty

After confirming that the pre-announcement drift is driven by heightened uncertainty before FOMC meetings and its subsequent resolution, we investigate whether investors use the CME FedWatch Tool, given its relatively high accuracy, to access the most up-to-date market expectations for future target rates, leading to a gradual resolution of uncertainty along the way rather than a last-minute resolution just before the actual announcement. To test the hypothesis, we rely on monthly website traffic data from SemRush. Given the limited number of FOMC meetings since the CME FedWatch gradually gained more attention (around 2020), we regress the VIX index two days prior to FOMC meetings on the monthly visit data from SemRush FedWatch, incorporating a control for the standard deviation of expected rates within the FOMC cycle. If investors closely follow the CME FedWatch and gain a clearer idea of the next potential target rate, we would expect a negative relationship between the VIX index and the popularity of CME FedWatch. Specifically, we run the following regression:

$$VIX_t = \alpha + \beta_1 \text{Trend}_{t-1} + \beta_2 \text{Uncertainty}_t + \varepsilon_t, \tag{7}$$

Since daily traffic data is only available for the current month, we use the website traffic data from the previous month, labeled as *Trend*, as a proxy to approximate the market participants influenced by CME FedWatch. Regression results are displayed in the first three columns of Table 5. We observe a negative correlation between CME FedWatch popularity and the VIX index in the days preceding FOMC meetings, supporting our hypothesis that the tool helps investors reduce uncertainty about future target rate decisions.

$$\Delta VIX_t = \alpha + \beta_1 \text{Trend}_{t-1} + \beta_2 \text{Uncertainty}_t + \varepsilon_t, \tag{8}$$

Next, we investigate the impact of the CME FedWatch Tool on the post-announcement drift. Gu et al. (2018) identifies significant positive average stock returns following FOMC announcements that include the release of the SEP and a press conference by the Fed Chair. However, after accounting for changes in the VIX, the unconditional mean returns after these FOMC announcements no longer persist. As a result, the study attributes the observed post-FOMC announcement drift in these specific meetings to the resolution of uncertainty. Furthermore, a recent paper by Gómez-Cram and Grotteria (2022) highlights that the most significant asset price movements occur during the press conference minutes, where the FOMC chairman elaborates on the newly issued policy statement and provides forward guidance. Both papers support the perspective that the post-FOMC announcement drift is driven by the resolution of uncertainty and/or the release of new information during the press conferences. Since the CME FedWatch Tool provides the market with probabilities of future target rate decisions and does not include information about future economic projections released after FOMC meetings, it is not possible to reduce uncertainty related to those projections. As a result, we hypothesize that the monthly visit to the CME FedWatch website should not contribute to the uncertainty change before/after the meetings. Specifically, the difference in the VIX index is calculated between the day following the meeting $(t + 1)$ and two days prior to the FOMC meeting $(t - 2)$. Similarly, the change in the VIX index is regressed on uncertainty derived from Fed funds futures and monthly CME FedWatch visit data, as expressed in Equation (8). The last three columns of Table 5 display the result. As anticipated, no significant impact of the monthly visits to CME FedWatch on the resolution of post-announcement uncertainty is observed.

5 Exploring Intermarket Mechanisms with FedWatch

The following section focuses on intermarket dynamics, exploring the intertwined relationship between FedWatch-based expectations and common market prices to better understand the mechanisms underlying our findings. The section is divided into three parts. First, leveraging rate expectations derived from the CME FedWatch, we examine the impact of surprise monetary policy decisions on bond yields. Second, we investigate how expectations formed using the tool explain the behavior of the yield curve. Finally, we employ a parsimonious vector autoregressive model to represent market dynamics and perform sensitivity analysis, providing deeper insights into the relationship between rate expectations and equity and bond prices.

5.1 Rate Surprises and Bond Yields

Earlier work by Kuttner (2001) examines the impact of unexpected rate surprises on bond yield changes, where the author decomposes changes in the Federal fund's target rate into the expected rate change and the unexpected rate surprise. Based on this decomposition, Kuttner (2001) demonstrates that unexpected rate surprises have a statistically and economically significant impact on bonds across all maturities, ranging from 3 months to 20 years.

Motivated by this seminal work, we decompose the Fed's rate decision into the expected rate change and unexpected rate surprise using the FedWatch unconditional rate outcome probabilities and study the impact of unexpected rate surprise through various market conditions. Put formally, we run the following regression:

$$\Delta y_t = \alpha + \beta_1 \Delta r_t^e + \beta_2 \Delta r_t^u + \beta_3 \text{High Yield Period} + \beta_4 \text{High Yield Period} \times \Delta r_t^u + \varepsilon_t, \quad (9)$$

where r_t^e (r_t^u) denotes the market expected (unexpected) interest rate. Specifically, on the day following a FOMC meeting, we calculate the market's expectation for the next FOMC rate decision using the weighted average of two possible outcomes.[6] Once the rate decision is announced during the FOMC meeting at time t, we calculate the unexpected rate surprise as the difference between the realized rate and the expected rate immediately following the previous FOMC meeting. The bond yield changes for different maturities (Δy_t) are calculated as the yield differences between the current and the last FOMC meeting dates. The "High Yield Period" is a binary variable indicating whether an FOMC meeting occurs during a period of high Treasury yields, defined as being within the top 20% of the 3-month T-bill rate.

Table 6 displays the results of the regression specification outlined in Equation (9). Consistent with the findings by Kuttner (2001), our results indicate that unexpected rate surprises affect bond yield changes across all maturities, while expected rate changes, having been

[6] Note that the CME FedWatch Tool employs a binary tree approach, which means there are always only two potential rate outcomes for the upcoming FOMC meeting – see Section 2 for further details.

already priced in, do not impact bond yield changes significantly. During normal (low yield) periods, the impact of unexpected rate surprises on bond yield changes is always positive, but it gradually decreases when bond maturities increase - as the interaction term illustrates. Short-term T-bills quickly adjust to this new information, reflecting the near-term economic expectations, which are largely influenced by the Federal Reserve's decision on the current target rate. However, long-term bonds are more influenced by long-term economic outlooks, making them less responsive to immediate rate changes. Furthermore, it is noteworthy that during high-yield periods, unexpected rate surprises may exert a less positive or even negative impact on the yield changes of longer-maturity bonds. We attribute the phenomenon to already priced-in inflation premiums, investors' expectations of slower economic growth, and increasing demands for long-term Treasury bonds, which are typically viewed as safe-haven assets during periods of Federal Reserve tightening cycles. This increased demand, therefore, drives up bond prices and lowers yields.

5.2 Expected Rate Changes and Bond Yields

While the previous test does not provide strong evidence of the effect of expected rate changes on bond yields, it overlooks day-to-day dynamics. To address this, we now investigate how daily changes in expected rate decisions for the upcoming FOMC meetings influence daily changes in the yield curve. To isolate the effects of FOMC meetings on bond yield changes, we focus exclusively on normal days, excluding the day before, the day of, and the day after FOMC meetings. The expected rates are calculated as the probability-weighted average of potential rate outcomes derived from the daily prices of Federal funds futures. The bond maturities range from 3 months to 20 years, consistent with the analysis from Section 5.1. To account for the varying effects of daily expected rate changes on bond yield changes across different yield regimes, we include a binary variable for High Yield Periods and an interaction term between this binary variable and the expected rate change.

Specifically, we run the following regression:

$$\Delta y_t = \alpha + \beta_1 \Delta r_t^e + \beta_2 \text{High Yield Period}_t + \beta_3 \text{High Yield Period}_t \times \Delta r_t^e + \varepsilon_t, \tag{10}$$

where Δy_t and Δr_t^e in Equation (10) represent daily yield and expected rate change, respectively. We report that regression results in Table 7. Panel A presents the full data sample spanning 1994 to 2024, while panels B and C provide regression analysis results for the period 1994 to 2007 and the period 2008 to 2024, respectively. For clearer visualization, we illustrate the effect of expected rate changes on bond yield fluctuations in Figure 9.

A couple of comments are in order. First, during normal (low yield) periods, the impact of daily rate expectation change on bond yield changes is statistically and economically significant, exhibiting a decreasing trend as bond maturities increase. We confirm that there is a close relationship between the Federal funds futures market and the Treasury bonds market, indicating that traders of these two products share similar beliefs about potential near-term FOMC rate decision changes.

Second, the expected rate change's impact on bond yield varies across two different yield regimes. In a high-yield environment, we anticipate the impact of expected rate changes on bond yields to be smaller because the heightened yields often reflect a significant risk premium associated with inflation and other macroeconomic uncertainties. However, we find that this relationship does not hold during the second period of analysis, primarily in the post-COVID high interest rate era of 2022 to 2024, when the Federal Reserve implemented rate hikes at an unprecedented pace, and market uncertainties reached exceptionally high levels. The impact of rate expectation changes on bond yield changes exhibits a hump-shaped pattern. As the market anticipates a rate hike in the near future, medium and long-term bonds become much less appealing. This shift in investor preference pushes down bond prices and drives up bond yields. We rationalize the phenomenon to various factors, including market anticipation of continuing monetary tightening, heightened inflation, increasing demand for uncertainty risk premiums upwards, liquidation need, and the need for portfolio rebalancing (Vissing-Jorgensen, 2021). From a risk management perspective, a potential rate hike in the near future tends to shorten the duration of liabilities. Consequently, asset managers end up selling medium to long-term bonds and purchasing short-term bonds to align the duration of their assets and liabilities. When comparing medium-term and long-term bonds, investors often find longer maturities more appealing as they provide an opportunity to lock in high yields over an extended period. Consequently, 20-year Treasury bonds experience a smaller yield increase than medium-term bonds.

Next, we move from contemporaneous into predictive regression analysis, where we investigate the effect of expected rate change on future changes in bond yields. In particular, we regress the bond yield changes on one-day-lagged expected rate changes, keeping all other regression settings unchanged, such that

$$\Delta y_t = \alpha + \beta_1 \Delta r^e_{t-1} + \beta_2 \text{High Yield Period}_t + \beta_3 \text{High Yield Period}_t \times \Delta r^e_{t-1} + \varepsilon_t. \tag{11}$$

We report the results of the regression model from Equation (11) in Table 8. Overall, Table 8 indicates that during normal (low) yield periods, the expected rate change influences bond yield changes, but the effect is limited to short-term bonds with a modest economic magnitude. On the other hand, expected rate changes do not have statistically significant predictive power for next-day yield changes in medium to long-term bonds with maturities greater than two years. During highyield periods, expected rate changes have a statistically significant impact on medium-maturity bonds, with a similar hump-shaped pattern observed. Across different periods, we find mixed evidence regarding the statistical significance of the regression coefficients. Furthermore, the magnitude of the impact of the expected rate changes on next-day bond yield changes is minimal. For instance, a 1% increase in the expected rate leads to a 9-basis-point increase in the 3-month Treasury Bill rate the following day. However, as shown in Table 1, the standard deviation of daily expected rate changes is approximately 4 basis points. This implies that a one-standard-deviation increase in the expected rate would result in only a 0.36-basis-point increase in the next day's T-Bill rate. The results are not surprising, as the Treasury bond market is known to respond quickly to movements in the Fed funds futures market (Rosa, 2014).

5.3 Vector Autoregression

Finally, we employ a parsimonious vector autoregressive (VAR) model to capture the dynamics between rate expectations and equity and bond prices. Specifically, we estimate the relationships among daily changes in expected rates, 3-month Treasury bill yields, and SPY returns using a VAR model of order 3, determined by the Akaike Information Criterion (AIC).[7] The model is specified as follows:

$$\begin{bmatrix} \Delta r_t \\ \Delta y_t \\ \Delta s_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} + \sum_{j=1}^{3} \begin{bmatrix} \beta_{11,j} & \beta_{12,j} & \beta_{13,j} \\ \beta_{21,j} & \beta_{22,j} & \beta_{23,j} \\ \beta_{31,j} & \beta_{32,j} & \beta_{33,j} \end{bmatrix} \begin{bmatrix} \Delta r_{t-j} \\ \Delta y_{t-j} \\ \Delta s_{t-j} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \end{bmatrix}. \tag{12}$$

Similar to the previous regression, Δr_t denotes expected rate changes, Δy_t represents changes in 3-month Treasury bill yields, and Δs_t corresponds to SPY returns. We display the regression results in Table 9 and plot the impulse response functions in Figure 10, illustrating how a shock to a single variable propagates in the system.

The VAR analysis reveals two significant relationships. First, changes in the expected rate have a one-directional causal relationship with the 3-month T-bill, indicating that adjustments in rate expectations influence bond yields but not vice versa. Second, the analysis indicates that daily SPY returns, reflecting stock market performance, positively influence market expectations of the future Fed target rate. Investors associate strong stock market performance with a potential future rate hike by the Fed to mitigate economic overheating and manage inflation.

[7] The order is selected based on the Akaike Information Criterion (AIC).

6 Concluding Remarks

The literature on price discovery from the derivative market is numerous and provides several implications for the forward-looking information value of these instruments. In this paper, we focus on a special tool that gained large popularity more recently with the central bank's hawkish policy to combat inflation. The tool is the CME FedWatch, which extracts the probability of future policy changes and, therefore, can be viewed as a public indicator that investors can use to price future rates and adjust their portfolios accordingly.

Our study examines the value added by this fast-growing tool and shows that it is a reliable predictor of future FOMC rate decisions, demonstrating remarkable accuracy. Furthermore, we find empirical evidence supporting its effectiveness in reducing market uncertainty ahead of monetary policy announcements. While the tool provides valuable insights into expected rate changes, its effectiveness for profitable trading strategies in the Treasury bond market is limited, since these moves are largely influenced by unexpected rate surprises. Nonetheless, with the emergence of large language models and artificial intelligence for financial applications (Xie et al., 2024), the question remains about the value of such technology in forming expectations about the future path of policy, especially when the CME FedWatch sets a robust benchmark. We leave this for future research.

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Figures

Figure 1: **Timeline of FOMC Meetings and EFFR Projection**
This figure presents a timeline illustrating the calculation of the projected start, end, and average effective Federal funds rate (EFFR) for various months. N represents the number of days in the month leading up to the FOMC meetings, while M denotes the number of days following them.

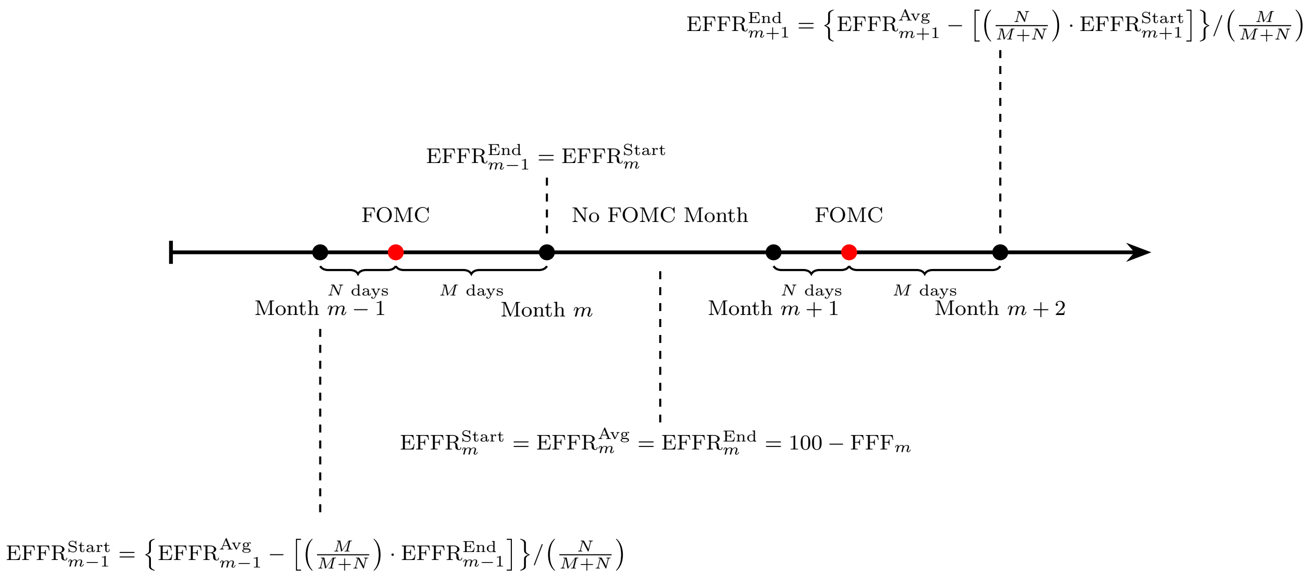


Figure 2: **Yields and Interest Rates Over Time**
This figure displays several key interest rates from 1994 to 2024 to provide a detailed financial overview. This includes the Federal Reserve's target rate, the EFFR, 3 and 6-month Treasury bills, and the 1, 2, 5, 10, and 20-year Treasury bond yields. The gray shaded areas represent periods when the 3-month T-bill yields exceeded the top 20th percentile in the whole data sample, which is 5.07%.

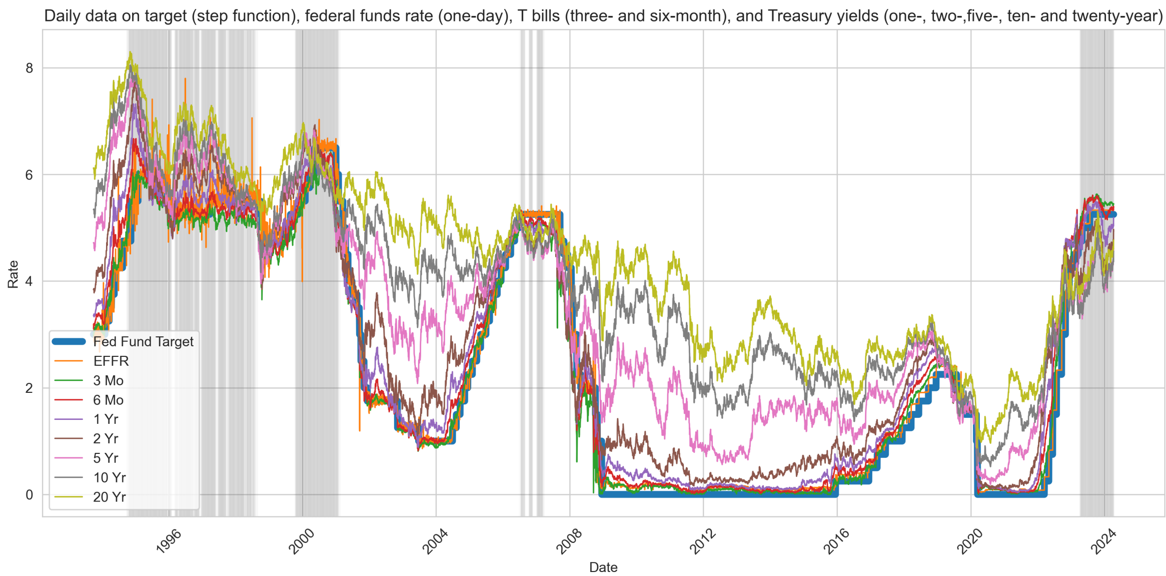
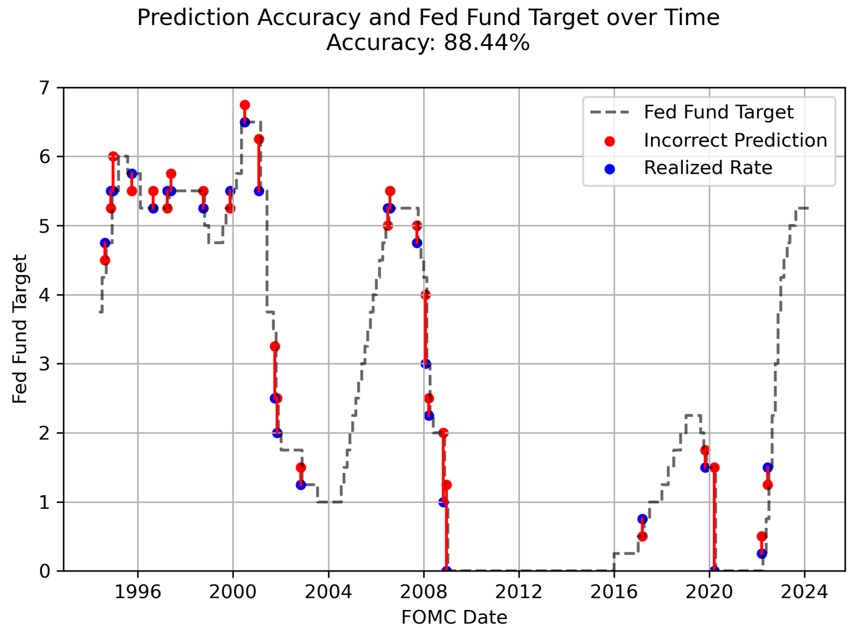
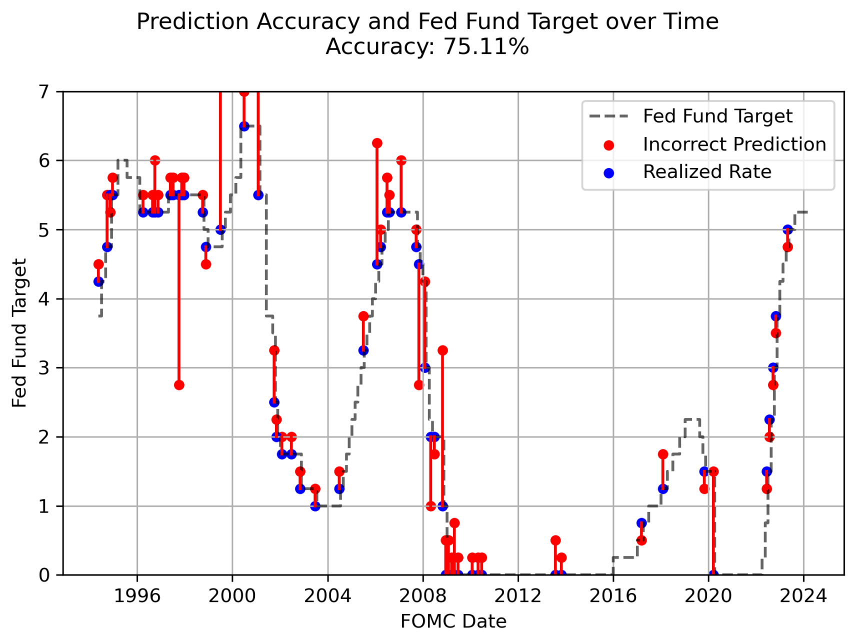


Figure 3: **Comparison of Prediction Accuracy Between CME FedWatch Tool and outright Fed funds futures**
We plot the accuracy of predictions for FOMC meetings occurring within the next 30 days. The Fed funds target rate is represented by a dashed line in the background, while incorrect predictions are marked with red dots and correctly realized rates are indicated with blue dots. The magnitude of the error is visually represented by the length of the red bar. The upper figure represents predictions based on the CME FedWatch methodology, while the lower figure illustrates predictions derived directly from Fed funds futures prices.



(a) **CME FedWatch Tool Accuracy**



(b) **outright Fed funds futures Accuracy**

Figure 4: **Economic Values of the CME FedWatch Tool**
This figure shows the cumulative return of the trading strategy (i.e., backtesting) that utilizes the next FOMC target rate decisions to trade the U.S. Aggregate Bond ETF, AGG, from 2009 to 2023. For further details, see Section 4.1.4.

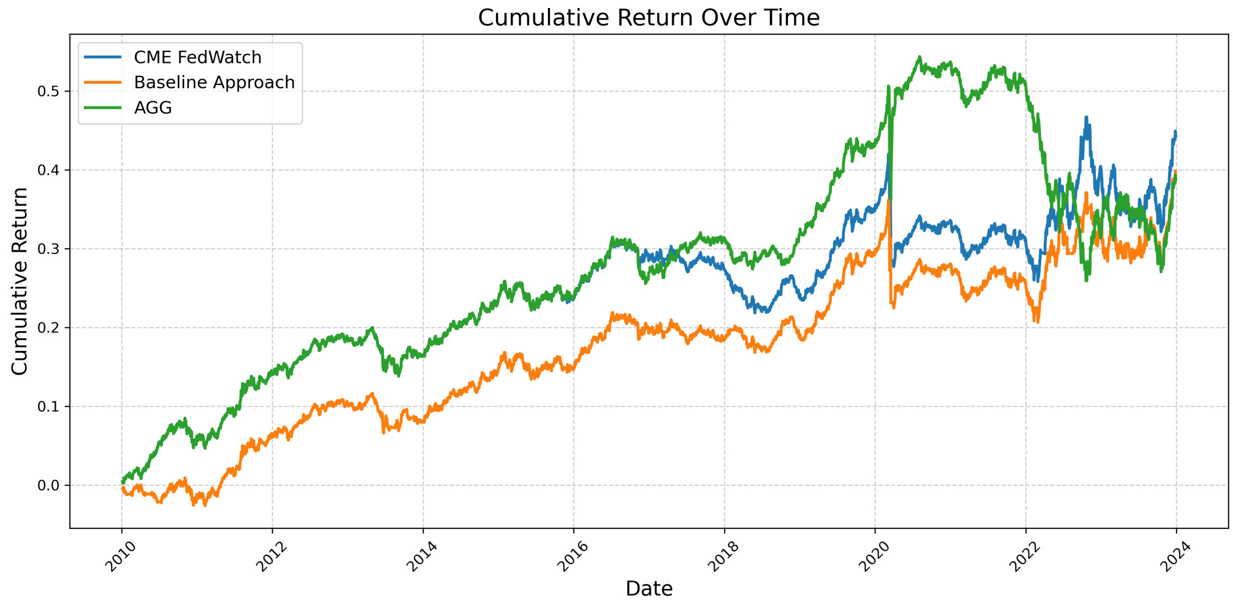


Figure 5: **Trend of Expected Rate Errors from the CME FedWatch Tool**
The expected rate for future FOMC meetings is calculated as the probability-weighted average of the possible rates provided by the CME FedWatch Tool, and expectation errors are defined as the absolute difference between the realized rate and the expected rate. The expectation error trend, beginning two meetings before the current one, is presented in this figure. To ensure consistency in each cycle, the date of the previous FOMC meeting is defined as *Day 0* and includes a 25-weekday window before and after that date. Following the Federal Reserve's formal announcement of its long-term inflation goal of 2% (known as the Fed Anchoring Effect), the figure plots the error trend separately for periods before and after 2012 to examine its impact. The blue dotted line represents the pre-2012 period, while the orange line represents the post-2012 period, with the shaded area indicating the 95% confidence interval.

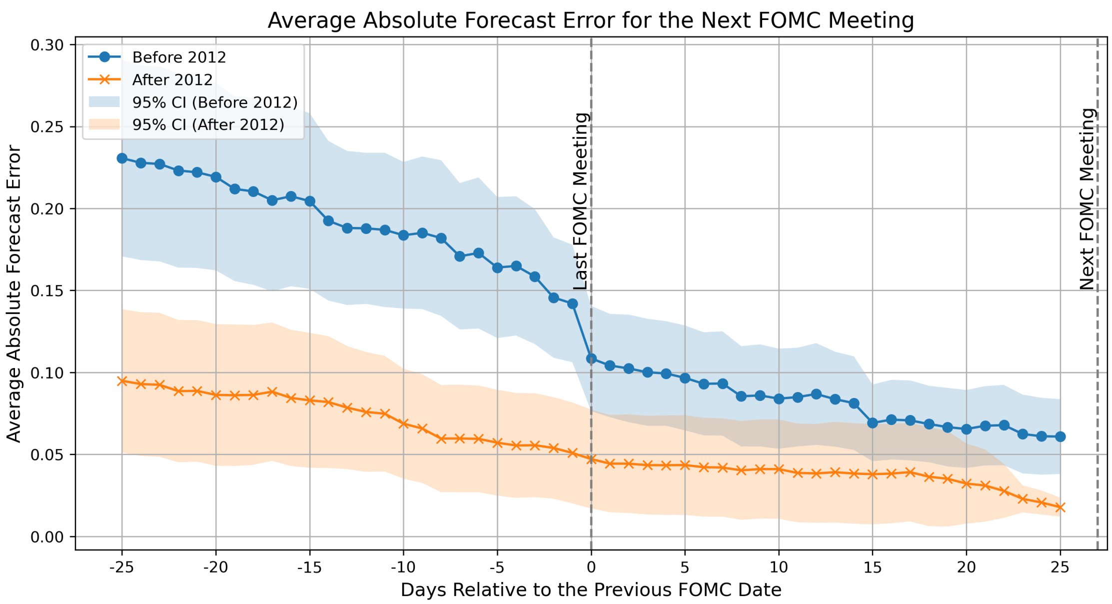


Figure 6: **CME FedWatch Tool Popularity**
This figure compares the web traffic volume of the CME FedWatch with that of the Atlanta Fed's Market Probability Tracker (MPT). In addition to actual web traffic data, Google Trends is a valuable tool for analyzing the popularity of a term over time, offering insights into how often specific terms are searched on Google across different regions and time frames. The left axis displays the web traffic volume data (in units of 1,000) for both the CME FedWatch and the Atlanta Fed's MPT. During the sample period, both the MPT and the CME FedWatch Tool underwent URL changes, marked by the orange and blue dashed lines. However, there are minimal differences in web traffic patterns before and after these changes. The right axis corresponds to the Google Trends data using the search term "CME FedWatch," showing a popularity trend that closely aligns with the website traffic volume data obtained from SemRush.

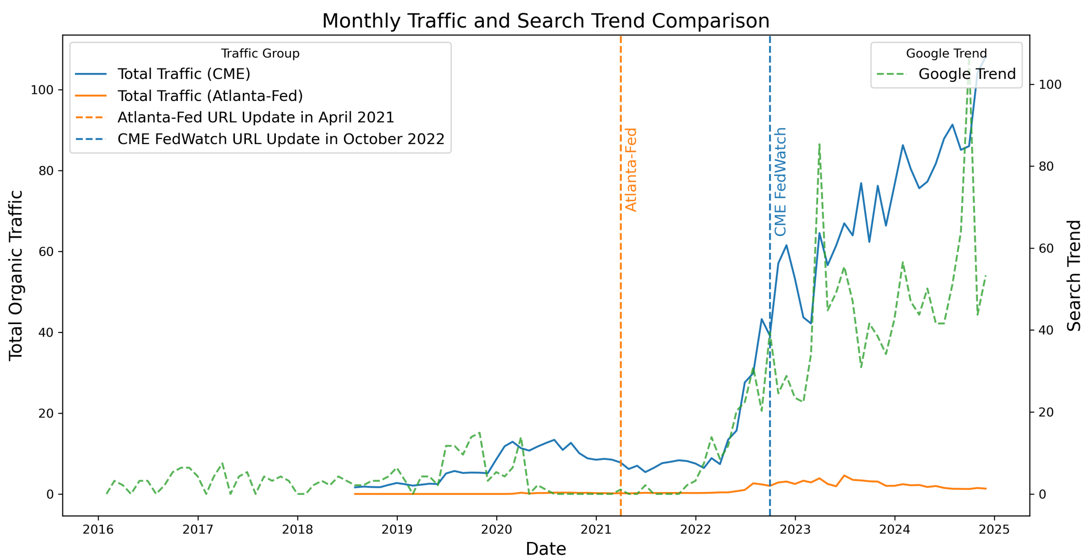


Figure 7: **FOMC Pre-Announcement Drift**

FOMC announcement days are defined as *Day 0*, with the three-day window spanning from 9:30 am on the preceding day *Day -1* to 9:30 am two days after *Day 2*. Within this period, the average cumulative returns of S&P 500 futures are computed for FOMC announcement days and compared to those of non-announcement days. Following Kurov et al. (2021), the announcement time is standardized at 2:15 pm on FOMC announcement days.

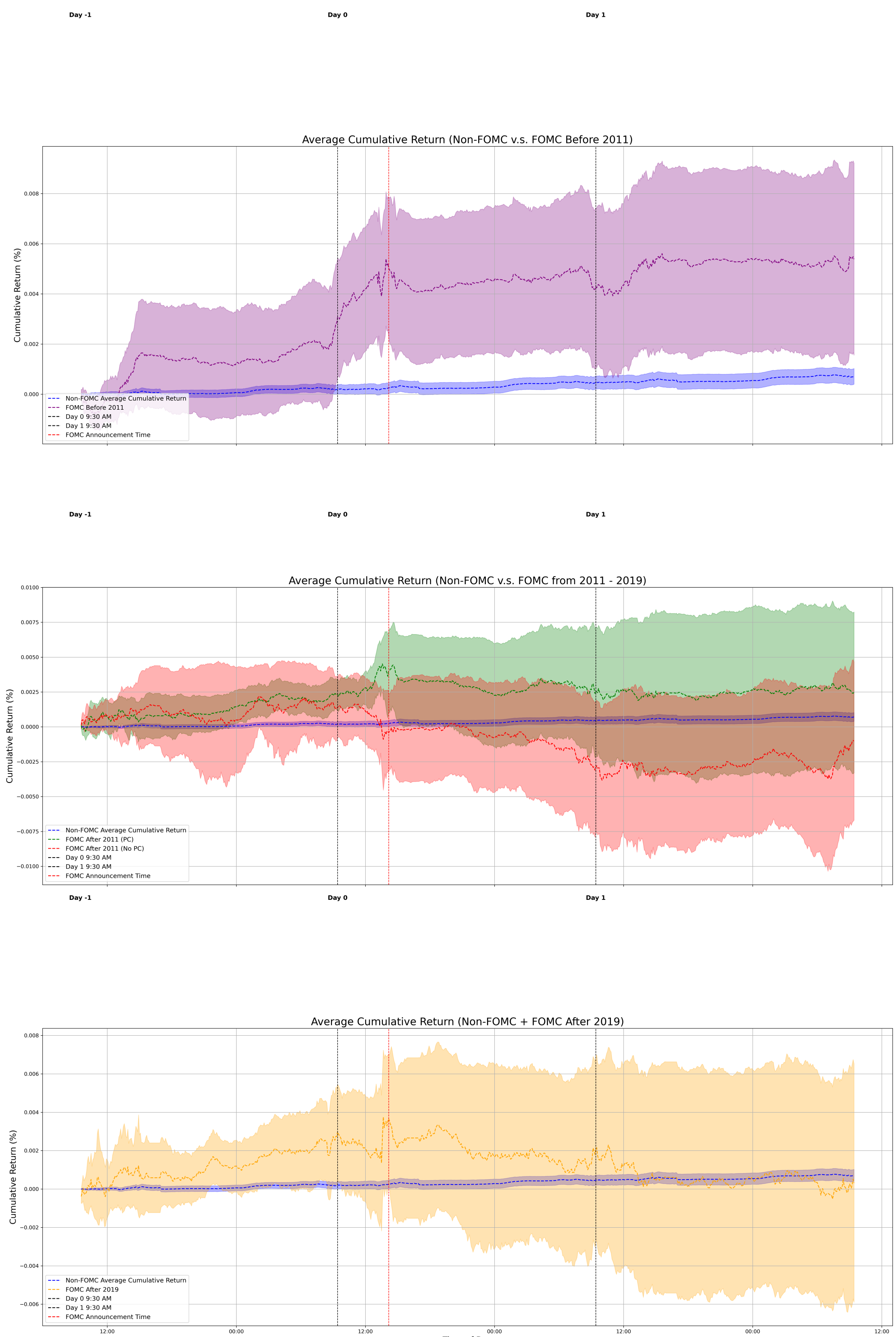
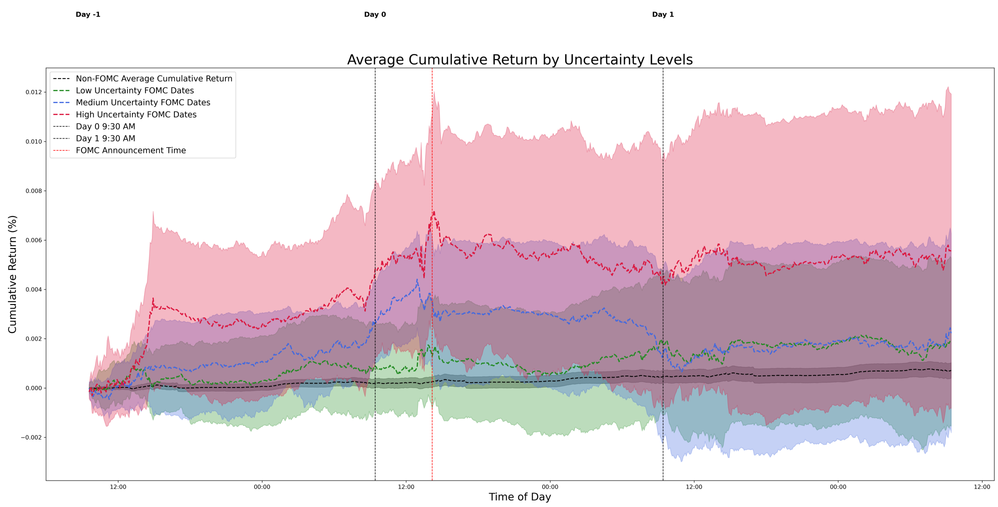
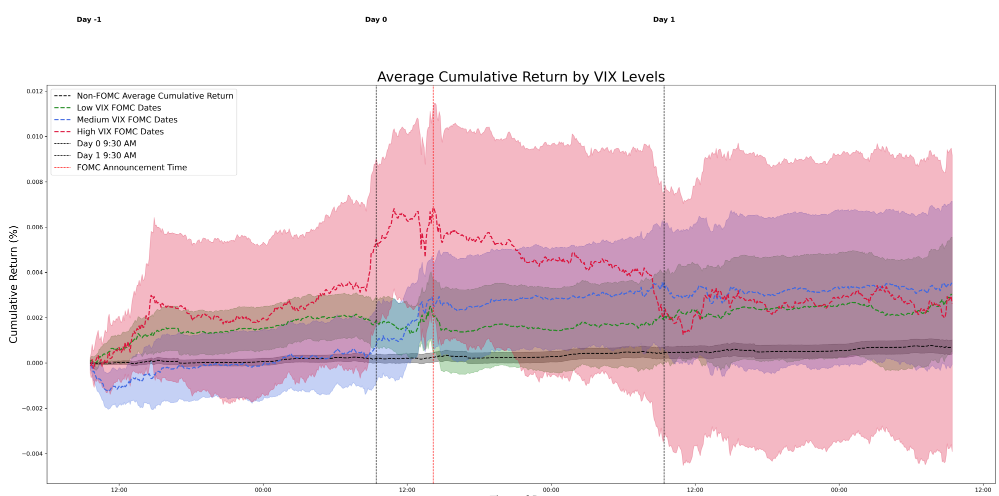


Figure 8: **FOMC Pre-Announcement Drift by Uncertainty**
To visually illustrate the relationship between uncertainty and pre-announcement drift, the plot categorizes the variable *uncertainty* and *VIX* into three groups (low, medium, and high). For each group, the average cumulative return is computed from the day before the FOMC meeting to the day after. The upper panel displays the results grouped by the standard deviation of the expected rate throughout the FOMC cycle, while the lower panel shows the results grouped by the z-score normalized VIX index two days before the FOMC meetings. The red dashed line represents FOMC cycles with high uncertainty, the blue line corresponds to medium uncertainty, and the green line indicates low uncertainty. The shaded areas indicate the 95% confidence interval for each group.

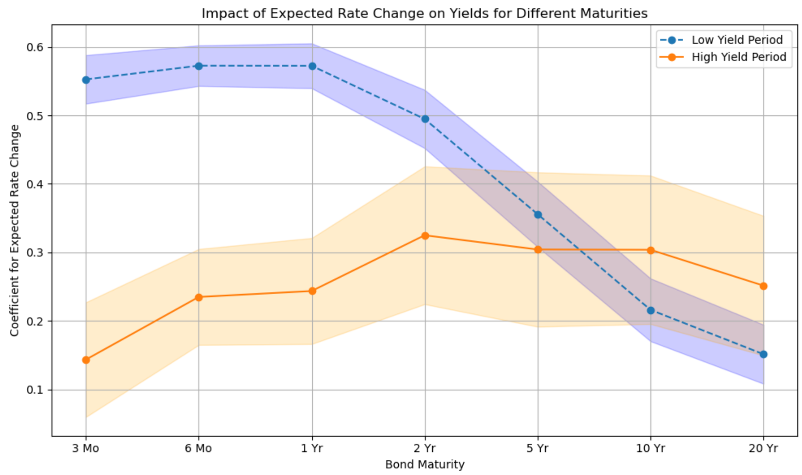


(a) **FOMC Pre-Announcement Drift by Expected Rate Fluctuation**

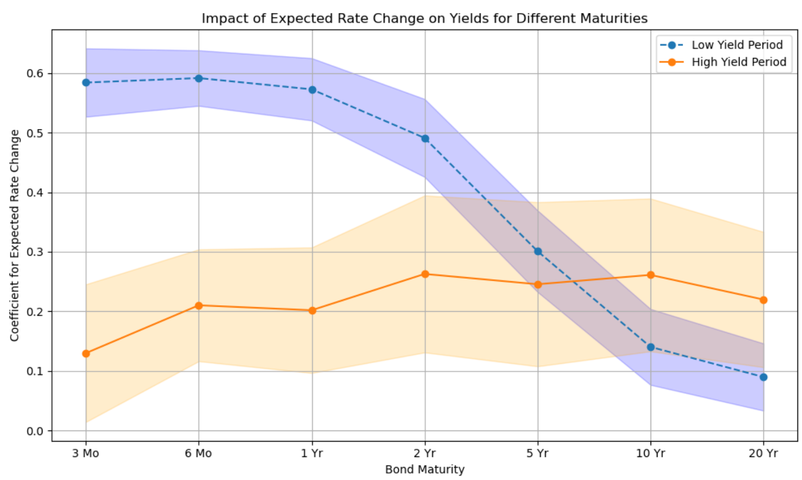


(b) **FOMC Pre-Announcement Drift by VIX**

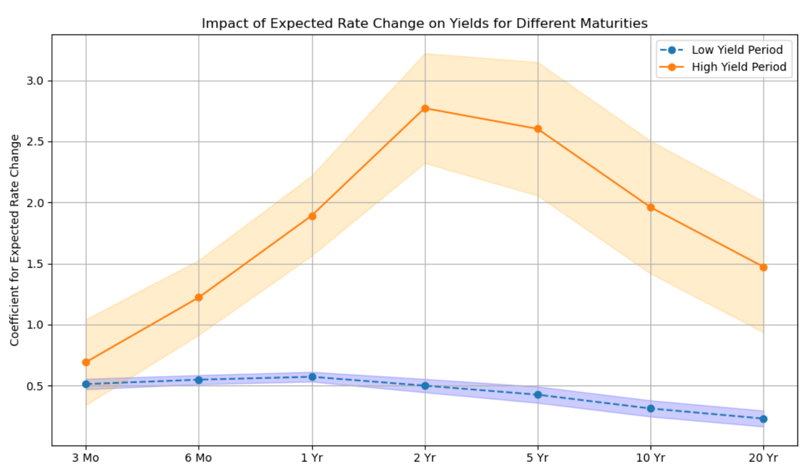
Figure 9: **Impact of Expected Rate Change on Yields for Different Maturities**
The figure depicts the coefficients of same-day expected rate changes on bond yield changes across various maturities, as estimated in Equation (10). The illustration follows from the regression results reported in Table 7.



(a) **Full Data Sample**

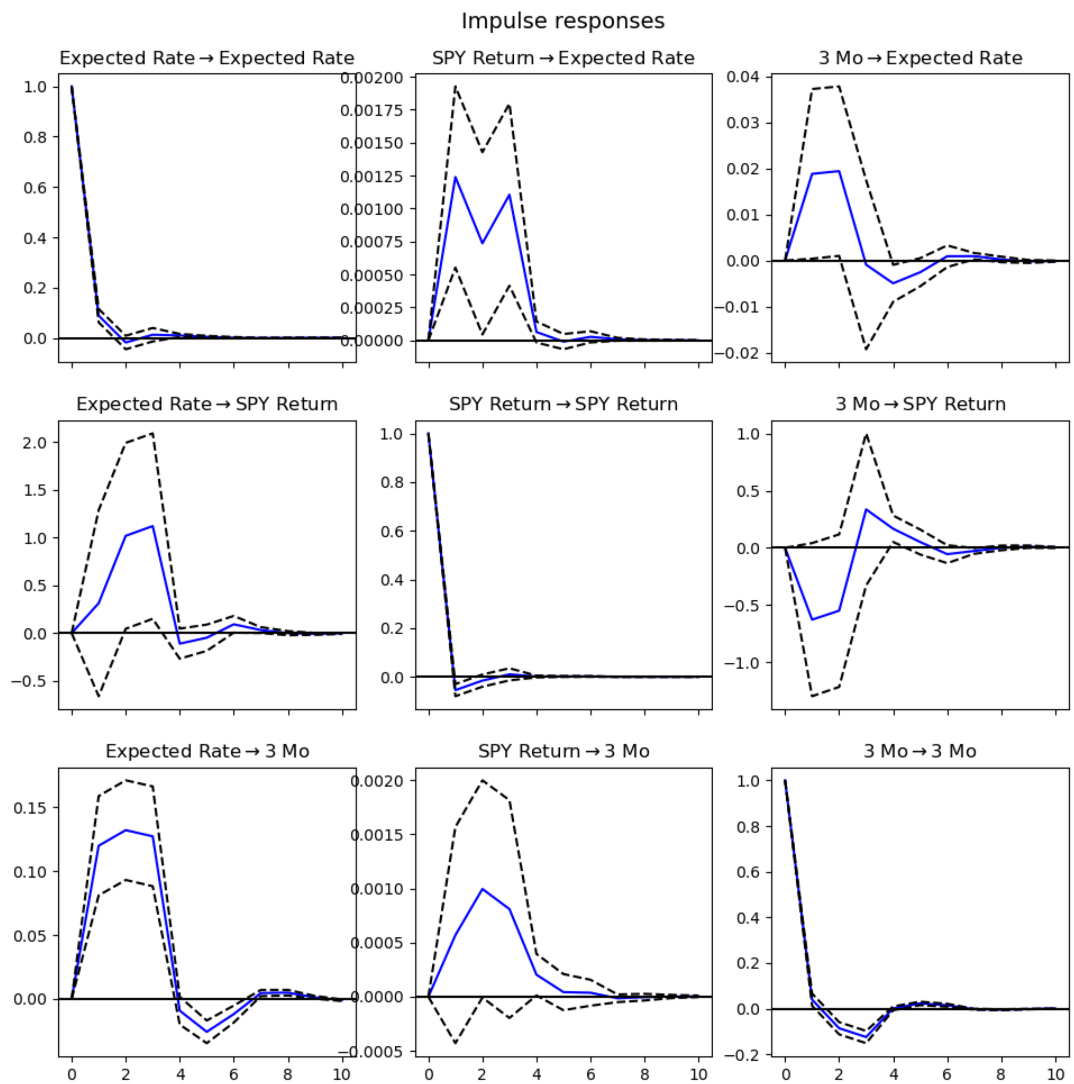


(b) **1994-2007**



(c) **2008-2024**

Figure 10: **Impulse Response Functions**
This figure illustrates the dynamic effects of shocks on expected rate changes, bond yields, and SPY return changes over time using impulse response functions derived using a vector autoregressive model of order 3, i.e., VAR(3) – see Equation (12). The responses capture how each variable reacts to a one-unit shock in the others, providing insights into their interdependencies and the transmission of monetary policy expectations into financial markets. For further details, see Section 5.3.



Tables

Table 1: **Summary of Statistics**
The data sample of unconditional probabilities of different potential target rate ranges for future FOMC meetings is constructed using daily Fed funds futures data from Bloomberg. Second, the daily yields of Treasury bills/bonds are obtained from the U.S. Department of the Treasury website, focusing on 3 and 6-month Treasury bills and the 1, 2, 5, 10, and 20-year Treasury bond yields to represent the yield curve. Third, the Python package *yfinance* is utilized to download daily SPY and VIX data from Yahoo Finance.

Variable	Count	Mean	Std	Min	25%	50%	75%	Max
Panel A: Main Variables								
WatchDate	6405			1994-03-24				2024-03-15
FOMCDate	232			1994-05-17				2024-03-20
Fed Fund Target	6405	2.25	2.23	0.00	0.00	1.50	4.75	6.50
Expected Rate	6405	2.30	2.25	0.00	0.02	1.66	4.93	6.81
3 Mo	6405	2.23	2.13	0.00	0.13	1.62	4.69	6.42
6 Mo	6405	2.35	2.16	0.02	0.19	1.71	4.88	6.67
1 Yr	6405	2.46	2.14	0.04	0.32	1.93	4.82	7.32
2 Yr	6405	2.67	2.09	0.09	0.72	2.19	4.66	7.71
5 Yr	6405	3.18	1.85	0.19	1.62	2.89	4.57	7.86
10 Yr	6405	3.69	1.64	0.52	2.33	3.67	4.78	8.05
20 Yr	6405	4.19	1.61	0.87	2.76	4.32	5.32	8.30
Panel B: Daily Changes								
SPY Return	6391	0.03	1.18	-10.94	-0.47	0.07	0.59	9.06
Expected Rate	6391	-0.00	0.04	-1.25	-0.00	0.00	0.00	0.34
3 Mo	6391	0.00	0.05	-1.01	-0.01	0.00	0.01	0.76
Panel C: Pre-FOMC Drift								
FOMCDate	226			1996-01-31				2024-03-20
Uncertainty	226	0.03	0.08	0.00	0.00	0.01	0.03	0.68
Pre-FOMC Drift (bps)	226	0.37	1.38	-3.76	-0.24	0.23	0.93	11.41
VIX (Normalized)	226	0.07	1.13	-1.33	-0.69	-0.11	0.54	7.64
VIX_diff	226	-0.40	3.06	-17.16	-1.66	-0.49	0.57	14.98
CME FedWatch Monthly Visits (in 1,000s)	46	23.67	26.13	1.63	5.47	9.37	42.53	86.25

Table 2: **Summary of CME FedWatch Prediction Accuracy**
The table lists two forward-looking prediction methods: days before and meetings before. The 'days before' method calculates accuracy using calendar days as the prediction time horizon. The 'meetings before' method, on the other hand, bases predictions on CME FedWatch data immediately following the prior FOMC meeting, utilizing the number of meetings as the reference time frame.

1 Meeting Before	**2 Meetings Before**	**3 Meetings Before**	**4 Meetings Before**
83.72%	72.81%	59.81%	48.57%
30 Days Before	**60 Days Before**	**90 Days Before**	**120 Days Before**
88.44%	76.52%	69.30%	58.85%

Table 3: **Economic Value of CME FedWatch Predictions**

This table presents the annualized mean return, volatility, Sharpe ratio, and max drawdown (MDD) of two trading strategies based on the next FOMC meeting (in 30 days) target rate predictions. In Panel A, the Fed funds futures contract is utilized as the trading asset. When a rate cut or no change is predicted, a long position is taken in the Fed funds futures contract set to expire in the month of the next FOMC meeting. Conversely, if a rate hike is anticipated, a short position is initiated. Similarly, in Panel B, the trading asset is the iShare Core U.S. Aggregate Bond ETF (AGG). When a rate cut or no change is predicted, a long position is taken. Conversely, when a rate hike is anticipated, a short position is initiated for the next FOMC meeting. After the actual rate decision is announced, if the prediction is incorrect, the position is closed until the next FOMC cycle. We report the performance of both the trading strategies based on the CME FedWatch predictions and a naive baseline model that relies on the outright use of Fed funds futures prices. In Panel B, we also report the performance of the AGG ETF itself.

Metric	**Annulized Return (%)**	**Annualized Volatility (%)**	**Sharpe Ratio**	**MDD (%)**
		Panel A: Trade on Fed Fund Futures		
CME FedWatch	1.9593	11.0882	0.4998	-0.4963
Baseline Model	0.9518	11.2203	0.2400	-0.6425
		Panel B: Trade on iShares Core U.S. Aggregate Bond ETF (AGG)		
CME FedWatch	0.0108	0.2867	0.6001	-11.39
Baseline Model	0.0098	0.2770	0.5614	-11.39
AGG	0.0097	0.2955	0.5235	-18.43

Table 4: **Pre-FOMC Announcement Drift**
The table reports the regression results of the Equation (6). The dependent variable is the pre-announcement drift on FOMC days. Fed Anchoring is a binary indicator variable set to 1 for periods after 2012 when the Federal Reserve formally announced its long-term inflation target of 2%. VIX represents the z-score normalized VIX index value on the day $t-2$. Uncertainty is measured as the standard deviation of target rate expectations over the last 20 days preceding the FOMC meetings. The control variable, 3Mo Rate, represents the 3-month Treasury bill rate.

	Pre-FOMC Announcement Drift					
	(1)	(2)	(3)	(4)	(5)	(6)
			Whole Sample Period			
const	0.004***	0.003***	0.003***	0.002	0.004**	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Fed Anchoring	-0.002			0.001	-0.001	0.001
	(0.002)			(0.002)	(0.002)	(0.002)
VIX		0.004***		0.004***		0.004***
		(0.001)		(0.001)		(0.001)
Uncertainty			0.017		0.016	-0.013
			(0.012)		(0.012)	(0.013)
3 Mo				0.051	0.001	0.058
				(0.048)	(0.049)	(0.049)
Observations	226	226	226	226	226	226
Adjusted R^2	-0.001	0.082	0.005	0.078	-0.002	0.078
			1996-2008			
const	0.005***	0.003**	0.003	-0.001	0.002	-0.002
	(0.002)	(0.001)	(0.002)	(0.003)	(0.004)	(0.003)
VIX		0.008***		0.008***		0.008***
		(0.001)		(0.001)		(0.001)
Uncertainty			0.049***		0.049***	0.017
			(0.018)		(0.018)	(0.016)
3 Mo				0.112	0.004	0.116
				(0.081)	(0.092)	(0.081)
Observations	104	104	104	104	104	104
Adjusted R^2	-0.000	0.296	0.059	0.302	0.050	0.302
			2008-2024			
const	0.009***	0.004***	0.004***	0.005*	0.008***	0.005*
	(0.003)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Fed Anchoring	-0.006**			-0.002	-0.006*	-0.001
	(0.003)			(0.003)	(0.003)	(0.003)
VIX		0.004***		0.004***		0.005***
		(0.001)		(0.001)		(0.001)
Uncertainty			0.020		0.016	-0.029
			(0.016)		(0.016)	(0.019)
3 Mo				0.039	0.004	0.064
				(0.089)	(0.094)	(0.090)
Observations	130	130	130	130	130	130
Adjusted R^2	0.025	0.127	0.004	0.116	0.017	0.125

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5: **Impact of CME FedWatch on VIX before/After FOMC**

The table reports the regression results of the Equation (7) and Equation (8). The dependent variable *VIX* for the first three columns is the z-score normalized VIX 2 days before the FOMC meetings from 2020. For the last three columns, *VIX_diff* is the difference in the VIX index calculated between the day following the meeting $(t+1)$ and two days prior to the FOMC meeting $(t-2)$. *Trend* is the monthly visit to the CME FedWatch website. *Uncertainty* is measured as the standard deviation of target rate expectations over the last 20 days preceding the actual meetings.

	Dependent Variable					
	VIX			*VIX_diff*		
const	1.097***	0.061	0.608***	-0.865	0.044	-0.152
	(0.366)	(0.144)	(0.173)	(1.182)	(0.752)	(1.137)
Trend	-0.021**		-0.018***	0.010		0.006
	(0.009)		(0.004)	(0.029)		(0.027)
Uncertainty		10.958***	10.708***		-15.700**	-15.610**
		(1.199)	(0.968)		(6.260)	(6.367)
Observations	34	34	34	34	34	34
R^2	0.138	0.723	0.826	0.004	0.164	0.166
Adjusted R^2	0.111	0.714	0.814	-0.027	0.138	0.112
Note:				*p<0.1; **p<0.05; ***p<0.01		

Table 6: **Impact of Unexpected Rate Surprise on Bond Yield Changes**
This table reports the results for the regression model from Equation (9). Specifically, on the day following a FOMC meeting, the market's expectation for the next FOMC rate decision (r_t^e) is calculated using the weighted average of two possible outcomes. Once the rate decision is announced during the FOMC meeting at time t, the unexpected rate surprise is calculated as the difference between the realized rate and the expected rate immediately following the previous FOMC meeting. The bond yield changes for different maturities (Δy_t) are calculated as the yield differences between the current and the last FOMC meeting dates. The "High Yield Period" is a binary variable indicating whether an FOMC meeting occurs during a period of high Treasury yields, defined as being within the top 20% of the 3-month T-bill rate.

	Dependent Variable						
	3Mo_change	6Mo_change	1Yr_change	2Yr_change	5Yr_change	10Yr_change	20Yr_change
const	0.040*	0.046**	0.048**	0.046*	0.036	0.020	0.010
	(0.023)	(0.019)	(0.021)	(0.028)	(0.033)	(0.032)	(0.030)
Expected Rate	0.021**	0.014*	0.007	-0.000	-0.002	0.003	0.005
	(0.009)	(0.008)	(0.009)	(0.011)	(0.014)	(0.013)	(0.012)
rate surprise	0.968***	1.067***	1.044***	0.913***	0.737***	0.534***	0.403***
	(0.085)	(0.071)	(0.079)	(0.102)	(0.124)	(0.120)	(0.111)
rate surprise * High Yield Period	0.237	0.145	-0.056	-0.242	-0.574***	-0.584***	-0.498**
	(0.147)	(0.124)	(0.137)	(0.177)	(0.215)	(0.209)	(0.193)
High Yield Period	-0.108*	-0.093*	-0.092*	-0.081	-0.088	-0.106	-0.121
	(0.060)	(0.050)	(0.055)	(0.072)	(0.087)	(0.085)	(0.078)
Observations	215	215	215	215	215	215	215
Adjusted R^2	0.523	0.636	0.548	0.323	0.137	0.074	0.050

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7: **Impact of Daily Expected Rate Changes on Bond Yield Changes**
This table reports the regression results of estimating Equation (10). The expected rate decisions are calculated as the probability-weighted average of potential rate outcomes for the next immediate FOMC meeting, derived from the daily prices of Federal funds futures. Based on these expectations, the daily changes Δr_t^e of expected rate decisions are computed. Δy_t is the daily changes in bond yields for bonds with maturities ranging from 3 months to 20 years. The "High Yield Period" is a binary variable indicating whether an FOMC meeting occurs during a period of high Treasury yields, defined as being within the top 20% of the 3-month T-bill rate.

	Dependent Variable						
	3 Mo	6 Mo	1 Yr	2 Yr	5 Yr	10 Yr	20 Yr
	Whole Sample Period						
const	0.002^{***}	0.002^{***}	0.001^{**}	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Expected Rate	0.553^{***}	0.573^{***}	0.572^{***}	0.495^{***}	0.356^{***}	0.216^{***}	0.151^{***}
	(0.018)	(0.015)	(0.017)	(0.022)	(0.024)	(0.023)	(0.022)
Expected Rate * High Yield Period	-0.409^{***}	-0.338^{***}	-0.329^{***}	-0.170^{***}	-0.052	0.088^{*}	0.100^{**}
	(0.039)	(0.032)	(0.036)	(0.046)	(0.052)	(0.050)	(0.047)
High Yield Period	0.001	0.000	-0.001	-0.002	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	6404	6404	6404	6404	6404	6404	6404
Adjusted R^2	0.130	0.190	0.161	0.083	0.038	0.020	0.013
	1994-2007						
const	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Expected Rate	0.584^{***}	0.592^{***}	0.573^{***}	0.491^{***}	0.301^{***}	0.140^{***}	0.090^{***}
	(0.029)	(0.024)	(0.027)	(0.033)	(0.035)	(0.033)	(0.029)
Expected Rate * High Yield Period	-0.454^{***}	-0.382^{***}	-0.371^{***}	-0.228^{***}	-0.055	0.121^{**}	0.130^{***}
	(0.051)	(0.042)	(0.047)	(0.058)	(0.061)	(0.057)	(0.050)
High Yield Period	0.002	0.001	-0.001	-0.003	-0.004	-0.004^{*}	-0.004^{*}
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Observations	2739	2739	2739	2739	2739	2739	2739
Adjusted R^2	0.129	0.193	0.150	0.082	0.034	0.018	0.014
	2008-2024						
const	0.002^{***}	0.002^{***}	0.001^{**}	0.001^{*}	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Expected Rate	0.512^{***}	0.548^{***}	0.572^{***}	0.499^{***}	0.425^{***}	0.312^{***}	0.230^{***}
	(0.022)	(0.019)	(0.020)	(0.028)	(0.034)	(0.034)	(0.033)
Expected Rate * High Yield Period	0.179	0.673^{***}	1.320^{***}	2.272^{***}	2.177^{***}	1.648^{***}	1.243^{***}
	(0.178)	(0.155)	(0.166)	(0.227)	(0.277)	(0.275)	(0.271)
High Yield Period	0.001	0.000	0.002	0.003	0.004	0.005	0.005
	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)
Observations	3665	3665	3665	3665	3665	3665	3665
Adjusted R^2	0.133	0.195	0.200	0.113	0.063	0.036	0.020

Note: *p<0.1; **p<0.05; ***p<0.01

Table 8: **Impact of Daily Expected Rate Changes on Next Day Bond Yield Changes**

This table reports the regression results of estimating Equation (11). The expected rate decisions are calculated as the probability-weighted average of potential rate outcomes for the next immediate FOMC meeting, derived from the daily prices of Federal funds futures. Based on these expectations, the daily changes Δr_t^e of expected rate decisions are computed. Δy_{t+1} is the daily changes in bond yields for bonds with maturities ranging from 3 months to 20 years. The "High Yield Period" is a binary variable indicating whether an FOMC meeting occurs during a period of high Treasury yields, defined as being within the top 20% of the 3-month T-bill rate.

	Dependent variable						
	3 Mo	6 Mo	1 Yr	2 Yr	5 Yr	10 Yr	20 Yr
	Whole Sample Period						
const	0.002***	0.001**	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Expected Rate	0.091***	0.103***	0.058***	0.030	0.018	0.004	-0.007
	(0.022)	(0.019)	(0.020)	(0.025)	(0.028)	(0.026)	(0.025)
Expected Rate * High Yield Period	0.048	0.057	0.133***	0.140***	0.132**	0.093*	0.063
	(0.042)	(0.036)	(0.039)	(0.049)	(0.054)	(0.051)	(0.048)
High Yield Period	-0.003	-0.001	-0.002	-0.003	-0.003*	-0.003*	-0.003*
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	6403	6403	6403	6403	6403	6403	6403
Adjusted R^2	0.015	0.034	0.018	0.004	0.005	0.002	0.001
	1994-2007						
const	0.002	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Expected Rate	0.035	0.039	0.035	0.029	0.025	-0.001	-0.021
	(0.035)	(0.030)	(0.033)	(0.040)	(0.040)	(0.037)	(0.033)
Expected Rate * High Yield Period	0.111**	0.119**	0.156***	0.131**	0.119*	0.095	0.072
	(0.056)	(0.048)	(0.052)	(0.063)	(0.064)	(0.059)	(0.052)
High Yield Period	-0.003	-0.002	-0.003	-0.005*	-0.006**	-0.006**	-0.006***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Observations	2739	2739	2739	2739	2739	2739	2739
Adjusted R^2	0.013	0.013	0.013	0.004	0.007	0.005	0.002
	2008-2024						
const	0.002***	0.002***	0.001	0.001	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Expected Rate	0.158***	0.180***	0.087***	0.044	0.018	0.015	0.009
	(0.026)	(0.023)	(0.025)	(0.033)	(0.040)	(0.039)	(0.038)
Expected Rate * High Yield Period	-0.236	-0.152	0.030	0.081	-0.135	-0.136	0.005
	(0.189)	(0.166)	(0.185)	(0.244)	(0.289)	(0.284)	(0.278)
High Yield Period	0.000	0.002	0.003	0.006*	0.007	0.007*	0.006
	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Observations	3664	3664	3664	3664	3664	3664	3664
R^2	0.049	0.094	0.032	0.011	0.009	0.004	0.004
Adjusted R^2	0.046	0.092	0.029	0.009	0.006	0.001	0.001

Note: *p<0.1; **p<0.05; ***p<0.01

Table 9: **Results for the Vector Autoregressive Model**
This table reports the estimated system using a vector autoregressive model of order 3 (VAR(3)) described in Equation 12. Δr_t represents expected rate changes, Δy_t represents changes in 3-month Treasury bill yields, and Δs_t represents SPY returns.

	Dependent Variable		
	Expected Rate	SPY	T-Bill Rate
const	-0.001^{***}	0.042^{***}	0.002^{***}
	(0.0004)	(0.015)	(0.001)
Expected Rate.l1	0.088^{***}	0.313	0.120^{***}
	(0.014)	(0.497)	(0.020)
SPY.l1	0.001^{***}	-0.055^{***}	0.001
	(0.0004)	(0.013)	(0.001)
T-Bill.l1	0.019^{**}	-0.629^{*}	0.040^{***}
	(0.009)	(0.342)	(0.014)
Expected Rate.l2	-0.029^{**}	1.083^{**}	0.117^{***}
	(0.014)	(0.497)	(0.020)
SPY.l2	0.001^{*}	-0.019	0.001^{*}
	(0.0004)	(0.013)	(0.001)
T-Bill.l2	0.018^{*}	-0.566^{*}	-0.089^{***}
	(0.009)	(0.340)	(0.014)
Expected Rate.l3	0.011	1.242^{**}	0.124^{***}
	(0.014)	(0.498)	(0.020)
SPY.l3	0.001^{***}	0.008	0.001
	(0.0004)	(0.013)	(0.001)
T-Bill.l3	-0.0001	0.236	-0.121^{***}
	(0.009)	(0.341)	(0.014)
Observations	6,391	6,391	6,391
Adjusted R^2	0.015	0.005	0.034
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Internet Appendix

IA.1 A Numerical Example for CME FedWatch

We use a numerical example available from the CME FedWatch Tool as an illustration. On September 12, 2022, the current target range is 225 - 250 bps. The next two FOMC meetings to be held would be on September 20-21 and November 1-2. The closing price for Fed funds futures for September (ZQU22) was 97.4475, October Federal funds future Contract (ZQV22) at 96.9400, and November (ZQX22) at 96.4300. Based on this information, one can calculate the probabilities for each possible target range for the next two meetings.

Since October would be the closest month with no FOMC scheduled, we can start by calculating October's projected month-end, month-start, and implied monthly average EFFR rate as 100 - 96.9400 = 3.0600.

By design, the month-start EFFR of the following month is set to be equal to the month-end EFFR of the current month. The implied month-end EFFR for September will match October's implied monthly average EFFR, which in turn will be equal to the EFFR rate at the start of November, with all three projected to be 3.0600.

The implied monthly average EFFR for September is 100 - contract price of ZQU2 = 100 - 97.4475 = 2.5525. As the September meeting is scheduled on 20-21, from the calendar, we know that there are 20 days in September before the FOMC meeting and 10 days after; namely, $N = 10$ and $M = 20$. From Equation (3), we establish that the projected month-start EFFR rate is 2.2987, resulting in a monthly EFFR change of 0.7613. Similarly, the implied monthly average EFFR rate for November is 96.4300; there is 1 day before the FOMC meeting and 29 days after, i.e., $N = 1$ and $M = 29$. Using Equation (4), the month-end EFFR rate corresponds to 3.5876 with a monthly EFFR change of 0.5276 in November.

For September, there would be 0.7613/25bps = 3.0450 rate hikes and 0.5276/25bps = 2.1103 rate hikes in November. Therefore, deriving from market expectation, it could be interpreted as in September, there will be a 95.50% probability (1- 0.0450) of a rate hike with a size of 75 bps and 0.045% probability with a hike of 100 bps. Similarly, for November, there would be an 88.97% probability (1 - 0.1103) with a rate hike of 50 bps and an 11.03% probability of a 75 bps rate hike.

With these unconditional probabilities calculated for each possible rate hike scenario for these two FOMC meetings, we can calculate the cumulative results for the November meeting. There are, in total, four possible paths derived from our previous calculations. First, there may be a 75 bps rate hike in September and a 50 bps rate hike in November with a probability of $0.890 \times 0.955 = 85.0\%$. Second, there is a 75 bps rate hike in both September and November with a possibility of $0.955 \times 0.110 = 10.5\%$. Third, there is a 100 bps rate hike in September and a 50 bps rate hike in November with a probability of $0.045 \times 0.890 = 4\%$. Finally, there is a 100 bps rate hike in September and a 75 bps rate hike in November with a possibility of 0.5%. In summary, from the CME FedWatch Tool calculation, there are three possible outcomes after the November FOMC meeting. A total of 125 bps rate hike with 85% probability, a 150 bps total rate hike with 14.5% probability, and a 175 bps rate hike with only 0.5% probability.