Informative Price Pressure *

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Abstract

Informed investors often hedge their stock bets right before FOMC meetings. The resulting price pressure, when aggregated across stocks, reveals their long-term view of the stock market (with a minus sign). Consistent with this, we find that the average stock market return on the day before recent FOMC meetings, while completely reverted the next day, strongly and negatively predicts stock market returns up to two years in the future. The market return predictability is robust to additional controls, various sample cuts and extends to other important macroeconomic announcements. The day before the FOMC meeting is associated with low informed trading intensity, which explains the decision of informed investors to hedge on that day. At the same time, the VIX index is higher on that day, resulting in detectable price pressure.

Keywords: Price pressure, hedging, informed trading, FOMC meetings
JEL Codes: G11, G12, G14

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1 Introduction

The stock market tends to react strongly to FOMC announcements. Informed investors therefore have incentives to hedge their stock bets right before the FOMC meetings (Bloomberg (2021)). Hedging-induced price pressure, when aggregated to the market level, harnesses the wisdom of this informed crowd and reveals their long-term view of the stock market as a whole, although with a minus sign. For example, negative market-level price pressure before the FOMC meeting suggests that informed investors, as a group, are selling the market to hedge, which in turn reveals a net long position in stocks and an optimistic long-term view of these positions. Hence, price pressure carries information and should negatively predict future market returns. In this paper, we provide supporting evidence for such an informative price pressure.

Specifically, we find that the average stock market return on the day before recent FOMC meetings strongly and negatively predicts stock market returns up to two years into the future. Averaging recent pre-FOMC-meeting returns reduces the noise in the price pressure estimate. In our baseline specification, we examine all prescheduled FOMC meetings in the past two years, but we emphasize that the results are robust to different choices of the window length and become stronger when we overweight more recent meetings, and when we focus on the intraday part of the return.

In the baseline specification, we focus on the post-1994 sample period (as is the standard in the recent literature on FOMC meetings), and we examine the return of the SPY ETF, which is easy to trade. However, we confirm that the main result extends to a longer post-1964 sample and using the CRSP value-weighted market return. The result ceases to be significant during the earlier 1964 – 1981 sample, before the introduction of index futures when hedging the market exposure is more difficult.

Could a negative pre-FOMC-meeting return capture increased uncertainty and therefore predict positive future returns due to the risk premium channel? Under this interpretation, we would expect positive future returns to mostly accrue during dates with important information releases such as future FOMC announcements or during even weeks in the FOMC meeting cycle (Cieslak et al. (2019)). In the data, we observe the opposite patterns. Specifically, the return predictability is only negative and significant for future non-FOMC days and during the odd weeks of future meeting cycles, when returns are less likely to be driven by news related to monetary policy.

The stock market also reacts strongly to other macroeconomic announcements, creating similar incentives for informed investors to hedge prior to the announcement. We extend our analyses to the nonfarm payroll and the CPI announcements, which experience high investor attention and announcement-window return volatility (second only to the FOMC meeting). We find similar patterns in the data: the average stock market return on the days before these recent macroeconomic announcements also negatively and significantly predicts future market returns.

The predictive power is economically significant. For instance, a one standard deviation (0.43%) decrease in the average pre-FOMC-meeting return predicts a market return that is 15.48% higher in the next two years. The predictive power is robust to a host of controls, including the set of predictors in Welch and Goyal (2008) and Goyal et al. (2024), the past change in the 10-year Treasury yield, and the actual FOMC announcement window return. The out-of-sample R^2 remains positive and significant across different out-of-sample periods, confirming the economic significance of the predictive result.

The average daily returns on other days around recent FOMC meetings (from Day -3 to Day $+3$) do not predict future market returns. Why do informed investors concentrate their hedging on the day right before the FOMC meeting? Hedgers certainly worry about trading against investors who might process private information regarding the upcoming FOMC announcement (e.g. Bradley et al., 2024; Mano, 2023; Bernile et al., 2016). Empirically, when we aggregate various measures of informed trading intensity (ITI) at the stock level of Bogousslavsky et al. (2024) for each day during the $[-3, +3]$ window around the FOMC meeting, we find that the ITI measures on the day before the meeting tend to be the lowest.

Hedgers therefore have incentives to hedge during this period of calm before the storm.

At the same time, the VIX index spikes on the day before the FOMC meeting. As Nagel (2012) shows, heightened uncertainty makes liquidity more costly as the required compensation for liquidity provision increases. In other words, by hedging on the day before the FOMC meeting, the hedgers minimize the risk of trading against other informed investors, but have to pay a higher liquidity cost. The higher liquidity cost makes it easier to detect the hedging-induced price pressure. Consistent with the price pressure interpretation, we find that the average stock market return on the day before recent FOMC meetings is almost completely reversed by the end of the next trading day.

Cross-sectional analyses provide further support for such an informative price pressure. To the extent that high-beta stocks require more aggressive hedging, the resulting price pressure better reveals informed traders' views on these stocks. Consistent with this conjecture, we find the average high-beta stock return on the day before recent FOMC meetings more negatively predicts their returns in the next two years. A one standard deviation (0.66%) decrease in the average pre-meeting return predicts a 19.14% higher return in the next two years among high-beta stocks. In contrast, a one standard deviation (0.32%) decrease in the average pre-meeting return predicts a 5.28% higher return in the next two years among low-beta stocks. Similarly, the return predictability is also stronger among illiquid stocks, as the price pressure is easier to detect for these stocks. That said, we find the return predictability to be negative and significant among low-beta and liquid stocks as well, confirming its robustness.

This paper contributes to a large literature on hedging-induced price pressure. For example, Ni et al. (2005) and Ni et al. (2021) show that hedging activities by option market makers result in price pressure among the underlying stocks. Barbon et al. (2021) examines such a price pressure at the end of the trading day. Baltussen et al. (2021) show that hedging-induced price pressure can also arise, even at the market level. Our contribution is to show that such a hedging-induced price pressure can also be informative, if it is done by informed traders. When aggregated across individual stocks to the market level, such a price pressure harnesses the wisdom of the crowd and reveals informed traders' net view on the stock market as a whole.

This study also adds to the existing literature on FOMC meetings. Extant empirical research on the equity market suggests that individual FOMC announcements may distort asset prices, with the price corrections occurring relatively quickly, at horizons of a few weeks or less (Boguth et al. (2023); Kroencke et al. (2021)). However, Hanson and Stein (2015) study the bond market reaction to multiple FOMC meetings and suggest that the distortionary effects of FOMC announcements are corrected over the following year. While the literature focuses on returns during and after the FOMC announcement, we examine the information revealed by the return on the day before the announcement.

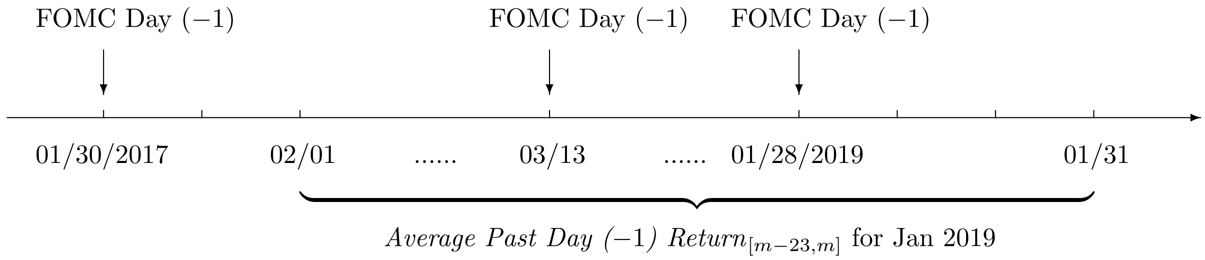
Finally, our study is related to the broad literature on return predictability. A large literature studying the cross-section of stock returns documents a momentum effect whereby a firm's past 12-month stock return positively predicts future 12-month returns (e.g. Jegadeesh and Titman (2001)). A separate accounting literature studies the cross-section of stock returns and finds that the three-day $(-1, +1)$ return around earnings announcements positively predicts future stock prices (e.g. Kishore et al. (2008)). We add to this literature by showing that aggregate stock market returns prior to FOMC and macroeconomic releases predict aggregate returns several years into the future. Moreover, this return predictability is difficult to reconcile with a risk-based explanation.

The rest of the paper is organized as follows. Section 2 details the data and variable construction. Section 3 discusses the main empirical results. Section 4 concludes.

2 Data and Variable Construction

This section describes the sample construction and the calculation of variables used in the baseline analyses. Detailed variable definitions are included in Appendix A.

2.1 Monthly Time Series



We define the pre-FOMC-meeting return as the stock market return on the day before the start of a FOMC meeting. To reduce estimation noise, we incorporate all prescheduled FOMC meetings over the past two years. Specifically, for each month m, the key independent variable, *Average Past Day (−1) Return*$_{[m-23,m]}$, is computed as the simple average of pre-FOMC-meeting returns over the previous 24 months in percentage, covering the period from month $m-23$ to month m.

The timeline above illustrates how we construct *Average Past Day (−1) Return*$_{[m-23,m]}$ for the monthly observation of January 2019. On the last trading day of January 2019, we identify all prescheduled FOMC meetings over the past two years.[1] We then take the simple average of the pre-meeting returns for all the 16 FOMC meetings from Feburary 1, 2017 to January 31, 2019.

The dependent variable, the subsequent two-year market return ($Return_{[m+1,m+24]}$), is similarly calculated as the compounded monthly stock market return over the future 24 months, covering the period from month $m+1$ to month $m+24$. In additional analyses, we also study market returns on other trading days around the FOMC meeting. For these tests, we calculate *Average Past Day (i) Return*$_{[m-23,m]}$ for each day i within the event window $[-3,+3]$ surrounding the FOMC meeting day, where Day (i) indexes the trading day relative to the meeting day.[2] These daily returns are also averaged over the past 24 months.

[1] We identify all the prescheduled FOMC meetings from Feburary 1, 2017 to January 31, 2019. The market return on March 13, 2017 is the first FOMC Day (−1) return and the market return on January 28, 2019 is the last FOMC Day (−1) return. The return on January 30, 2017 is excluded from the calculation.

[2] Day (0) is defined as the FOMC meeting day. For one-day FOMC meeting, Day (0) is the announcement day. For two-day FOMC meeting, Day (0) covers both meeting days.

2.2 Control Variables

We include a comprehensive set of control variables in the regression analyses. First, we account for the contemporaneous change in the 10-year Treasury yield on FOMC Day (−1), *Average Past Day (−1) Dgs10*$_{[m-23,m]}$, which is calculated as the simple average of daily change in the 10-year Treasury yield (DGS10) on FOMC Day (−1) over the past 24 months. Additionally, we control for the actual announcement window return ($FOMC[0,3]$) from the most recent FOMC meeting, as Boguth et al. (2023) document a significant reversal of event-window returns by announcement-cycle end. We also include the set of monthly predictors in Welch and Goyal (2008) measured at month m. These controls are the dividend price ratio (dp_m), the dividend-yield (dy_m), the earnings-price ratio (ep_m), stock volatility ($svar_m$), book-to-market (bm_m), net issuing activity ($ntis_m$), the Treasury-bill rate (tbl_m), the long-term yield (lty_m), the long-term bond rate of return (ltr_m), the default yield (dfy_m), the default rate of return (dfr_m), and the inflation rate ($infl_m$).[3]

For robustness checks, we further control for a more comprehensive set of variables in Goyal et al. (2024) measured at month m with no missing value in the sample period. These additional variables include the forward implied variances ($impvar_m$), the variance premium (vp_m), the variance risk premium (vrp_m), the aggregate illiquidity ($lzrt_m$), output gap of industrial production ($ogap_m$), oil price changes ($wtexas_m$), optimized investor sentiment index ($sntm_m$), new orders to shipments of durable goods ($ndrbl_m$), average stock skewness ($skvw_m$), the tail risk ($tail_m$), the single factor from B/M cross-section (fbm_m), nearness to Dow 52-week high ($dtoy_m$), nearness to Dow 52-week high ($dtoat_m$), stock-bond yield gap ($ygap_m$), stock-return dispersion ($rdsp_m$), scaled risk-neutral vix ($rsvix_m$), technical indicators ($tchi_m$), average correlation of daily stock returns ($avgcor_m$), short interest ($shtint_m$), and analyst forecast disagreements ($disag_m$).

[3] The term-spread (tms_m) and dividend-payout ratio (de_m) are dropped due to multicollinearity issues. tms_m is defined as $lty_m - tbl_m$. de_m is defined as dp_m/ep_m, and for the subsample from 1964 - 1981, the R^2 from the regression of de_m on dp_m and ep_m is more than 0.95.

2.3 Daily Time Series

To measure daily informed trades, we use the firm-day informed trading intensity (*ITI*) metric introduced by Bogousslavsky et al. (2024). Their approach applies machine learning models to a comprehensive dataset of informed trades, including Schedule 13D filings, opportunistic insider trades, and short selling data, to develop several *ITI* measures. Specifically, $ITI(13D)_{i,t}$ is trained on Scheduled 13D data; $ITI(Patient)_{i,t}$ and $ITI(Impatient)_{i,t}$ are trained on the first 40 days and the last 20 days of the 60-day Scheduled 13D filing window, respectively; $ITI(Insider)_{i,t}$ is based on opportunistic insider trading data; and $ITI(Short)_{i,t}$ is derived from short selling data. To measure the market-wide informed trading intensity, we calculate the daily aggregate weighted-averaged *ITI* using the market value of each stock at the previous day's close. A higher value of aggregate *ITI* indicates more informed trading. To measure daily market-wide liquidity, we use the closing value of the VIX index for each trading day from CBOE website. A higher value of VIX index suggests worsen liquidity.

2.4 Summary Statistics

Consistent with recent FOMC literature, we focus on the post-1994 sample period for the baseline analysis. Our analysis examines the return of the SPY ETF, a widely traded and accessible investment vehicle. Additionally, we use CRSP value-weighted market return as a robustness check to validate our findings.

To build the sample, we compile SPY return data from 1994 to 2023, with the monthly time series starting in January 1996 and ending in December 2021. This sample period is based on the availability of the past two years of daily SPY return data to calculate the past two-year average pre-FOMC-meeting return, the key independent variable, and the future two years of monthly SPY return data to calculate the next two-year market return, the dependent variable.

The final sample used in the baseline analysis consists of 312 monthly observations between 1996 and 2021. Panel A of Table 1 reports descriptive statistics for this sample.

The mean of the average past two-year pre-FOMC-meeting returns (*Average Past Day (-1)* $Return_{[m-23,m]}$) is 0.05% and the median is 0.04%. In contrast, the mean of the average past two-year FOMC-meeting-day returns (*Average Past Day (0)* $Return_{[m-23,m]}$ has a relatively larger value of 0.25%, with a median of 0.20%. This is consistent with the significantly positive average stock market return around FOMC announcements (e.g. Lucca and Moench (2015); Hu et al. (2022)). The future two-year compounded market return ($Return_{[m+1,m+24]}$) has a mean of 21.4% and a median of 23.2%.

Panel B of Table 1 reports descriptive statistics for the sample with other specifications. For robustness, we also use CRSP valued-weighted returns to measure market returns, which has a similar distribution for both key monthly variables (pre-FOMC-meeting return and future two-year return) compared to those calculated with SPY data. We also find that the distributions of pre-FOMC-meeting returns remain consistent whether calculated with intraday or overnight returns, or with increasing versus decreasing weights to calculate the average of past returns. However, there is a significant difference when comparing portfolio characteristics: monthly observations using high-beta portfolio returns show a higher standard deviation than those using low-beta portfolio returns. For example, one standard deviation in pre-FOMC-meeting return for the high-beta portfolio is 0.66%, compared to 0.32% for the low-beta portfolio.

Lastly, the sample used in the daily analyses from 1994 to 2023 is reported in Table 1 Panel C. Since our baseline sample is based on SPY ETF return data, we calculate the daily weighted-averaged ITI_t among S&P500 firms. The sample period for ITI_t is from 1994 to 2019, given the availability of *ITI*. We also construct two VIX-related variables: the daily change in VIX index on day t (ΔVIX_t) and the daily percentage change in VIX index on day t ($\%\Delta VIX_t$).

3 Empirical Results

3.1 Baseline Analyses

We begin our analysis by conducting a visual inspection of whether pre-FOMC-meeting price pressure negatively predicts future market returns. Figure 1 illustrates the patterns. The two lines representing the monthly time series of pre-FOMC-meeting returns (*Average Past Day (-1) Return*$_{[m-23,m]}$) over the past two years and the future two-year compounded market returns (*Return*$_{[m+1,m+24]}$) display a negative correlation.

We verify the negative predictability in the regression analyses. We estimate the following ordinary least squares (OLS) model:

$$Return_{[m+1,m+24]} = \alpha + \beta Average\ Past\ Day\ (i)\ Return_{[m-23,m]} + \gamma Controls_m + \epsilon_m. \quad (1)$$

The sample is at the month level, with subscript m indexing month. The dependent variable *Return*$_{[m+1,m+24]}$ is the compounded SPY monthly returns for the next 24 months. The key independent variable *Average Past Day (i) Return*$_{[m-23,m]}$ is the simple average of SPY daily returns on FOMC Day (i) over the past 24 months in percentage. $Controls_m$ include those discussed in the previous section. To account for the autocorrelation in the cumulative returns that result from overlapping periods, standard errors are adjusted using Newey-West corrections with 23 lags.[4]

In Table 2 Panel A, we present the univariate results regarding the predictive ability of pre-FOMC-meeting returns for the days around FOMC meetings ($[-3,+3]$). As is shown in column (1), pre-FOMC-meeting returns on FOMC Day (-1) have a significant and negative coefficient estimate in predicting market returns for up to the next two years. In terms of economic magnitudes, a one standard deviation decrease in *Average Past Day (-1) Return*$_{[m-23,m]}$ (0.43%) predicts a market return that is 15.48% higher in the next two years. Pre-FOMC-meeting returns on other FOMC days exhibit no significant predictability.

[4]The dependent variable *Return*$_{[m+1,m+24]}$ has 23 months of overlapping monthly periods.

Among the adjusted R^2, the regression model for FOMC Day (-1) in column (1) has the highest value of 0.34, while the value for regressions testing other FOMC days is less than 0.03.

Turning to the multivariate analyses, Panel B of Table 2 reports the results. Consistent with the univariate analyses, average pre-FOMC-meeting returns on FOMC Day (-1) negatively predict future two-year returns. The predictive power is robust to a host of controls, including the set of predictors in Welch and Goyal (2008) and Goyal et al. (2024), the past change in the 10-year Treasury yield (*Average Past Day (-1) Dgs10*$_{[m-23,m]}$), and the actual FOMC announcement window return ($FOMC[0,3]$). Column (2) shows that a one standard deviation decrease in *Average Past Day (-1) Return*$_{[m-23,m]}$ (0.43%) predicts a market return that is 11.78% higher in the next two years. Among the controls, the dividend price ratio and net issuing activity positively predict future returns. The long-term yield and book-to-market are negatively correlated with future returns. As a robustness check, Column (3) shows that the average pre-FOMC-meeting returns remain significant after controlling for additional variables in Goyal et al. (2024).

In addition, we emphasize that the results are robust to different choices of window length. If we expand the window of compounded future returns, we find stronger predictability of average returns on FOMC Day (-1). Figure 2 plots the coefficient estimates from the predictive model for future returns with increasing compounding periods from the next 1 month to 24 months. The magnitude of the predictability increases with the window length of compounded future returns. We find this pattern extending to both univariate and multivariate models.

To confirm that the main result is robust when using other stock market return measures, we reestimate equation (1) with controls substituting CRSP value-weighted returns for SPY returns to measure of market returns. Columns (1) and (2) of Table 3 report the regression results using the same sample period from 1996 to 2021. Column (1) shows that average pre-FOMC-meeting returns on FOMC Day (-1) negatively predict future two-year returns, which is consistent with the results using SPY returns. For the interpretation of economic magnitude, a one standard deviation decrease in pre-FOMC-meeting return (0.4%) predicts a market return that is 15.52% higher in the next two years.

The result ceases to be significant during an earlier 1964 – 1981 sample, before the introduction of index futures when hedging is more difficult.[5] Columns (3) and (4) of Table 3 report the regression results using CRSP value-weighted returns for this earlier sample. The coefficient estimates in these two columns are insignificant. In contrast, Columns (5) and (6) of Table 3 report the regression results for the more recent sample period from 1982 to 2021, after index futures became widely available. The coefficient estimates remain negative and significant.

Our analysis thus far has been in-sample, where we utilize all the available data to get more efficient parameter estimates and more precise return forecasts. Additionally, we conduct out-of-sample tests to evaluate the return predictability in real time and mitigate the over-fitting issue. We calculate the out-of-sample (OOS) R^2 for univariate analyses following the methodology in Campbell and Thompson (2008). The OOS R^2 statistic is computed as

$$R^2_{OS} = 1 - \frac{\sum_{t=1}^{T}(r_t - \hat{r}_t)^2}{\sum_{t=1}^{T}(r_t - \bar{r}_t)^2}$$

where $\hat{r}_t$ is the fitted value from a predictive regression estimated through period $t-1$, and $\bar{r}_t$ is the historical average return estimated through period $t-1$.

We first analyze the case of predicting the next one-year return, as shown in Figure 3. To ensure robustness, we calculate the OOS R^2 while incrementally shifting the forecast beginning date by one month, from January 2005 to December 2013. Panel A of Figure 3 presents results from the univariate predictive model. The blue solid line, representing the OOS R^2, ranges from 7% to over 30%. We also compute the Clark and West (2007) MSFE-adjusted statistic to derive the 95% confidence interval, depicted by the red dashed line. Since the red dashed line remains above zero, the results indicate that the OOS R^2 is

[5]S&P 500 futures contracts were first introduced by the Chicago Mercantile Exchange in 1982.

positively significant across different out-of-sample periods. Panel B reports the results from the univariate predictive model after excluding observations from January 2006 through June 2011.[6] The OOS R^2 remains positive and significant, suggesting that the results are robust to excluding the crisis period. Panel C reports the results of the multivariate analyses using a simple equally-weighted average of univariate regression forecasts, following Rapach et al. (2010). Although the values of OOS R^2 become lower, they remain positive and significant.

We then assess the out-of-sample performance of the pre-FOMC-meeting return in predicting the next two-year return by repeating the above three analyses. Figure 4 presents a larger OOS R^2 from the univariate predictive model, the analysis excluding the crisis period, and the multivariate analysis, comparing to results in Figure 3. Together, results in Figures 3 – 4 suggest that beyond the in-sample significance, pre-FOMC-meeting return exhibits significant out-of-sample forecasting power and outperforms the random walk benchmark model.

3.2 Additional Analyses

In this subsection, we explore several alternative specifications of the baseline results.

First, we study the difference in the return predictability between the intraday and overnight returns. Following the methodology in Lou et al. (2019), we define the intraday return of SPY, $r_{intraday}$, as the SPY price change from the market open to close of the same trading day ($\frac{P_{Close}}{P_{Open}} - 1$). Then we compute the overnight return, $r_{overnight}$, based on the previously calcuated intraday return and the daily close-to-close return of SPY (r), as $\frac{1+r}{1+r_{intraday}} - 1$.

We reestimate equation (1) using SPY intraday and overnight returns instead of SPY daily close-to-close returns to calculate pre-FOMC-meeting return on FOMC Day (-1). Columns (1) and (3) of Table 4 Panel A reports the univariate regression results using SPY intraday and overnight returns respectively. A one standard deviation decrease in pre-

[6] These observations are affected by the crisis period of December 2007 to June 2009, given the construction of the variables.

FOMC-meeting intraday return (0.23%) predicts a market return that is 16.58% higher in the next two years. In contrast, a one standard deviation decrease in pre-FOMC-meeting overnight return (0.27%) predicts a market return that is 11.34% higher in the next two years. For the multivariate analyses, the predictability for SPY intraday is still significant but the coefficient estimate for SPY overnight return becomes insignificant, which are reported in columns (2) and (4) of Table 4 Panel A. These results suggest that intraday returns have stronger predictive power than overnight returns, since traders face institutional constraints and overnight risks out of trading hours (Bogousslavsky (2021)).

Second, we study whether the results become stronger when we overweight more recent FOMC meetings. We start by applying the structure of linearly increasing weights. We assume that there have been N FOMC meetings over the past two years for each monthly end. To overweight the most recent FOMC meeting, we first define the time series $X_t = t * \textit{Day } (-1) \textit{ Return}_t$ for $t = 1, ..., N$, where $\textit{Average Past Day } (-1) \textit{ Return}_N$ is the daily SPY return on the day before the most recent FOMC meeting for each monthly m. Then, we calculate the weighted sum of returns for FOMC Day (-1) over the past two years with linearly increasing weights as $S_N = \sum_{t=1}^{N} \frac{X_t}{\sum_{t=1}^{N} t}$. Therefore, we calculate *Average Past Day* (-1) $\textit{Return}_{[m-23,m]}$ in the case of linearly increasing weights as S_N. In this structure, the weight assigned to the first and the last FOMC meeting are $\frac{2}{N(N+1)}$ and $\frac{2}{N+1}$ respectively, with the increment of $\frac{2}{N(N+1)}$. For the baseline case, all FOMC meetings receive the same weight as $\frac{1}{N}$.

Similarly, to apply the structure of linearly decreasing weights, we redefine X_t as $X_t = t * \textit{Day } (-1) \textit{ Return}_{N-t+1}$. Then we follow the same steps as described above to calculate S_N as *Average Past Day* (-1) $\textit{Return}_{[m-23,m]}$. In this structure, we underweight the most recent FOMC meeting by using the weight $\frac{2}{N(N+1)}$.

Comparing with the case of equal weights in baseline analyses, there is no significant difference in the distribution of the independent variable using different weights. As is suggested by Panel B of Table 1, the means (standard errors) for *Day* (-1) $\textit{Return}_{[m-23,m]}$

using increasing and decreasing are both 0.05% (0.5%).

To examine the predictability of average pre-FOMC meeting returns with linearly increasing and decreasing weights, we re-estimate Equation (1) using *Average Past Day (*-1*) Return*$_{[m-23,m]}$ with both increasing and decreasing average weights. Columns (5) and (7) of Table 4 Panel A present the univariate regression results for the regressions employing increasing and decreasing weights, respectively. A one-standard-deviation decrease in pre-FOMC-meeting returns, measured with increasing weights (0.5%), is associated with a 16.7% higher market return in the next two years. In comparison, a one-standard-deviation decrease in pre-FOMC-meeting returns with decreasing weights (0.5%) predicts a market return that is 13.8% higher over the same period.

The difference in predictive power becomes even more pronounced in the multivariate analyses. Column (6) of Table 4 Panel A shows that a one-standard-deviation decrease in pre-FOMC-meeting returns with increasing weights predicts a 12.2% higher market return over the next two years, after accounting for additional control variables. In comparison, Column (8) shows that the same decrease in returns with decreasing weights predicts a 6.7% higher market return over the same period with controls.

A negative pre-FOMC-meeting return might capture increased uncertainty and therefore predict positive future returns due to the risk premium channel. Under this hypothesis, we would expect positive future returns to mostly accrue during dates with important information releases such as future FOMC announcements or during even weeks in the FOMC meeting cycle (Cieslak et al. (2019)).

To look into this, we first decompose the dependent variable into returns on future non-FOMC days and FOMC days. We define trading days during the event window $[-1,+1]$ as FOMC days. We find that the return predictability is only negative and significant for future non-FOMC days. Columns (1) and (2) of Table 4 Panel B show the regression results for predicting non-FOMC-day returns, and we observe significant coefficient estimates for the key independent variable *Average Past Day (-1) Return*$_{[m-23,m]}$. The coefficient estimates are not negatively significant in Columns (3) and (4) of Table 4 Panel B when predicting FOMC-day returns.

Next, we study how the return predictability for future returns varies between the future odd weeks versus even weeks within the FOMC meeting cycle. We follow Cieslak et al. (2019) to decompose the next two-year return into returns during odd weeks and even weeks.[7] Cieslak et al. (2019) show that the equity premium is earned during even weeks in the FOMC meeting cycle, which is driven by the informal communication of Fed officials with market participants. We find that the predictability is only significant for future returns during the odd weeks of meeting cycles. Columns (5) and (6) of Table 4 Panel B show the regression results for predicting odd-week returns. We find that the coefficient estimates for *Average Past Day (-1) Return*$_{[m-23,m]}$ are all negative and significant. Columns (7) and (8) of Table 4 Panel B report the regression results of predicting future even-week returns. The coefficient estimates in these two columns are insignificant.

Together, results in Table 4 Panel B suggest that the documented predictability of pre-FOMC-meeting return is not driven by the risk premium channel.

3.3 Other Macroeconomic Events

In addition to FOMC meetings, we find that investors pay significant attention to other macroeconomic announcements, creating similar incentives for informed investors to hedge their bets before the announcement. Therefore, we further examine whether this negative return predictability extends to a wider set of macroeconomic announcement events. These macroeconomic events include nonfarm payroll announcements, CPI announcements, PPI announcements, and ISM Manufacturing data (PMI) announcements. We collect the announcement dates and times for these macroeconomic events from Bloomberg.

We begin by analyzing investor attention and daily return square around the announcement windows. Panel A of Table 5 reports the sum of the scaled daily return square during

[7] Cieslak et al. (2019) define week 0 in FOMC cycle time as days -1 to 3, and week 1 as days 4 to 8.

the three-day announcement window $[-1, +1]$. This measure is calculated as the sum of the daily return square during the event window divided by the average daily return square over the past year. The empirical results indicate that FOMC meetings, nonfarm payroll announcements, and CPI announcements exhibit relatively higher scaled return square during the announcement windows compared to PPI and ISM announcements. The results are robust when using both SPY daily returns and CRSP value-weighted returns. This finding is corroborated by Figure 5, which shows elevated Google search attention for CPI, FOMC meetings, and nonfarm payroll announcements over time. Consequently, our subsequent analysis focuses on the nonfarm payroll and CPI announcements as the most impactful macroeconomic events.

To assess whether there is return predictability associated with these events, we reestimate equation (1) using nonfarm payroll and CPI announcement dates to construct the variables. We define Day (-1) for these two events if the next day has either nonfarm payroll or CPI announcement, and does not coincide with nonfarm payroll, CPI announcement, and FOMC Day (-1). Specifically, we identify a trading day t as Day (-1) if the next day has nonfarm payroll (or CPI) announcement, and day t is not in the $[-1, +1]$ event window for CPI (or nonfarm payroll) announcement. At the same time, day t is not on FOMC Day (-1).

Panel B of Table 5 reports the regression results. The sample period begins in 1999 given that the availability of announcement dates for nonfarm payroll and CPI events start in 1997. Columns (1) – (3) replicate the baseline analyses for FOMC meetings using the updated sample period. Columns (4) – (6) report the results of nonfarm payroll and CPI announcements. Across all specifications, the coefficient estimates are consistently negative and statistically significant.

Our evidence indicates that the significant negative return predictability extends to a broader set of macroeconomic events. These results suggest that informed investors have incentives to hedge right before uncertain macroeconomic announcements, and the hedging-induced price pressure gradually reverts over the next two years.

3.4 Informed Trading and VIX

Informed investors concentrate their hedging on the day right before the FOMC meeting. This timing reflects a strategic response to mitigate the risks of trading against other investors who may possess private information about the upcoming FOMC announcement. We expect to observe less informed trading right before the FOMC meeting.

To measure market-wide informed trading, we aggregate stock-level measures of informed trading intensity (ITI) as constructed by Bogousslavsky et al. (2024) for each trading day using market value of each stock at previous close as weights. To empirically analyze the dynamics of aggregate informed trading activities, we estimate the following OLS model:

$$\mathit{Daily\ Measure}_t = \alpha + \sum_{i=-3}^{+3} \beta_i \mathit{Day\ (i)}_t + \gamma \mathit{Controls}_t + \epsilon_t, \tag{2}$$

where $\mathit{Daily\ Measure}_t$ is the market-wide ITI and $\mathit{Day\ (i)}_t$ is an indicator that equals one if day t falls on FOMC Day (i).

Table 6 reports the results of regressing daily market-wide ITI on a set of indicators for each day during the $[-3, +3]$ window around the FOMC meeting. Column (1) of Table 6 uses $\mathit{ITI(13D)}_t$, where the firm-level ITI is trained on Schedule 13D data at day t. Columns (2) – (5) uses patient ITI, impatient ITI, insider ITI, and short-selling ITI respectively, as defined by Bogousslavsky et al. (2024). Across the five columns, the coefficient estimates for $\mathit{Day\ (-1)}_t$ are consistently negative and significant, except for *ITI(Insider)*. In contrast, the coefficient estimates for other day indicators during the $[-3, +3]$ window are not negatively significant. These results highlight that aggregate ITI measures on the day before the meeting tend to be the lowest out of all days around the FOMC window. Informed investors therefore have incentives to hedge during this period of calm before the storm.

At the same time, Nagel (2012) suggest that VIX is a proxy for liquidity provision and the risk-bearing appetite of financial intermediaries. If these intermediaries reduce their liquidity provision or risk-bearing appetite on the day before the FOMC meeting, we predict that the VIX will increase on Day (-1).

We reestimate equation (2) using VIX-related measures as the dependent variable. Table 7 reports the results. Column (1) reports the results of using the daily change of the VIX index, ΔVIX_t, as the dependent variable. The coefficient estimate on *Day (*-1*)*$_t$ is positive and significant, indicating an increase in market uncertainty and liquidity cost in anticipation of the FOMC meeting. Interestingly, the coefficient estimate on *Day (*0*)*$_t$ is negative and significant, indicating the resolution of market uncertainty on the announcement day. The results are quantitatively similar for daily percentage change of VIX index, $\%\Delta VIX_t$, which is reported in Column (2) of Table 7.

These results collectively suggest that the market uncertainty spikes on the day before the FOMC meeting. In addition, the increased uncertainty raises liquidity costs, as the compensation required for liquidity provision becomes more substantial (Nagel (2012)). While hedging on the day prior to the FOMC meeting allows investors to minimize the risk of trading against informed investors, it comes at the expense of higher liquidity costs. These elevated costs, in turn, make it easier to detect the price pressure induced by hedging activity.

To further analyze the price pressure hypothesis, we study the intraday SPY price movement surrounding FOMC meetings. The intraday SPY prices are detected from TAQ by using the latest trade price for each intraday window. Figure 6 closely examines the cumulative intraday SPY return from one trading day before the meeting day to the first meeting day. We set the event period to start from one trading day before FOMC meeting day and end on the first FOMC meeting day. We first calculate the cumulative hourly SPY returns for a given intraday trading window [*9:30am* on FOMC Day (-1), t] of the FOMC meeting, then average the cumulative intraday returns over the past 24 months. We find that for the quartile group with the lowest average pre-FOMC-meeting return, it exhibits a negative trend on Day (-1), and then completely reverts on the next trading day. While for the quartile group with the highest average pre-FOMC-meeting return, it drifts upward on Day (-1), then continues the positive momentum, and finally reverts back in the last two trading hours.

The results in the intraday event study are consistent with the price pressure interpretation. Specifically, the average stock market return on the day before recent FOMC meetings is almost entirely reversed by the close of the next trading day, suggesting the presence of temporary price pressure induced by hedging. Taken as a whole, our results are consistent with the view that the temporary price pressure reveals the positions of informed traders and also leads to long-run return predictability.

3.5 Cross-Sectional Analyses

In the last subsection, we conduct two cross-sectional analyses.

First, we construct two stock portfolios based on the stock beta. To do this, we use a rolling window to estimate the FOMC event beta using daily observations in the previous two years.[8] At the end of each month m, stocks are ranked by the value of the estimated market beta. We focus on common stocks and exclude stocks with price less than \$5. The high-beta portfolio is defined as the group of stocks with estimated beta in the top 20th percentile, while the low-beta portfolio includes stocks with estimated beta in the bottom 20th percentile as of month m. For each month m, we fix the portfolio two years before and two years after to compute the average pre-FOMC-meeting returns and the compounded future returns. Daily portfolio returns are calculated as the weighted average of daily stock returns within each portfolio, using market capitalization at the previous close as weights.

High-beta stocks tend to require more aggressive hedging due to their heightened sensitivity to market movements. As a result, the price pressure generated by such hedging activities better reflects the informed traders' views on these stocks. We expect that the average high-beta stock return on the day before recent FOMC meetings will exhibit stronger

[8] We apply the Fama-French three-factor model to estimate market beta coefficients using the daily observations during FOMC event window $[-3, +3]$ over the past two years.

negative predictability for returns in the next two years.

We reestimate equation (1) using high-beta and low-beta daily portfolio returns respectively. Columns (1) and (2) of Table 8 report the regression results. For high-beta stocks, a one standard deviation (0.66%) decrease in the average pre-meeting return predicts a 19.14% higher return in the next two years. In contrast, for low-beta stocks, a one standard deviation (0.32%) decrease in the average pre-meeting return predicts a 5.28% higher return in the next two years. The difference between the coefficient estimates is statistically significant, with a t-statistic of -2.21 for the difference in the coefficient estimate on *Average Past Day (-1) Return*$_{[m-23,m]}$ between columns (1) and (2), adjusted by robust standard errors. These results suggest that hedging-induced price pressure is more likely to be detected for high-beta stocks, which reflects more aggressive hedging.

Similarly, hedging induces stronger price pressure for illiquid stocks. We expect that the return predictability is also stronger among illiquid stocks, as the price pressure is easier to detect for these stocks.

To test this empirically, we construct two stock portfolios based on stock liquidity. Liquidity is measured using the daily Amihud ratio following Amihud (2002).[9] We compute the daily Amihud ratio for each stock day and then average it across daily observations from the previous year. At the end of each month m, we rank the stocks based on the average Amihud ratio. We focus on the common stocks and exclude the stocks with price below $5. Stocks in the top 20th percentile of the Amihud ratio distribution are assigned to the low-liquidity portfolio, while those in the bottom 20th percentile are assigned to the high-liquidity portfolio as of month m. For each month m, these portfolios are fixed two years prior and two years after to compute the average pre-FOMC-meeting returns and the compounded future returns. Likewise, daily portfolio returns are calculated as the weighted average of daily stock returns within each portfolio, using market capitalization at the previous close as weights.

[9] Amihud ratio is calculated as the absolute value of the daily stock return divided by daily dollar trading volume.

We reestimate equation (1) using high-liquidity and low-liquidity daily portfolio returns respectively. Similarly, the return predictability is also stronger among illiquid stocks, as the price pressure is easier to detect for these stocks. Columns (3) and (4) of Table 8 report the regression results. For high-liquidity stocks, a one standard deviation (0.39%) decrease in the average pre-meeting return predicts a 13.5% higher return in the next two years. In contrast, for low-liquidity stocks, a one standard deviation (0.31%) decrease in the average pre-meeting return predicts a 20.8% higher return in the next two years. The difference between the coefficient estimates is statistically significant, with a t-statistic of 5.77 for the difference in the coefficient estimate on *Average Past Day (-1) Return*$_{[m-23,m]}$ between columns (3) and (4), adjusted by robust standard errors. These results suggest that hedging-induced price pressure is more likely to be detected for low-liquidity stocks.

4 Conclusion

The stock market tends to react strongly to macroeconomic announcements, creating incentives for informed investors to hedge their positions right before these events. These hedging activities could generate informative price pressures. When aggregated across individual stocks to the market level, such a price pressure harnesses the wisdom of the crowd and reveals informed traders' net view on the stock market.

In this study, we document a robust and economically significant negative predictability of pre-FOMC-meeting returns for future returns in support of this argument. Specifically, we find that the average stock market return on the day before recent FOMC meetings in the past two years strongly and negatively predicts stock market returns up to two years into the future. These results are consistent across varying window lengths and become even more pronounced when greater weight is assigned to more recent meetings or when we focus on the intraday component of the return. Furthermore, we find that this predictability extends to a wider set of macroeconomic announcements, such as nonfarm payroll and CPI announcements.

We also observe that aggregate informed trading intensity on the day before the meeting tends to be the lowest. It reflects investors' strategic response to reduce the risks of trading against other investors who may possess private information about the upcoming FOMC announcement. At the same time, the VIX index spikes on the day before the FOMC meeting. By hedging on the day before the FOMC meeting, the hedgers minimize the risk of trading against informed investors, but have to pay a higher liquidity cost. The higher liquidity cost makes it easier to detect the hedging-induced price pressure. The average stock market return on the day before recent FOMC meetings is almost completely reversed by the end of the next trading day.

Finally, we find that high-beta stocks, which typically require more aggressive hedging, exhibit a stronger negative predictability of future returns. Similarly, this return predictability is more pronounced for illiquid stocks, where the price pressure is easier to detect.

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Appendix A: Variable Definitions

This appendix describes the calculation of variables used in the core analyses. m indexes month, i indexes the trading day relative to the FOMC meeting day, and t indexes the trading day.

Variable	**Definition**
Monthly Observations	
$Return_{[m+1,m+24]}$	The the compounded stock market returns over the future 24 months, from month $m+1$ to month $m+24$.
Average Past Day (i) Return$_{[m-23,m]}$	The simple average of stock market returns on FOMC Day (i) over the past 24 months in percentage, from month $m-23$ to month m.
Average Past Day (-1) *Dgs10*$_{[m-23,m]}$	The simple average of daily changes of 10-year U.S. Treasury Securities market yield (DGS10) on FOMC Day (i) over the past 24 months, from month $m-23$ to month m.
$FOMC[0,3]$	The cumulative aggregate returns of days $[0,3]$ around the most recent FOMC meeting, following Boguth et al. (2023).
dp_m	Dividend price ratio at month m.
dy_m	Dividend yield at month m.
ep_m	Earning price ratio at month m.
$svar_m$	Stock volatility at month m.
bm_m	Book-to-market at month m.
$ntis_m$	Net equity issuing activity at month m.
tbl_m	Treasury-bill rate at month m.
lty_m	The long-term yield at month m.
ltr_m	The long-term bond rate of return at month m.
dfy_m	The default yield at month m.
dfr_m	The default rate of return at month m.
$infl_m$	The inflation rate at month m.
Daily Observations	
ITI(13D)$_t$	Informed trading intensity trained on Schedule 13D data at day t.
ITI(Patient)$_t$	Informed trading intensity trained on the first 40 days of the 60-day Schedule 13D filing window at day t.
ITI(Impatient)$_t$	Informed trading intensity trained on the last 20 days of the 60-day Schedule 13D filing window at day t.
ITI(Insider)$_t$	Informed trading intensity trained on opportunistic insider trading data at day t.
ITI(Short)$_t$	Informed trading intensity trained on short selling data at day t.
VIX_{t-1}	The closing value of VIX index at day $t-1$.
ΔVIX_t	The daily change of VIX index on day t relative to the previous trading day.
$\%\Delta VIX_t$	The daily percentage change of VIX index on day t relative to the previous trading day.
Day (i)	An indicator that equals one if day t falls on FOMC Day (i).

Figure 1: Pre-FOMC-Meeting Return and Next Two-Year Return

This figure plots the pre-FOMC-meeting stock market return and the next two-year stock market return over time from 1996 to 2021, respectively. The x-axis indicates the year-month. Pre-FOMC-meeting (*Average Past Day* (-1) *Return*$_{[m-23,m]}$) is calculated as the simple average of daily SPY return on FOMC Day (-1) over the previous 24 months in percentage. The next two-year return (*Return*$_{[m+1,m+24]}$) is calculated as the compounded monthly SPY returns over the future 24 months. The blue line indicates *Average Past Day* (-1) *Return*$_{[m-23,m]}$ and the red line indicates *Return*$_{[m+1,m+24]}$.

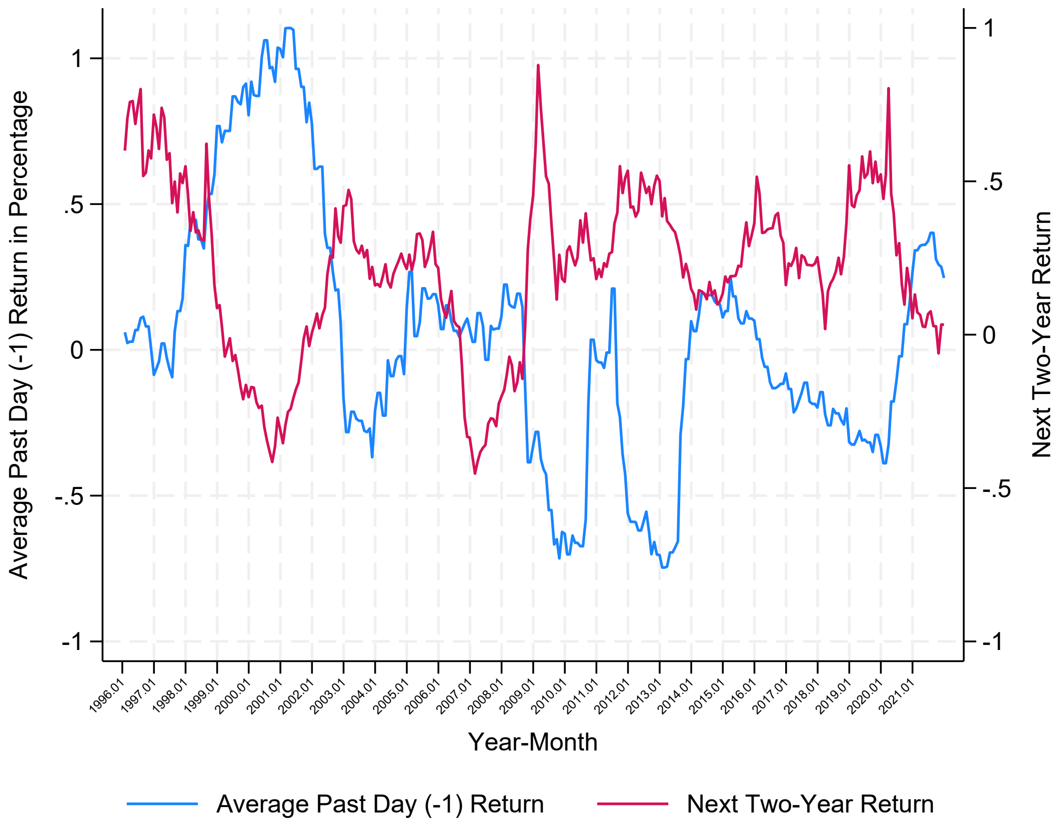
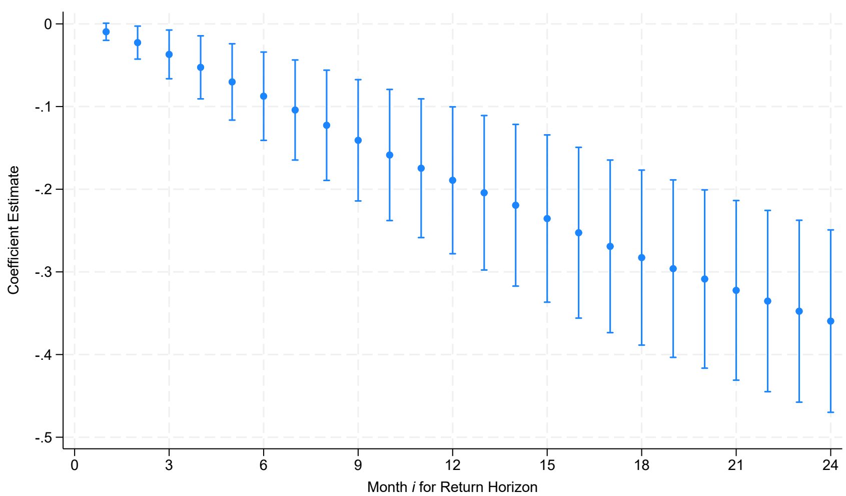


Figure 2: Prediction over Expanding Time Horizons

Panel A plots the coefficient estimates along with 95% confidence intervals from the regressions of future return ($Return_{[m+1,m+i]}$) on pre-FOMC-meeting return ($Average\ Past\ Day\ (-1)\ Return_{[m-23,m]}$) for expanding windows starting from month $m+1$. Panel B plots the coefficient estimates along with 95% confidence intervals from the regressions of future return ($Return_{[m+1,m+i]}$) on pre-FOMC-meeting return ($Average\ Past\ Day\ (-1)\ Return_{[m-23,m]}$) and additional controls for expanding windows starting from month $m+1$. Controls include the contemporaneous change in the 10-year Treasurey yield, the actual FOMC announcement window return, and the set of predictors in Welch and Goyal (2008). The x-axis indicates month i for the future return horizon $[m+1, m+i]$. $Return_{[m+1,m+i]}$ is calcualted as the compounded monthly SPY returns from month $m+1$ to month $m+i$. Standard errors are adjusted using Newey-West corrections with 23 lags.

Panel A: Univariate Analyses



Panel B: Multivariate Analyses

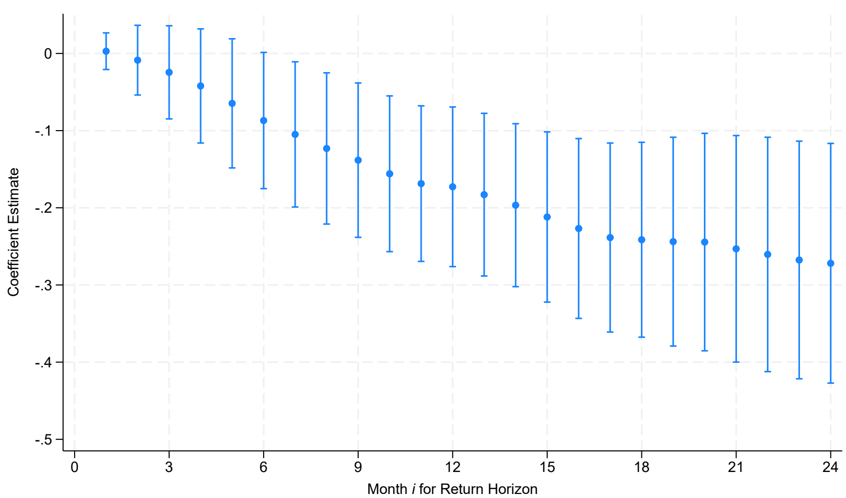
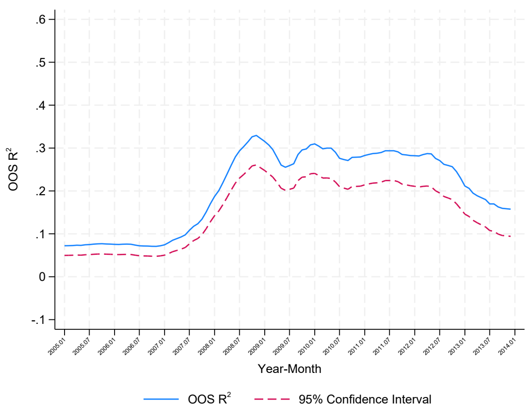


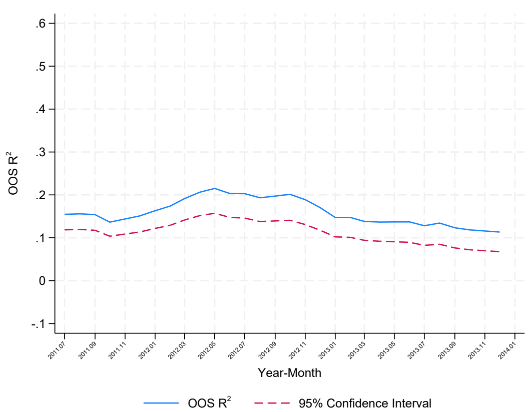
Figure 3: Out-of-Sample R^2 for Predicting Next One-Year Return

This figure plots the out-of-sample R^2 (OOS R^2) of the pre-FOMC-meeting stock market returns in predicting the next one-year returns. Panel A reports the results of the univariate analyses. Panel B reports the results of the univariate analyses while excluding the crisis period (January 2006 through June 2011). Panel C reports the results of the multivariate analyses using a simple equally-weighted average of univariate regression forecasts, following Rapach et al. (2010). In each panel, the x-axis indicates the forecast beginning date. The blue solid line represents the OOS R^2 following the methodology in Campbell and Thompson (2008). The red dashed line represents the 95% confidence interval derived from the Clark and West (2007) MSFE-adjusted statistic.

Panel A: Univariate Analyses



Panel B: Univariate Analyses Excluding Crisis Period



Panel C: Multivariate Analyses

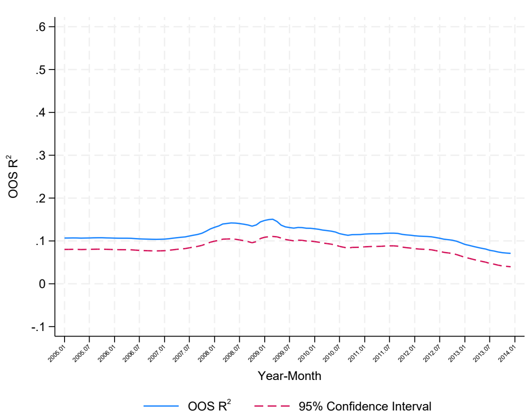
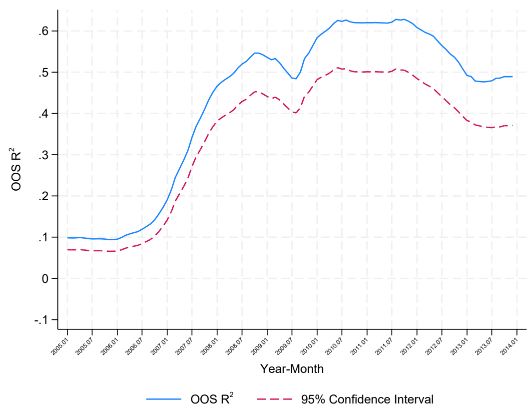


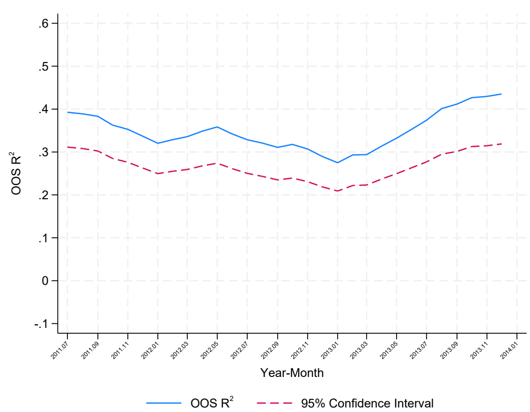
Figure 4: Out-of-Sample R^2 for Predicting Next Two-Year Return

This figure plots the out-of-sample R^2 (OOS R^2) of the pre-FOMC-meeting stock market returns in predicting the next two-year returns. Panel A reports the results of the univariate analyses. Panel B reports the results of the univariate analyses while excluding the crisis period (January 2006 through June 2011). Panel C reports the results of the multivariate analyses using a simple equally-weighted average of univariate regression forecasts, following Rapach et al. (2010). In each panel, the x-axis indicates the forecast beginning date. The blue solid line represents the OOS R^2 following the methodology in Campbell and Thompson (2008). The red dashed line represents the 95% confidence interval derived from the Clark and West (2007) MSFE-adjusted statistic.

Panel A: Univariate Analyses



Panel B: Univariate Analyses Excluding Crisis Period



Panel C: Multivariate Analyses

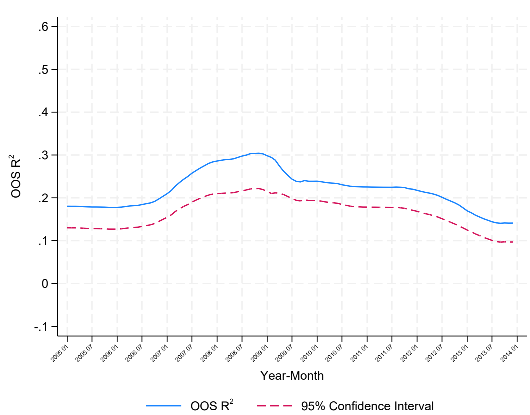


Figure 5: Google Search Volume Index of Macroeconomic Events

This figure plots the monthly Google search volume index of different macroeconomic events from 2004 to 2021. These events include FOMC meetings, Nonfarm payroll announcements, CPI announcements, PPI announcements, and ISM Manufacturing data (PMI) announcements.

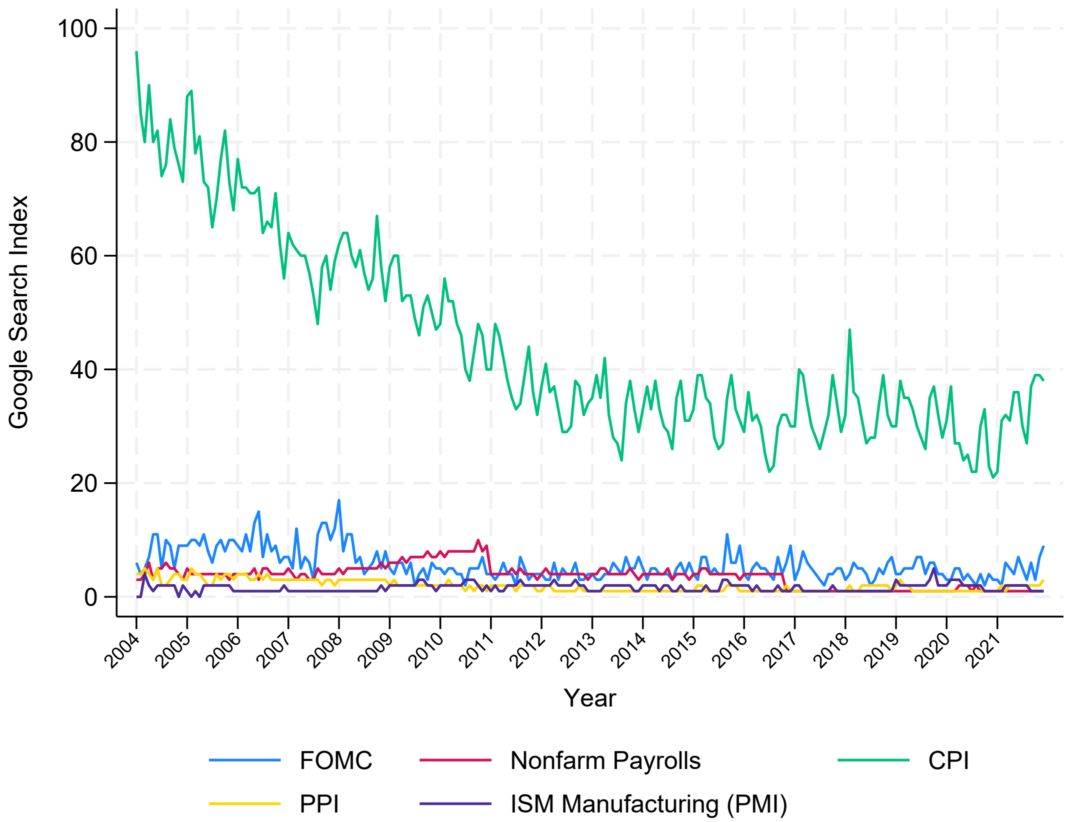


Figure 6: Intraday Cumulative Return Around FOMC Day

This figure plots the cumulative intraday SPY return around the FOMC meeting day sorting on the average pre-FOMC-meeting return. We set the event period to start from one trading day before FOMC meeting day and end on the first FOMC meeting day. For each time point t on the x-axis, the cumulative return is calculated as the intraday return compounded over the window [*9:30am* on FOMC Day (-1), t], and then averaged over the past 24 months. The blue solid line represents the group with pre-FOMC-meeting return (*Average Past Day (−1) Return*$_{[m-23,m]}$) below the first quartile (Q1) and the red solid line represents the group with average pre-FOMC-meeting return above the last quartile (Q4).

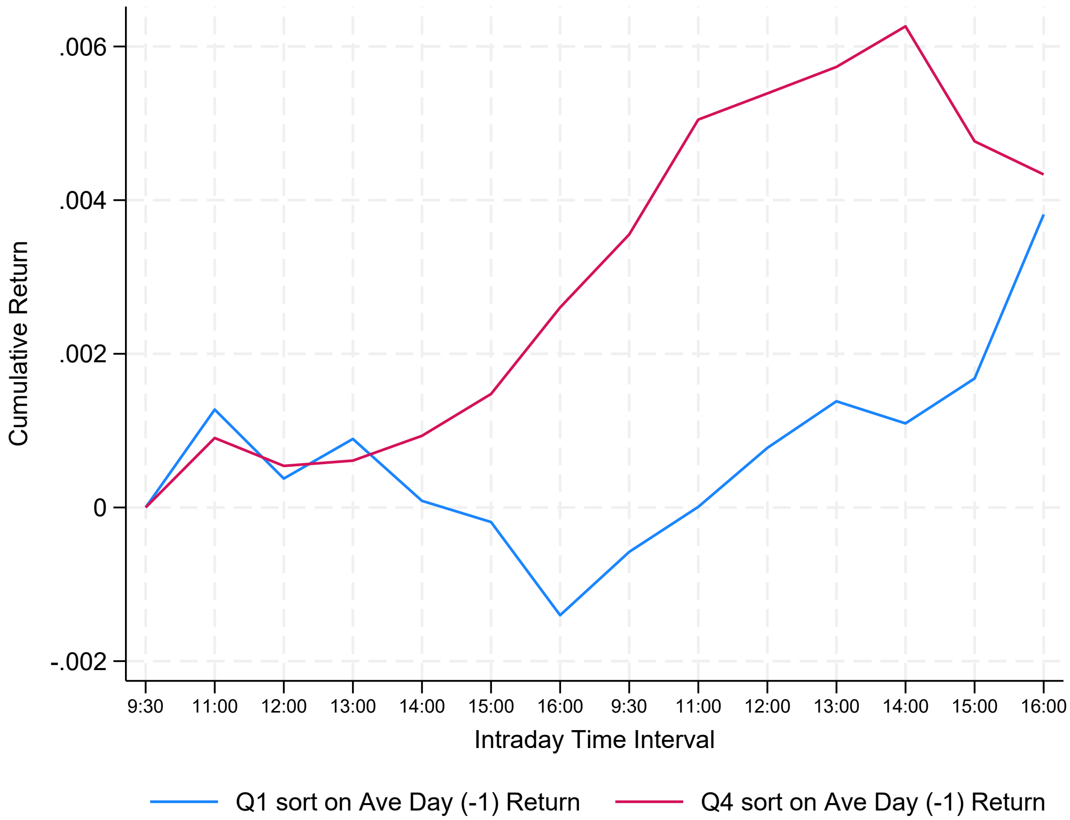


Table 1: Summary Statistics

This table reports summary statistics of the main variables used in the regression analyses, including the number of observations (Obs), mean, standard deviation (SD), 25th percentile (P25), median (P50), and 75th percentile (P75) for all continuous variables. Panel A reports the monthly observations used in baseline analyses from 1996 to 2021. Panel B reports the monthly observations with other specifications from 1996 to 2021. Panel C reports the daily observations from 1994 to 2023. Detailed variable definitions are in Appendix A.

Panel A: Monthly Observations

Variable	Obs	Mean	SD	P25	P50	P75
$Return_{[m+1,m+24]}$	312	0.214	0.268	0.068	0.232	0.396
Average Past Day (-1) $Return_{[m-23,m]}$	312	0.048	0.433	-0.223	0.037	0.210
Average Past Day (0) $Return_{[m-23,m]}$	312	0.248	0.322	0.070	0.195	0.316
Average Past Day (1) $Return_{[m-23,m]}$	312	-0.042	0.324	-0.223	-0.027	0.139
Average Past Day (2) $Return_{[m-23,m]}$	312	-0.036	0.249	-0.197	0.004	0.105
Average Past Day (3) $Return_{[m-23,m]}$	312	0.105	0.394	-0.163	0.029	0.265
Average Past Day (-2) $Return_{[m-23,m]}$	312	-0.061	0.303	-0.283	-0.029	0.179
Average Past Day (-3) $Return_{[m-23,m]}$	312	0.124	0.270	-0.093	0.115	0.319
Average Past Day (-1) $Dgs10_{[m-23,m]}$	312	-0.000	0.014	-0.005	0.000	0.009
$FOMC[0,3]$	312	0.002	0.020	-0.008	0.002	0.014
dp_m	312	0.018	0.004	0.016	0.019	0.020
dy_m	312	0.018	0.004	0.016	0.019	0.020
ep_m	312	0.044	0.012	0.036	0.044	0.053
$svar_m$	312	0.003	0.006	0.001	0.002	0.003
bm_m	312	0.267	0.072	0.218	0.270	0.325
$ntis_m$	312	0.000	0.019	-0.013	0.005	0.015
tbl_m	312	0.020	0.020	0.001	0.013	0.044
lty_m	312	0.041	0.017	0.027	0.043	0.054
ltr_m	312	0.006	0.030	-0.014	0.005	0.024
dfy_m	312	0.010	0.004	0.007	0.009	0.011
dfy_m	312	0.000	0.018	-0.007	0.001	0.008
$infl_m$	312	0.002	0.004	0.000	0.002	0.004

Panel B: Monthly Observations with Other Specifications

Variable	Obs	Mean	SD	P25	P50	P75
CRSP Value-Weighted Market Returns (1996 – 2021)						
$Return_{[m+1,m+24]}$	312	0.206	0.261	0.065	0.231	0.383
Average Past Day (-1) $Return_{[m-23,m]}$	312	-0.003	0.403	-0.262	0.012	0.213
CRSP Value-Weighted Market Returns (1964 – 1981)						
$Return_{[m+1,m+24]}$	216	0.183	0.233	0.042	0.173	0.334
Average Past Day (-1) $Return_{[m-23,m]}$	216	-0.148	0.186	-0.265	-0.139	-0.013
CRSP Value-Weighted Market Returns (1982 – 2021)						
$Return_{[m+1,m+24]}$	480	0.256	0.246	0.131	0.259	0.429
Average Past Day (-1) $Return_{[m-23,m]}$	480	0.042	0.347	-0.143	0.061	0.214
SPY Intraday Returns						
Average Past Day (-1) $Return_{[m-23,m]}$	312	0.052	0.229	-0.107	0.020	0.166
SPY Overnight Returns						
Average Past Day (-1) $Return_{[m-23,m]}$	312	-0.004	0.267	-0.130	0.036	0.165
Increasing Weights						
Average Past Day (-1) $Return_{[m-23,m]}$	312	0.049	0.473	-0.224	0.049	0.232
Decreasing Weights						
Average Past Day (-1) $Return_{[m-23,m]}$	312	0.047	0.469	-0.197	0.035	0.220

Table 1: Summary Statistics – Cont'd

Panel B - Cont'd						
Variable	Obs	Mean	SD	P25	P50	P75
Non-FOMC Days						
$Return_{[m+1,m+24]}$	312	0.159	0.281	0.003	0.193	0.373
FOMC Days						
$Return_{[m+1,m+24]}$	312	0.061	0.116	-0.008	0.051	0.130
Odd Weeks						
$Return_{[m+1,m+24]}$	312	0.010	0.221	-0.148	0.011	0.169
Even Weeks						
$Return_{[m+1,m+24]}$	312	0.207	0.233	0.054	0.176	0.362
Nonfarm Payroll + CPI (1999 – 2021)						
Average Past Day (-1) $Return_{[m-23,m]}$	276	-0.004	0.213	-0.053	0.056	0.129
High-Beta Portfolio Returns						
$Return_{[m+1,m+24]}$	312	0.241	0.377	0.027	0.233	0.472
Average Past Day (-1) $Return_{[m-23,m]}$	312	-0.107	0.664	-0.420	-0.176	0.290
Low-Beta Portfolio Returns						
$Return_{[m+1,m+24]}$	312	0.209	0.250	0.040	0.229	0.349
Average Past Day (-1) $Return_{[m-23,m]}$	312	0.102	0.323	-0.093	0.067	0.240
High-Liquidity Portfolio Returns						
$Return_{[m+1,m+24]}$	312	0.217	0.256	0.083	0.237	0.380
Average Past Day (-1) $Return_{[m-23,m]}$	312	-0.023	0.390	-0.261	-0.006	0.205
Low-Liquidity Portfolio Returns						
$Return_{[m+1,m+24]}$	312	0.197	0.306	-0.000	0.237	0.406
Average Past Day (-1) $Return_{[m-23,m]}$	312	-0.154	0.310	-0.301	-0.104	0.003

Panel C: Daily Observations

Variable	Obs	Mean	SD	P25	P50	P75
$ITI(13D)_t$	6,473	0.292	0.049	0.263	0.290	0.318
$ITI(Patient)_t$	6,473	0.210	0.036	0.189	0.209	0.231
$ITI(Impatient)_t$	6,473	0.434	0.055	0.398	0.432	0.466
$ITI(Insider)_t$	6,473	0.436	0.043	0.413	0.438	0.463
$ITI(Short)_t$	6,473	0.419	0.032	0.401	0.419	0.438
VIX_{t-1}	6,473	19.472	8.050	13.580	17.620	22.960
ΔVIX_t	7,548	0.000	1.694	-0.700	-0.070	0.580
$\%\Delta VIX_t$	7,548	-0.002	0.066	-0.040	-0.004	0.033

Table 2: Baseline Analyses: SPY Return

This table reports results from the ordinary least squares (OLS) regressions of the future two-year market returns on pre-FOMC-meeting returns for FOMC Day (i), $i \in [-3, +3]$, over the past 24 months from 1996 to 2021. *Average Past Day (i) Return*$_{[m-23,m]}$ is the simple average daily of SPY returns on FOMC Day (i) over the past 24 months in percentage, from month $m-23$ to month m. *Return*$_{[m+1,m+24]}$ is the compounded SPY monthly returns for the next 24 months, from month $m+1$ to month $m+24$. Panel A reports the univariate analyses and Panel B reports the multivariate analyses. Controls include *Average Past Day* (-1) *Dgs10*$_{[m-23,m]}$, the simple average of daily changes of 10-year U.S. Treasury Securities market yield on FOMC Day (-1) over the past 24 months, *FOMC*$[0,3]$, the cumulative daily SPY returns during days $[0,3]$ around the most recent FOMC meeting, and a set of macroeconomic indicators in Welch and Goyal (2008) measured at month m. For robustness check, we further control for a more comprehensive set of variables in Goyal et al. (2024) with no missing value in the sample period. Detailed variable definitions are in Appendix A. Standard errors are adjusted using Newey-West corrections with 23 lags. t statistics are in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Univariate Analyses

	Return$_{[m+1,m+24]}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	i=−3	i=−2	i=−1	i=0	i=1	i=2	i=3
Average Past Day (i) *Return*$_{[m-23,m]}$	-0.166	0.133	-0.360***	0.032	-0.151	0.063	0.023
	(-0.85)	(0.77)	(-6.39)	(0.33)	(-1.27)	(0.44)	(0.26)
Observations	312	312	312	312	312	312	312
Adjusted R^2	0.025	0.019	0.336	-0.002	0.030	0.000	-0.002

Table 2: Baseline Analyses: SPY Return – Cont'd

Panel B: Multivariate Analyses

	$Return_{[m+1,m+24]}$		
	(1)	(2)	(3)
Average Past Day (-1) Return$_{[m-23,m]}$	-0.373***	-0.274***	-0.268***
	(-5.50)	(-3.44)	(-5.35)
Average Past Day (-1) Dgs10$_{[m-23,m]}$	0.814	2.006	1.799
	(0.56)	(1.00)	(1.03)
$FOMC[0,3]$	-0.464	-0.668	-0.439
	(-0.97)	(-1.53)	(-1.32)
dp_m		54.532***	33.315**
		(5.30)	(2.58)
dy_m		17.700	7.893
		(1.57)	(0.66)
ep_m		2.305	5.699
		(0.82)	(0.85)
$svar_m$		0.890	-5.022
		(0.47)	(-0.83)
bm_m		-2.197***	-0.569
		(-3.97)	(-0.99)
$ntis_m$		9.525***	2.529
		(6.09)	(1.62)
tbl_m		0.689	-1.899
		(0.24)	(-0.75)
lty_m		-4.040**	5.534
		(-2.26)	(1.57)
ltr_m		-0.035	0.282*
		(-0.15)	(1.66)
dfy_m		1.284	-9.503
		(0.13)	(-0.99)
dfr_m		-0.130	0.324
		(-0.38)	(0.84)
$infl_m$		-0.505	2.376
		(-0.15)	(0.96)
Additional Controls in Goyal et al. (2024)	No	No	Yes
Observations	312	312	312
Adjusted R^2	0.335	0.662	0.796

Table 3: Baseline Analyses: CRSP Value-Weighted Market Return

This table reports results from the OLS regressions of the future two-year market returns on average pre-FOMC-meeting returns over the past 24 months using CRSP value-weighted market return. Columns (1) and (2) use the same sample period as in Table 2. Columns (3) and (4) use the sample period from 1964 to 1981, before S&P 500 futures contracts were introduced. Columns (5) and (6) use the sample period from 1982 to 2021, after S&P 500 futures contracts were introduced. *Average Past Day* (-1) $Return_{[m-23,m]}$ is the simple average of returns on FOMC Day (-1) over the past 24 months in percentage, from month $m-23$ to month m. $Return[m+1, m+24]$ is the compounded aggregate market returns of future 24 months, from month $m+1$ to month $m+24$. Controls include *Average Past Day* (-1) $Dgs10_{[m-23,m]}$, the simple average of daily changes of 10-year U.S. Treasury Securities market yield FOMC Day (-1) over the past 24 months, $FOMC[0,3]$, the cumulative aggregate market returns during days $[0,3]$ around the most recent FOMC meeting, and a set of macroeconomic indicators in Welch and Goyal (2008) measured at month m. Detailed variable definitions are in Appendix A. Standard errors are adjusted using Newey-West corrections with 23 lags. t statistics are in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	$Return_{[m+1,m+24]}$					
	(1)	(2)	(3)	(4)	(5)	(6)
	1996 – 2021		1964 – 1981		1982 – 2021	
Average Past Day (-1) $Return_{[m-23,m]}$	-0.388***	-0.387***	-0.004	-0.297	-0.313***	-0.320***
	(-5.36)	(-4.19)	(-0.02)	(-1.60)	(-3.29)	(-4.00)
Controls	No	Yes	No	Yes	No	Yes
Observations	312	312	216	216	480	480
Adjusted R^2	0.355	0.655	-0.005	0.781	0.192	0.479

Table 4: Alternative Specifications

This table reports results from the OLS regressions of the future two-year market returns on pre-FOMC-meeting returns for FOMC Day (-1) over the past 24 months, from 1996 to 2021, with alternative specifications. Panel A reports the results of independent variables with alternative specifications. Panel B reports the results of dependent variables with alternative specifications. In Panel A, *Average Past Day (-1) Return*$_{[m-23,m]}$ is the simple average of intraday SPY returns on FOMC Day (-1) over the past 24 months (in percentage) in columns (1) and (2); the average of overnight SPY returns (in percentage) in columns (3) and (4); the average of daily SPY returns with linearly increasing weights (in percentage) in columns (5) and (6); and the average of daily SPY returns with linearly decreasing weights (in percentage) in columns (7) and (8). *Return*$_{[m+1,m+24]}$ is the compounded SPY monthly returns for the next 24 months, from month $m+1$ to month $m+24$. In Panel B, *Return*$_{[m+1,m+24]}$ is the compounded SPY daily returns on non-FOMC days for the next 24 months in columns (1) and (2); *Return*$_{[m+1,m+24]}$ is the compounded SPY daily returns on FOMC days for the next 24 months in columns (3) and (4); *Return*$_{[m+1,m+24]}$ is the compounded SPY daily returns during odd weeks for the next 24 months in columns (5) and (6); *Return*$_{[m+1,m+24]}$ is the compounded SPY daily returns during even weeks for the next 24 months in columns (7) and (8). Controls include *Average Past Day (-1) Dgs10*$_{[m-23,m]}$, the simple average of daily changes of 10-year U.S. Treasury Securities market yield on FOMC Day (i) over the past 24 months, $FOMC[0,3]$, the cumulative daily SPY returns during days $[0,3]$ around the most recent FOMC meeting, and a set of macroeconomic indicators in Welch and Goyal (2008) measured at month m. Detailed variable definitions are in Appendix A. Standard errors are adjusted using Newey-West corrections with 23 lags. t statistics are in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Independent Variables with Alternative Specifications

	Return$_{[m+1,m+24]}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Intraday Return		Overnight Return		Increasing Weights		Decreasing Weights	
Average Past Day (-1) Return$_{[m-23,m]}$	-0.721***	-0.589***	-0.420***	-0.168	-0.333***	-0.243***	-0.275***	-0.133*
	(-7.64)	(-5.12)	(-2.79)	(-1.34)	(-5.73)	(-3.92)	(-3.88)	(-1.82)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	312	312	312	312	312	312	312	312
Adjusted R^2	0.376	0.695	0.172	0.614	0.343	0.665	0.230	0.628

Panel B: Dependent Variables with Alternative Specifications

	Return$_{[m+1,m+24]}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Non-FOMC Days		FOMC Days		Odd Weeks		Even Weeks	
Average Past Day (-1) Return$_{[m-23,m]}$	-0.439***	-0.257**	0.084*	-0.004	-0.272***	-0.339***	-0.036	0.161
	(-10.19)	(-2.20)	(1.70)	(-0.06)	(-4.20)	(-2.74)	(-0.33)	(1.22)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	312	312	312	312	312	312	312	312
Adjusted R^2	0.457	0.666	0.097	0.494	0.283	0.467	0.001	0.537

Table 5: Other Macroeconomic Events

This table reports results from the analyses of other macroeconomic events. These macroeconomic events include nonfarm payroll announcement, CPI announcement, PPI announcement, and ISM Manufacturing data (PMI) announcement, in additional to FOMC meeting. Panel A presents the sum of the scaled daily return square during the announcement window $[-1, +1]$, which is calculated as the sum of the daily return square during the event window divided by the average daily return square over the past year. Panel B presents the baseline analyses for FOMC meeting and nonfarm payroll + CPI announcements from 1999 to 2021. *Average Past Day (-1) Return*$_{[m-23,m]}$ is the simple average of daily SPY returns on Event Day (-1) over the past 24 months. For nonfarm payroll and CPI announcements, we define Day (-1) for these two events if the next day has either nonfarm payroll or CPI announcement, and does not coincide with nonfarm payroll, CPI announcement, and FOMC Day (-1). Controls include *Average Past Day* (-1) *Dgs10*$_{[m-23,m]}$, the simple average of daily changes of 10-year U.S. Treasury Securities market yield on Event Day (-1) over the past 24 months, $FOMC[0, 3]$, the cumulative daily SPY returns during days $[0, 3]$ around the most recent FOMC meeting, and a set of macroeconomic indicators in Welch and Goyal (2008) and Goyal et al. (2024) measured at month m. Detailed variable definitions are in Appendix A. Standard errors are adjusted using Newey-West corrections with 23 lags. t statistics are in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Sum of Return Square during Announcement Window [-1,+1]

	SPY Return			CRSP VW Return		
	Obs	mean	Std	Obs	mean	Std
FOMC	215	3.78	6.77	215	3.75	6.50
Nonfarm Payrolls	317	3.71	7.75	317	3.71	7.63
CPI	321	3.61	6.55	321	3.70	6.80
PPI	311	3.33	6.95	311	3.44	7.51
ISM	324	3.33	4.36	324	3.37	4.50

Panel B: Repeat Baseline Analyses (Monthly Sample Period: 1999 – 2021)

	Return$_{[m+1,m+24]}$					
	(1)	(2)	(3)	(4)	(5)	(6)
		FOMC			Nonfarm Payrolls + CPI	
Average Past Day (-1) Return$_{[m-23,m]}$	-0.390***	-0.285***	-0.273***	-0.472***	-0.321*	-0.162**
	(-10.53)	(-3.47)	(-5.66)	(-2.63)	(-1.76)	(-1.99)
Controls	No	Yes	Yes	No	Yes	Yes
Goyal et al. (2024) Controls	No	No	Yes	No	No	Yes
Observations	276	276	276	276	276	276
Adjusted R^2	0.489	0.718	0.847	0.158	0.657	0.810

Table 6: Informed Trading Intensity around FOMC Days $[-3, +3]$

This table reports results from the OLS regressions of aggregate informed trading intensity (*ITI*) on FOMC Day indicators $[-3, +3]$. We use the firm-day level *ITI* from Bogousslavsky et al. (2024) and then calculate the daily aggregate weighted-average *ITI* using market value of each stock at the previous close among S&P500 firms. Column (1) uses $ITI(13D)_t$, *ITI* trained on Schedule 13D data at day t. Column (2) uses $ITI(Patient)_t$, *ITI* trained on the first 40 days of the 60-day Schedule 13D filing window at day t. Column (3) uses $ITI(Impatient)_t$, *ITI* trained on the last 20 days of the 60-day Schedule 13D filing window at day t. Column (4) uses $ITI(Insider)_t$, *ITI* trained on opportunistic insider trading data at day t. Column (5) uses $ITI(Short)_t$, *ITI* trained on short selling data at day t. *Day* (i) is an indicator that equals one if day t falls on FOMC Day (i). Control variable is VIX_{t-1}, the closing value of VIX index at day $t-1$. Detailed variable definitions are in Appendix A. Standard errors are adjusted using Newey-West corrections with 30 lags. t statistics are in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	ITI(13D)	*ITI(Patient)*	*ITI(Impatient)*	*ITI(Insider)*	*ITI(Short)*
	(1)	(2)	(3)	(4)	(5)
Day (-3)	0.006***	0.004**	0.009***	0.004*	0.006***
	(2.87)	(2.39)	(3.45)	(1.91)	(3.87)
Day (-2)	0.010***	0.007***	0.017***	-0.005**	0.013***
	(3.25)	(3.39)	(4.16)	(-2.13)	(5.13)
Day (-1)	-0.007***	-0.005***	-0.009***	-0.000	-0.006***
	(-2.73)	(-2.67)	(-3.24)	(-0.17)	(-3.82)
Day (0)	0.020***	0.014***	0.017***	0.005***	0.007***
	(8.68)	(7.41)	(6.18)	(2.64)	(5.34)
Day (1)	0.019***	0.012***	0.020***	0.006***	0.008***
	(5.82)	(5.35)	(6.50)	(2.67)	(5.58)
Day (2)	0.020***	0.008***	0.028***	-0.007**	0.014***
	(5.39)	(3.41)	(6.18)	(-2.29)	(5.05)
Day (3)	-0.004	-0.004*	-0.001	0.001	0.002
	(-1.41)	(-1.92)	(-0.28)	(0.31)	(0.93)
VIX_{t-1}	0.001***	0.001***	0.002***	-0.000**	0.001***
	(6.38)	(5.61)	(7.59)	(-2.57)	(3.05)
Observations	6,473	6,473	6,473	6,473	6,473
Adjusted R^2	0.076	0.058	0.073	0.009	0.047

Table 7: Changes of VIX around FOMC Days $[-3, +3]$

This table reports results from the OLS regressions of changes of VIX on FOMC Day indicators $[-3, +3]$. Column (1) reports the results of level change of VIX index and Column (2) reports the results of the percentage change of VIX index. ΔVIX_t is the daily change of VIX index on day t relative to the previous trading day. $\%\Delta VIX_t$ is the daily percentage change of VIX index on day t relative to the previous trading day. *Day (i)* is an indicator that equals one if day t falls on FOMC Day (i). Detailed variable definitions are in Appendix A. Standard errors are adjusted using Newey-West corrections with 30 lags. t statistics are in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	ΔVIX	$\%\Delta VIX$
	(1)	(2)
Day (-3)	-0.141	-0.005
	(-1.61)	(-1.22)
Day (-2)	0.033	-0.002
	(0.33)	(-0.38)
Day (-1)	0.485***	0.025***
	(4.50)	(5.96)
Day (0)	-0.404***	-0.018***
	(-4.27)	(-4.77)
Day (1)	0.079	0.000
	(0.60)	(0.02)
Day (2)	-0.123	-0.005
	(-1.36)	(-1.14)
Day (3)	0.119	0.007
	(0.91)	(1.47)
Observations	7,548	7,548
Adjusted R^2	0.005	0.008

Table 8: Cross-Sectional Analyses

This table reports the cross-sectional analyses of the OLS regression results of the future two-year portfolio returns on average pre-FOMC-meeting returns for FOMC Day (-1) portfolio returns over the past two years from 1996 to 2021. Columns (1) and (2) explore the cross-sectional cuts on beta and columns (3) and (4) explore the cross-sectional cuts on liquidity (Amihud (2002) measure). Column (1) uses high-beta portfolio returns. Column (2) uses low-beta portfolio returns. Column (3) uses high-liquidity portfolio returns. Column (4) uses low-liquidity portfolio returns. *Average Past Day (-1) Return*$_{[m-23,m]}$ is the simple average of daily portfolio returns on FOMC Day (-1)) over the past 24 months, from month $m-23$ to month m. *Return*$[m+1, m+24]$ is the compounded daily portfolio returns of future 24 months, from month $m+1$ to month $m+24$. Controls include *Average Past Day* (-1) *Dgs10*$_{[m-23,m]}$, the average daily changes of 10-year U.S. Treasury Securities market yield on FOMC Day (-1) over the past 24 months, *FOMC*$[0,3]$, the cumulative daily SPY returns during days $[0,3]$ around the most recent FOMC meeting, and a set of macroeconomic indicators in Welch and Goyal (2008) measured at month m. Detailed variable definitions are in Appendix A. Standard errors are adjusted using Newey-West corrections with 23 lags. t statistics are in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Return$_{[m+1,m+24]}$			
	(1)	(2)	(3)	(4)
	High-Beta	Low-Beta	High-Liquidity	Low-Liquidity
Average Past Day (-1) Return$_{[m-23,m]}$	-0.290***	-0.165*	-0.345***	-0.670***
	(-3.15)	(-1.72)	(-4.06)	(-6.10)
Controls	Yes	Yes	Yes	Yes
t-stat of difference	-2.21		5.77	
Observations	312	312	312	312
Adjusted R^2	0.559	0.493	0.665	0.583