Noisy FOMC Returns? Information, Price Pressure, and Post-Announcement Reversals

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ABSTRACT

Extending methods from microstructure studies, we show that stock-market prices following FOMC announcements appear "noisy". Standard predictive regressions confirm significant reversal of event-window returns by announcement-cycle end. Consistent with theories of announcement information and price pressure, we find that reversal predictors include VIX changes, abnormal volume, and ETF flows. We further document surging post-announcement trade volume, pinpoint intra-cycle return predictability, and show sustained effects of monetary policy surprises on post-event price dynamics. FOMC announcements inform markets but also trigger intense liquidity demands that impact prices, highlighting the importance of connecting public information to price pressure in future theories.

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1. Introduction

Policy announcements of the Federal Open Market Committee are key dates in the calendar of financial news. These events move the stock market (Bernanke and Kuttner, 2005), earn large risk premia and reduce uncertainty (Savor and Wilson, 2013, Lucca and Moench, 2015), can convey information about economic conditions and policy (Nakamura and Steinsson, 2018, Bauer and Swanson, 2023a), and significantly raise both investor and media attention (Ben-Rephael, Carlin, Da, and Israelsen, 2021, Fisher, Martineau, and Sheng, 2022).[1] In leading theories of announcement risk premia such as Ai and Bansal (2018), information plays the lead role and prices are always efficient.

At the same time, sudden demand for trade can move prices beyond their efficient values when intermediaries must be compensated for providing immediacy, as in theories of "price pressure" (Grossman and Miller, 1988, Campbell, Grossman, and Wang, 1993, Hendershott and Menkveld, 2014). To distinguish efficient price movements from noise, the microstructure literature uses "unbiasedness" regressions (Biais, Hillion, and Spatt, 1999, Van Kervel and Menkveld, 2019), based on the idea that fundamental price movements permanently impact prices while noise mean reverts.[2]

We apply unbiasedness regressions to Federal Open Market Committee (FOMC) announcements and find new evidence of sustained price pressure. Compared to other days, returns following FOMC announcements have abnormally low predictive power for future market prices, and tend to reverse. Figure 1 shows this using the unbiasedness regression methodology. We plot sequences of univariate regression R^2 where the left-hand-side is always the cumulative logarithmic return in windows beginning ten trading days before announcements to thirty days after. The univariate regressors on the right-hand-side are

[1] See also Cieslak, Morse, and Vissing-Jorgensen (2019), Brusa, Savor, and Wilson (2020), Boguth, Grégoire, and Martineau (2019), Ai, Bansal, and Han (2022), and Andrei, Cujean, and Wilson (2023).

[2] Additional applications of unbiasedness regressions include Barclay and Hendershott (2003) and Akey, Grégoire, and Martineau (2022). Related logic motivates high-frequency studies of microstructure noise (e.g., Jacod, Li, and Zheng, 2017, Li and Linton, 2022).

cumulative returns in expanding windows, beginning ten days before announcement, and ending at day $-10 < t < 29$ relative to announcement. With this procedure, a natural benchmark is a linear increase in R^2, starting at zero and ending at one, shown by the red dotted line. If an event-day return reflects increased information flow, the unbiasedness-regression R^2 should jump upward, illustrated by the green solid-dotted line created from a sample of earnings announcements. FOMC announcements (solid blue line, S&P 500 index returns) are different. The event date and days immediately following have low explanatory power for total-window returns.

We use predictive regressions to quantify the reversals in subsequent windows. Returns from the FOMC announcement to three days after strongly predict reversals over intervals ranging from four to thirty subsequent trading days ($p < .01$, $R^2 \approx 7\%$). By point estimate, 60% of market returns in a four-day window beginning on the announcement date are reversed before the next announcement in the FOMC cycle.

We draw on theories of i) announcement-day information and ii) price pressure to illuminate the mechanisms driving post-announcement return reversals. In the basic theory of Ai and Bansal (2018), announcement informativeness and investor preferences explain risk premia, but do not predict post-announcement reversals.[3] Ai, Han, and Xu (2023) allow announcements that can increase or decrease uncertainty. In this case, uncertainty has a contemporaneously negative correlation with market returns and positive relationship with post-announcement risk-premia, qualitatively consistent with post-announcement reversal. In such information-based theories, a key predictor of reversal is the contemporaneous change in VIX.[4] Alternatively, price-pressure theories suggest that reversals are driven by demand for

[3] Wachter and Zhu (2022) model announcement risk premia using disaster risk. Ai, Bansal, and Han (2022) develop a theory of pre-announcement drift. Cujean and Jaeger (2023) build a model where pre-FOMC drift depends on the equilibrium and state of the world.

[4] See in particular Hu, Pan, Wang, and Zhu (2022), who show how pre-FOMC changes in VIX relate to announcement returns. In related work, Liu, Tang, and Zhou (2022) fit a model to pre-FOMC option prices and recover risk premium estimates correlated with announcement returns. Ai, Bansal, Guo, and Yaron (2023) use pre-announcement option prices to test preference for early resolution of uncertainty.

trade immediacy, implying predictors such as abnormal volume, as in Campbell, Grossman, and Wang (1993). We consider additional price-pressure proxies including equity and bond ETF flows. Information-based and price-pressure theories also differ in the timing implied for reversals. Absent slow learning or other frictions, information-based theories imply that the announcement drives immediate changes in uncertainty and risk premia. Price-pressure theories imply that periods of abnormal demand for trade predict subsequent reversals.[5]

Conditions are ripe for price pressure for several days following FOMC announcements. First, trade volumes remain high. For the SPY exchange-traded fund (ETF), which provides basket exposure to the S&P 500 index, volume spikes on the announcement day and remains high while declining over the following two to three days. Corroborating sustained high trade volume, attention to monetary policy news remains high for several days following announcements, showing continuing demand for information. Finally, we document increased fails-to-deliver in the SPY ETF three to five days following announcements, consistent with liquidity provision by intermediaries and inventory risk that should be compensated.

Additional evidence elaborates the particular nature of liquidity demands and intermediary risks following FOMC announcements. We provide new evidence of a liquidity pecking order following FOMC announcements. The underlying individual stocks of the S&P 500 also show elevated trade volume on the announcement day, but not to the extent of the SPY ETF. Further, their trading volumes continue to rise after announcement, peaking two days after the announcement while ETF volumes have already begun to decline. Thus, the most

[5] Grossman and Miller (1988) and Campbell, Grossman, and Wang (1993) predict reversals following market-wide demand for immediacy. Numerous studies emphasize large or long-lived price impacts and reversals associated with market makers or arbitrageurs responding to uninformed demand, including De Long, Shleifer, Summers, and Waldmann (1990a), Greenwood (2005), Andrade, Chang, and Seasholes (2008), Hendershott and Menkveld (2014), and Hendershott, Menkveld, Praz, and Seasholes (2022). A broader literature emphasizes limited risk-bearing capacity and capital immobility for intermediaries, with applications to time-varying profitability of arbitrage strategies, distressed selling and recoveries, and aggregate liquidity risk. See for example Shleifer and Vishny (1997), Aiyagari and Gertler (1999), Gromb and Vayanos (2002), Pastor and Stambaugh (2003), Mitchell, Pedersen, and Pulvino (2007), Brunnermeier and Pedersen (2009), Duffie and Strulovici (2012), Nagel (2012), and He and Krishnamurthy (2013).

immediate demand for trade following FOMC announcements is for basket exposure to the market, and trading volume takes time to work through to individual stocks. We further show the role of ETF intermediaries in this process through ETF creation and destruction. The delayed volume reaction of individual stocks suggests that some traders first adjust market exposures using liquid basket products, then trade into longer-run positions in individual stocks over the following days while unwinding temporary basket positions. Consistent with this hypothesis, we show that following good FOMC news, equity ETF fund flows ramp up, then unwind over the following twenty days. Conversely, following bad FOMC news fund flows to the equity ETF are muted, but instead bond ETF flows increase and subsequently unwind. Thus, while FOMC announcements are first and foremost informational events, they also create intense and temporary liquidity demands that are at least partly satisfied by intermediaries. Such market-wide price pressures should predict return reversals, according to theories written more than thirty years ago.

With these facts in hand we seek to better understand our findings of price noise and post-FOMC return reversals. First, price noise and reversals appear strongest not based on the announcement day alone, but after combining announcement returns with the immediately following days. Our base results focus on four-day windows beginning on the announcement date, to roughly coincide with the period of abnormally high trade volume and attention following announcements. These longer windows strengthen evidence of low price informativeness and subsequent return reversals. We further test whether key proxies from information-based and price-pressure theories predict reversals. The central predictor of changes in risk premia from information-based theories is uncertainty, proxied by the change in VIX. For price-pressure proxies, we use abnormal volume as in the original study of Campbell, Grossman, and Wang (1993), press conferences which coordinate attention and raise trade volume (Boguth, Grégoire, and Martineau, 2019), and fund flows to equity versus bond ETFs. Changes in VIX do help to predict reversals as implied by information-based theories;

however, the predictability is again strongest for VIX changes aggregated over several days post-announcement as opposed to the announcement itself. All of the price pressure proxies significantly predict post-FOMC return reversals, confirming rewards to liquidity-providing intermediaries.

We further illuminate how the fundamental information in FOMC announcements relates to post-announcement return dynamics. We decompose announcement-window returns into a component spanned by the monetary policy surprise measure of Bauer and Swanson (2023b) and an orthogonal component. The decomposition reveals important differences. The fitted component of announcement returns (and therefore the monetary policy surprise itself), *positively* predicts returns for up to ten days following announcement. As a consequence, the orthogonal component of returns reverses even more strongly than returns. Thus, the dynamics of post-announcement FOMC returns have two distinct components. One, corresponding to fundamental news in the monetary policy surprise, is characterized by initial underreaction and slow price adjustment.[6] Meanwhile, the orthogonal component reverses. At different points, the relative contributions of continuation and reversal vary, contributing to the overall picture of informativeness shown in Figure 1. We conclude that trade and return dynamics following FOMC announcements are not simply about price pressure and reversal, but also mask slow incorporation of fundamental news into prices. The combination of intense trade, slow adjustment to fundamental news, and reversal of orthogonal components of returns offers a rich environment for future theoretical study.

Thus, while FOMC announcement returns appear as "noise" in unbiasedness regressions, we argue that market movements around these announcements are highly informative about the drivers of risk premia and how news aggregates through trade. Noise is always defined relative to a model, as a residual from theoretical expectations or predictions.[7] Our findings

[6] Brooks, Katz, and Lustig (2020) document longer-lived underreaction in long-term interest rates to monetary policy shocks, focusing on a pre-financial crisis sample.

[7] The broader literature on noise in prices includes Blume and Stambaugh (1983), Lo and MacKinlay (1988), Lo and MacKinlay (1990), Asparouhova, Bessembinder, and Kalcheva (2013), Boguth, Carlson,

provide guidance for future theoretical research. Specifically, theories that combine the informational aspects of macroeconomic announcements with the high liquidity demands that new information can generate, as studied in the market microstructure literature, are essential.

We do not claim that FOMC announcements are unique as important scheduled informational events; however, we find no systematic evidence of noise or price reversal associated with other macroeconomic announcements. We explain this as related to prior findings that among macroeconomic announcements, scheduled FOMC releases have the largest risk premia (Ai and Bansal, 2018), the largest increase in investor attention (Ben-Rephael, Carlin, Da, and Israelsen, 2021), and the largest increase in trading volume (Bollerslev, Li, and Xue, 2018), all related to price pressure.

The broader literature on price pressure and inelastic financial markets addresses institutional trades, index inclusion, mergers, government bonds, mutual fund flows, market closing, and dividend payments.[8] Studies often consider individual parts of the market, and emphasize uninformed flows as a source of price pressure (e.g., Scholes, 1972). We differ by showing market-wide price pressure and reversals following a key public announcement. Prior evidence of market-wide inelasticity includes Bollerslev, Li, and Xue (2018), who investigate high-frequency movements in the SPY ETF around FOMC announcements and document low volume-volatility elasticity (high price impact) that decreases with measures of disagreement and uncertainty. They interpret this as "agreeing to disagree" around public news (Kandel and Pearson, 1995). In quarterly data, Gabaix and Koijen (2022) build on the demand system of Koijen and Yogo (2019) and emphasize flows, also finding inelasticity in the overall market. Campbell, Grossman, and Wang (1993) first investigate price pressure in market returns by assessing variation in daily autocorrelations with volume as an

Fisher, and Simutin (2016), and Brogaard, Nguyen, Putniņš, and Wu (2022).

[8]See for example Kraus and Stoll (1972), Harris and Gurel (1986), Shleifer (1986), Mitchell, Pulvino, and Stafford (2004), Greenwood and Vayanos (2010), Ben-Rephael, Kandel, and Wohl (2011), Hendershott and Menkveld (2014), Bogousslavsky and Muravyev (2023), Hartzmark and Solomon (2021).

instrument. Our findings connect price pressure and market inelasticity to: (i) public FOMC announcements and announcement risk premia, and (ii) significant predictability in highly variable short-run returns.

Return reversals naturally invite comparisons to prior studies of overreaction in the stock market and other settings.[9] Short-horizon reversals have been studied for individual stocks (e.g., Lehmann, 1990, Bremer and Sweeney, 1991, Antweiler and Frank, 2006, Savor, 2012), the broad stock market (Campbell, Grossman, and Wang, 1993, Tetlock, 2007), and long-term interest rates (Hanson, Lucca, and Wright, 2021). Our results provide a new context for studying predictable turnarounds: stock market returns following a key macroeconomic announcement.[10]

Our results also have implications for the literature that studies connections between monetary policy shocks and asset prices (e.g., Kuttner, 2001, Bernanke and Kuttner, 2005, Nakamura and Steinsson, 2018, Bauer and Swanson, 2023a,b). We show that short-term interest rates have no significant decline in informativeness around FOMC announcements, giving no reason to doubt the reliability of monetary surprise measures. However, our results call into question the common assumption that short-window stock returns capture the complete effects of monetary policy news. We show delayed stock-market reaction or underreaction to monetary policy surprises, combined with reversal in the orthogonal component of returns. These findings suggest that a full understanding of the connections between monetary policy, the macroeconomy, and asset-price movements cannot rely on classical assumptions of market efficiency. The market microstructure of intense trading and price formation that follows monetary policy announcements is a key part of the story of how

[9] See for example De Bondt and Thaler (1985), De Long, Shleifer, Summers, and Waldmann (1990b), Barberis, Shleifer, and Vishny (1998), Greenwood and Hanson (2015), and Afrouzi, Kwon, Landier, Ma, and Thesmar (2023).

[10] Future research may seek to relate our findings to biases in beliefs or updating (e.g., Bordalo, Gennaioli, Ma, and Shleifer, 2020). See also Coibion and Gorodnichenko (2015), Bordalo, Gennaioli, La Porta, and Shleifer (2019), and Pflueger, Siriwardane, and Sunderam (2020). Specific to the FOMC context, Han (2022) uses surveys and finds evidence of forecast-error correction in announcement-day returns.

investors learn from and react to monetary policy news.

2. Unbiasedness Regressions and Price Informativeness

Our study of price informativeness around FOMC announcements builds on the unbiasedness regression framework of Biais, Hillion, and Spatt (1999). They investigate pre-opening price informativeness of the Paris bourse, using methods closely related to earlier studies of exchange rate predictability from futures prices (e.g., Hodrick, 1987). We adapt the prior frameworks to examine price informativeness around a scheduled news announcement.

Let t index time and consider an event, such as an FOMC announcement, occurring at the normalized time $t = 0$. We consider fixed windows $[T_1, T_2]$ around the event, i.e., $T_1 < 0 < T_2$. Assuming a sample of events indexed by i, let $Ret_{i,t}$ denote the S&P 500 index log return at date t. We regress the full-window return from T_1 to T_2 on partial returns from T_1 to $t \in \{T_1 + 1, T_1 + 2, ..., T_2\}$:

$$Ret_{i[T_1,T_2]} = \alpha_t + \beta_t Ret_{i[T_1,t]} + \varepsilon_{i,t}. \tag{1}$$

The coefficient β_t has received considerable attention in prior literature. When log prices form a random-walk with drift, $\beta_t = 1$ for all t. Using the language of the forecasting literature dating to Mincer and Zarnowitz (1969), when $\beta_t = 1$ the partial return from T_1 to t provides an "efficient" forecast of the full window return from T_1 to T_2, in the sense that no amplification or attenuation of the partial return can improve the residual variance of the forecast error. If $\beta_t < 1$, then the partial return is attenuated or partially reversed in the total return, which is often interpreted as a symptom of price noise, a temporary component in prices, or "overreaction" (Barclay and Hendershott, 2003). Conversely, if $\beta_t > 1$, the partial return is amplified in the total return, suggesting "underreaction" or slow information processing.

We highlight an important caveat. Interpreting deviations from $\beta = 1$ as evidence of noise or underreaction relies on an assumption of risk premia that are adequately captured by the regression intercepts α_t. Biais, Hillion, and Spatt (1999) explicitly acknowledge this when they explain that their framework accommodates risk premia captured by the intercepts as long as they are constant across sample events i. We allow the intercepts α_t to vary with event time, which accommodates higher risk premia on FOMC announcement days relative to other days, as in Ai and Bansal (2018). In other words, the intercepts of equation (1) accommodate time-varying risk premia, as long as variation is a function of event-time only. Other types of time-varying risk premia, such as higher risk premia following low returns or vice versa, could result in estimates of β different than one and therefore be difficult to distinguish from noise. We keep this caveat in mind when interpreting our empirical results.

Prior studies emphasize the beta coefficients from regression (1). We focus more on the regression R^2. To relate R^2 and beta at each date t, consider the decomposition:

$$R_t^2 = \beta_t^2 VR_t, \tag{2}$$

which expresses the R^2 as the product of the squared slope coefficient and a variant of the variance ratios of Lo and MacKinlay (1988):

$$VR_t = \frac{Var\left(Ret_{i[T_1,t]}\right)}{Var\left(Ret_{i[T_1,T_2]}\right)}. \tag{3}$$

When returns are i.i.d., VR_t grows linearly with the number of days $t - T_1 + 1$ in the numerator. The R^2 thus combines information from betas and variance ratios. Intuitively, VR_t determines whether a high-volatility event happened, and β_t determines whether the event is persistent or not. The importance of this is that neither beta nor volatility alone gives a complete picture of price informativeness. For example, with uncorrelated returns, beta will be constant at a value of one, but unable to distinguish highly informative announcements from days with typically low information content. Conversely, days with high volatility need not always be more informative, since volatility can be driven by either news (permanent) or noise (mean reverting).

We describe additional characteristics of the unbiasedness regression R^2. As a function of t, R_t^2 must start at zero and reach one when $t = T_2$. The exact path of R_t^2 depends on volatility and autocorrelations. With constant information flow and no autocorrelation, R_t^2 increases linearly. If all autocorrelations are zero ($\beta_t = 1$) but returns are heteroskedastic, the change in R^2 each period reflects variance, and high variance days will have larger increases in R^2. But when beta differs from unity the possibilities are richer. If a day's return tends to be partially reversed by T_2, then the increase in R^2 will be smaller than in the random walk case. If a day's return adds no new information, the R^2 plot will be flat. The unbiasedness regression R^2 conveniently summarizes informativeness about long-window price changes.

Figure 2 illustrates the use of unbiasedness regressions on simulated data. In each panel, the first column shows beta, the second column the variance ratio VR_t, and the third column the R^2. Panel A shows simple cases of event-day news and noise. For news (solid green), fundamentals follow a random walk with an event-day news shock (i.e., permanent price impact) three times larger than other days. For noise (dashed red), fundamentals follow the same random walk, with no event-day news but instead noise of the same three-times magnitude that immediately mean reverts. Beta detects noise on the announcement date by falling. However, beta cannot detect heightened news as it remains flat throughout the announcement date in the news case. The variance ratios both increase on the announcement date, permanently for news, and immediately reversing for noise. The regression R^2 combines information from both slopes and variance ratios revealing a temporary decline in price informativeness in the noise case, but a permanent increase in informativeness for news. Panel B shows a richer simulation of sustained noise on the event date, with more gradual mean reversion at an exponential rate (details of the dynamics in Appendix A). We see a persistent increase in the variance ratio, similar to the news case in Panel A. Heightened variance can be caused by either news or noise, and the variance ratio alone is not enough to distinguish between the two. The R^2 plot in Panel B correctly reveals a sustained decline in price informativeness associated with the persistent noise shock. The unbiasedness regression R^2 thus provides a useful measure of price informativeness.

To quantify how one or several days' returns contribute to the R^2 relative to a typical day, we define:

$$\text{Excess } \Delta R_t^2(t, K) = \frac{T}{K}(R_t^2 - R_{t-K}^2) - 1, \tag{4}$$

where $T = T_2 - T_1 + 1$ is the number of trading days in the full window of the unbiasedness regression, and K is the number of days over which we analyze the changes in R^2. When price changes are independent and information flow is constant, the Excess ΔR_t^2 is zero everywhere. A value above zero indicates faster than normal information flow, and a value below zero the opposite. In the special case where Excess ΔR_t^2 equals -1, the R^2 plot will be flat, and if the value is below -1 the R^2 declines. We thus interpret the Excess ΔR_t^2 as abnormal information flow per day, measured in units of an average day's information flow.

To further understand the marginal effects of a subset of days, we augment the standard unbiasedness regression with an additional partial return:

$$Ret_{i[T_1,T_2]} = \alpha_t + \beta_t Ret_{i[T_1,t]} + \beta_{t,h}^{marginal} Ret_{i[t-h,t]} + \varepsilon_{i,t}, \tag{5}$$

where $\beta_{t,h}^{marginal}$ captures the marginal effect of returns from days $t-h$ to t. If the marginal beta is zero, returns from days $t-h$ to t are like other days. If marginal beta is less than zero, returns from days $t-h$ to t tend to be reversed more than other days. Under the random walk null, the average beta coefficient β_t can be set to one. This restriction increases precision of the marginal beta estimate and enhances ability to detect reversal or amplification. The regression (5) thus provides a convenient test of reversal or amplification of returns from a subset of days.

3. FOMC Announcements

The reaction of stock prices to new information has been a foundation of financial economics since at least Fama, Fisher, Jensen, and Roll (1969).[11] Reactions to FOMC announcements are particularly important to understand. We use the sample of all scheduled FOMC announcements from February 1994 to 2021, a total of 223 events. We begin in February 1994 because that is when the Federal Reserve first began making public announcements of changes in policy rates (Kuttner, 2001).

Figure 3 shows event-time behavior of variables related to information processing. The VIX declines sharply on the FOMC announcement date (Panel A), consistent with prior evidence.[12] The VIX rises three to four days before the event, and afterwards remains low for three to four days before building back up throughout the cycle, consistent with the theory of Ai and Bansal (2018). Panel B shows economic policy uncertainty (EPU, Baker, Bloom, and Davis, 2016), derived from news articles and other data. Panel C shows the macroeconomic attention index for monetary policy of Fisher, Martineau, and Sheng (2022). Both EPU and attention increase around FOMC announcements, with the largest peaks the day after announcement. Panel D shows abnormal trade volume in the SPY ETF. Volume is often associated with information processing.[13] The SPY volume spikes on FOMC announcement dates and remains elevated while declining for several days afterward, an important pattern that has not been previously documented. In sum, the VIX index, attention, and volume appear consistent with sustained news processing related to FOMC announcements.

[11] More recently, see Hu, Pan, and Wang (2017), Chordia, Green, and Kottimukkalur (2018), and Gregoire and Martineau (2022).

[12] See Savor and Wilson (2013) and Bauer, Lakdawala, and Mueller (2021).

[13] See for example French and Roll (1986), Ross (1989), Andersen (1996), Beber and Brandt (2009), and Andrei and Hasler (2014).

3.1. Price Informativeness

Figure 1 showed that unbiasedness-regression R^2 remain essentially flat for several days following FOMC announcements. The earnings announcements from the same figure show a sharp jump in R^2 on the event day, consistent with important fundamental information emerging.[14] We now implement two statistical tests of informativeness. The first bootstraps the distribution of the Excess $\Delta R^2(t, K)$ from equation (4). Second, we test whether the marginal beta coefficients from equation (5) are different from zero.

The bootstrap procedure draws with replacement 100,000 samples from the data of the same size as our empirical sample of FOMC dates. Each sample date is randomly matched by calendar year, quarter, and day of the week to a placebo event date. We generate p-values for the likelihood of observing, from the bootstrapped distribution, the Excess $\Delta R^2(t, K)$ statistics observed in the data or lower. The p-values thus test whether the Excess $\Delta R^2(t, K)$ observed in the FOMC data are abnormally low relative to other dates.[15]

Table 1, Panel A reports ΔR^2 and Excess ΔR^2 on the day of the FOMC announcement ($t = 0$) and the following three days ($t =$1, 2, 3). The columns refer to different unbiasedness regression windows, varying from 5 to 20 trading days before the announcement date to 10 to 30 trading days after. These show the effects of changing window sizes while avoiding overlap. The first row corresponds to the announcement day $t = 0$. For all windows ending 30 days after the announcement (first three columns), the increase in R^2 is abnormally low relative to other days ($p < 0.10$). Further, the point estimates show R^2 decreasing, a reduction in informativess about future prices. For example, in the $[-5, 30]$ window the Excess ΔR^2 is -1.915 , indicating almost two days' less information than usual, and a net loss

[14] See also Ball and Shivakumar (2008), Beaver, McNichols, and Wang (2020), Gregoire and Martineau (2022), and Martineau (2022).

[15] We present in Table IA1 of the Internet Appendix an alternative bootstrap distribution by simply redrawing, with replacement, the sample of actual FOMC dates, and generating p-values to test that Excess $\Delta R^2(t, K) \geq 0$. This test is thus based on the actual empirical distribution of the statistics Excess $\Delta R^2(t, K)$ and the frequency of observing values above and below zero.

of information about future prices. The results are qualitatively unaffected by the window starting point (i.e., are similar for $[-5, 30]$, $[-10, 30]$, and $[-20, 30]$). Shortening the window endpoint weakens the results, consistent with it taking some time (more than 10 days) for prices to fully revert. Our remaining discussion focuses on the longest windows ending thirty days after announcement.

Rows 2-4 of Panel A investigate the three days following the announcement, one day at a time. Immediately following the announcement, the next day $t = 1$ shows a negative but not quite as severe Excess ΔR^2 (-1.24 in the $[-5, 30]$ window), with p-values remaining below 0.10. For days $t = 2$ and $t = 3$, the point estimates attenuate further while remaining negative (-0.51 and -0.69), but cannot be statistically distinguished from other days. Therefore in one-day tests, significantly low price informativeness concentrates on the announcement date and one day immediately following.

Panel B aggregates information across four-day windows. We choose four-day windows because Figure 3 and additional evidence provided later in the paper show that the volume and attention impacts of FOMC announcements last at least several days following the event. The first row of Panel B corresponds to $t = [0, 3]$, and shows even stronger statistical evidence of low price informativeness. The point estimates of Excess ΔR^2 per day are -1.09, -1.08, and -1.17, consistent with the flat R^2 plot in that region, and all significantly negative ($p = 0.017, 0.022,$ and 0.016). In the second row, corresponding to $t = [4, 7]$, the point estimates of ΔR^2 remain negative but not as extreme, ranging from -0.78 to -0.86, with p-values still less than 0.05. For the window $t = [8, 11]$ in the third row, the point estimates of ΔR^2 remain negative ranging from -0.5 to -0.6, but are no longer statistically significant. Finally, the window $t = [12, 15]$ shows strong reversal. The point estimates in the first three columns range from 1.03 to 1.13, and the p-values indicate that the estimates are in approximately the ninety-ninth percentile of the bootstrapped distribution. Thus, the flattening of the R^2 plot in Figure 1 and subsequent reversal are both highly statistically significant.

Panel C of Table 1 considers the "pre-announcement" dates $t = -1$ and $t = [-3, -1]$. Lucca and Moench (2015) find that most of the equity premium on FOMC announcement dates occurs 24 hours prior to the announcement. The panel shows that pre-announcement dates do not show low price informativeness.

Marginal beta regressions (5) provide an alternative way to test specific subsets of days. We plot in Figure 4 the average betas from standard unbiasedness regressions (Panel A), as well as marginal betas with subsets of $h = 1$ (Panel B) and $h = 4$ (Panel C) days. The slope coefficients in Panel A from the standard unbiasedness regressions show a slow decrease below one following announcement. The coefficient falls significantly below one six to ten days after announcement before beginning to increase, approximately matching the inflection point of the R^2 plot. The one-day marginal betas in Panel B are highly variable, but spike downward on the announcement date, and remain low for most of the next ten days. The four-day marginal beta (Panel C) smooths the pattern, showing a clear downward trend following the announcement. The values are significantly negative for $t = 3$, corresponding to the window $[0, 3]$, and significantly negative values remain until $t = 10$. The marginal betas then increase to become significantly positive about twelve days after the announcement. The significantly negative and positive regions of the marginal beta estimates correspond to the flat and steeply rising portions of the R^2 plot from Figure 1. These results confirm that stock returns on FOMC announcement days and the days immediately after tend to be reversed in long-window returns.

3.2. Predictive Regressions and Return Reversals

The unbiasedness regression R^2 and marginal betas are useful diagnostic tools. They tell us whether a particular return or cluster of returns in event time tends to be permanent, reversed, or amplified in longer windows. An advantage of the unbiasedness regressions is that the empiricist need not specify when the eventual reversals occur, but we are still interested in this question.

We use predictive regressions to connect FOMC returns with their subsequent reversals. The predictive regressions are of the form:

$$Ret_{i[t_1,t_2]} = \gamma_0 + \gamma_1 Ret_{i[0,h-1]} + \epsilon_i, \tag{6}$$

where 0 is the event date, and the right-hand side variable $Ret_{i[0,h-1]}$ is the h-day return beginning at 0. We enforce $h < t_1$ to ensure the left- and right-hand-side returns do not overlap. Following prior analysis we focus on subsets of $h = 1$ or $h = 4$ days beginning on the announcement day, i.e., Ret_0 and $Ret_{[0,3]}$. We predict short-window returns of various lengths up until the day before the next announcement, i.e., until $\tau_1 - 1$. Since the return windows on the left-hand-side are short-window and non-overlapping, the common problem of long-horizon predictive regressions with highly persistent residuals is not present (e.g., Hansen and Hodrick, 1980). Similarly, since the right-hand-side predictors are also short-window and non-overlapping, the persistent regressors problem pointed out by Stambaugh (1999) does not apply. The predictive regressions (6) allow us to assess the timing and magnitude of return reversals.

Table 2 shows results. The first row uses the announcement-day return to predict future returns, while the second row uses the four-day return $Ret_{[0,3]}$. Columns correspond to the subsequent returns being predicted. The point estimates can be interpreted as the (negative) proportion of announcement day returns that are reversed within the prediction window. For one-day windows, all point estimates are negative, indicating reversals, ranging from 7-11% in the first ten days, increasing to about 47% by the next announcement date. One of the reversal coefficients, for the $[1, 20]$ window, is statistically significant at the 10% level in a two-tailed test. Aggregating returns over four-day windows, the results are qualitatively similar, but much stronger in statistical significance. Across all three windows, $[4, 10]$, $[4, 20]$, and $[4, \tau_1 - 1]$, p-values in a two-tailed test for predictability are less than 0.01, t-statistics are about three in absolute value, and R^2 range from 5.6-6.7%. In Table IA2 of the Internet Appendix, we show that alternative predictor windows, two to five days in length, give similar results. By any standards, the R^2 of these market-return predictive regressions are large, but especially so for short-horizon returns of seven to less than thirty days. Moreover, the economic magnitudes of reversals are sizeable. By day ten after announcement, 29% of the four-day announcement return has reversed. The reversal coefficients increase to 45% by day twenty, and 60% by the last day before the next announcement. Thus, more than half of the four-day announcement return is reversed by the end of the announcement cycle.

3.3. Robustness and Comparisons

We provide additional evidence that low price informativeness concentrates in equity markets in the post-1994 period when the Federal Reserve began publicly announcing target rates, and is robust in that setting. Table 3 reports Excess ΔR^2 and p-values for the S&P 500 index in FOMC subsamples (Panel A), for alternative assets in the post-1994 FOMC sample (Panel B), and for the S&P 500 index around other announcements. The table shows results for an event window $[-5, 30]$. Results for the full range of windows used in Table 1 are provided in Table IA3 of the Internet Appendix.

The FOMC subsamples in Panel A show that in the pre-1994 period (columns 1 and 2) point estimates of Excess ΔR^2 are very close to zero, with no evidence of underreaction or reversal. Panel A also shows two post-1994 subsamples, 1994-2009 and 2010-2021. Both show very negative Excess ΔR^2. For $t = [0, 3]$ the estimates are respectively -.88 and -1.31 ($p = 0.094$ and 0.017). Figure IA1 of the Internet Appendix further plots rolling three-year estimates of Excess ΔR^2. These are mostly negative and about half fall below negative one. Low informativeness of equity prices following FOMC announcements occurs throughout the post-1994 FOMC sample.

Panel B shows price informativeness for three additional assets following FOMC announcements: the nearest-to-maturity Fed fund futures, 3-month Eurodollar futures, and the 1-3 year Treasury bond ETF (iShares ticker: SHY). Interest rates are widely known to react strongly to FOMC news (Gürkaynak, Sack, and Swanson, 2005a,b). All but two of the Excess ΔR^2 are positive, but not statistically significant. The informativeness of Eurodollar futures is consistent with their use in measuring monetary policy news shocks as in Nakamura and Steinsson (2018) and Bauer and Swanson (2023b).

Panel C considers Treasury futures, showing that announcement-day price informativeness decreases in maturity. The point estimate on announcement days are 0.846, -0.721, and -1.829 for the 2-, 5-, 10-year futures, respectively, with a significant p-value of 0.028 for the 10-year contract, corresponding to low announcement-day price informativeness. This result is consistent with the short-term overreaction in long-term interest rates documented by Hanson, Lucca, and Wright (2021). Baker, McPahail, and Tuckman (2018) further discuss that the 10-year maturity bond future is the most heavily traded Treasury future and that these contracts play an important role on liquidity challenged days with large price movements. Over the longer windows $[0, 3]$, price informativeness for the 10-year future is unremarkable (point estimate 0.483, $p = 0.819$). Thus, evidence of low price informativeness is confined to the most heavily traded, longer-maturity ten-year contract, and is shorter-lived than in equity markets.

Panel D shows stock market price informativeness following initial GPD, employment, and inflation announcements.[16] For all three types the Excess ΔR^2 are mildly positive on the announcement date and statistically insignificant. Including the following three days, the Excess ΔR^2 for GDP is somewhat negative but all p-values are insignificant. In prior literature, scheduled FOMC releases stand out among other macroeconomic announcements by having the largest risk premia (Ai and Bansal, 2018), the largest increase in investor attention (Ben-Rephael, Carlin, Da, and Israelsen, 2021), and the largest increase in trading

[16]For inflation announcements, on each month, we select either the CPI or PPI announcement depending on which announcement occurs first

volume (Bollerslev, Li, and Xue, 2018), all related to price pressure. We confirm in our data that abnormal trade volume is significantly higher for FOMC than GDP, employment, or inflation announcements. Further, neither GDP nor inflation have significantly higher volume than days without macro announcements, and the increase in volume for employment is half as large as for FOMC announcements (Internet Appendix, Table IA5).

Figure 5 provides an alternative depiction of return reversals following FOMC announcements. We sort announcements according to announcement-day return into quintiles. The figure shows average cumulative returns of the top, middle, and bottom groups, as well as the overall average, from 10 days before announcement to thirty days after. The widest spread between the top and bottom quintiles occurs on and just after the announcement day, progressively dissipating to a much smaller difference thirty days after announcement. The figure thus visually confirms the statistical evidence from unbiasedness regressions and standard predictive regressions. FOMC return reversals are a robust feature of the data.

Prior literature has emphasized predictability of the aggregate stock market primarily at lower frequencies (e.g., Cochrane, 2011). What is surprising about our results is that very short-window returns following FOMC announcements predict reversal in the remainder of that FOMC cycle. Further, the apparently low price informativeness occurs on and immediately after FOMC announcements, perhaps the most widely followed news days of the year in financial markets.

4. What Predicts Post-FOMC Reversals?

In this section, we begin the effort to understand FOMC return reversals by providing additional empirical evidence that may be relevant for theory. We focus on two channels that are clearly important around FOMC announcements, i) information and resolution of uncertainty, and ii) price pressure.

4.1. The Information Channel

We first consider the role of information in generating risk premia, since announcements are most fundamentally about information (Ai and Bansal, 2018). In their model, the clear driver of announcement risk premia is resolution of uncertainty, as occurs on average around FOMC announcements (their Figure 1). Ai, Han, and Xu (2023) provide an extension in which resolution of uncertainty varies stochastically across announcements, including the possibility of increases in uncertainty.

The return reversals we have empirically documented are large, and we are not aware of purely information-based theories that claim to generate such substantial short-run variation in risk premia. At the same time we take seriously the observation that predictability in discretely observed prices cannot rule out efficiently priced arbitrage-free markets (Harrison and Kreps, 1979).[17] Our approach then will be to seek reduced-form evidence for the role of changing uncertainty in post-FOMC reversals, since changing uncertainty is the primary channel that drives time-varying risk premia in information-based theories. Following a large prior literature, we use changes in VIX as a proxy for changing uncertainty (Hu, Pan, Wang, and Zhu, 2022). In addition to uncertainty proxied by VIX, we also consider complementary evidence from a measure of attention to monetary policy. Theories of endogenous attention predict that attention increases when uncertainty or the price of risk is high, since attention is an indicator of desire to learn and learning has more value when uncertainty or the price of risk are high (e.g., Sims, 2003, Bansal and Shaliastovich, 2011, Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2016).

Figure 6 partitions all FOMC announcements into above- and below-mean announcement-

[17] The inability to rule out arbitrage-free markets from a discretely observed time series alone follows since all discrete-time processes have an equivalent martingale measure. Maheswaran and Sims (1993) discuss that in continuous time the restriction to martingale-equivalent measures is meaningful because infinite variation in a finite time interval, or mean-reversion at arbitrarily fine time scales, can be ruled out. The FOMC events we consider occur at a specific time and we characterize the time scale of mean reversion as beginning several days after the event.

day returns (left-hand panels) and changes in VIX (right-hand panels). For each group, we show cumulative post-announcement returns (Panel A), changes in VIX (Panel B), and attention to monetary policy news (Panel C). The left-hand figure of Panel A shows the previously documented mean reversion in returns (see Figure 5), but here we consider only two groups for simplicity. The right-hand plot of Panel A shows that, if anything, mean reversion is stronger when conditioning on announcement-day VIX changes. Panel B shows that the VIX itself mean reverts conditioning on either returns or VIX changes. Panel C shows attention to monetary policy news. On average, attention spikes after announcements and then begins to fall. But attention remains higher for longer following low returns (also increases in VIX) than after high returns (or decreases in VIX). The panels of Figure 6 thus show higher returns, higher VIX, and greater investor attention following "bad" FOMC news, all consistent with higher risk premia. These results appear at least qualitatively consistent with a risk-based channel for reversals related to information.

Table 4 formally tests the role of changes in uncertainty, proxied by VIX, in predicting return reversals. Panel A uses VIX changes (ΔVIX) to predict the same set of post-announcement returns as Table 2. We consider both one-day changes (announcement-day only) and four-day changes. As in Table 2, the one-day changes go in the expected direction of positive coefficients on ΔVIX, but are not statistically significant. The four-day changes are highly significant predictors, with R^2 comparable to those of four-day announcement returns from Table 2 (7.2, 3.3, and 5.0% for ΔVIX vs. 6.2, 5.6, and 6.7% for the four-day announcement return). In Panel B, we decompose the four-day return predictor from Table 2 into a contemporaneous projection onto ΔVIX and a residual. We then ask which components of returns explain the return reversals. This decomposition shows that the projection of returns onto ΔVIX is important to reversals. The coefficient estimates reveal that this component is both a substantial contributor to contemporaneous returns (52.5% R^2 in column 2), and predictably reverses in future returns: 43% by day ten, 48%

by day twenty, and 72% by the end of cycle. The residual components also have negative signs corresponding to reversal and meaningful economic magnitudes, but their t-statistics are less than 1.5 in absolute value. FOMC return reversals are predicted by VIX changes, a key proxy for uncertainty changes, which are the driving force of information-based theories of announcement risk premia.

Based on existing theory, a purely information-based explanation of FOMC return reversals appears at odds with other aspects of our findings. In particular, return reversals are not strongest based on announcement-day information alone, but when days $t = [0, 3]$ are grouped together (Tables 2 and 4). We acknowledge that current theories (e.g., Ai, Han, and Xu, 2023) might be extended to better accommodate this aspect of our findings, for example by incorporating slow learning about fundamentals (as we provide empirical evidence for in Section 5). We also acknowledge the potential importance of price pressure following FOMC announcements, and therefore turn now to develop further empirical evidence in this direction.

4.2. Price Pressure, Liquidity Cascade, and Return Reversals

To explore the importance of price pressure and how it relates to liquidity around FOMC announcements, Figure 7, Panel A shows abnormal volume for the SPY ETF versus the underlying S&P 500 stocks. A liquidity pecking order around FOMC announcements emerges. The SPY ETF spikes upward on the day of the announcement, and remains high but at a lower level for two days thereafter. In contrast, the underlying S&P 500 stocks do not spike upward as significantly on the announcement day, increase further the day after, and have their largest volume spike two days after announcement. Further confirming the liquidity demands FOMC announcements put on markets, Panel B shows that the SPY ETF fails-to-deliver, scaled by shares outstanding, increase significantly three-to-five days following the FOMC announcements, consistent with naked ETF creation by some authorized participants/market makers and therefore inventory risk.[18]

These findings suggest a complex diffusion of trading volume following FOMC news. The SPY ETF provides an important vehicle for trading on systematic market news. Certain institutional managers may be constrained from using other sources of basket trading such as futures. Additionally, derivatives linked to the SPY ETF have appeared in an increasingly rich range of maturities in recent years, providing an important means by which traders can adjust market exposures or speculate on FOMC announcement days. The delayed reaction of individual stocks suggests that traders and investment managers immediately adjust their market exposures using basket ETFs, futures, or derivatives on these underlyings, and then later trade into longer-run positions in individual stocks while unwinding their basket exposures.

Figure 8 further investigates this hypothesis of temporary demand for liquid basket assets around FOMC announcements. We follow Kroencke, Schmeling, and Schrimpf (2021) and retrieve daily equity and bond ETF fund flows from Bloomberg to measure temporary asset demand.[19] The left-hand side panels show that flows into equity ETFs increase dramatically following good FOMC news, proxied either by increases in returns or reductions in VIX. The equity fund flows then unwind until they are back to normal after approximately 15 days. Conversely, following bad news funds flow into bond ETFs and again slowly unwind.

Thus, while FOMC announcements are first and foremost important informational events, they also create unusual liquidity demands. Assets show a strong liquidity pecking order and

[18]When faced with "excess buying" pressure for ETF shares, an authorized participant/market marker has two choices: (1) Sell shares from inventory or locate the shares in the secondary market and deliver at T+3. (2) Sell shares "naked" and then locate or create the shares at a later time up to T+6 for "bona fide" market making (Evans, Moussawi, Pagano, and Sedunov, 2022). In the latter case, shares are included in the fail-to-deliver measure after T+3 even if authorized participants are within their allowed delivery window. The fail-to-deliver data is from the Securities and Exchange Commission website.

[19]We collect ETF data from Bloomberg that covers almost all ETFs traded in the U.S January 2006 to December 2021. We select equity ETF data that belong to the "blend" category and "aggregate" and "government" for bond ETF data. As in Kroencke, Schmeling, and Schrimpf (2021), we normalize fund flows by their moving average and standard deviation.

demand for liquid basket assets is temporarily high. The temporary flows into ETFs imply need for temporary ETF creation and unwinding, and we see evidence of inventory risk in ETF fails-to-deliver. Price pressure theories imply that intermediaries should be compensated for their services in times of high demand for immediacy in the form of predictable return reversals (Grossman and Miller, 1988, Campbell, Grossman, and Wang, 1993, Hendershott and Menkveld, 2014).

To test the role of price pressure in FOMC return reversals, we estimate regressions

$$Ret_{i[4,20]} = \gamma_1 Ret_{i[0,3]} + \gamma_2 Pressure_i \times Ret_{i[0,3]} + \gamma_3 Pressure_i + \epsilon_i, \tag{7}$$

where $Pressure$ corresponds to one of three empirical proxies. First, following Campbell, Grossman, and Wang (1993) we use abnormal log volume in the window $[0, 3]$. Second, we use an indicator variable equal to one if an FOMC announcement is followed by a press conference, since press conferences coordinate attention and are associated with stronger market price reactions (Boguth, Grégoire, and Martineau, 2019). The third proxy is an indicator variable equal to one if the absolute value of the orthogonalized monetary policy news shock of Bauer and Swanson (2023b) belongs to the top quintile. Prior evidence shows that macroeconomic surprises of larger magnitude raise more attention (Fisher, Martineau, and Sheng, 2022). We further show in the Internet Appendix, Table IA5, that both press conferences and large monetary policy surprises are associated with significantly larger trade volume on FOMC announcement days (by 14% and 39%, respectively).

Table 5 reports the regression results. Column (1) shows the already established base result that the announcement return $Ret_{i[0,3]}$ negatively predicts the post-announcement return $Ret_{i[4,20]}$. Columns (2)-(4) include interaction terms with the price-pressure proxies. The coefficients on the interaction terms are all negative and statistically significant, indicating that return reversals are more pronounced when the price-pressure proxies are high. Economically, if the abnormal volume in the window $[0, 3]$ increases by one standard deviation (1.37), we anticipate larger post-announcement reversal in the amount of 30 percent of the realized return from the same days ($1.37 \times -0.22 \approx 0.30$). The economic magnitudes of the interaction point estimates associated with press conferences and monetary policy surprises, in columns (3) and (4), are even larger. Price pressure proxies strongly predict post-FOMC return reversals.

We also consider the effect of ETF fund flows on post-FOMC return reversals. We compute equity ETF and bond ETF fund flows from the announcement date to three days after, as well as their difference. Because of fund flow data availability, this sample begins in January 2006. To show the relationship between fund flows and *contemporaneous* returns in the window $[0, 3]$, we estimate variations of

$$Ret_{i[0,3]} = \gamma_1 EqtFlow_{i[0,3]} + \gamma_2 BndFlow_{i[0,3]} + \gamma_2 NetFlow_{i[0,3]} + \epsilon_i, \quad (8)$$

where $Ret_{[0,3]}$, $EqtFlow_{[0,3]}$, $BndFlow_{[0,3]}$, and $NetFlow_{[0,3]}$ correspond to cumulative S&P 500 logarithmic returns, equity ETF fund flows, bond ETF fund flows, and the fund-flow difference between equity and bond ETFs, respectively. To test the *predictive* power of ETF flows for price reversal, we estimate

$$Ret_{i[4,20]} = \alpha + \gamma_1 EqtFlow_{i[0,3]} + \gamma_2 BndFlow_{i[0,3]} + \gamma_3 NetFlow_{i[0,3]} + \gamma_4 Ret_{i[0,3]} + \epsilon_i, \quad (9)$$

which also controls for the contemporaneous return.

Table 6 presents results for the fund-flow regressions (8) and (9). Columns (1)-(3) show that equity flows and net flows positively relate to contemporaneous FOMC announcement returns while bond flows negatively associate with the same returns. Column (4) shows that in a multivariate regression, only the net flow remains statistically significant. Columns (5)-(6) present the results of the predictive regression. Column (5) confirms our baseline result of return reversal in this shorter time series. Column (6) shows the additional effect of fund flows, which subsume the predictive power of announcement-window returns, at least in statistical significance (the coefficient on announcement-window returns remains economically meaningful at -0.37, but the t-statistic is just below standard significance levels). Comparing regressions (4) and (6), the coefficients on net flows are close to the opposite of one another, i.e., in the contemporaneous window 0.217 and in the future window -0.166. Therefore, about $0.166/0.217 \approx 76\%$ of the effect of fund flows on contemporaneous returns predictably reverses in future returns. The sum of this evidence leads to the conclusion that price pressure plays an important role in return reversals following FOMC announcements.

5. Additional Findings and Future Research

We show additional implications of our findings for understanding monetary policy shocks and their effects on the stock market. We also assess reversal in components of market returns related to beta and volatility around FOMC announcements.

5.1. The Role of Monetary Policy Shocks

Monetary policy surprise measures (MPS) are constructed from high-frequency movements in interest rates around FOMC announcements. These have been widely used to infer the effects of monetary policy on asset prices and the relation to the macroeconomy and policy rules.[20] We previously showed in Table 3, Panel B that short-term interest rates display no significant decline in informativeness around FOMC announcements. We therefore have no reason to doubt the reliability of monetary surprise measures themselves. However, numerous studies seek to measure the impact of monetary policy surprises on the stock market, typically using short one-day or intraday return windows (e.g., Bernanke and Kuttner, 2005, Bauer and Swanson, 2023a,b). Our findings of low FOMC stock-price informativeness and return reversals naturally raise the question of how monetary policy surprises relate to post-announcement return dynamics.

[20] See for example Kuttner (2001), Cochrane and Piazzesi (2002), Bernanke and Kuttner (2005), Nakamura and Steinsson (2018), and Stock and Watson (2018).

Table 7, Panel A, regresses returns from various windows on and after the FOMC announcement on the orthogonalized MPS of Bauer and Swanson (2023b).[21] Column one regresses the announcement-day return on the monetary policy surprise. The statistically significant point estimate implies that a 100 basis point surprise tightening is associated with a 5.6% decline in stock prices. This estimate closely matches the coefficient obtained by Bauer and Swanson (2023b) in shorter 30-minute return intervals, and also aligns with estimates from prior literature using related measures (Bernanke and Kuttner, 2005, Gürkaynak, Sack, and Swanson, 2005a, Bauer and Swanson, 2023a). Columns (2-6) show that the MPS also predicts *future* returns in windows up to ten days following announcement, with the same negative sign as in the announcement window. Thus, the stock price reaction to monetary surprises is persistence, not reversal. Column (3) in particular reveals that in the ten-day window immediately following announcement, the MPS coefficient of -0.092 implies a continuation of the response of -0.056 on the announcement day. Thus, monetary policy surprises predict continuations, not reversals.

Panel B further investigates these result by considering predictive regressions that decompose announcement returns into a component spanned by the monetary policy surprise and an orthogonal component. Logically, if FOMC announcement returns predict future reversals but monetary policy surprises predict continuation, then the orthogonal component of returns must reverse. The results of Panel B bear this logic out. Based on announcement-day information alone, the fitted component of returns strongly predicts continuation in the window $[1, 10]$ (1% significance), while 82% of the orthogonal component reverses over the longer window $[1, 20]$ (5% significance). Using the announcement window $[0, 3]$ the concentration of reversals in the orthogonal component of returns becomes even more statistically significant. Columns 5 and 6 show that continuation of the fitted portion of returns remains

[21] This measure is orthogonalized with respect to macroeconomic and financial data observed prior to the announcement. See Bauer and Swanson (2023b) Section 5.E. Earlier literature (e.g., Cieslak, 2018) documents predictability of monetary policy surprises from prior data.

significant in the window $[4, 10]$, while reversal of the orthogonal component is significant at the one percent level in the windows $[4, 10]$ and $[4, 20]$. These results reveal complex dynamics in post-FOMC returns related to monetary policy surprises. The simple reversals of FOMC returns that we began with mask more complex dynamics: the MPS predicts continuation of announcement returns, while reversals concentrate in the orthogonal component of announcement returns. The importance of both continuation and reversal components of announcement returns, and their changing relative influence throughout the cycle, contribute to the intricate picture of price informativeness in Figure 1.[22]

These findings on the role of monetary policy surprises in continuations and reversals have important implications for both empirical research and theory. First, our results call into question the common assumption, in an important and wide-ranging literature, that short-window stock returns capture the complete effects of monetary policy news. Bauer and Swanson (2023a,b) invoke slow learning when they propose that market participants must deduce from FOMC actions not just the surprise itself, but also what the surprise conveys about the Fed's policy rule. They argue that private-sector learning about the Fed's policy response function is slow in practice because of the high dimensionality and complexity of the inference problem. Our results provide a different kind of evidence of slow learning. We find delayed reaction or underreaction to the fundamental news contained in the monetary policy surprise, combined with return reversals associated with orthogonal components of returns. A theory capturing these facts would seem to require non-trivial extensions of benchmark models such as Bauer and Swanson (2023a,b).[23]

[22]In Section IA.1 of the Internet Appendix we carry out a related but different return decomposition, using the principal components of Kroencke, Schmeling, and Schrimpf (2021). Their components relate to risk-free rates, a "risk-shift," and a residual. They show that their risk-shift component reverses. Using their methodology, we show that the residual from their decomposition also reverses at a similar rate. Further, the residual is economically the largest contributor to returns (65% of FOMC variation vs. 27% for the risk shift). We conclude that return reversals are not limited to the risk-shift component of this decomposition but instead a broader phenomenon.

[23]Potential directions to microfound our results in models of learning about monetary policy could involve heterogeneous agents, information aggregation through trade, and price pressure.

5.2. Post-FOMC Market Rotation

We finally consider whether post-FOMC reversals concentrate in any particular part of the market. Professional investors describe rotation as a shift in the relative valuations of different components of the market, such as between value and growth stocks, or defensive and cyclical sectors. We investigate whether the market return reversals following FOMC announcements can be linked to any particular types of stocks, which may provide additional useful evidence to theorists.

Figure 9 shows cumulative returns to portfolios of stocks sorted into quintiles by market beta (Panel A) and idiosyncratic volatility (Panel B), following above- and below-average FOMC announcement-day returns (left and right panels).[24] Following good news, high-, medium-, and low-beta stocks have high, medium, and low upward movements on the announcement day as expected, and all groups move upward with similar trends over the following thirty days. However, following bad news, the initially beta-sorted downward movements on the announcement day subsequently reshuffle. The cumulative returns of high-beta stocks remain low for the full thirty days, but medium beta, and to a lesser extent low beta stocks recover substantially. Thus, medium- and low-beta stocks contribute more to post-FOMC price reversals than high-beta stocks. The pattern in Panel B is similar but stronger. Following good news, high-, medium-, and low-volatility stocks initially move upward with different sensitivities, but their paths are more or less parallel for the following thirty days. Following bad FOMC news, however, the recovery is clearly led by low- and to a lesser extent medium-volatility stocks, while the cumulative returns of high-volatility stocks continue to deteriorate.

These findings of market rotation provide further empirical paths for theorists to pursue. Price reversals following FOMC announcements are significantly led by rotations into low-

[24]We retrieve the sorted portfolios from Lu Zhang's personal website https://global-q.org/testingportfolios.html.

to-medium beta and low-to-medium volatility stocks.

6. Conclusion

Building on the methodology of unbiasedness regressions (Biais, Hillion, and Spatt, 1999), we show that on FOMC announcement days and the days immediately following, stock market returns are abnormally uninformative about future prices. Using standard predictive regressions, market returns over four-day windows beginning with the FOMC announcement reliably predict return reversals over the following 15-30 days with high statistical and economic significance. In other words, high short-window returns predict low returns over the remainder of the FOMC cycle, and low announcement returns predict high future returns.

We propose that combining theories of macroeconomic announcement information (Ai and Bansal, 2018, Ai, Han, and Xu, 2023) and price pressure (Campbell, Grossman, and Wang, 1993, Hendershott and Menkveld, 2014) can help to explain these findings. The information channel seems promising because high announcement-day returns are associated with a contemporaneous drop in VIX, lower future returns, and decreasing future monetary policy news attention, while low announcement-day returns produce the opposite. The necessity of accounting for price pressure is suggested by the fact that reversals begin most strongly about four days following announcements, approximately matching to the period of sustained high volume and a clear liquidity pecking order that follow FOMC announcements. Further, a variety of price pressure proxies, including abnormal volume and differentials in equity and bond ETF fund flows predict return reversals as well as or better than announcement-window returns themselves. Our study thus highlights the importance of research that integrates perspectives from standard information-based asset pricing and market microstructure. Future theoretical contributions in this direction should be valuable, since important new macroeconomic information provides a natural source of speculative, hedging, and rebalancing motives that can initiate price pressure.

We also highlight implications for studies that seek to understand the response of the stock market to monetary policy surprises (e.g., Bernanke and Kuttner, 2005, Nakamura and Steinsson, 2018), and for the hypothesis that investors slowly learn from FOMC announcements about the Fed's policy rule (Bauer and Swanson, 2023a,b). Our findings of sustained stock market responses to FOMC announcements suggest that investor learning and information processing occurs not just at the instant of an FOMC announcement, but throughout the period of high trading activity that follows. Further, return reversals concentrate in the component of returns orthogonal to monetary policy news, while the monetary policy surprise itself shows if anything persistent effects on stock market returns. These findings provide fertile ground for new theory that integrates slow learning about policy with the intense trade and rich return dynamics that follow FOMC announcements.

A. Appendix

A.1. Simulations

In this section, we present in more details the simulations used to produce Figure 2. In each case, we simulate 100,000 sample paths from $t = -10$ to $t = 30$. As a benchmark, we assume that the stock price p_t follows a random walk with an innovation component and a noise component,

$$p_t = \sum_{t=-10}^{t} \epsilon_t + \nu_t. \tag{10}$$

Both components are normally distributed. $\epsilon_t \sim \mathcal{N}(0, \sigma_t^2)$ is independent over time. Unless otherwise specified, we set $\sigma_t = \sigma^2 = 0.0008\ \forall$. $\nu_t \sim \mathcal{N}(0, \omega_t^2)$ can exhibit autocorrelation.

For the case of additional information at $t = 0$ (Panel A, blue solid line), the innovation ϵ_0 is three times larger than on other days, i.e. $\sigma_0 = 3\sigma$. The noise component is zero ($\nu_t = 0\ \forall t$).

For the case of a temporary noise shock at $t = 0$ (Panel A, red dashed line), the noise shock ν_0 is three times larger than the innovation, i.e. $\omega_0 \sim 3\sigma$. The noise component remains zero at other times, $\nu_t = 0$ for $t \neq 0$.

For the case with persistent noise shocks (Panel B), the noise process ν_t follows:

$$\nu_t = \begin{cases} 0 & \text{if } t < 0, \\ \rho_\nu^t \nu_{t-1} + \xi_t & \forall t \geq 0 \end{cases} \tag{11}$$

where $\xi_t \sim \mathcal{N}(0, \sigma_{\xi_t}^2)$ and $\sigma_{\xi_t} = \rho_\xi^t \times 2\sigma$. The persistence parameters are $\rho_\nu = \rho_\xi = 0.9$. The initial noise shock has a standard deviation twice as large as the innovation, and it decays at a rate of 10% (or $1 - \rho_\nu$) per day. However, new shocks occur at every period $t \geq 1$. Their magnitude decays also decays at at a rate of 10% ($1 - \rho_\xi$).

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Table 1
Unbiasedness Regression Excess R^2

This table reports the change in R^2 (ΔR^2) and Excess ΔR^2 around FOMC announcements. The R^2 are computed from the following unbiasedness regression:

$$Ret_{i[T_1,T_2]} = \alpha_t + \beta_t Ret_{i[T_1,t]} + \varepsilon_{i,t},$$

where $T_1 < t \leq T_2$, and $Ret_{i[t_1,t_2]}$ are the cumulative S&P 500 index log returns from day t_1 to day t_2 in event time relative to FOMC announcement i at time $t = 0$. Excess $\Delta R^2_t(t, K) = \frac{T}{K}(R^2_t - R^2_{t-K}) - 1$, where $T = T_2 - T_1 + 1$ is the length of the event window and $K = 1$ (Panels A and C), $K = 3$ (Panel C), and $K = 4$ (Panels B). The interval $[T_1, T_2]$ is shown in the column headers. The single-day, multi-day, and pre-announcement windows are reported in Panels A to C, respectively. p-values shown in italics are derived from 100,000 placebo events randomly matched to each FOMC announcement by calendar year, quarter, and day of the week. The sample consist of FOMC announcements between January 1994 and December 2021.

	$[-5,30]$		$[-10,30]$		$[-20,30]$		$[-5,20]$		$[-5,10]$	
	ΔR^2	Excess ΔR^2 *p-val*	ΔR^2	Excess ΔR^2 *p-val*	ΔR^2	Excess ΔR^2 *p-val*	ΔR^2	Excess ΔR^2 *p-val*	ΔR^2	Excess ΔR^2 *p-val*
A. One-day windows										
$t = 0$	-0.025	-1.915	-0.020	-1.838	-0.018	-1.904	-0.010	-1.253	0.056	-0.098
		0.050		*0.061*		*0.058*		*0.115*		*0.475*
$t = 1$	-0.007	-1.240	-0.007	-1.286	-0.008	-1.399	-0.003	-1.084	0.034	-0.448
		0.075		*0.071*		*0.068*		*0.065*		*0.100*
$t = 2$	0.014	-0.513	0.012	-0.500	0.010	-0.469	0.013	-0.671	0.014	-0.776
		0.374		*0.364*		*0.375*		*0.367*		*0.218*
$t = 3$	0.009	-0.691	0.008	-0.676	0.002	-0.904	0.016	-0.585	0.033	-0.469
		0.395		*0.401*		*0.342*		*0.393*		*0.388*
B. Multi-day windows										
$t = [0, 3]$	-0.010	-1.090	-0.007	-1.075	-0.013	-1.169	0.016	-0.898	0.138	-0.448
		0.017		*0.022*		*0.016*		*0.021*		*0.074*
$t = [4, 7]$	0.024	-0.784	0.021	-0.782	0.011	-0.857	0.084	-0.455	0.180	-0.279
		0.024		*0.025*		*0.018*		*0.078*		*0.097*
$t = [8, 11]$	0.045	-0.591	0.049	-0.494	0.038	-0.516	0.084	-0.453		
		0.118		*0.171*		*0.162*		*0.116*		
$t = [12, 15]$	0.226	1.032	0.208	1.129	0.163	1.082	0.249	0.619		
		0.989		*0.991*		*0.985*		*0.996*		
C. Pre-announcement										
$t = -1$	0.047	0.676	0.041	0.664	0.033	0.675	0.066	0.709	-0.000	-1.008
		0.518		*0.510*		*0.494*		*0.624*		*0.142*
$t = [-3, -1]$	0.105	0.263	0.102	0.391	0.077	0.312	0.151	0.311	0.231	0.234
		0.714		*0.767*		*0.712*		*0.872*		*0.871*

Table 2
Predictive Regressions and FOMC Return Reversals

This table reports results from predictive regressions of S&P 500 index log returns onto FOMC announcement returns. The regression is

$$Ret_{i[t_1,t_2]} = \gamma_0 + \gamma_1 Ret_{i[0,h-1]} + \epsilon_i,$$

where $Ret_{[t_1,t_2]}$ are cumulated over intervals t_1 to t_2, measured in days relative to the current announcement at $t = 0$ and the right-hand side variable $Ret_{[0,h-1]}$ is the h-day return beginning at 0. τ_1 refers to the date of the following FOMC announcement. Heteroskedasticity-robust standard errors are reported in parentheses, and *,**, and *** indicate associated p-values below $0.1, 0.05$, and 0.01, respectively. The sample consist of FOMC announcements between January 1994 and December 2021 (N=223).

	Dependent variable							
	$\text{Ret}_{[1,3]}$	$\text{Ret}_{[1,\tau_1-1]}$	$\text{Ret}_{[4,10]}$		$\text{Ret}_{[4,20]}$		$\text{Ret}_{[4,\tau_1-1]}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ret_0	-0.075	-0.503	-0.110		-0.472*		-0.428	
	(0.136)	(0.349)	(0.158)		(0.282)		(0.351)	
$\text{Ret}_{[0,3]}$				-0.291***		-0.453***		-0.602***
				(0.089)		(0.165)		(0.197)
Intercept	0.000	0.009***	-0.001	-0.000	0.005*	0.005**	0.009**	0.009***
	(0.001)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
R^2	0.002	0.014	0.003	0.062	0.017	0.056	0.010	0.067

Table 3
Subsamples, Other Assets, and Other Announcements

This table reports Excess ΔR^2 for different FOMC subsamples in Panel A, for alternative asset classes on FOMC announcements in Panels B and C, and for alternative macroeconomic announcements in Panel D. R^2 is computed from the following unbiasedness regression:

$$Ret_{i[T_1,T_2]} = \alpha_t + \beta_t Ret_{i[T_1,t]} + \varepsilon_{i,t},$$

where $T_1 < t \leq T_2$, $Ret_{i[t_1,t_2]}$ are the S&P 500 index log returns from day t_1 to t_2 relative to the day of macroeconomic announcement i at $t = 0$ in Panels A and D, and the 30-day Fed Fund futures, 3-month Eurodollar (ED) futures, and 1-3 years Treasury bond ETF (iShares ticker SHY) in Panel B and 2-, 5-, 10-year treasury futures in Panel C. Excess $\Delta R_t^2(t, K) = \frac{T}{K}(R_t^2 - R_{t-K}^2) - 1$, where $T = T_2 - T_1 + 1$ is the length of the event window. The interval $[T_1, T_2]$ is fixed to $[-5, 30]$. Excess ΔR^2 are measured for either the announcement day ($K = 1, t = 0$) or a four-day window starting on the announcement day ($K = 4, t = [0, 3]$). p-values shown in italics are derived from 100,000 placebo events randomly matched to each FOMC announcement by calendar year, quarter, and day of the week. The sample consist of FOMC announcements between 1979 and 2021 in Panel A and January 1994 and December 2021 in Panels B and C. In Panel D, the sample is given by announcements of initial GDP, unemployment, or inflation (measured as the earlier of CPI or PPI) between 1994 and 2021. The ETF data is retrieved from Yahoo finance, the Fed Fund and Eurodollar futures from the Federal Reserve of Economic Data wesbite, and the treasury futures from Bloomberg.

Excess $\Delta R^2(t)$ / *p-val*					
$t=0$	$t=[0,3]$	$t=0$	$t=[0,3]$	$t=0$	$t=[0,3]$
A. FOMC subsamples					
1979-1993		1994-2009		2010-2021	
-0.050	-0.121	-1.416	-0.884	-2.706	-1.314
0.622	*0.558*	*0.119*	*0.094*	*0.073*	*0.017*
B. Short-term rates					
FF futures		ED futures		SHY ETF	
-0.694	1.504	1.468	0.583	1.155	0.479
0.300	*0.898*	*0.616*	*0.787*	*0.641*	*0.732*
C. Treasury futures					
2-year		5-year		10-year	
0.846	-0.197	-0.721	1.061	-1.829	0.483
0.757	*0.431*	*0.271*	*0.920*	*0.028*	*0.819*
D. Other announcements					
GDP		Employment		Inflation	
0.290	-0.462	0.250	0.293	0.267	-0.031
0.741	*0.114*	*0.773*	*0.770*	*0.593*	*0.546*

Table 4
Predictive Regressions and Changes in VIX

This table reports results from predictive regressions of S&P 500 index log returns onto changes in VIX (ΔVIX), divided by 100, at FOMC announcements (Panel A) and components of FOMC announcement returns (Panel B). $Ret_{i[t_1,t_2]}$ corresponds to S&P 500 returns over intervals t_1 to t_2, measured in days relative to the current announcement at $t = 0$. τ_1 refers to the date of the following FOMC announcement. ΔVIX_0 is the single-day change in VIX and $\Delta\text{VIX}_{[0,3]}$ is the four-day change starting at $t = 0$. $\text{Ret}^{Fit}_{[0,3]}$ and $\text{Ret}^{Resid}_{[0,3]}$ in Panel B are the returns $\text{Ret}_{[0,3]}$ decomposed into a fitted part and a residual from univariate regressions of returns onto ΔVIX, as in columns (1) and (2). Heteroskedasticity-robust standard errors are reported in parentheses, and *,**, and *** indicate associated p-values below 0.1, 0.05, and 0.01, respectively. The sample consist of FOMC announcements between January 1994 and December 2021 (N=223).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable							
A. Prediction with Δ VIX								
	$\text{Ret}_{[1,3]}$	$\text{Ret}_{[1,\tau_1-1]}$	$\text{Ret}_{[4,10]}$		$\text{Ret}_{[4,20]}$		$\text{Ret}_{[4,\tau_1-1]}$	
ΔVIX_0	0.020	0.230	0.088		0.117		0.209	
	(0.053)	(0.152)	(0.096)		(0.120)		(0.144)	
$\Delta\text{VIX}_{[0,3]}$				0.201***		0.223**		0.332***
				(0.076)		(0.089)		(0.106)
Intercept	0.000	0.009***	-0.001	-0.000	0.005*	0.005*	0.009***	0.009***
	(0.001)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
R^2	0.000	0.008	0.004	0.072	0.003	0.033	0.006	0.050
B. Prediction with return components								
	Ret_0	$\text{Ret}_{[0,3]}$	$\text{Ret}_{[4,10]}$		$\text{Ret}_{[4,20]}$		$\text{Ret}_{[4,\tau_1-1]}$	
ΔVIX_0	-0.463***							
	(0.082)							
$\Delta\text{VIX}_{[0,3]}$		-0.465***						
		(0.053)						
$\text{Ret}^{Fit}_{[0,3]}$			-0.432***	-0.432***	-0.481**	-0.481***	-0.715***	-0.715***
			(0.163)	(0.161)	(0.191)	(0.181)	(0.228)	(0.216)
$\text{Ret}^{Resid}_{[0,3]}$				-0.134		-0.423		-0.478
				(0.149)		(0.304)		(0.371)
Intercept	0.000	0.001	0.000	0.000	0.005**	0.005**	0.010***	0.010***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
R^2	0.589	0.525	0.072	0.079	0.033	0.056	0.050	0.070

Table 5
Price Pressure and Reversals

This table reports results from predictive regressions of S&P 500 index log returns onto FOMC announcement returns, different proxies of price pressure, and their interaction. The regression is

$$Ret_{i[4,20]} = \gamma_1 Ret_{i[0,3]} + \gamma_2 Pressure_i \times Ret_{i[0,3]} + \gamma_3 Pressure_i + \epsilon_i,$$

where returns $Ret_{i[4,20]}$ and $Ret_{i[0,3]}$ are S&P 500 log returns over intervals [4,20] and [0,3], respectively, measured in days relative to the current FOMC announcement i at $t = 0$. $Pressure$ corresponds to one of three proxies for price pressure: total detrended log trading volume (Vlm) for SPY ETF from the announcement to three days after, an indicator variable $\mathbb{1}_{PC}$ equal to one if the FOMC announcement is followed by a press conference and zero otherwise, and an indicator variable $\mathbb{1}_{MPS}$ if the absolute orthogonalized monetary policy news shock of Bauer and Swanson (2023b) is in the top quintile and zero otherwise. Heteroskedasticity-robust standard errors are reported in parentheses, and *,** , and *** indicate associated p-values below $0.1, 0.05$, and 0.01, respectively. The sample consist of FOMC announcements from January 1994 to December 2021 in columns (1)-(3), N=223, and to December 2019 in column (4), N=208.

		Price-pressure proxies		
		Vlm	$\mathbb{1}_{PC}$	$\mathbb{1}_{MPS}$
	(1)	(2)	(3)	(4)
$\text{Ret}_{[0,3]}$	-0.450***	-0.171	-0.308*	-0.230*
	(0.165)	(0.143)	(0.176)	(0.131)
$\text{Ret}_{[0,3]} \times$ Pressure		-0.222*	-0.793***	-0.897**
		(0.114)	(0.274)	(0.439)
Pressure		-0.000	-0.001	-0.001
		(0.002)	(0.007)	(0.007)
Intercept	0.005**	0.004	0.005*	0.004
	(0.003)	(0.003)	(0.003)	(0.003)
R^2	0.055	0.095	0.080	0.101

Table 6
Fund Flows and Reversals

This table reports the results of the following regression

$$Ret_{i[t_1,t_2]} = \gamma_1 EqtFlow_{i[0,3]} + \gamma_2 BndFlow_{i[0,3]} + \gamma_2 NetFlow_{i[0,3]} + \gamma_4 Ret_{i[0,3]} + \epsilon_i,$$

where returns $Ret_{i[t_1,t_2]}$ are the cumulative S&P 500 index log returns from day t_1 to day t_2 in event time relative to FOMC announcement i at time $t = 0$. Equity flows ($EqtFlow$) and bond flows ($BndFlow$) are the sum of flows from the announcement to three days after, and $NetFlow = EqtFlow - BndFlow$. We follow Kroencke, Schmeling, and Schrimpf (2021) and retrieve daily equity and bond ETF fund flows from Bloomberg starting from 2006. We normalize fund flows by their moving average and standard deviation. Heteroskedasticity-robust standard errors are reported in parentheses, and *,**, and *** indicate associated p-values below $0.1, 0.05$, and 0.01, respectively. The sample consist of FOMC announcements between January 2006 and December 2021 (N=127).

	Dependent variable					
	$\text{Ret}_{[0,3]}$				$\text{Ret}_{[4,20]}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{EqtFlow}_{[0,3]}$	0.287***			0.042		
	(0.078)			(0.157)		
$\text{BndFlow}_{[0,3]}$		-0.242***				
		(0.075)				
$\text{NetFlow}_{[0,3]}$			0.217***	0.199**		-0.166**
			(0.047)	(0.095)		(0.069)
$\text{Ret}_{[0,3]}$					-0.510**	-0.371
					(0.220)	(0.244)
Intercept	0.003	0.003	0.003*	0.003*	0.006*	0.005
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)
R^2	0.115	0.106	0.182	0.183	0.079	0.106

Table 7
Monetary Policy News Shock and Return Dynamics

This table reports results from regressions of S&P 500 index log returns onto the orthogonalized monetary policy surprise (MPS) from Bauer and Swanson (2023b) at FOMC announcements. $Ret_{i[t_1,t_2]}$ are the cumulative S&P 500 index log returns from day t_1 to day t_2 in event time relative to FOMC announcement i at time $t = 0$. In Panel B, announcement returns Ret_0 and $\text{Ret}_{[0,3]}$ are decomposed into a fitted and a residual components from univariate regressions of returns onto MPS. Heteroskedasticity-robust standard errors are reported in parentheses, and *,**, and *** indicate associated p-values below $0.1, 0.05$, and 0.01, respectively. The sample consist of FOMC announcements between January 1994 and December 2019 (N=208).

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable					
	Ret_0	$\text{Ret}_{[1,10]}$	$\text{Ret}_{[1,20]}$	$\text{Ret}_{[0,3]}$	$\text{Ret}_{[4,10]}$	$\text{Ret}_{[4,20]}$
A. MPS effects on current and future returns						
MPS	-0.056***	-0.092**	-0.101	-0.071**	-0.077**	-0.086
	(0.019)	(0.036)	(0.072)	(0.031)	(0.039)	(0.078)
Intercept	0.003***	-0.001	0.003	0.003**	-0.002	0.003
	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)
R^2	0.062	0.029	0.015	0.028	0.024	0.011
B. Prediction with return components						
Ret_0^{Fit}		1.653***	1.814			
		(0.629)	(1.184)			
Ret_0^{Resid}		-0.278	-0.824**			
		(0.183)	(0.362)			
$\text{Ret}_{[0,3]}^{Fit}$					1.069**	1.180
					(0.490)	(0.975)
$\text{Ret}_{[0,3]}^{Resid}$					-0.323***	-0.506***
					(0.097)	(0.186)
Intercept		-0.006**	-0.002		-0.005**	-0.001
		(0.003)	(0.005)		(0.003)	(0.005)
R^2		0.042	0.061		0.099	0.079

Figure 1. Unbiasedness Regression R^2

This figure shows R_t^2 estimated from unbiasedness regressions:

$$Ret_{i[-10,30]} = \alpha_t + \beta_t Ret_{i[-10,t]} + \varepsilon_{i,t},$$

where $Ret_{i,t}$ is the log return on day t in event time relative to announcement i. The dependent variables are the returns from 10 days prior to 30 days after each announcement, and the independent variables are the returns of the partial announcement window from 10 days prior to the announcement to t. The solid and solid-dotted lines correspond to FOMC (using S&P 500 index returns) and earnings announcements (using firms' stock returns), respectively. The FOMC announcement sample period is from January 1994 to December 2021. The sample of earnings announcements consists of all announcements of U.S. firms with analyst coverage in I/B/E/S between January 2010 and December 2021.

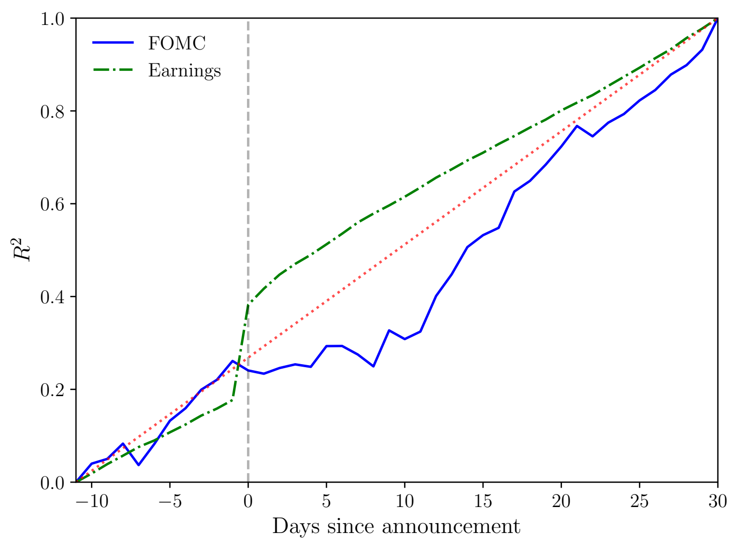


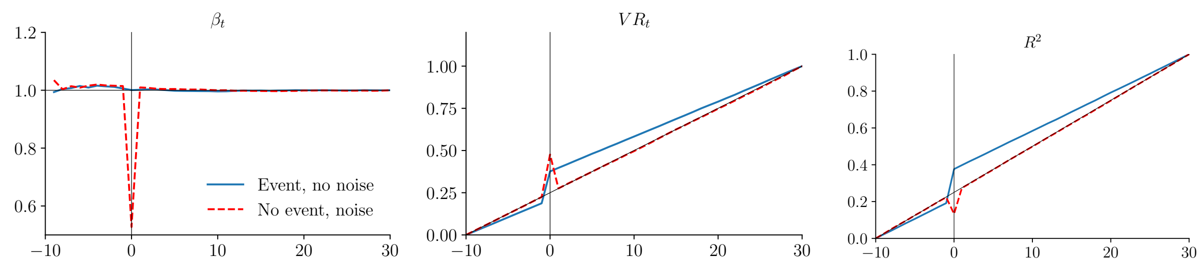
Figure 2. Beta, Variance-Ratio and R^2 in Simulated Data

This figure shows betas (β), variance-ratios (VR), and R^2 estimated from unbiasedness regressions:

$$Ret_{i[-10,30]} = \alpha_t + \beta_t Ret_{i[-10,t]} + \varepsilon_{i,t},$$

where $Ret_{i[t_1,t_2]}$ are the cumulative log returns from day t_1 to day t_2 in event time relative to announcement i at time $t = 0$. The dependent variables are the returns from 10 days prior to 30 days after each event, and the independent variable is the returns of the partial event window from 10 days prior to the event to t. Panel A displays the dynamics of these variables from 100,000 simulated events in which stock prices following a random walk with either a permanent event information shock at $t = 0$ (blue solid line) or with a temporary noise shock at $t = 0$. The magnitude of both shocks is three times larger than that of daily information flow (red dashed line). In Panel B, stock prices experience persistent noise shocks starting at $t = 0$ that is twice the magnitude of the daily information flow. For $t \geq 1$ both the prior noise shocks and the standard deviation of future noise shocks decay at a rate of 10% daily. Simulations are described in details in the Appendix.

Panel A: Noise and information shocks at $t = 0$



Panel B: Persistent noise shocks starting at $t = 0$

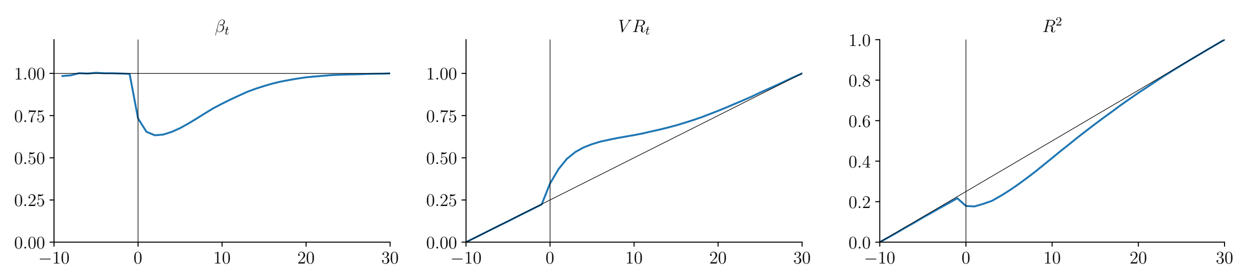


Figure 3. VIX, EPU, Monetary Attention, and SPY Volume

This figure shows the change in log VIX, EPU (Baker, Bloom, and Davis, 2016), attention to monetary news (Fisher, Martineau, and Sheng, 2022), and log SPY trade volume around FOMC announcements in Panels A to D, respectively. In Panel A, the change in VIX is relative to the day before FOMC announcements whereas the change in Panels B to D is relative to their corresponding daily average from 20 to 6 days before FOMC announcements. The shaded areas show 95% confidence intervals based on White standard errors. The sample consist of FOMC announcements between January 1994 and December 2021.

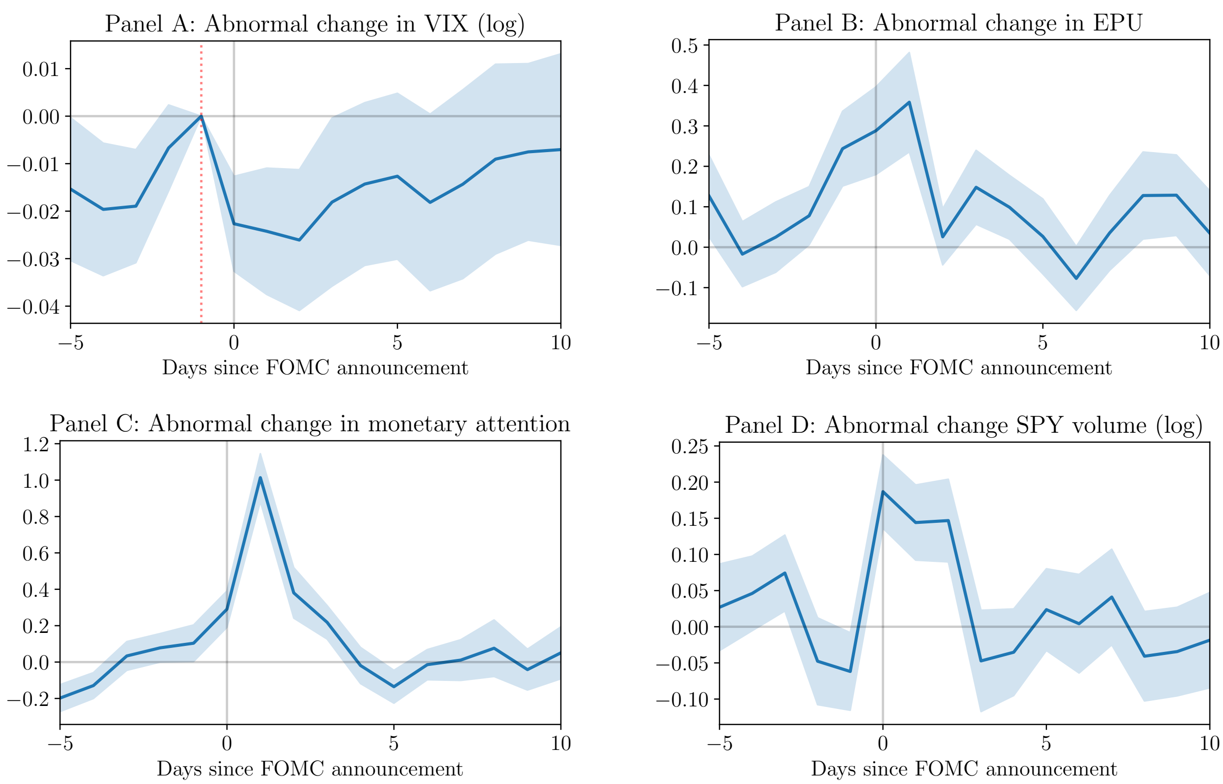


Figure 4. Unbiasedness Regressions Betas

Panel A of this figure shows betas (β) estimated from unbiasedness regressions:

$$Ret_{i[-10,30]} = \alpha_t + \beta_t Ret_{i[-10,t]} + \varepsilon_{i,t},$$

where $Ret_{i[t_1,t_2]}$ are the cumulative S&P 500 index log returns from day t_1 to day t_2 in event time relative to FOMC announcement i at time $t = 0$. The dependent variables are the returns from 10 days prior to 30 days after each announcement, and the independent variable is the returns of the partial announcement window from 10 days prior to the announcement to t. Panels B and C plot $\beta_{t,h}^{marginal}$ for $h = 1$ and $h = 4$, respectively, from the following augmented unbiasedness regression:

$$Ret_{i[-10,30]} = \alpha_t + \beta_t Ret_{i[-10,t]} + \beta_{t,h}^{marginal} Ret_{i[t-h,t]} + \varepsilon_{i,t},$$

where we fix $\beta_t = 1$. The dotted lines corresponds to the 90% confidence intervals around one in Panel A and around zero in Panels B and C. The sample consist of FOMC announcements between January 1994 and December 2021.

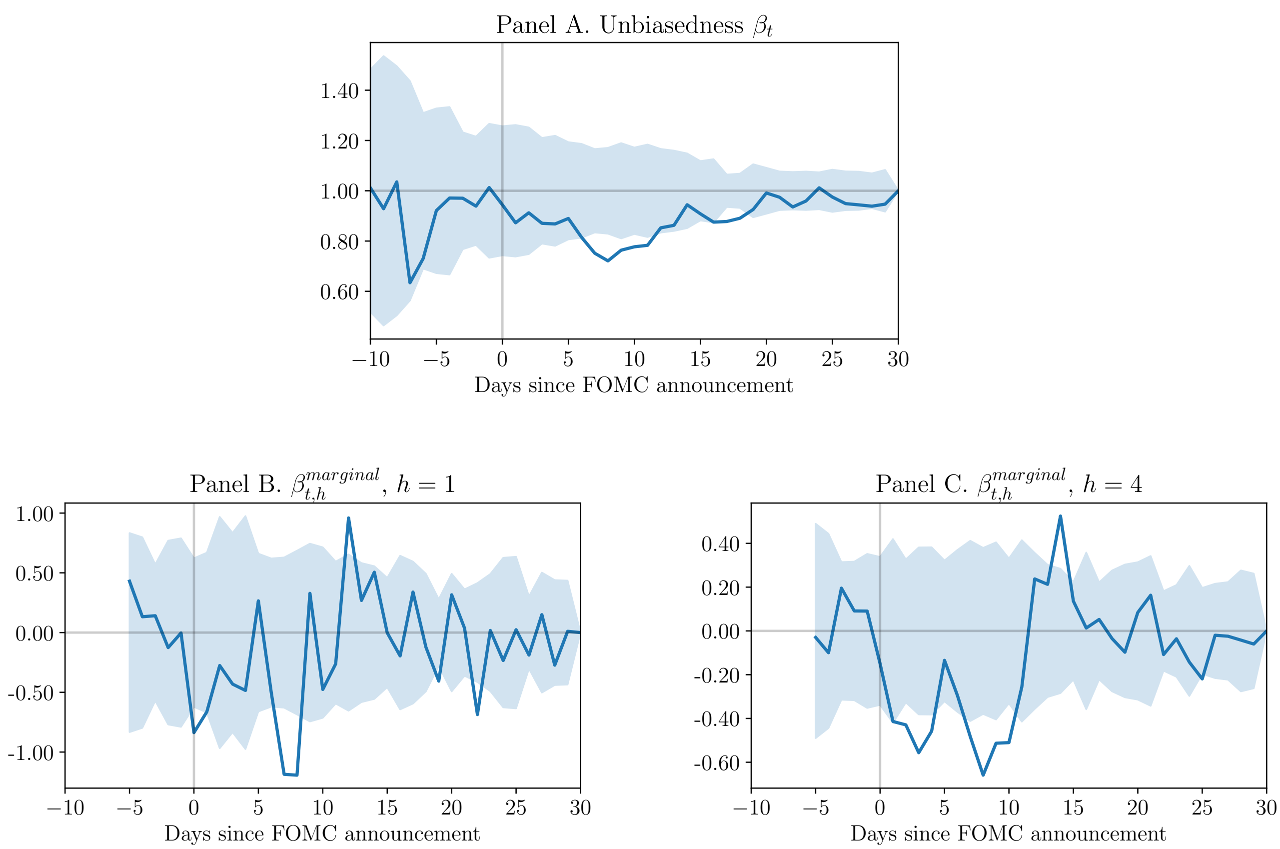


Figure 5. FOMC Reversals

This figure shows average cumulative S&P 500 index log returns from 10 days before to 30 days after FOMC announcements conditioned on a quintile sort of announcement day returns. The second, third, and fourth quintiles are combined together to form the "middle" group, and cumulative returns are normalized to zero at $t = -1$. The sample consist of FOMC announcements between January 1994 and December 2021.

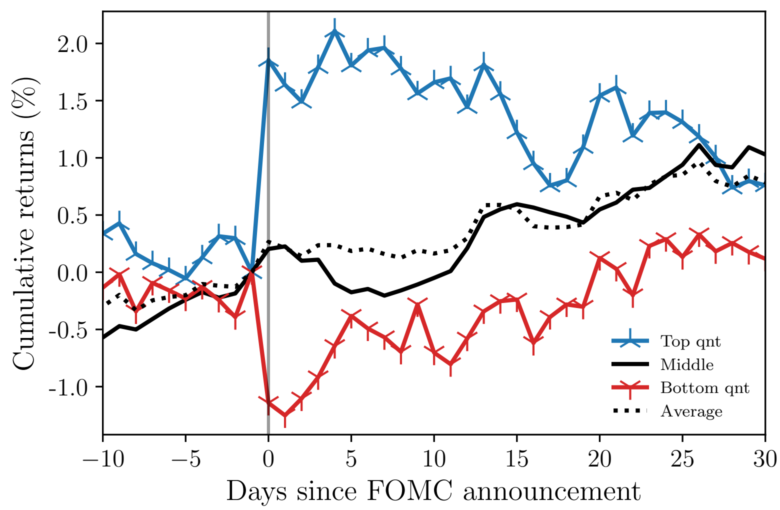
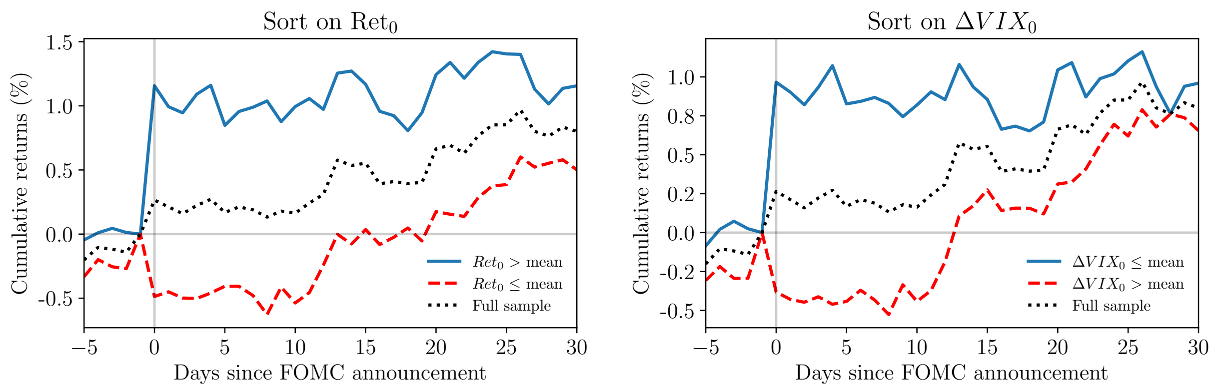


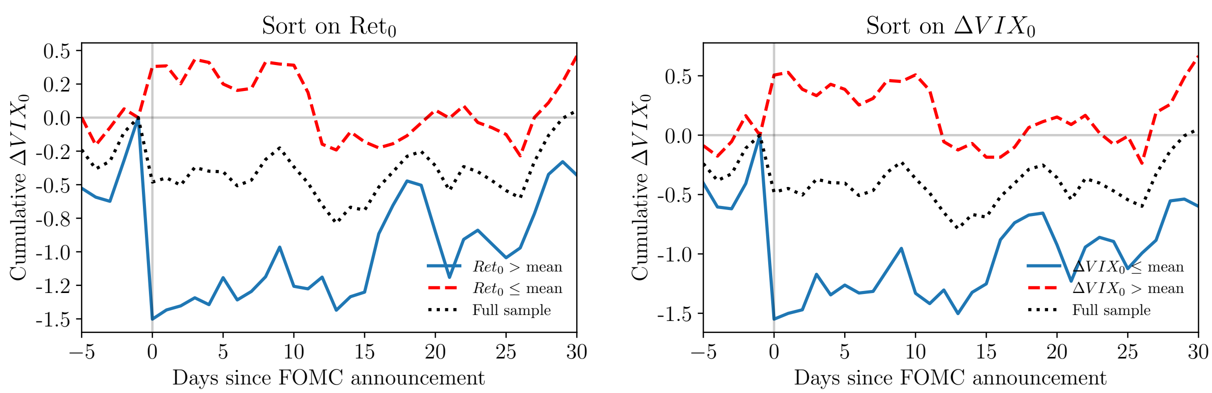
Figure 6. Post-FOMC Announcement Cumulative Returns, VIX, and Attention

This figure shows average cumulative S&P 500 index log returns, cumulative changes in VIX, and cumulative attention to monetary policy news (Fisher, Martineau, and Sheng, 2022) sorted on announcement day returns (Ret_0, left figures) or announcement day changes in VIX (ΔVIX_0, right figures) being above or below their unconditional mean. In Panels A and B, the cumulative returns and ΔVIX are normalized to zero at $t = -1$. Attention to monetary news is computed as the attention from time $t + 1$ minus the average attention over three trading days prior to FOMC announcements. The sample consist of FOMC announcements between January 1994 and December 2021.

Panel A: Cumulative returns



Panel B: Cumulative ΔVIX



Panel C: Cumulative attention to monetary policy news

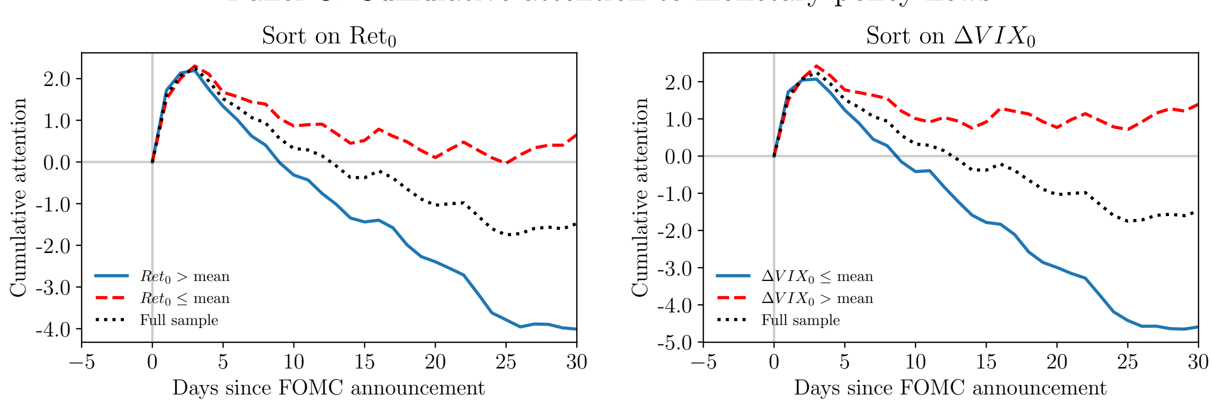
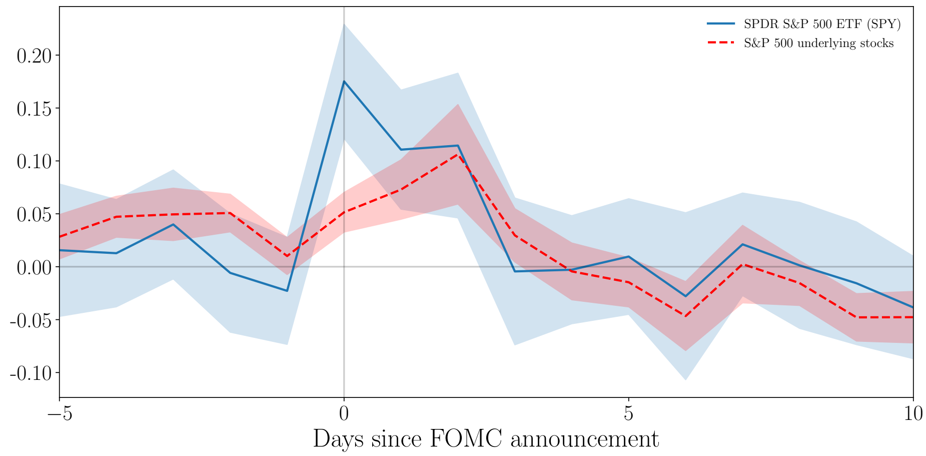


Figure 7. Liquidity Differentials and SPY Fails-to-Deliver

This figure shows the change in SPY and S&P 500 trading volume in Panel A and the change in the SPY ETF fails-to-deliver, scaled by shares outstanding in Panel B. The change is relative to their corresponding daily average from 20 to 6 days before FOMC announcements. The shaded areas show 95% confidence intervals based on White standard errors. The sample consist of FOMC announcements between January 1994 and December 2021 in Panel A, and those between March 2004 and December 2021 in Panel B.

Panel A. SPY ETF and S&P 500 trade volume



Panel B. SPY ETF fail-to-deliver

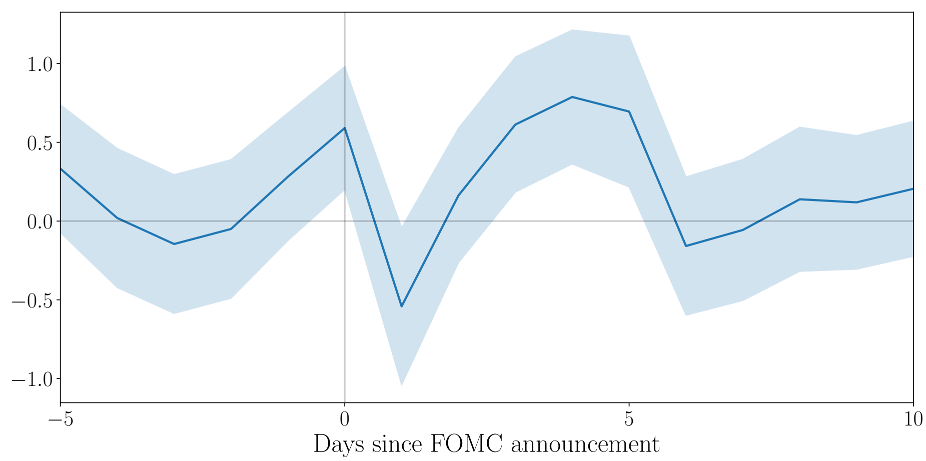
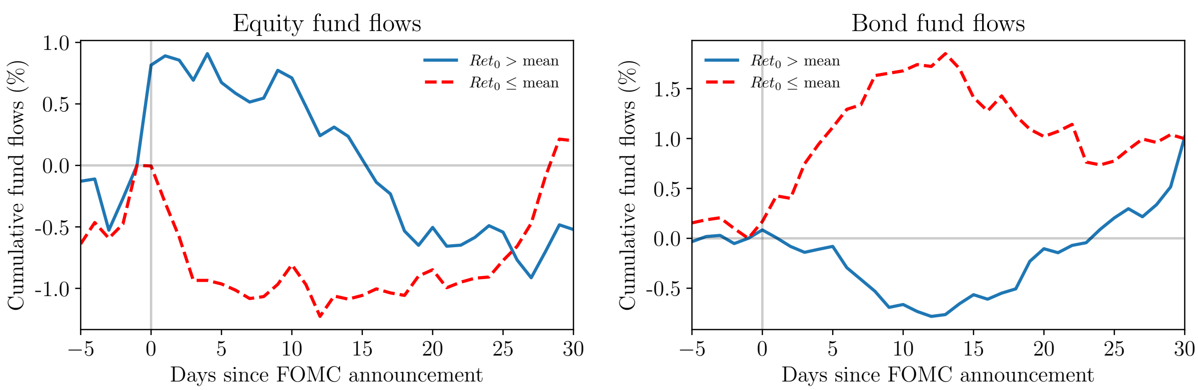


Figure 8. ETF Fund Flows

This figure shows the cumulative flows in equity and bond ETF around FOMC announcements conditioned on FOMC announcement date returns (Ret_0) above and below the mean in Panel A and conditioned on FOMC announcement date changes in VIX (ΔVIX_0) above and below the mean in Panel B. The cumulative fund flows are normalized to zero at $t = -1$. The sample consist of FOMC announcements between January 2006 and December 2021.

Panel A: Sort on FOMC announcement returns



Panel B: Sort on FOMC announcement ΔVIX

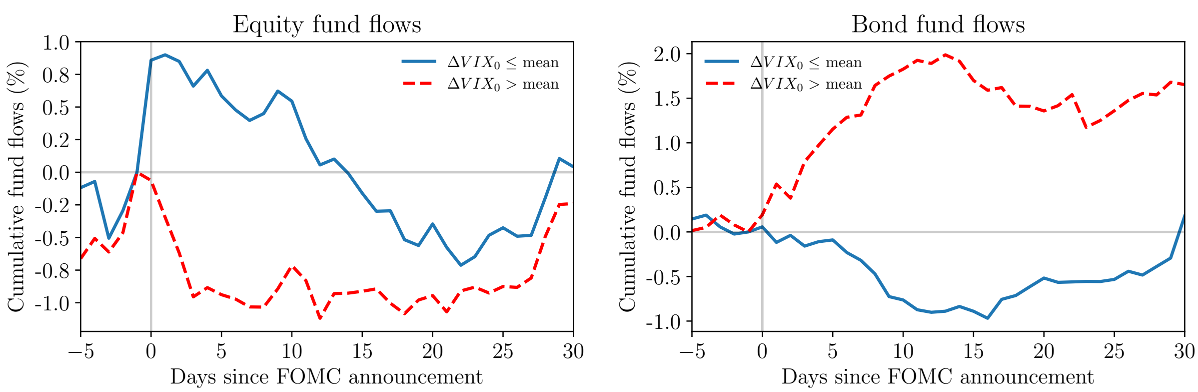
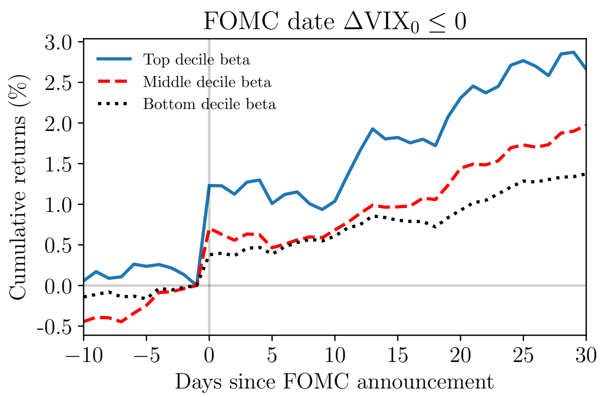
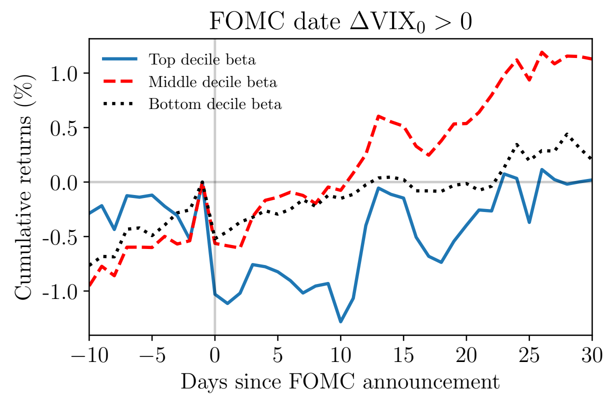


Figure 9. Market Rotation

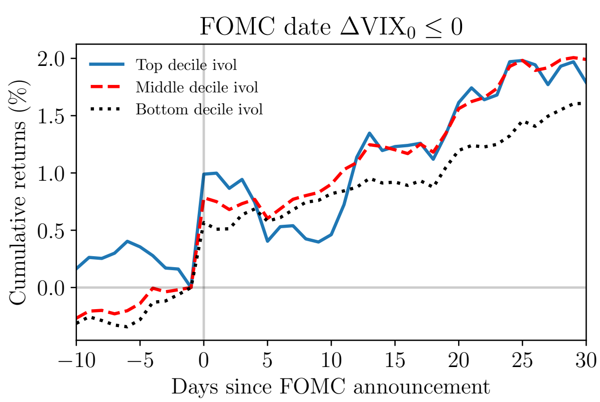
This figure shows the cumulative returns for the top, middle, and bottom decile CAPM-beta sorted portfolios in Panel A and IVOL-sorted portfolios in Panel B. The left figures show the cumulative returns when $\Delta VIX_0 < 0$ on FOMC dates and the right figures show the cumulative returns when $\Delta VIX_0 \geq 0$. We scale the plots such that the y-axis equals to zero at $t = -1$. The sample consist of FOMC announcements between January 1994 and December 2021.

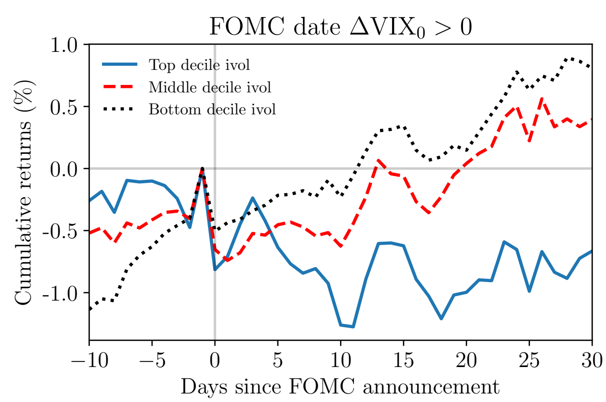
Panel A: CAPM-beta-sorted portfolios





Panel B: IVOL-sorted portfolios





Internet Appendix to

Noisy FOMC Returns? Information, Price pressure, and Post-Announcement Reversals

Intended for online publication

IA. Supplementary Results

- Figure IA1 expands on Table 3, Panel A of the paper to give rolling 3-year estimates of Excess ΔR^2.
- Figure IA2 shows that the "risk-shift" component of Kroencke, Schmeling, and Schrimpf (2021) and residuals both mean-revert. See Section IA.1 for more details.
- Table IA1 reproduces Table 1 of the paper with an alternative bootstrap distribution and p-values. Here we simply redraw samples of the same size as the data from the population of all announcements, with replacements, to obtain the bootstrapped distribution of Excess ΔR^2 statistics. We use this distribution to test the hypothesis that Excess $\Delta R^2 \geq 0$.
- Table IA2 reproduces Table 2 with alternative predictive windows around FOMC announcements.
- Table IA3 expands on Table 3 of the paper to give results for a greater variety of window sizes.
- Table IA4 shows the contribution of pre-announcement returns to low announcement-date and post-announcement price informativeness. The only statistically significant reversal of pre-announcement returns in the post-announcement period is from day -1 to the announcement day 0.
- Table IA5 reports the increase in abnormal volume on macroeconomic announcement days.

IA.1. Comparison to risk-shift reversal

Kroencke, Schmeling, and Schrimpf (2021) describe reversal of a "risk-shift" component of FOMC announcement returns that they obtain through principal components decomposition. We show here that the residual from their decomposition reverses just as strongly as their risk-shift, and is larger in magnitude. Return-reversal is a general property of FOMC returns.

Their method decomposes monetary policy news from a set of indicators into orthogonal principal components that they identify as risk-free rate news, a "risk shift" related to risky asset prices, and a residual:

$$r_i = \gamma_0 + \gamma_1 SR_i + \gamma_2 LR_i + \gamma_3 RS_i + \varepsilon_i, \tag{12}$$

where SR_i is short-run interest rate news, LR_i is long-run interest rate news, RS_i is is their risk-shift component, and the remainder of variation is in the residual. They show that the risk shifts explain 27% of stock market announcement return variation compared to only 9% for the two risk-free rate components combined. They also show that risk shifts predict a price reversal following FOMC announcements, which is an important predecessor to our findings. However, since their news components combined explain only 36% of announcement day market returns, the majority (64%) of market return variation on announcement days is in their residual.

Figure IA2 shows that mean reversion of future market returns is just as strongly predicted by the residual component of returns as the risk-shift component of returns. Following their methodology, we regress future returns on the risk-shift and residual components of FOMC returns:

$$r_{i[0,t+h]} = \alpha_h + \beta_{1,h} Risk\ shift + \beta_{2,h} Residual + \epsilon_h, \tag{13}$$

where the *Risk shift* and *Residual* variables are normalized so that both generate unit regression coefficients on the announcement date, i.e., $\beta_{1,0} = \beta_{2,0} = 1$. The figure then plots for each date h the sum of beta coefficients from zero to h. If the cumulative sum of beta coefficients declines, then that component of returns predicts mean reversion in future market returns. The figure shows that *both* the risk-shift component and the residual equally predict mean reversion in market returns. Their date $t = 0$ impacts on FOMC returns are both close to entirely dissipated after twenty days, with somewhat stronger mean reversion for the residual than for the risk-shift by day 20, and no statistical difference between the two (Panel B). Moreover, since the residual variance is approximately 2.5 times larger than the risk-shift variance (64% vs. 27%), it is quantitatively more important in explaining the return reversal. Thus, mean-reversion is not limited to the risk-shift component identified by KSS, but is a more general property of FOMC returns.

Figure IA1. Rolling Excess ΔR^2 Around FOMC Announcements

This figure shows the excess ΔR^2 from FOMC announcement date until the third day after the announcement ($[0,3]$) from the following unbiasedness regression:

$$Ret_{i[-5,30]} = \alpha_t + \beta_t Ret_{i[-5,t]} + \varepsilon_{i,t},$$

where $Ret_{i[t_1,t_2]}$ are the cumulative S&P 500 index log returns over intervals t_1 to t_2 relative to the day of FOMC announcement i at $t = 0$. The dependent variables are the returns from 5 days prior to 30 days after each announcement, and the independent variables are the returns of the partial announcement window from 5 days prior to the announcement to t. The regression is estimated using a 3-year rolling window (24 FOMC announcements). The sample period is from January 1 1994 to December 31 2021.

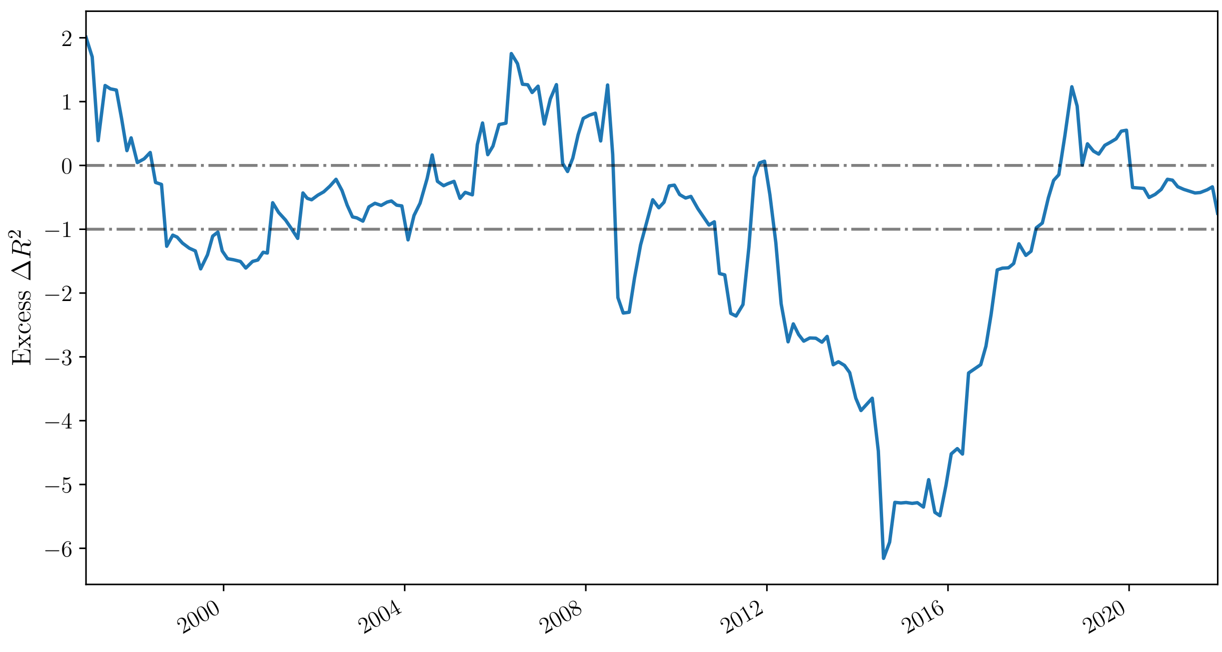


Figure IA2. FOMC Risk Shift

Panel A of this figure shows the cumulative sum of the coefficients of the following regression:

$$r_{i[0,t+h]} = \alpha_h + \beta_{1,h} Risk\ shift_i + \beta_{2,h} Residual_i + \epsilon_h, \tag{14}$$

where $r_{i[0,t+h]}$ is the S&P 500 index log return from the FOMC announcement day to h=20 days after. *Risk shift* corresponds to the fitted values from regressing announcement day returns onto the risk shift component, and *Residual* corresponds to the residual from regressing announcement day returns onto the risk shift, and the long-run and short-run news computed from changes in yields for treasuries and eurodollars. The risk shift, short-run, and the long-run components are from Kroencke, Schmeling, and Schrimpf (2021) and are available from January 1 2006 to December 31 2019. Panel B shows the difference in the cumulative betas and the 90% corresponding confidence intervals around zero computed from 1000 bootstraps.

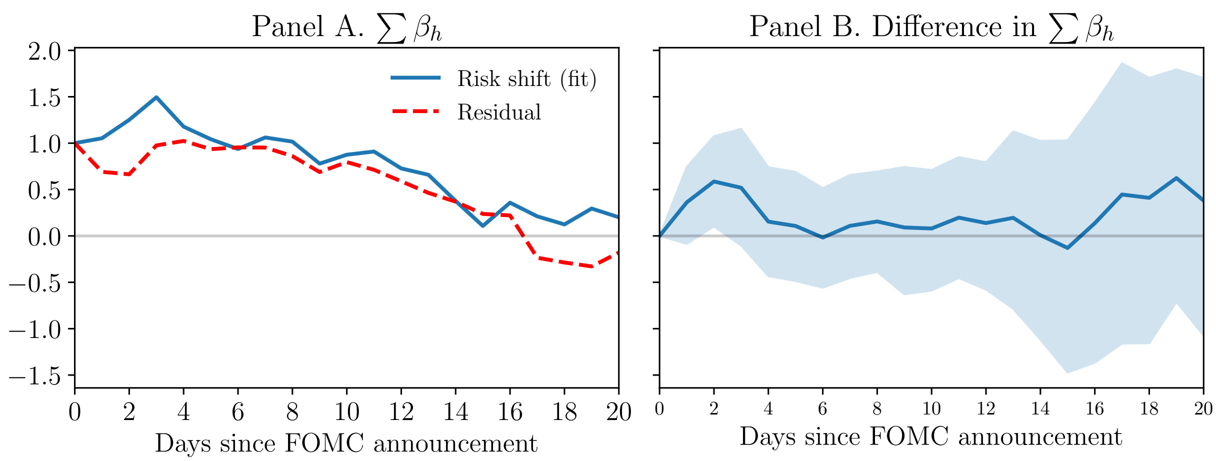


Table IA1
Unbiasedness Regressions - Bootstraps

This table reports the change in R^2 (ΔR^2) and excess ΔR^2 around the day of the FOMC announcement. The R^2 are computed from the following unbiasedness regression:

$$Ret_{i[T_1,T_2]} = \alpha_t + \beta_t Ret_{i[T_1,t]} + \varepsilon_{i,t},$$

where $T_1 < t \leq T_2$, $Ret_{i[t_1,t_2]}$ are the cumulative S&P 500 index log returns over intervals t_1 to t_2 relative to the day of FOMC announcement i at $t = 0$. We define excess $\Delta R^2 \equiv \frac{T}{K}\Delta R^2_t - 1$, where $T = T_2 - T_1 + 1$ is the length of the event window and $K = 1$. The interval $[T_1, T_2]$ is shown in the column headers. The single-day or multi-day windows $[T_1, t]$ are shown in the left column. Outliers-robust bootstrap p-values shown in italics are derived from 100,000 random samples. The sample consist of FOMC announcements between January 1, 1994 to December 31, 2021. The table reports the results for one-day window, multi-day window, and pre-announcement windows in Panels A to C, respectively.

	$[-5,30]$		$[-10,30]$		$[-20,30]$		$[-5,20]$		$[-5,10]$	
	ΔR^2	Excess ΔR^2	ΔR^2	Excess ΔR^2	ΔR^2	Excess ΔR^2	ΔR^2	Excess ΔR^2	ΔR^2	Excess ΔR^2
A. One-day windows										
$t = 0$	-0.025	-1.915	-0.020	-1.838	-0.018	-1.904	-0.010	-1.253	0.056	-0.098
		0.039		*0.041*		*0.037*		*0.091*		*0.411*
$t = 1$	-0.007	-1.240	-0.007	-1.286	-0.008	-1.399	-0.003	-1.084	0.034	-0.448
		0.154		*0.166*		*0.158*		*0.169*		*0.238*
$t = 2$	0.014	-0.513	0.012	-0.500	0.010	-0.469	0.013	-0.671	0.014	-0.776
		0.361		*0.382*		*0.391*		*0.270*		*0.037*
$t = 3$	0.009	-0.691	0.008	-0.676	0.002	-0.904	0.016	-0.585	0.033	-0.469
		0.313		*0.336*		*0.287*		*0.327*		*0.150*
B. Multi-day windows										
$t = [0,3]$	-0.010	-1.090	-0.007	-1.075	-0.013	-1.169	0.016	-0.898	0.138	-0.448
		0.013		*0.017*		*0.014*		*0.015*		*0.022*
$t = [4,7]$	0.024	-0.784	0.021	-0.782	0.011	-0.857	0.084	-0.455	0.180	-0.279
		0.024		*0.036*		*0.029*		*0.090*		*0.049*
$t = [8,11]$	0.045	-0.591	0.049	-0.494	0.038	-0.516	0.084	-0.453		
		0.054		*0.099*		*0.100*		*0.079*		
$t = [12,15]$	0.226	1.032	0.208	1.129	0.163	1.082	0.249	0.619		
		0.975		*0.982*		*0.982*		*0.954*		
C. Pre-announcement										
$t = -1$	0.047	0.676	0.041	0.664	0.033	0.675	0.066	0.709	-0.000	-1.008
		0.637		*0.639*		*0.646*		*0.685*		*0.071*
$t = [-3,-1]$	0.105	0.263	0.102	0.391	0.077	0.312	0.151	0.311	0.231	0.234
		0.668		*0.747*		*0.700*		*0.779*		*0.761*

Table IA2
Predictive Regressions and FOMC Return Reversals with Alternative Windows

This table reports results from predictive regressions of S&P 500 index log returns onto FOMC announcement returns. The regression is

$$Ret_{i[t_1,t_2]} = \gamma_0 + \gamma_1 Ret_{i[0,t_1-1]} + \epsilon_i,$$

where $Ret_{[t_1,t_2]}$ are cumulated over intervals t_1 to t_2, measured in days relative to the current announcement at $t = 0$ and the right-hand side variable $Ret_{[0,t_1-1]}$ is the $t_1 - 1$ day return beginning at 0. τ_1 refers to the date of the following FOMC announcement. Coeff. and Int. corresponds to the estimated parameters γ_0 and γ_1, respectively. Heteroskedasticity-robust standard errors are reported in parentheses, and *,**, and *** indicate associated p-values below $0.1, 0.05$, and 0.01, respectively. The sample consist of FOMC announcements between January 1994 and December 2021 (N=223).

	$[t_1,\ 10]$			$[t_1,\ 20]$			$[t_1,\ \tau_1 - 1]$		
$t_1 - 1$	Coeff.	Int.	R^2	Coeff.	Int.	R^2	Coeff.	Int.	R^2
0	-0.185	-0.001***	0.006	-0.546*	0.006***	0.022	-0.503	0.009***	0.014
	(0.167)	(0.002)		(0.306)	(0.003)		(0.349)	(0.003)	
1	-0.265***	0.000***	0.027	-0.543***	0.006***	0.045	-0.685***	0.010***	0.050
	(0.098)	(0.002)		(0.174)	(0.003)		(0.225)	(0.003)	
2	-0.291***	0.000***	0.045	-0.471***	0.006***	0.046	-0.614***	0.010***	0.055
	(0.097)	(0.002)		(0.145)	(0.003)		(0.188)	(0.003)	
3	-0.291***	-0.000***	0.062	-0.453***	0.005***	0.056	-0.602***	0.009***	0.067
	(0.089)	(0.002)		(0.165)	(0.003)		(0.197)	(0.003)	
4	-0.267**	-0.000***	0.061	-0.346***	0.005***	0.038	-0.585***	0.009***	0.069
	(0.108)	(0.001)		(0.122)	(0.003)		(0.166)	(0.003)	

Table IA3
Subsamples, Alternative Asset Classes and Macroeconomic Announcements

This table reports the excess ΔR^2 for different FOMC subsamples in Panel A, for alternative asset classes on FOMC announcements in Panel B, and for alternative announcements in Panel C. The R^2 are computed from the following unbiasedness regression:

$$Ret_{i[T_1,T_2]} = \alpha_t + \beta_t Ret_{i[T_1,t]} + \varepsilon_{i,t},$$

where $T_1 < t \leq T_2$, $Ret_{i[t_1,t_2]}$ are the cumulative S&P 500 index log returns over intervals t_1 to t_2 relative to the day of FOMC announcement i at $t = 0$. In Panel B, the regression equation is the same, except that we replace Ret by changes in the yield of the corresponding asset on day t relative to the day of FOMC announcement. We define excess $\Delta R^2 \equiv \frac{T}{K}\Delta R_t^2 - 1$, where $T = T_2 - T_1 + 1$ is the length of the event window and $K = 1$ or $K = 4$. The interval $[T_1, T_2]$ is shown in the column headers. The $[T_1, t]$ windows are shown in the left column. p-values shown in italics are derived from 100,000 placebo events randomly matched to each announcement by calendar year, quarter, and day of the week. The sample in Panel A consist of FOMC announcements between January 1, 1979 to December 31, 2021 and between January 1, 1994 to December 31, 2021 in Panels B to D.

	$[-5,30]$		$[-10,30]$		$[-20,30]$		$[-5,20]$		$[-5,10]$	
	ΔR^2	Excess ΔR^2	ΔR^2	Excess ΔR^2	ΔR^2	Excess ΔR^2	ΔR^2	Excess ΔR^2	ΔR^2	Excess ΔR^2
A. FOMC announcement - subsamples										
1979-1993										
$t=0$	0.026	-0.050	0.025	0.007	0.016	-0.209	0.056	0.463	0.096	0.541
		0.622		*0.632*		*0.547*		*0.787*		*0.689*
$t=[0,3]$	0.098	-0.121	0.097	-0.002	0.055	-0.294	0.196	0.271	0.291	0.166
		0.559		*0.619*		*0.434*		*0.716*		*0.646*
1994-2009										
$t=0$	-0.012	-1.416	-0.007	-1.284	-0.008	-1.397	-0.012	-1.324	0.036	-0.427
		0.118		*0.135*		*0.123*		*0.088*		*0.242*
$t=[0,3]$	0.013	-0.884	0.016	-0.836	0.007	-0.911	0.042	-0.729	0.114	-0.544
		0.093		*0.109*		*0.093*		*0.108*		*0.099*
2010-2021										
$t=0$	-0.047	-2.706	-0.044	-2.795	-0.036	-2.831	-0.009	-1.242	0.062	-0.010
		0.076		*0.083*		*0.085*		*0.388*		*0.654*
$t=[0,3]$	-0.035	-1.314	-0.032	-1.328	-0.030	-1.381	-0.014	-1.091	0.171	-0.316
		0.017		*0.026*		*0.032*		*0.028*		*0.226*
B. FOMC announcement - Alternative asset classes										
1-3 years treasury bond ETF										
$t=0$	0.060	1.155	0.057	1.353	0.044	1.224	0.051	0.317	0.084	0.342
		0.639		*0.725*		*0.773*		*0.362*		*0.433*
$t=[0,3]$	0.164	0.479	0.118	0.213	0.125	0.591	0.221	0.434	0.339	0.357
		0.735		*0.629*		*0.889*		*0.766*		*0.869*
30-day Fed fund futures										
$t=0$	0.009	-0.694	-0.007	-1.306	-0.012	-1.603	0.024	-0.374	0.011	-0.830
		0.301		*0.092*		*0.107*		*0.435*		*0.248*
$t=[0,3]$	0.278	1.504	0.174	0.782	0.057	-0.277	0.411	1.672	0.535	1.139
		0.897		*0.733*		*0.513*		*0.995*		*0.992*
3-month Eurodollar futures										
$t=0$	0.069	1.468	0.058	1.371	0.036	0.824	0.169	3.405	0.252	3.036
		0.617		*0.637*		*0.593*		*0.904*		*0.893*
$t=[0,3]$	0.176	0.583	0.162	0.663	0.108	0.373	0.415	1.699	0.623	1.492
		0.789		*0.825*		*0.780*		*0.954*		*0.983*

Table IA3
Subsamples, Alternative Asset Classes and Macroeconomic Announcements (cont.)

	$[-5, 30]$		$[-10, 30]$		$[-20, 30]$		$[-5, 20]$		$[-5, 10]$	
	ΔR^2	Excess ΔR^2	ΔR^2	Excess ΔR^2	ΔR^2	Excess ΔR^2	ΔR^2	Excess ΔR^2	ΔR^2	Excess ΔR^2
C. Treasury futures										
2-year futures										
$t = 0$	0.051	0.846	0.047	0.931	0.034	0.747	0.052	0.341	0.036	-0.418
		0.757		*0.786*		*0.759*		*0.529*		*0.320*
$t = [0, 3]$	0.089	-0.197	0.070	-0.285	0.064	-0.178	0.129	-0.164	0.175	-0.301
		0.432		*0.369*		*0.463*		*0.352*		*0.262*
5-year futures										
$t = 0$	0.008	-0.721	0.003	-0.896	0.008	-0.592	0.023	-0.413	0.040	-0.360
		0.272		*0.204*		*0.315*		*0.332*		*0.270*
$t = [0, 3]$	0.229	1.061	0.200	1.052	0.188	1.394	0.341	1.215	0.442	0.766
		0.922		*0.904*		*0.952*		*0.961*		*0.945*
10-year futures										
$t = 0$	-0.023	-1.829	-0.024	-1.993	-0.014	-1.710	0.007	-0.809	0.033	-0.475
		0.027		*0.021*		*0.036*		*0.130*		*0.213*
$t = [0, 3]$	0.165	0.483	0.149	0.523	0.141	0.798	0.301	0.956	0.422	0.689
		0.819		*0.820*		*0.881*		*0.938*		*0.956*
D. Alternative announcements										
Initial GDP										
$t = 0$	0.036	0.290	0.032	0.300	0.024	0.211	0.047	0.214	0.101	0.608
		0.739		*0.737*		*0.693*		*0.738*		*0.814*
$t = [0, 3]$	0.060	-0.462	0.059	-0.394	0.041	-0.480	0.096	-0.376	0.153	-0.386
		0.115		*0.156*		*0.107*		*0.130*		*0.097*
Unemployement										
$t = 0$	0.035	0.250	0.033	0.361	0.032	0.615	0.047	0.224	0.036	-0.427
		0.769		*0.774*		*0.841*		*0.816*		*0.523*
$t = [0, 3]$	0.144	0.293	0.134	0.374	0.114	0.449	0.195	0.267	0.322	0.288
		0.772		*0.808*		*0.834*		*0.813*		*0.944*
Inflation										
$t = 0$	0.035	0.267	0.032	0.316	0.034	0.710	0.050	0.308	0.115	0.844
		0.595		*0.608*		*0.742*		*0.615*		*0.859*
$t = [0, 3]$	0.108	-0.031	0.098	0.001	0.099	0.260	0.125	-0.189	0.222	-0.114
		0.547		*0.561*		*0.766*		*0.392*		*0.579*

Table IA4
Pre-FOMC Returns

This table reports results from predictive regressions of S&P 500 index log returns onto pre-FOMC announcement returns. The regression is

$$Ret_{i[t_1,t_2]} = \gamma_0 + \gamma_1 Ret_{i[-1,h-1]} + \epsilon_i,$$

where $Ret_{i[t_1,t_2]}$ are cumulative returns over intervals t_1 to t_2 measured in days relative to the current FOMC announcement i at $t = 0$ and the right-hand side variable $Ret_{[-1,h-1]}$ is the h-day return beginning at $t = -1$. Ret_0 and Ret_{-1} refer to the return on and before the FOMC announcement date, respectively. Heteroskedasticity-robust standard errors are reported in parentheses, and *,**, and *** indicate associated p-values below $0.1, 0.05$, and 0.01, respectively. The sample consists of FOMC announcements between January 1994 and December 2021 (N=223).

	Dependent variable						
		Ret_0		$\text{Ret}_{[1,3]}$		$\text{Ret}_{[4,10]}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ret_{-1}	-0.187**		-0.198**	0.082	0.074	-0.344	-0.259
	(0.078)		(0.081)	(0.130)	(0.128)	(0.307)	(0.228)
$\text{Ret}_{[-5,-2]}$		-0.000	-0.020		0.014		0.220**
		(0.055)	(0.051)		(0.080)		(0.101)
$\text{Ret}_{[-10,-6]}$			-0.028		-0.055		0.160**
			(0.060)		(0.077)		(0.079)
Intercept	0.003***	0.003***	0.003***	-0.000	-0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
R^2	0.045	0.000	0.049	0.003	0.008	0.032	0.085

Table IA5
Abnormal Volume on Macroeconomic Announcements

This table reports results of the following regression:

$$Vlm_t = \alpha + \mathbb{1}_{Macro,t} + \mathbb{1}_{Unemp,t} + \mathbb{1}_{Infl,t} + \mathbb{1}_{GDP,t} + \varepsilon_t \text{ in column (1),}$$
$$Vlm_t = \alpha + \mathbb{1}_{FOMC,t} + \mathbb{1}_{PC,t} + \varepsilon_t \text{ in column (2), and}$$
$$Vlm_t = \alpha + \mathbb{1}_{FOMC,t} + \mathbb{1}_{MPS,t} + \varepsilon_t \text{ in column (3).}$$

The dependent variable, Vlm, is the SPY detrended log trading volume. $\mathbb{1}_{Macro,t}$ is a dummy equal to one if there is a macroeconomic announcement {FOMC, Unemployment, Inflation, GDP} on date t, zero otherwise. $\mathbb{1}_{Unemp,t}$, $\mathbb{1}_{Infl,t}$, $\mathbb{1}_{GDP,t}$, $\mathbb{1}_{FOMC,t}$, $\mathbb{1}_{PC,t}$, $\mathbb{1}_{MPS,t}$ are dummies equal to one if there is a unemployment, inflation, GPD (first initial release), FOMC, FOMC with press conference, FOMC with a monetary policy surprise in the top absolute quintile, zero otherwise. The sample period is January 1994 to December 2021, January 2011 to December 2018, January 1994 to December 2019, columns (1)–(2), (3), and (4) respectively.

	Abnormal SPY volume			
	Macro announcements		Press conferences	MPS
	(1)	(2)	(3)	(4)
Intercept	-0.012*	-0.012*	-0.137***	0.002
	(0.007)	(0.007)	(0.009)	(0.007)
$\mathbb{1}_{Macro}$	0.162***			
	(0.030)			
$\mathbb{1}_{Unemp}$	-0.079**	0.084***		
	(0.040)	(0.029)		
$\mathbb{1}_{Infl}$	-0.135***	0.027		
	(0.042)	(0.029)		
$\mathbb{1}_{GPD}$	-0.132***	0.031		
	(0.041)	(0.028)		
$\mathbb{1}_{FOMC}$		0.162***	0.128*	0.103***
		(0.030)	(0.073)	(0.034)
$\mathbb{1}_{PC}$			0.144	
			(0.095)	
$\mathbb{1}_{MPS}$				0.385***
				(0.078)
N	7051	7051	2012	6546
R^2	0.004	0.004	0.009	0.006